Risk Spillover and Macroeconomic Interactions Across Energy, Stock and Agricultural Markets

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ABSTRACT

Energy related topics are very common in the literature of economics since the oil crisis in 1973. So, energy economics became one of the hottest topics in the world's agenda. On the other hand, energy markets are also known as commodity markets and these are complex, dynamic and increasingly global markets all around the world. As we know from the literature, fluctuation of oil prices affects the economy as a whole and has a huge impact on the economy. Their impacts are changed from national to international levels. Therefore, because of this reason, this makes oil market very important and everybody tries to follow and understand the impacts of both current and future changes on the economy.

In this study, we focus on the oil market and try to see the relationship between oil prices, stock exchange market and real effective exchange rate. On the other hand, using a time-varying parameter VAR we study the coherence, conditional volatility and impulse responses of the exchange rates and stock markets to oil price shocks over specific periods and policy regimes for GCC countries.

On the other hand, another chapter of this study is used Time Varying Parameter Stochastic Volatility in Mean (TVP – SVM) model in order to measure the impact of uncertainty shocks on food prices in G-7 countries. The estimation results show important evidence of the time variation in the impact of food price uncertainty on food price.

Finally, this study is also aimed to investigate the relationship between oil price movements and macroeconomic aggregates, such as GDP, CPI, and unemployment, for OECD countries. To do this, second generation econometric methods have been employed to panel data including panel unit root tests, panel cointegration tests, and panel long-run models.

Keywords: Energy, GCC, G-7, OECD, oil prices, stock exchange market, real effective exchange rate, food prices, GDP, CPI, and unemployment

ÖZ

Enerji ile ilgili konular 1973 yılında gerçekleşen petrol krizinden bu yana ekonomi literatüründe oldukça yaygındır. Bu nedenle, enerji ekonomisi tüm dünyanın gündemindeki en popüler konularından biridir. Öte yandan, enerji piyasaları emtia piyasaları olarak da bilinir ve bunlar tüm dünya genelinde karmaşık, dinamik ve gittikçe artan bir şekilde küresel pazarlardır. Literatürden de bilindiği gibi, petrol fiyatlarındaki dalgalanmalar, ekonomiyi bir bütün olarak etkiler ve ekonomi üzerinde çok büyük bir etkiye sahiptir. Etkileri ise ulusal seviyeden uluslararası seviyeye değişiklik gösterir. Bu nedenler, petrol piyasasını çok önemli hale getirmekte ve herkes mevcut ve gelecekteki değişimlerin ekonomi üzerindeki etkilerini takip etmeye ve anlamaya çalışmaktadır.

Bu çalışmada, GCC ülkelerinde petrol piyasasına odaklanarak, petrol fiyatları, borsa piyasası ve reel efektif döviz kuru arasındaki ilişki incelenmeye çalışılmıştır. Öte yandan, zamanla değişen parametre – vektör otoregresif model kullanılarak, uyuşma, koşullu oynaklık testleri yapılmış petrol fiyat şoklarının döviz kurları ve borsalar üzerindeki etki tepki analizleri yapılmıştır.

Bununla birlikte, bu çalışmanın başka bir bölümünde, belirsizlik şoklarının G-7 ülkelerindeki gıda fiyatları üzerindeki etkisini ölçmek için TVP-SVM modeli kullanılmıştır. Tahmin sonuçları, gıda fiyat belirsizliğinin gıda fiyatına etkisinin en önemli kanıtının zaman değişimi olduğunu göstermektedir.

Ayrıca, bu çalışma petrol fiyatlarındaki dalgalanmaların OECD ülkelerinin temel makro ekonomik değişkenleri (Gayri Safi Yurtiçi Hasıla, Tüketici Fiyat Endeksi, İşsizlik Oranı) üzerindeki etkilerini araştırmaktadır. Çalışmada ikinci jenerasyon

ekonometrik metodlar kullanılmıştır, çünkü bu metodların ölçüm sonuçları daha güvenilirdir.

Anahtar Kelimeler: Enerji, GCC, G-7, OECD, petrol fiyatları, borsa, reel efektif döviz kuru, gıda fiyatları, GSYİH, TÜFE, İşsizlik oranı

To My Family

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LIST OF ABBREVIATIONS

ADF	Augmented Dickey Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
AUG Full	Augmented Mean Group Estimator
CADF	Cross Sectionally Augmented Dickey Fuller
CEE Full Robust	Common Correlated Effects Mean Group Estimator
Cereals	Cereals Price Index
CIPS	Cross Sectionally Augmented Panel Unit Root Test
CPI	Consumer Price Index
Dairy	Dairy Price Index
Durbin-H Test	Durbin Hausman Test
ECM	Error Correction Model
ER	Real Effective Exchange Rate
FMLS	Fully Modified Least Squares
Fats	Fats Price Index
Food	Food Price Index
GARCH	Generalized Autoregressive Conditional Heteroskedasticity
GDP	Gross Domestic Production
IRF	Impulse Response Functions
KPSS	Kwiatkowski Phillips Schmidt Shin Stationarity Test
LM_{adj} Test	Bias Adjusted Cross Sectional Dependence Lagrange Multiplier Test
LM Test	Lagrange Multiplier Test
MADF Test	Multivariate Augmented Dickey Fuller test

MCMC	Markov Chain Monte Carlo
Meat	Meat Price Index
MENA	Middle East and North Africa
MGARCH	Multivariate Generalized Autoregressive Conditional Heteroskedasticity
OECD	Organisation for Economic Co-operation and Development Countries
Oil	Oil Price
PP	Phillips and Perron Unit Root Test
S & P 500	The Standard & Poor's 500
SE	Stock Exchange
Sugar	Sugar Price Index
SUR	Seemingly Unrelated Regression
SURADF	Seemingly Unrelated Regression Augmented Dickey Fuller
SVM	Stochastic Volatility Model
TVP - SVM	Time Varying Parameter Stochastic Volatility Model
TVP - VAR	Time Varying Parameter Vector Auto Regression
UAE	United Arab Emirates
UK	United Kingdom
UR	Unemployment Rate
US	United States
US T-Bill	United States Treasury Bill
VAR	Vector Auto Regression
VAR GARCH	Vector Auto Regression Generalized Autoregressive Conditional Heteroskedasticity

VECM	Vector Error Correction Model
VDC	Variance Decomposition
WTI	Western Texas Intermediate

Chapter 1

INTRODUCTION

Energy related topics are very common in the literature of economics since the oil crisis in 1973. So, energy economics became one of the hottest topics in the world's agenda. Also, the fluctuation of oil prices affects the economy as a whole and has a huge impact on the economy. The fluctuation of oil prices has impact on almost every sector of the economy such as financial, manufacturing, electricity, transportation, shipping and etc.

On the other hand, agricultural sector is also very important for the country's especially those who are in a developing process. For instance, the food price volatility has impact on a specific food prices and this impact may cause to decrease the consumption of foods.

To this end, Chapter 2 investigates the relationship between the oil prices, asset prices, and foreign exchange rates in the selected GCC economies, namely United Arab Emirates (UAE), Qatar, Kuwait and Saudi Arabia. Using a time-varying parameter VAR we study the coherence, conditional volatility and impulse responses of the exchange rates and stock markets to oil price shocks over specific periods and policy regimes. The model is identified using sign-restrictions imposed on the impulse responses over contemporaneous and long horizons.

Chapter 3 covers the impact of food price volatility on each food prices which are cereals, dairy, fats, meat and sugar. Time Varying Parameter Stochastic Volatility in Mean (TVP – SVM) model is used to measure the impact of uncertainty shocks on food prices in G-7 countries. In our estimations, we considered the results of volatility, posterior moments of the stochastic volatility in mean model parameters and finally the evolution of volatility and the impact of volatility on each food price.

Chapter 4 focuses on the relationship between oil price movements and macroeconomic aggregates, such as gross domestic product (GDP), consumer prices (CPI), and unemployment rate (UR), for OECD countries. To do this, second generation econometric methods have been employed to panel data including panel unit root tests, panel cointegration tests, and panel long-run models. All of these estimations are done by using the Lagrange Multiplier test and the bias adjusted cross sectional dependence Lagrange Multiplier test. Also, CADF unit root test are used for testing cross sectional dependency and structural breaks. On the other hand, Durbin – H test is used to see whether or not there is cointegration between series. Lastly, CCE Full Robust and AUG Full are used to estimate the possibility of long run relationship between variables.

Chapter 5 provides a general conclusion of the each chapter separately and it reflects the whole idea of the thesis.

Chapter 2

DYNAMICS OF OIL PRICES, EXCHANGE RATES AND ASSET PRICES IN THE GCC COUNTRIES

2.1 Introduction

Energy related topics are very common in the literature of economics since the oil crisis in 1973. So, energy economics became one of the hottest topics in the world's agenda. On the other hand, energy markets are also known as commodity markets and these are complex, dynamic and increasingly global markets all around the world. As we know from the literature, fluctuation of oil prices affects the economy as a whole and has a huge impact on the economy. Their impacts are changed from national to international levels. Therefore, because of this reason, this makes oil market very important and everybody tries to follow and understand the impacts of both current and future changes on the economy.

In this study, we focus on the oil market and try to see the relationship between oil prices, stock exchange market and real effective exchange rate. It is obvious that, oil price fluctuations play a key role on the economy especially those who produce and export the oil like selected GCC countries, namely United Arab Emirates (UAE), Qatar, Kuwait and Saudi Arabia. These countries are the top oil exporter countries in the world ranking. For instance, Saudi Arabia is the first and top oil exporter country in the world with US$ 133.3 billion/year which is equal to 17% of the total crude oil export of the world. Then, UAE exports US$ 51.2 billion which is equal to 6.5%, Kuwait exports US$ 34.1 billion which is equal to 4.3% and Qatar exports US$ 10.6 billion which is equal to 1.3% of the total crude oil export of the world. So, we expect to see the impact of the oil price fluctuations on the economy of these countries. On the other hand, using a time-varying parameter VAR we study the coherence, conditional volatility and impulse responses of the exchange rates and stock markets to oil price shocks over specific periods and policy regimes.

The model is identified using sign-restrictions as Mumtaz and Sunder Plassmann (2013) used and imposed on the impulse responses over contemporaneous and long horizons. Therefore, our approach is parallel with the Mumtaz and Sunder Plassmann (2013) so, we use the same methodology of them in this study.

Our results suggest that the impact of oil prices on the exchange rate and asset prices are time dependent. Hence, there is a loss in information when using standard linear models that average out effects over time which is also mentioned in Mumtaz and Sunder Plassmann's (2013) study. The response of the exchange rates and asset prices to oil prices weakens and strengthens depending on the regime of the markets. The period following financial crisis uniformly strengthens the relationships between the variables. The responses also vary across the GCC economies, emphasizing the fact that differences exists across these economies although their economic structures increasingly becoming similar.

The contribution of the study to the literature is by studying how the selected GCC countries reacted to the fundamental shocks especially to see the sign of the co-movements with the shocks over time. Another contribution is that, we use TVP

VAR model rather than using VAR model in order to capture the important changes to the economy.

This study is organized as follows; Section 2 provides an overview of the existing literature on the concepts of oil prices, stock exchange market and real effective exchange rate. Section 3 presents the data and empirical techniques that are used in this paper, respectively. Section 4 reports the empirical findings from TVP-VAR model. Lastly, Section 5 provides the final remarks and policy recommendations.

2.2 Literature Review

Amano and Norden (1998) investigate the linkage between oil prices and real exchange rates for United States, Germany, and Japan by using monthly data between 1973 – 1993 years. Augmented Dickey Fuller (1979) and Phillips and Perron (1988) unit root tests are done for stationarity, then they move to Johansen and Juselius (1990) cointegration test in order to see the long run relationship between oil prices and real exchange rates. Also, they apply to other methods like Phillips and Hansen's (1990) fully modified least squares (FMLS) and Hansen's (1992) in order to see the stability of the parameter. According to estimation results, Granger causality test shows that, although oil prices Granger cause real exchange rate in the long run, real exchange rate does not Granger cause oil prices. Moreover, oil prices play a significant role on other macroeconomic variables of the long term exchange rates.

Amano and Norden (1998) estimate the relationship between oil prices and United States real exchange rate by using monthly data over the periods 1972.2 – 1993.1 for United States. Augmented Dickey Fuller (ADF) and Phillips and Perron (PP) unit root tests and Kwiatkowski Phillips Schmidt Shin (KPSS) stationarity test are done in order to estimate the stationarity and they run for Johansen Juselius cointegration test to check whether or not there is long term relationship between two variables. Johansen and Granger causality tests are used separately and Error Correction Model (ECM) is used as a method. As a result, they find causality which runs from oil prices to the real exchange rate, but not runs from real exchange rate to oil in the long run. Also, ECM has significant ability to predict out of sample for the sign and the size of the changes in real exchange.

Hammoudeh and Choi (2006) investigate the effect of oil price and financial markets of US on GCC stock markets. They use daily data for the period 15 February, 1994 – 28 December, 2004. Also, two different oil price series are used which are US Western Texas Intermediate (WTI) and UK Brent spot, then US Treasury bill rate, S&P 500 index as a US stock market return and five GCC stock markets are used to estimate the results. They find that, although WTI or Brent oil price and S&P 500 index do not have direct impact on GCC stock markets, profitability and liquidity have direct impact on them. Also, direct impact of US T-bill is found on some of the GCC stock markets. In contrast, impulse response results show that, there is positive dynamic impact of S&P 500 index shocks on all of the GCC markets in twenty weeks forecast horizon. On the other hand, the findings show that, while US market becomes more valuable, then the value of GCC stock markets increase as well.

Zarour (2006) estimates the effect of increase in oil prices on stock market returns for five GCC countries (Bahrain, Kuwait, Oman, Saudi Arabia, and Abu Dhabi) by using vector autoregression model (VAR). Daily data is used and it begins in 25 May, 2001 and ends in 24 May, 2005. Estimation results show that, when the price of oil is doubled in these periods, this causes to big cash surplus in GCC stock market returns and influence them positively. On the other hand, impulse response functions prove that, when the price of oil increased, the response of stock markets to the oil price shocks raised fastly. Moreover, responses of Saudi Arabian stock market returns to the shocks are more and vice versa.

Chen and Chen (2007) try to estimate the long run relationship between oil price and real exchange rate. They use a monthly data between 1972 – 2005 years and try to estimate the relationship on G-7 countries. Estimation results provide a linkage between these two variables and also oil prices are the main source of real exchange rate fluctuations. On the other hand, they try to see if oil prices are able to forecast the future real exchange rates and find a significant result at the end.

Using a daily data, Malik and Hammoudeh (2007) focus on the impact of oil prices on United States and some of GCC (Saudi Arabia, Kuwait, and Bahrain) equity markets. They use standard Box Jenkins techniques as a method in order to estimate the impact of oil prices. They find a significant transmission into the second moments. On the other hand, there is volatility which runs from oil market only to Saudi Arabian equity market in all cases and there is significant volatility spillover from Saudi market to oil market. Also, estimation results make a guidance for building asset pricing model, forecasting of future equity and oil price return volatility and also the analyzing the link between GCC stock market, United States equity market and oil market.

Maghyereh and Al-Kandari (2007) focus on the relationship between oil prices and stock market returns in GCC countries. They use Breitung's method which is rank tests of nonlinear cointegration estimations over the period 1 January, 1996 – 31 December, 2003. They find nonlinear relationship between oil prices and stock market returns in GCC countries.

Zhang et.al. (2008) investigate the spillover impact of US dollar exchange rate on oil prices by using cointegration tests, VAR model, ARCH models and Granger causality test in risk. They find three types of spillover effect which are mean, volatility and risk spillover. Also, rigorous appraisal analysis is done in order to see the impact of US dollar exchange rate on oil price over the periods 4 January, 2000 – 31 May, 2005. They find that, there is a linkage between exchange rate and oil prices in the long run. On the other hand, Granger causality test shows changes in US dollar exchange rate Granger cause the volatility of oil price but not vice versa. However, volatility spillover effect is not significant. In other words, both the price volatility of US dollar exchange rate and oil are not dependent to each other which means they follow different ways and also this shows if US dollar exchange rate fluctuations may not cause any significant changes in oil price market. Moreover, risk spillover effect seems to be limited and price risk effect of US dollar exchange rate on price of oil is partial.

Arouri and Rault (2009) analyze the impact of oil prices on the stock markets of Gulf Corporation Countries (GCC) in the long term by using bootstrap panel cointegration techniques and Seemingly Unrelated regression (SUR) methods. They also use two sets of data which are weekly and monthly. One of the data set starts from 7 June, 2005 and ends with 21 October, 2008 and second dataset starts from January 1996 and December 2007. On the other hand, the estimation results provide that there is long run relationship between oil prices and stock markets in GCC countries and also increases in oil price has positively significant effect on stock prices, but it is not same in Saudi Arabia.

Arouri and Rault (2010) investigate the same relationship as mentioned above. In other words, they try to investigate the sensitivity of GCC stock markets to oil price shocks by using the same methods but adding the Granger causality test and the same dataset for the same periods. They find bidirectional causality which means oil price shocks Granger cause GCC stock price changes for Saudi Arabia, but do not find the Granger causality for the other GCC countries. As a result, both stock market and oil market investors should be aware of the price changes of both markets in Saudi Arabia.

Lizardo and Mollick (2010) investigate the relationship between oil price fluctuations and US dollar exchange rates by using VAR model during 1970 – 2008 periods on both oil exporter and importer countries. The results show that, when oil prices increase, US dollar starts to depreciate significantly against net oil exporter currencies. Moreover, net oil importers currencies which is Japanese Yen depreciates while real oil price increases.

Mohanty et. al. (2011) estimate the relationship between oil price fluctuations and stock market prices for GCC countries over the June 2005 - December 2009 period by using weekly both country level and industry level stock return data and linear factor pricing model. They found negative effect of decreases in oil price on stock market returns in all GCC countries, but, in contrast, positive and significant effect of increases in oil prices on stock market returns only in two GCC countries which are United Arab Emirates and Saudi Arabia at the country level. On the other hand, they found a positive effect of oil price shocks on stock market returns in 12 out of 20 industries at the industry level estimations.

Fayyad and Daly (2011) examine how the oil price shocks influence stock market returns. They use daily data for GCC countries and two more countries which are US and UK over the period 2005 – 2010. Vector Auto Regression (VAR) analysis is used to estimate the results and find that, when the price of oil increases, it has more impact on stock market return and also it is affected more from Global Financial Crises. They find that, United Kingdom in advanced countries and United Arab Emirates and Qatar in GCC countries give more response to the oil price shocks comparing with other countries.

Arouri et. al. (2011) apply to VAR-GARCH model in order to analyse the volatility transmission and the return links between oil prices and stock markets of GCC countries during 2005 – 2010 periods by using daily data set of the GCC stock market prices and world oil prices. Estimation results show that, there are significant shock and volatility spillovers between oil prices and stock markets mainly during the crisis. On the other hand, volatility of GCC stock markets increases while world oil prices increase and affecting the both demand and supply sides of the oil.

Benhmad (2012) studies on both linear and nonlinear Granger causality between oil price and real effective exchange rate on US by using wavelet approach. According to estimation results, bidirectional causality is found between oil price and exchange rate and also this relationship varies over time. Another important result is that, causality is only running from oil prices to real effective exchange rate.

Reboredo (2012) examine the dependency of oil price and exchange rate by using both linear and nonlinear dependency measures which are Pearson correlation for linear, Spearman and Kendall rank correlation for nonlinear and copula function for estimating the tail and asymmetric dependence. Daily data span from 4 January, 2000 to 15 June, 2010. US oil prices and European Union exchange rate data sets are used for estimations. The results show that, dependency between oil price and exchange rate are weak, but it increases after global financial crisis largely and they do not find high degree of dependency between oil and exchange rate market.

Akoum et. al. (2012) investigate the dependencies between stock market returns and OPEC basket oil returns both in the short run and long run by using wavelet coherency method during 2002 – 2011 years for GCC countries, Egypt and Jordan. According to estimation results, co movements of oil prices and stock market prices are changed in the long run (over 6 months). Also, market dependencies have become more powerful after 2007 and market dependencies are weak in the short run (between 2 weeks and 6 months periods). As a result of the study, dependencies between stock market returns and oil prices differ from country to country.

Beckman and Czudaj (2013) focus on the relationship between oil prices and effective dollar exchange rate on twenty six currencies by using Markov switching vector error correction model. This model can separate short term and long term time varying dynamics. Estimation results show that, they do not only depend on the choice of exchange rate measure. In addition, time varying causality runs from nominal real effective exchange rate to nominal oil prices.

Naifar and Dohaiman (2013) focus on the effect of crude oil prices on stock market returns by using Markow regime – switching model which are crisis and non-crisis regimes. The period of the study starts in 7 July, 2004 and ends in 10 November, 2011 which means using daily basis data for GCC countries. They find that, the linkage between volatility of crude oil prices and stock market return are regime dependent.

Khalfaoui et. al. (2015) estimate the relationship between stock market and crude oil market and also focus on the volatility spillovers of oil and stock market prices by using two approaches which are multivariate GARCH models and wavelet based MGARCH approach in G-7 countries. Daily data span from 2 June, 2003 to 7 February, 2012. As a result of the study, the volatility spillovers between oil and stock markets are highly significant and the correlation is time varying between them.

Maghyereh and Awartani (2016) investigate the effect of oil price uncertainty on the stock market by using GARCH (Generalized Autoregressive Conditional Heteroskedasticity) in mean VAR (Vector Autoregression) model in MENA region. The weekly data is used during 2001 – 2014 years. The empirical findings prove that, the effects of oil price uncertainty on stock market returns are negative and significant in MENA region. Another important finding is that, the effect of oil price is more critical if the economy of the country depends on the oil revenue and also if it has effect on economic growth.

2.3 Methodology

We use monthly data from 2004M01 to 2016M09 for United Arab Emirates (UAE), from 2002M01 to 2015M09 for Qatar, from 2004M02 to 2016M09 for Kuwait and from 2003M12 to 2016M07 for Saudi Arabia. The data is taken from Data Stream. We use three different variables which are crude oil price, stock exchange price index and real effective exchange rate of each country and we calculate the growth of each variable.

In our study, we follow the same methodology of Mumtaz and Sunder – Plassmann (2013), but the basic empirical model is determined by the Clarida and Gali (1994). The TVP – VAR builds on Pricimeri (2005). On the other hand, we use the same approach like Mumtaz and Sunder – Plassmann (2013) which is sign restrictions in order to identify the shocks. But, Pricimeri (2005) used Cholesky decomposition. In our analysis, three different shocks are defined which are oil price, stock exchange and real effective exchange rate shock. When the shocks are given to variables in each country, the responses of the variables are same to the each shock. Also, responses of these variables are confirmed the economic theory with assigned signs. As a result, oil price shock increases stock exchange and real effective exchange rate and increases the price of oil too. When the stock exchange shock is given, it reduces the oil prices and appreciates the real effective exchange rate and it has positive impact on itself. A final shock is the real effective exchange rate shock and it increase oil prices and appreciating real effective exchange rate but depreciates the stock exchange.

The sign restrictions are summarized and contemporaneous as following;

Table 1: The Sign Restrictions

	Oil (Oil Price)	SE (Stock Exchange)	ER (Real Effective Exchange Rate)
Oil Price Shock	+	+	+
Stock Exchange Shock	-	+	+
Real Effective Exchange Shock	+	-	+

Our estimated TVP -VAR model is shown as following;

$$Z_t = c_t + \sum_{l=1}^{L} \varphi_{l,t} Z_{t-l} + v_t \qquad (1)$$

Where $Z_t = \Delta oil_t, \Delta se_t, \Delta er_t$ (oil = crude oil price US$/BBL, se = stock exchange price index, er = real effective exchange rate domestic currency/US$) and the meaning of L is the lag length.

As we mentioned above, we use the Clarida and Gali’s (1994) empirical model as a basic model so the main difference of our empirical model is to allow for time variation in the parameters of VAR and the covariance of residuals.

We assume to have the following law of motion for the parameters;

$$\hat{\varphi}_{l,t} = \hat{\varphi}_{l,t-1} + \eta_t \qquad (2)$$

Where $\hat{\varphi}_{l,t} = \{vec\ (c_t), vec\ (\varphi_{l,t})\}$ denotes the time varying parameters bulked in one vector and η_t denotes the confortable vector innovations. The covariance matrix of the innovations is factored as follows;

$$VAR(v_t) \equiv \Omega_t = A_t^{-1} H_t (A_t^{-1})' \qquad (3)$$

The time varying matrices which are H_t and A_t are defined as follows;

$$H_t \equiv \begin{pmatrix} h_{1,t} & 0 & 0 \\ 0 & h_{2,t} & 0 \\ 0 & 0 & h_{3,t} \end{pmatrix} A_t \equiv \begin{pmatrix} 1 & 0 & 0 \\ \alpha_{21,t} & 1 & 0 \\ \alpha_{31,t} & \alpha_{32,t} & 1 \end{pmatrix} \qquad (4)$$

The parameter in H_t which is $h_{i,t}$ developing as geometric random walks;

$lnh_{i,t} = lnh_{i,t-1} + \hat{v}_t$.

On the other hand, as Pricimeri (2005) used in his study, we accept non one and non-zero elements of matrix A_t to develop as driftless random walks;

$$\alpha_t = \alpha_{t-1} + \tau_t \qquad (5)$$

Then, the distribution of vector of innovations is shown below;

$$\begin{pmatrix} v_t \\ \eta_t \\ \tau_t \\ \tilde{v}_t \end{pmatrix} \sim \text{N (0, V), with} V = \begin{pmatrix} \Omega_t & 0 & 0 & 0 \\ 0 & Q & 0 & 0 \\ 0 & 0 & S & 0 \\ 0 & 0 & 0 & G \end{pmatrix} \text{ and } G = \begin{pmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \sigma_2^2 & 0 \\ 0 & 0 & \sigma_3^2 \end{pmatrix} \qquad (6)$$

TVP – VAR model is written compactly as;

$$y_t = x_t' \tilde{B}_t + A_t^{-1} H_t \varepsilon_t \qquad (7)$$

Where $y_t = vec(Z_t)$, $x_t = I \otimes [1, Z_{t-1}, Z_{t-2}, \ldots]$, $\tilde{B}_t = ([c_t, \varphi_{1,t}, \varphi_{2,t}, ...])$ and $VAR(\varepsilon_t) = I$.

As it is mentioned before, TVP – VAR model will be used in our study and Equation (7) will be our structure of the study. However, we need to rewrite the equation (7) again for estimating the results. Also, this equation takes into consideration of the changes in the role and transmission of structural shocks.

Rewriting of equation (7) is as following;

$$y_t = x_t \tilde{B}_t + \tilde{A}_{0,t} \varepsilon_t \qquad (8)$$

On the other hand, $\tilde{A}_{0,t}$ is a TVP – VAR structural effect matrix and it is not always lower triangular.

$$\Omega_t = \tilde{A}_{0,t}' \tilde{A}_{0,t}$$

Since there is a structural VAR in equation (8), it provides flexibility at two dimensions. First of all, it allows them to have the simultaneous relationships between v_t to be different within a time period. Also, this approach is suited for the economy of the each country in the study.

Moreover, $\tilde{A}_0$ which is known as fixed impact matrix is not able to estimate the feature of the data in our study. So, when we take the structural changes into consideration in the economy, it is shown that, the cause of structural changes are not only the because of policy rules. Then, this brings independent shifts in different structural changes (equations) of the model. On the other hand, when there is independent time variation lagged and contemporaneous coefficient, then the model seems to be a good proxy for the structural changes. In addition, TVP –VAR model allows having shifts in the shock volatility and these shifts are independent from the changing in the coefficients B_t.

2.4 Estimation Results

2.4.1 Time Varying Volatility

Time variation gives chance to model the conditional and unconditional volatility. We can estimate the time varying volatility at each point in time with standard deviations. The estimated unconditional variances are;

$$\int_{-\pi}^{\pi} \hat{f}_{t|T^{ii}(\omega) d\omega} \qquad (9)$$

$\hat{f}_{t|T^{ii}(\omega)}$ shows the spectrum of the ith endogenous variable at frequency ω. According to Hamilton (1994), diagonal values of $\hat{f}_{t|T^{ii}(\omega)}$ are non-negative and real valued for all ω but off-diagonal values are complex numbers. The calculated spectral density matrix is;

$$\hat{f}_{t|T^{i}(\omega)} = \left(I_4 - \hat{\varphi}_{t|T} e^{-i\omega}\right) \frac{\hat{\Omega}_{t|T}}{2\pi} \left[\left(I_4 - \hat{\varphi}_{t|T} e^{-i\omega}\right)^{-1}\right]' \qquad (10)$$

$\hat{\Omega}_{t|T}$ and $\hat{\varphi}_{t|T}$ are the estimation of TVP VAR error covariance and coefficients of VAR model. In addition, the existence of time variation in the model shows that, the estimation of each point in time can be done by using equation (10). So, we can get the estimated time varying volatility by using equation (9).

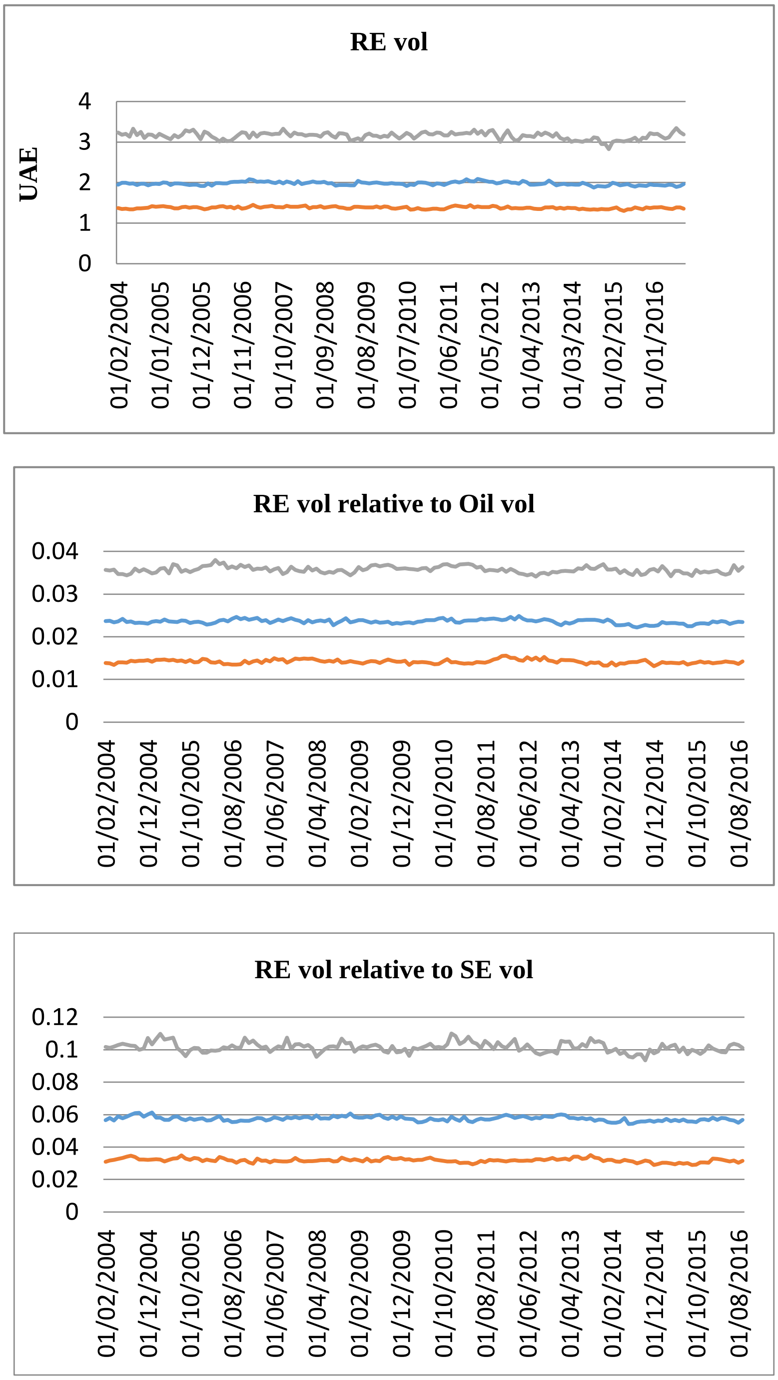
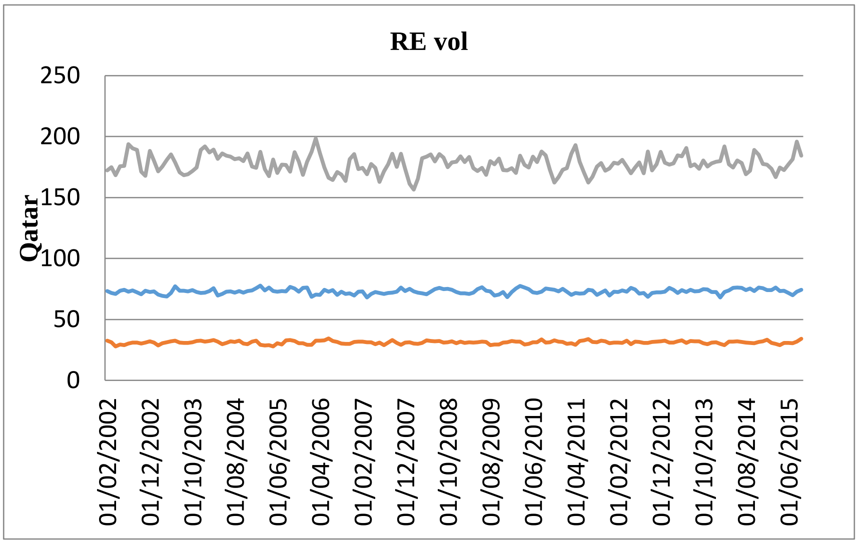
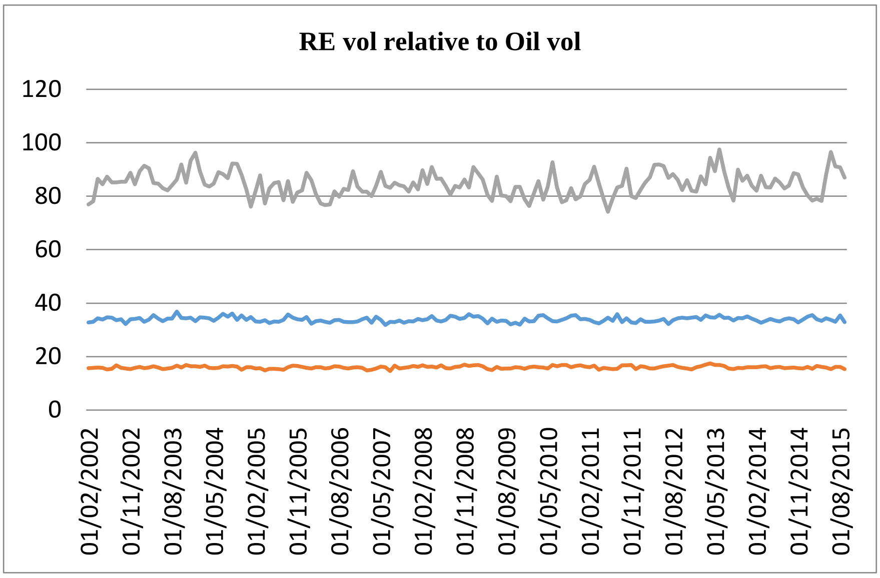


Figure 1: Conditional and unconditional exchange rate volatility (with standard errors)





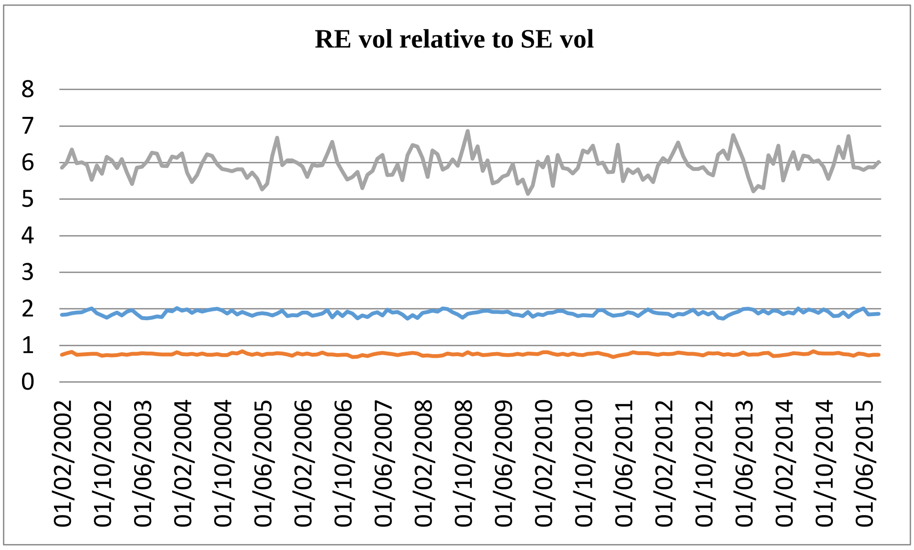


Figure 2 (continued): Conditional and unconditional exchange rate volatility (with standard errors)

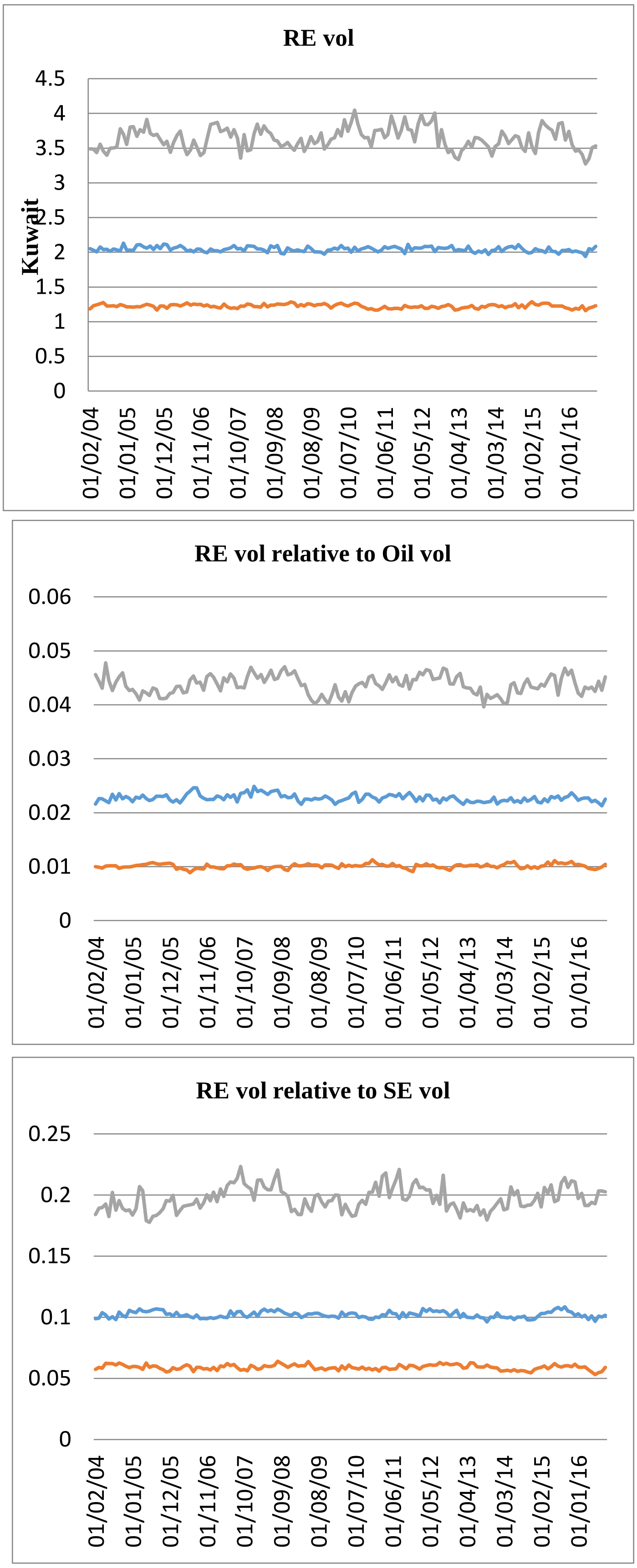


Figure 3 (continued): Conditional and unconditional exchange rate volatility (with standard errors)

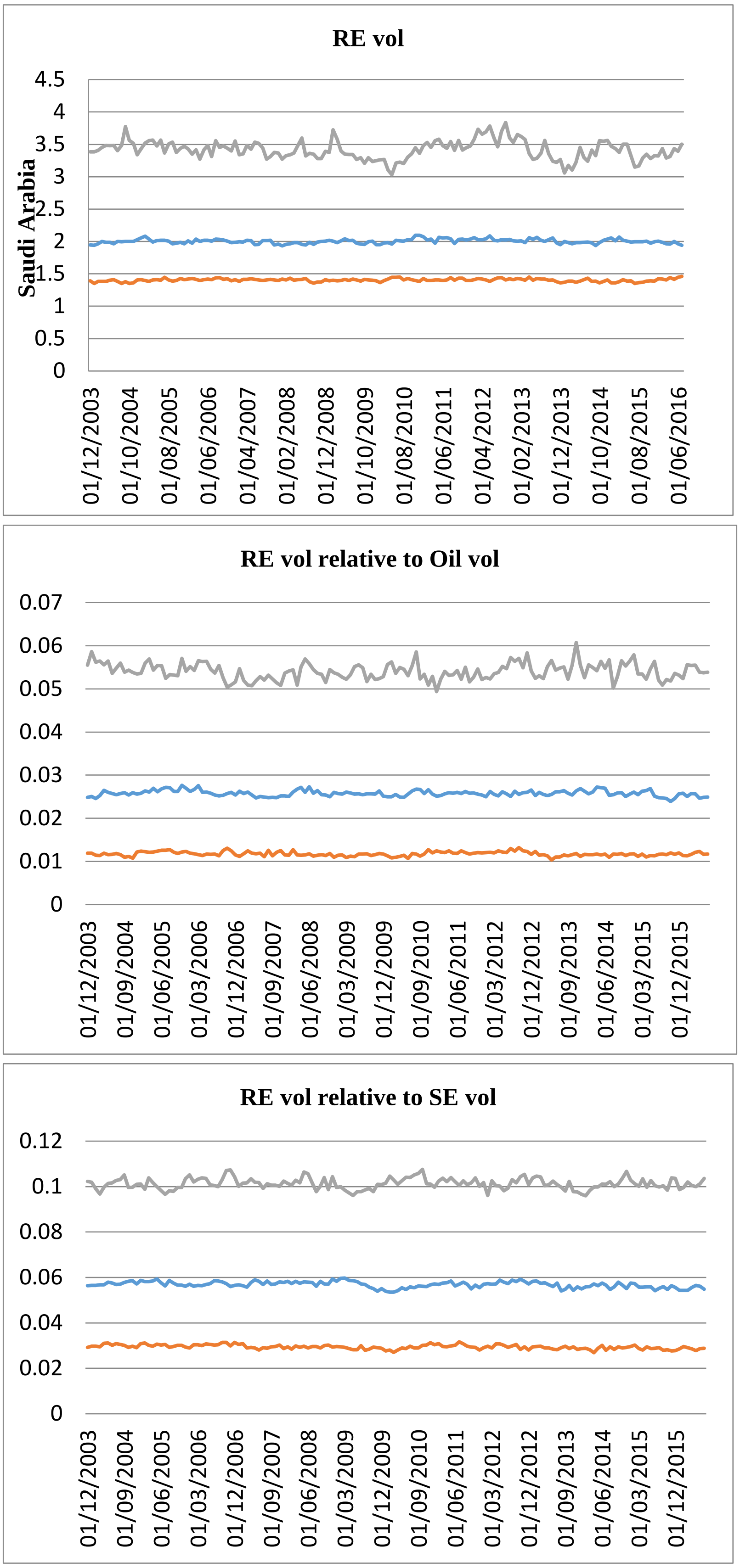


Figure 4 (continued): Conditional and unconditional exchange rate volatility (with standard errors)

We now discuss about the time varying volatility of real effective exchange rate and the relationship between the real effective exchange rate and fundamentals which are oil and stock exchange. Our estimation covered four countries which are UAE, Qatar, Kuwait and Saudi Arabia respectively. Above the Figure 1 shows the conditional and unconditional exchange rate volatility (standard deviation) of countries separately.

In general, real effective exchange rate volatility itself is stable in each country. When the analyses are done for each country, the results are almost same in each country except Qatar. For UAE, Kuwait and Saudi Arabia, the real effective exchange rate is 2.5% less volatile relative to oil. Also, for UAE and Saudi Arabia 6% less volatile relative to stock exchange and for Kuwait 10% less volatile relative to stock exchange. Moreover, stock exchange is more volatile than oil in these countries. On the other hand, for Qatar, real effective exchange rate is 34% less volatile relative to oil and 2% less volatile relative to stock exchange. Also, oil is more volatile than stock exchange.

In addition to these results, we investigate the relationship between oil and the fundamentals by using time varying VAR in order to check how series are jointly influenced by cycles at various frequencies. The off-diagonal elements of the spectral-density matrix give a summary of this relationship in equation (10). We concentrate on the measure of relationship by using coherence. The definition of coherence is known as the degree to which the two series are jointly influenced by cycles of frequency ω.

The calculation of the coherence is;

$$\hat{h}_{ij}(\overline{\omega}) = \frac{[\hat{c}_{ij}(\overline{\omega})]^2 + [\hat{q}_{ij}(\overline{\omega})]^2}{\hat{f}^{ii}{}_{t|T^i(\omega)}\,\hat{f}^{jj}{}_{t|T^i(\omega)}} \qquad (11)$$

$\hat{c}_{ij}(\overline{\omega})$ represents the co-spectrum which means the real component of the off-diagonal elements of the spectral density matrix $\hat{f}_{t|T(\omega)}$. On the other hand, $\hat{q}_{ij}(\overline{\omega})$ represents the quadrature spectrum which means the imaginary component of the off-diagonal elements of the spectral density matrix $\hat{f}_{t|T(\omega)}$. Hamilton (1994) investigate that, co-spectrum tests the covariance between the series at difference frequencies. Also, he found that, the series are at a different phase in the cycle in quadrature spectrum. High values of $\hat{h}_{ij}(\overline{\omega})$ shows that, series i and j share a common cycle at a specific frequency. Also, it is know that $0 < \hat{h}_{ij}(\overline{\omega}) < 1$. Moreover, if there is high values of $\hat{h}_{ij}(\overline{\omega})$, we know that, the relationship between oil and the fundamentals which are stock exchange and real effective exchange rate would be at various horizons. Below the Figure 2a, 2b, 3a, 3b, 4a, 4b, 5a and 5b measure the level of coherence of the oil with stock exchange and real effective exchange rate for UAE, Qatar, Kuwait and Saudi Arabia respectively.

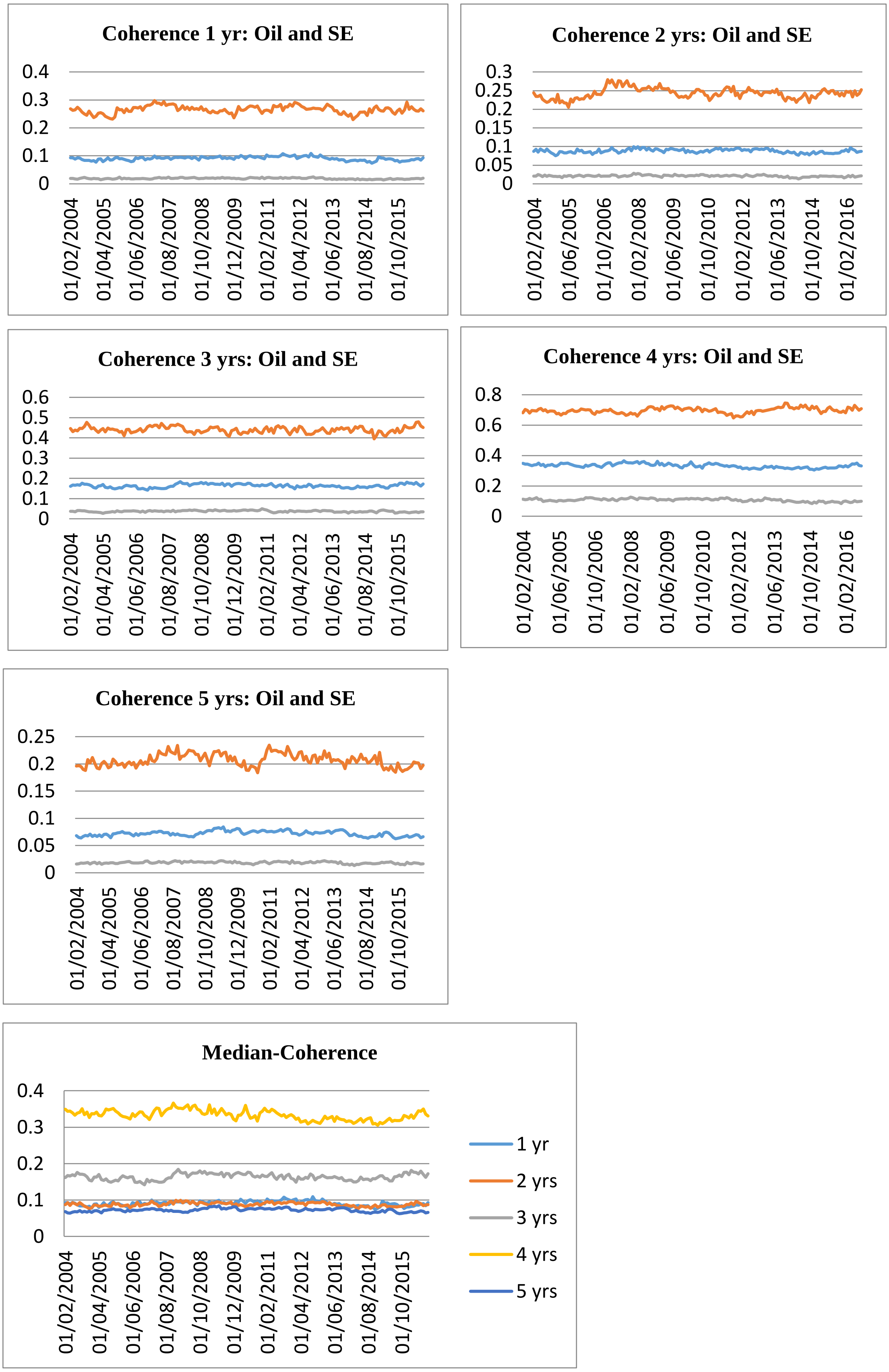


Figure 2a: Coherence between Oil and SE for UAE

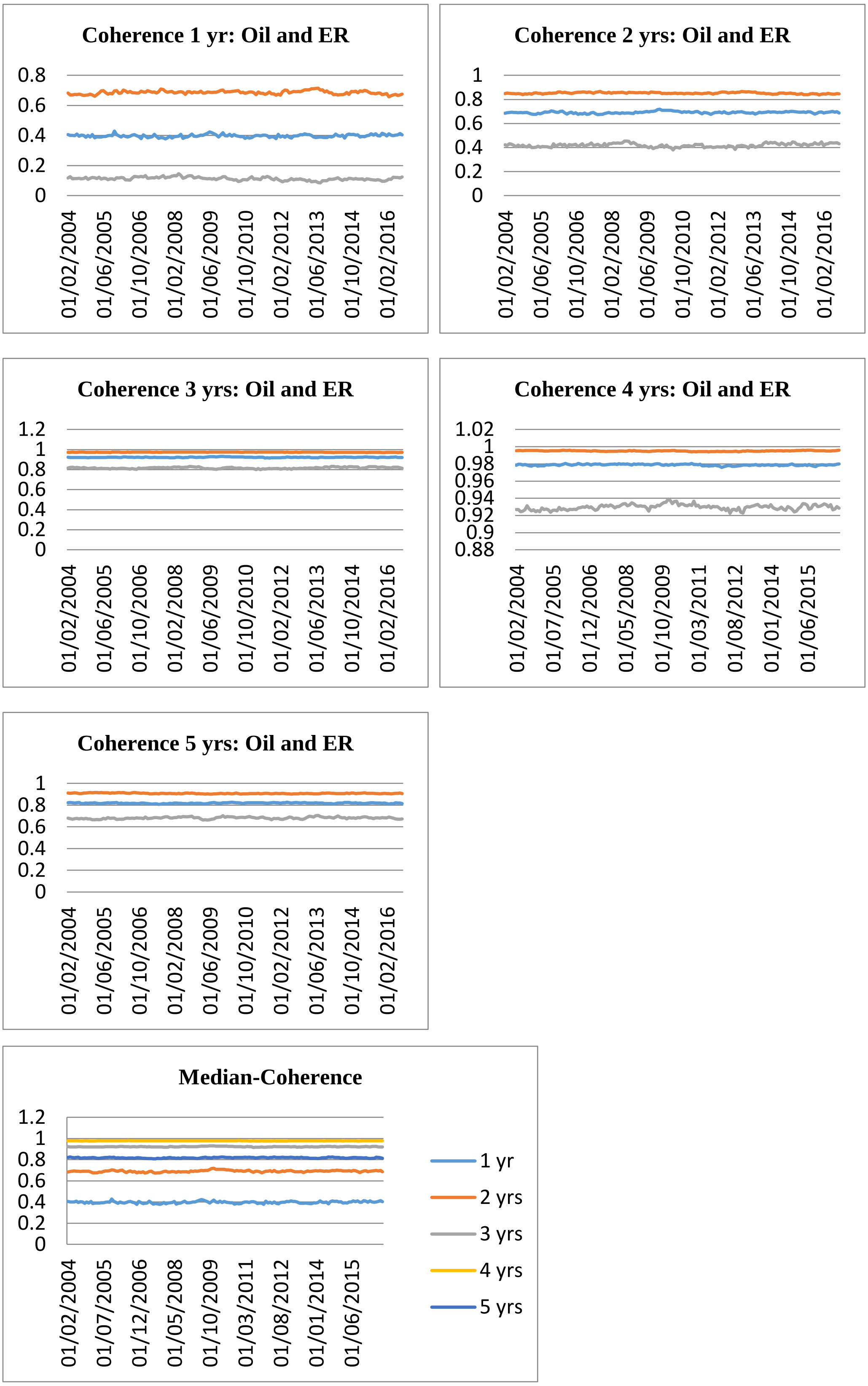


Figure 2b: Coherence between Oil and ER for UAE

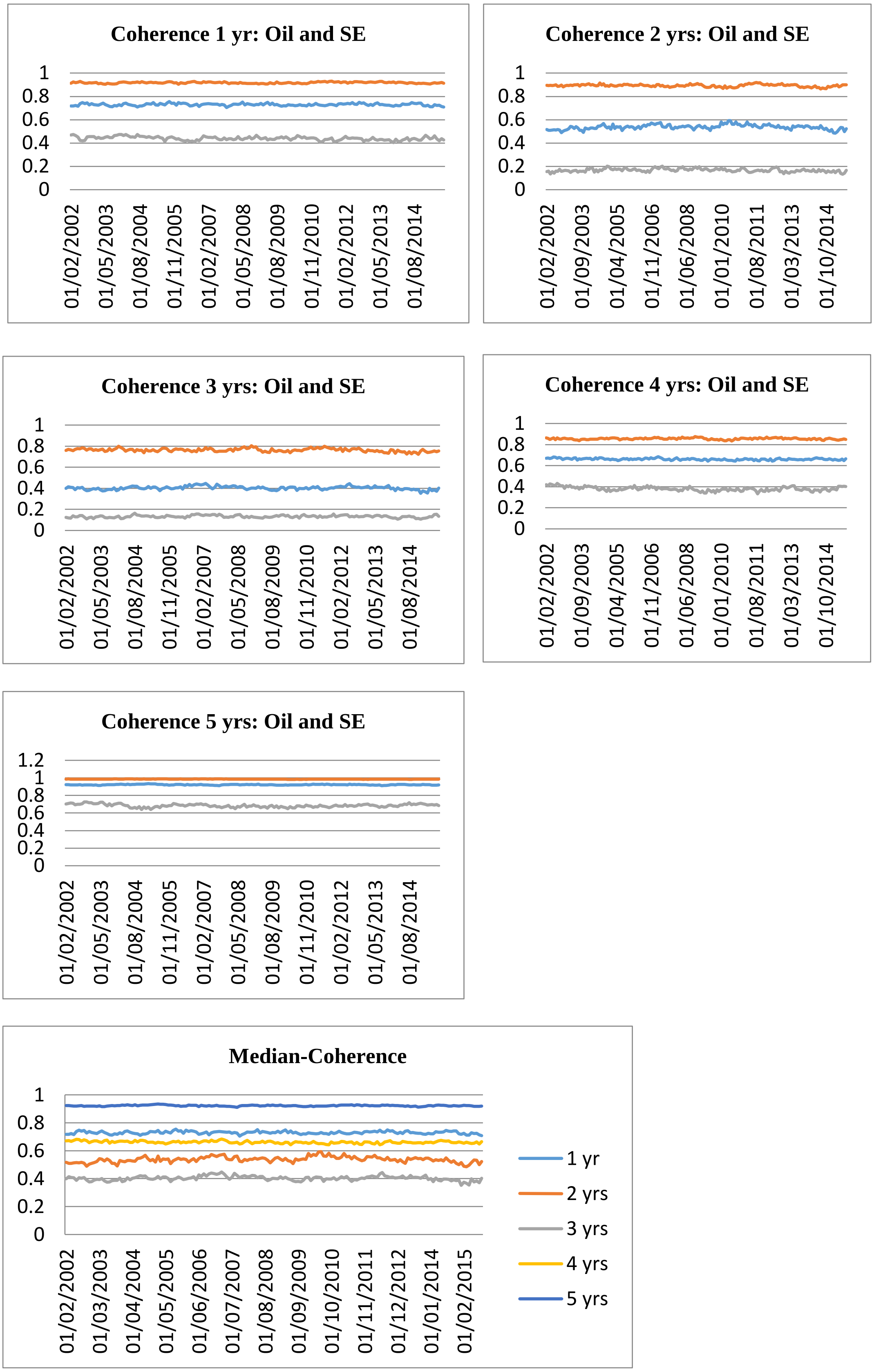


Figure 3a: Coherence between Oil and SE for Qatar

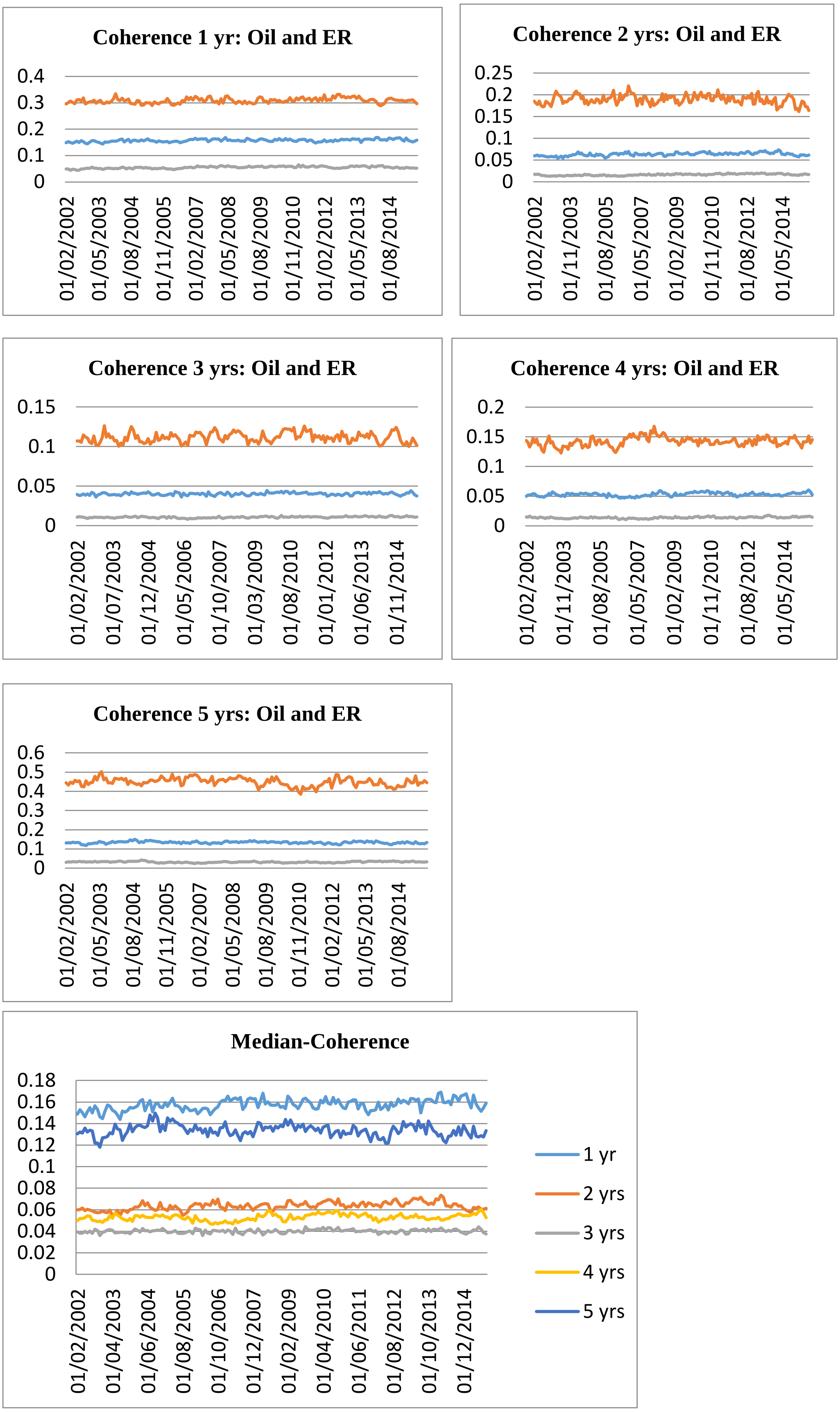


Figure 3b: Coherence between Oil and ER for Qatar

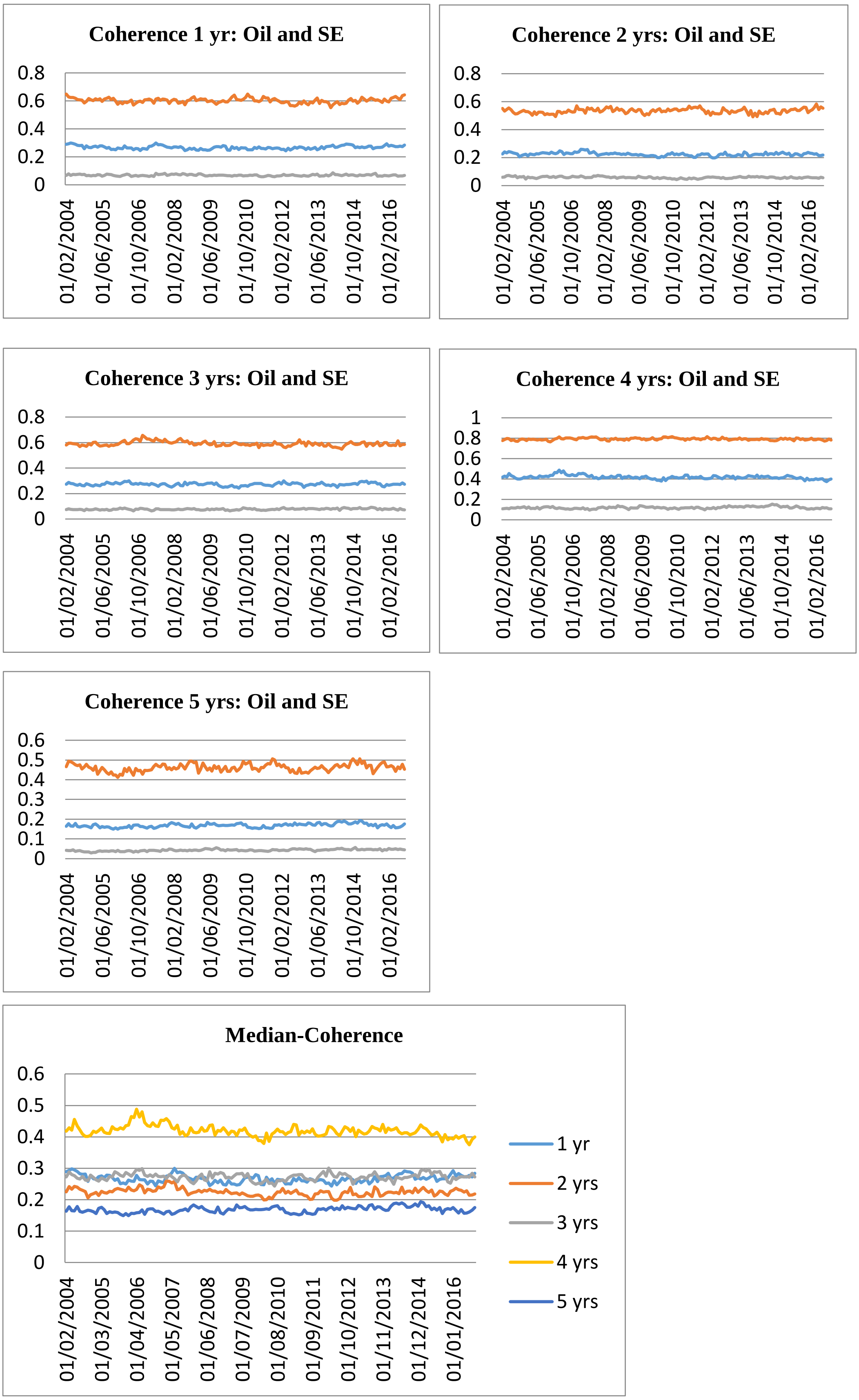


Figure 4a: Coherence between Oil and SE for Kuwait

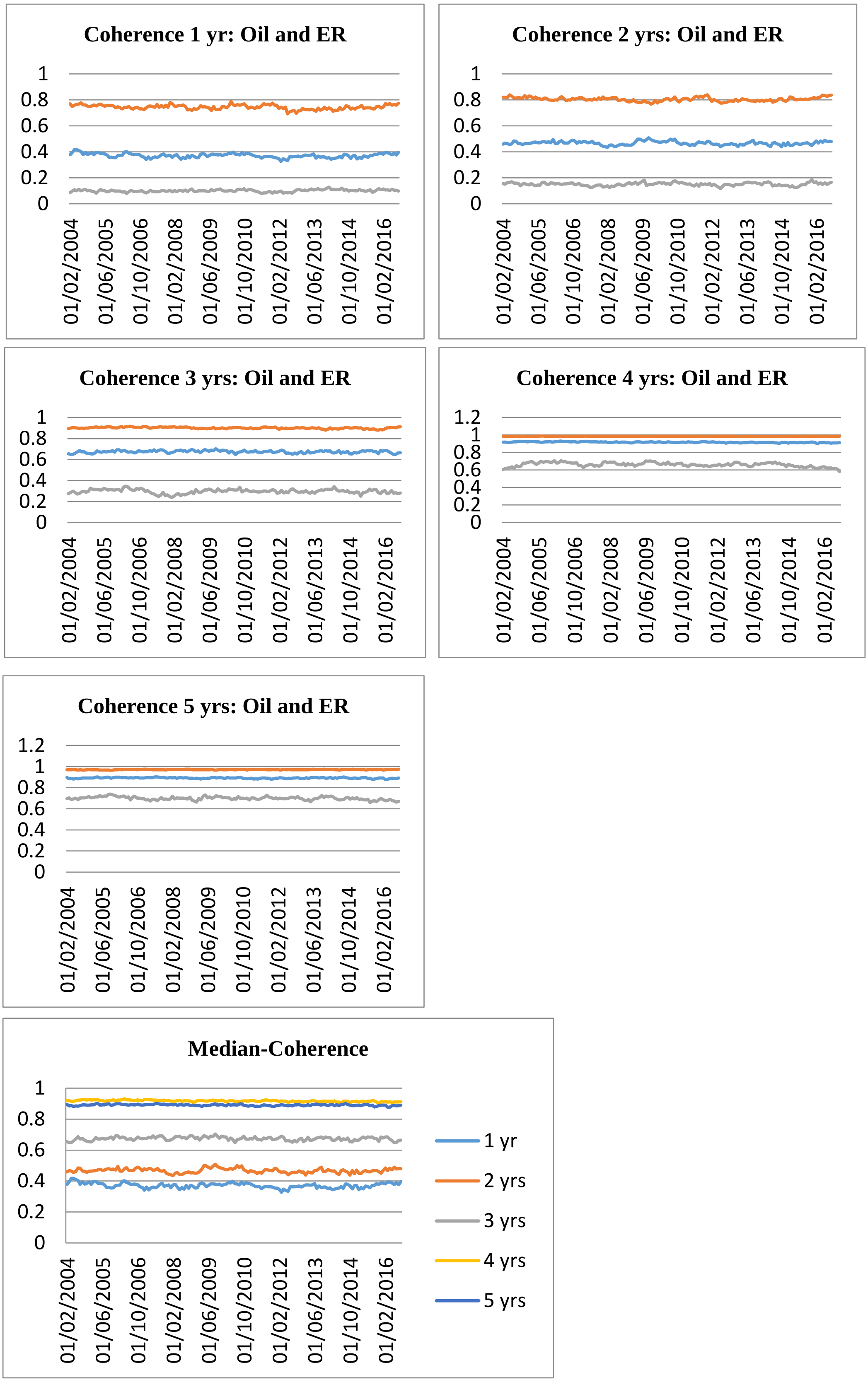


Figure 4b: Coherence between Oil and ER for Kuwait

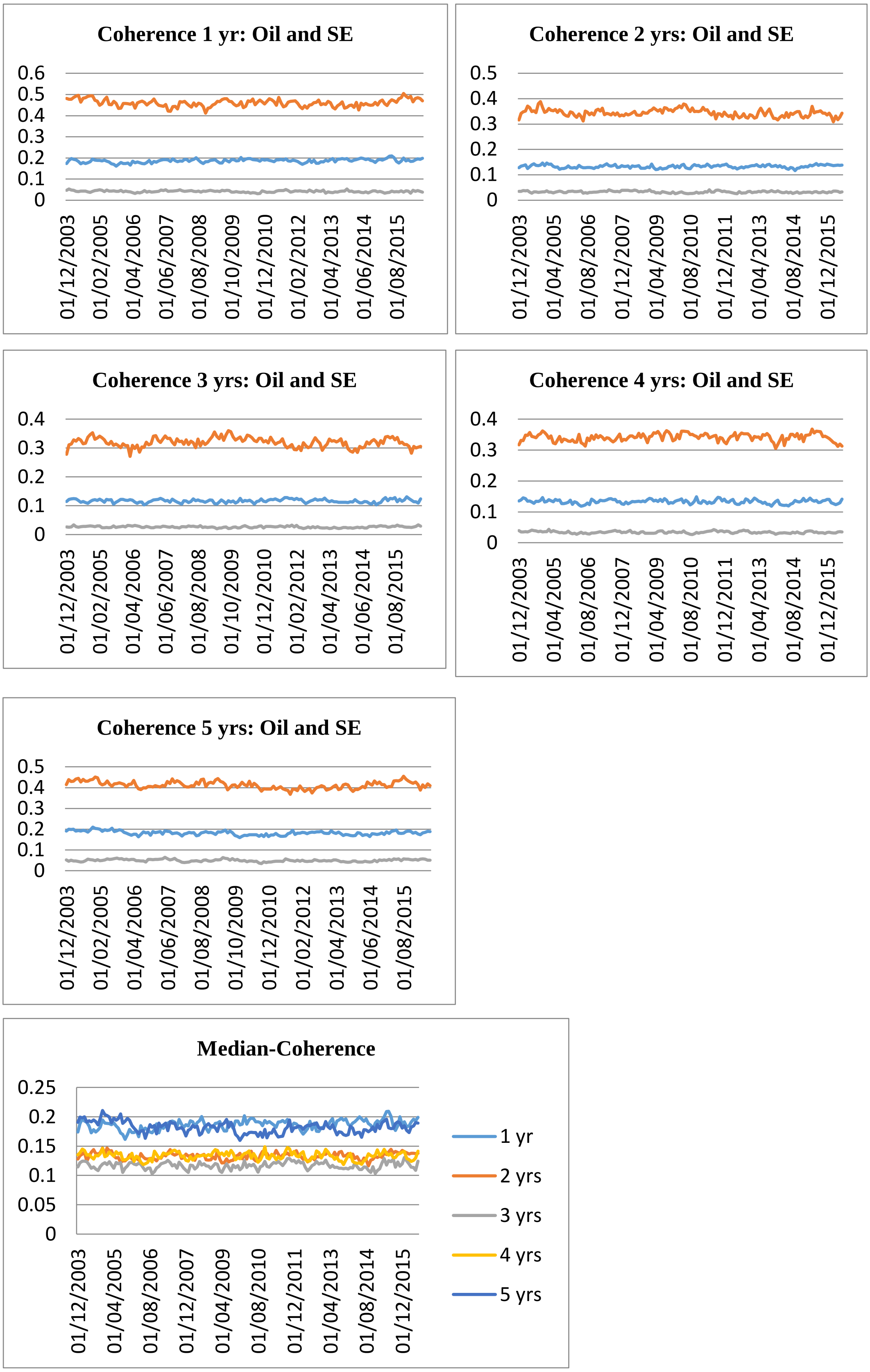


Figure 5a: Coherence between Oil and SE for Saudi Arabia

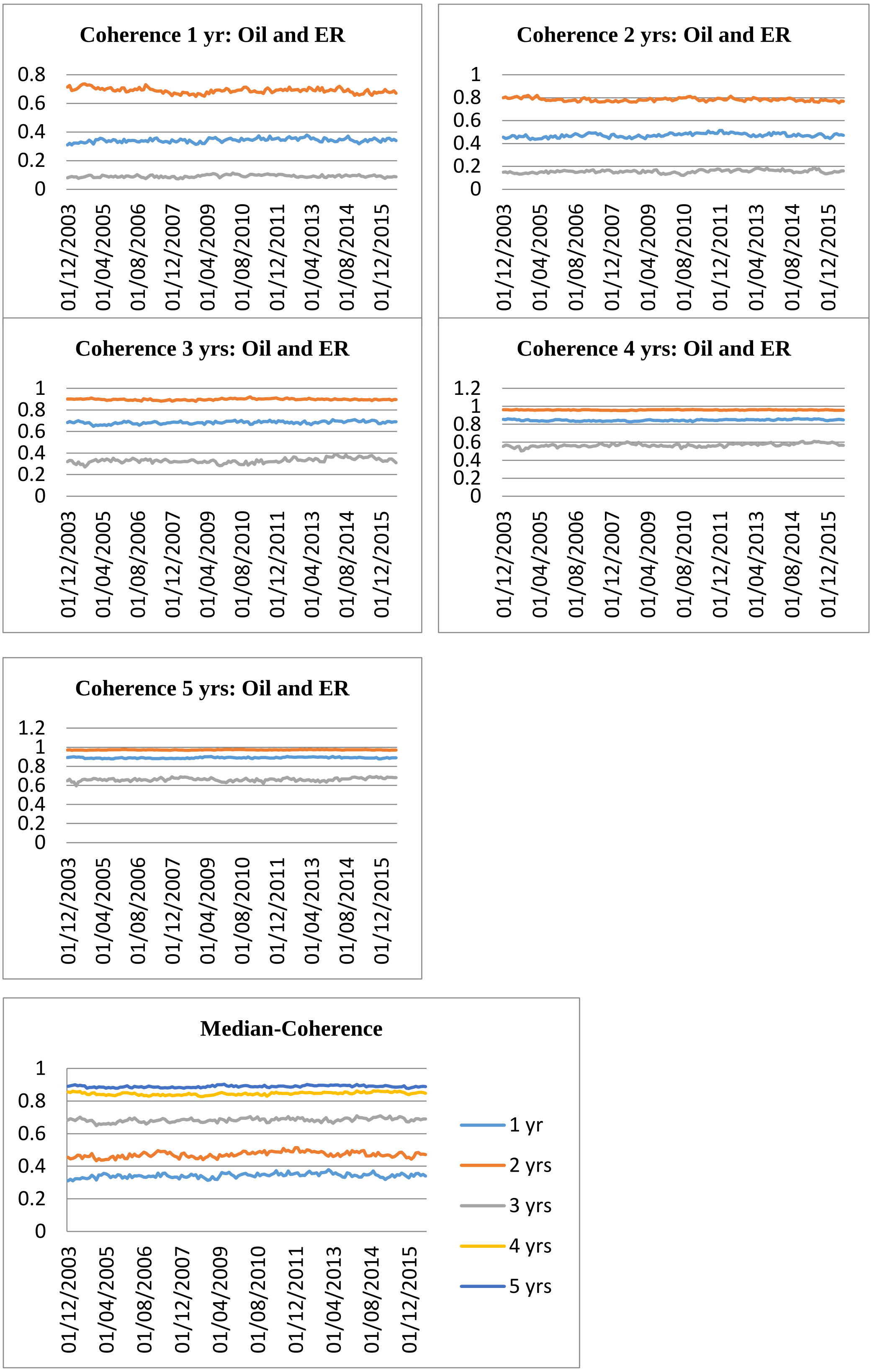


Figure 5b: Coherence between Oil and ER for Saudi Arabia

The level of coherence between the oil - stock exchange and oil – real effective exchange rate differentials at various horizons and over various business cycle frequencies (1, 2, 3, 4, and 5 years) has increased over time and then started to lose the impact after some years.

For UAE, there is a little relationship between oil and stock exchange in the first year but then it starts increasing in the second year. The impact is the maximum in the fourth year and then it starts losing the impact in the fifth year. On the other hand, coherence between oil and real effective exchange rate is high and it increases year by year until the fourth year which is almost 98%. It starts losing the impact in the fifth year. For Qatar, there is different scenario. The relationship between oil and stock exchange are huge which is almost 75% but the impact starts reducing in second and third year and then increases in the fourth year and reach to the maximum level in the fifth year interestingly. Similarly, the relationship between oil and real effective exchange rate are almost 15% in the first year then it reduces and reaches to the maximum level of impact in the fifth year. Moreover, for Kuwait, the coherence between oil and stock exchange becomes more powerful after three years and reach to the maximum impact in forth year. Later, it loses the impact in the fifth year. Also, the relationship between oil and real effective exchange rate has 40% association in first year. Then, this impacts increases year by year and reach to the 90-92% level in four years time then reducing to 89% in the fifth year. Finally, for Saudi Arabia, the coherence between oil and stock exchange are almost same for first four years but reaches to the maximum level in the fifth year. Lastly, the relationship between oil and real effective exchange rate increases year by year from 35% to 83% at the end of year four. Then, it increased to maximum level and become 90%.

2.4.2 Impulse Response Analysis of the Variables in Each Country:

In this study, we define the time varying oil price, stock exchange and real effective exchange rate dynamics by investigating the impulse response analyses to the identified structural shocks which are oil price, stock exchange and real effective exchange rate shocks. The model is identified using sign restrictions imposed on the impulse responses over contemporaneous and long horizons. On the other hand, we use the same way of Koop et. al. (1996) and also follow the Monte Carlo integration to give an explanation for uncertainty of future coefficient.

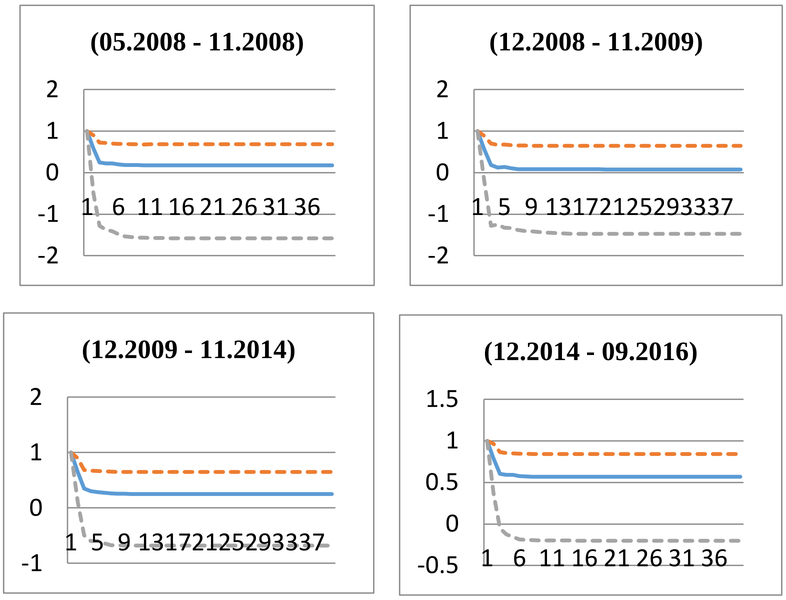
Moreover, impulse response functions are defined at each point in time as follows;

$$IRF_t = E(Z_{t+k} / \psi_t, Z_{t-1}, \mu) - E(Z_{t+k} / \psi_t, Z_{t-1}) \qquad (12)$$

Where ψ_t represents the all the parameters and hyper parameters of the of the VAR model, k represents the horizon under consideration and μ represents the shock. Equation (12) clarifies that, impulse response functions are calculated by taking the difference between two conditional expectations. The equation is in two folds, first part denotes the endogenous variable which its forecast is the condition of one of the structural shocks μ. The second term represents the baseline forecast and the shock is equal to zero which is conditioned on the scenario. In addition to this, Koop et. al. (1996) defines the estimation of these conditional expectations by stochastic simulation of the VAR model.

Figure 6 (from a to i), Figure 7 (from a to i), Figure 8 (from a to i) and Figure 9 (from a to i) show the TVP-VAR cumulated impulse responses to shocks which we defined them as oil price, stock exchange and real effective exchange rate shocks for UAE, Qatar, Kuwait and Saudi Arabia, respectively.

(a) Impulse of Oil Shock on Oil between terms



(b) Impulse of Oil Shock on Stock Exchange between terms

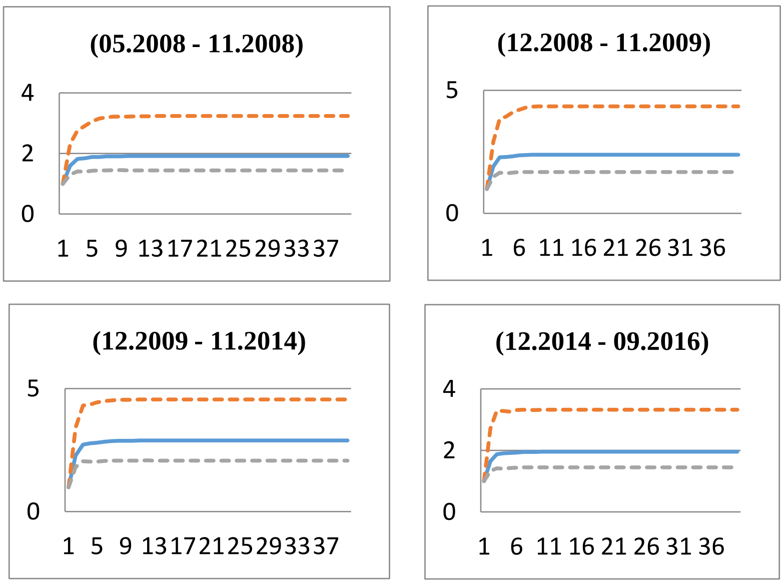
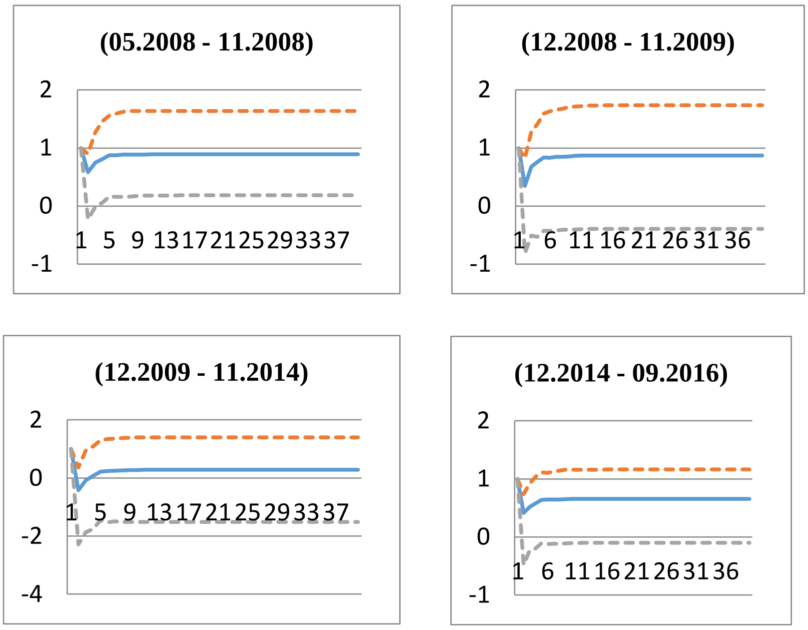


Figure 6: Impulse Response Analysis for United Arab Emirates

(c) Impulse of Oil Shock on Real Effective Exchange Rate between terms



(d) Impulse of Stock Exchange on Oil between terms

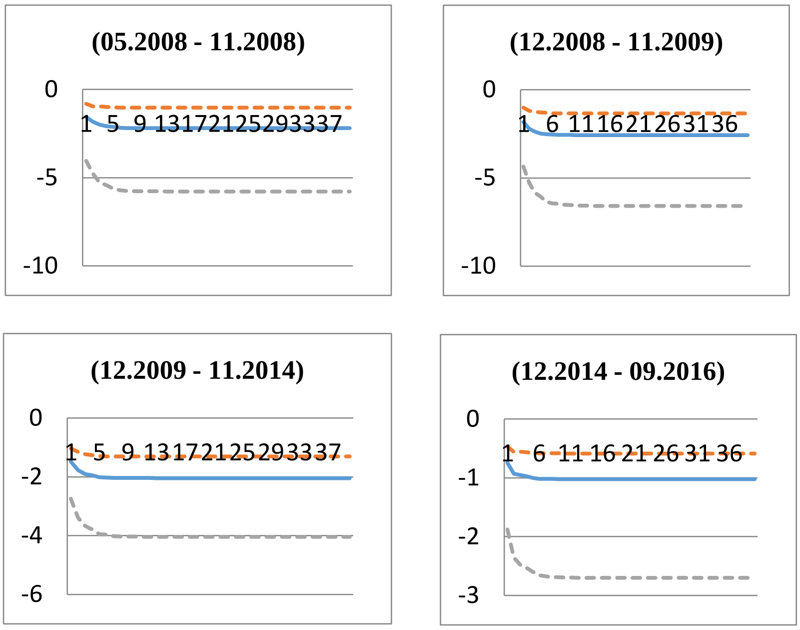
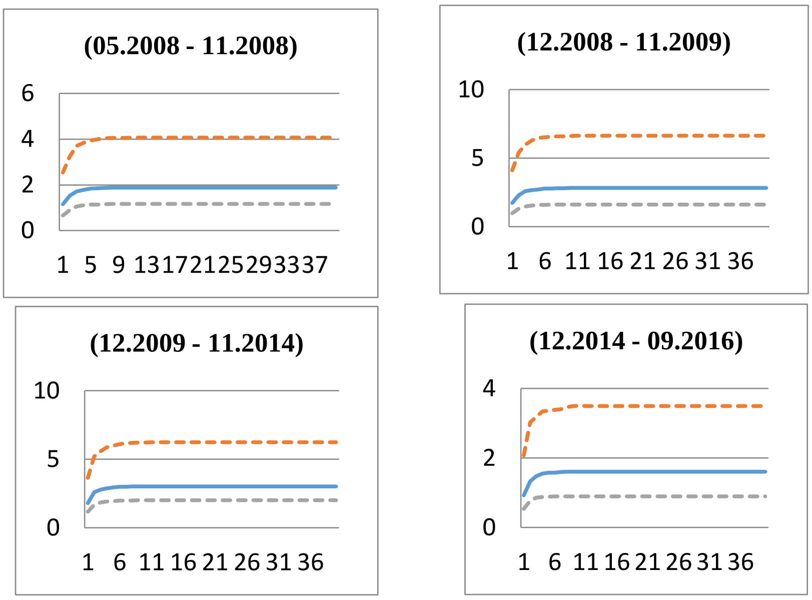


Figure 6 (continued): Impulse Response Analysis for United Arab Emirates

(e) Impulse of Stock Exchange on Stock Exchange between terms



(f) Impulse of Stock Exchange on Real Effective Exchange Rate between terms

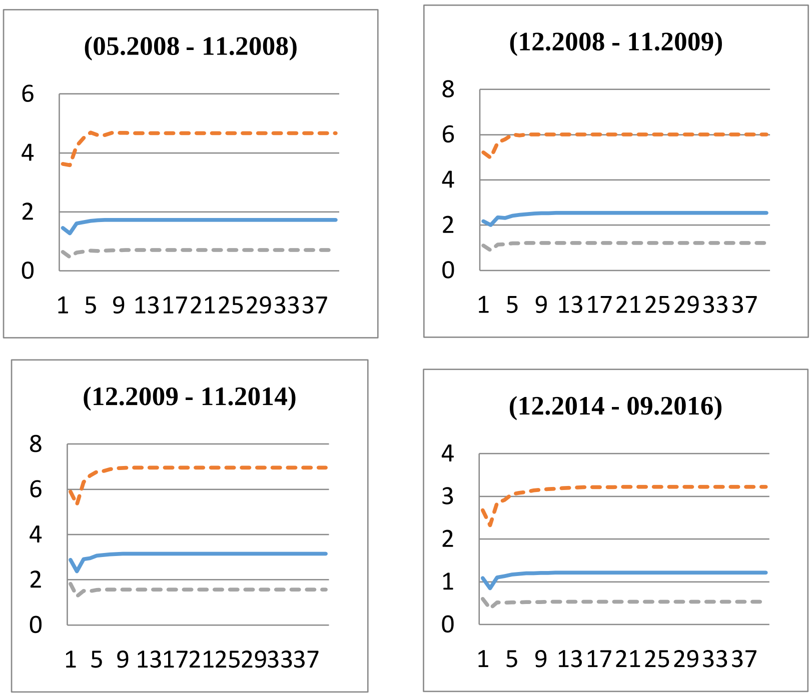
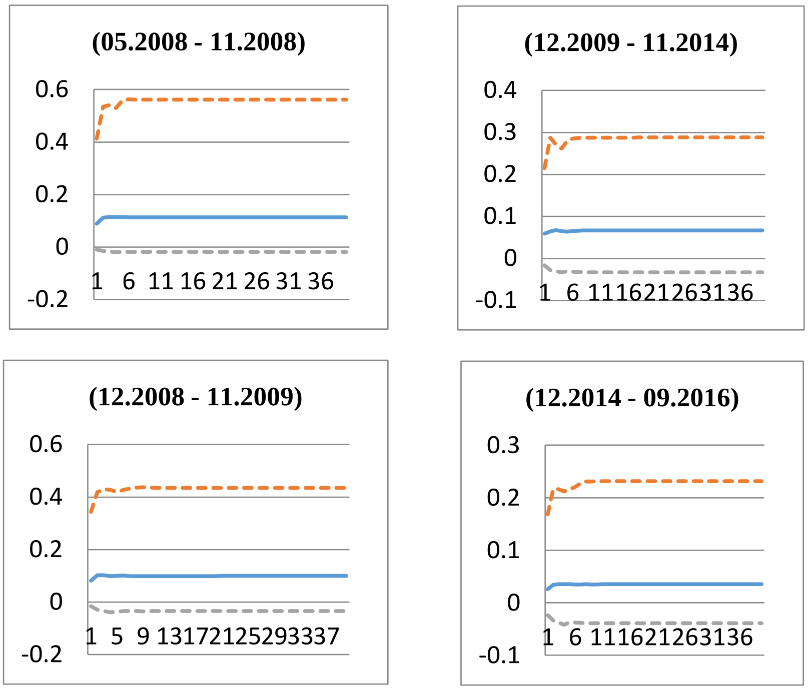


Figure 6 (continued): Impulse Response Analysis for United Arab Emirates

(g) Impulse of Real Effective Exchange Rate on Oil between terms



(h) Impulse of Real Effective Exchange Rate on Stock Exchange between terms

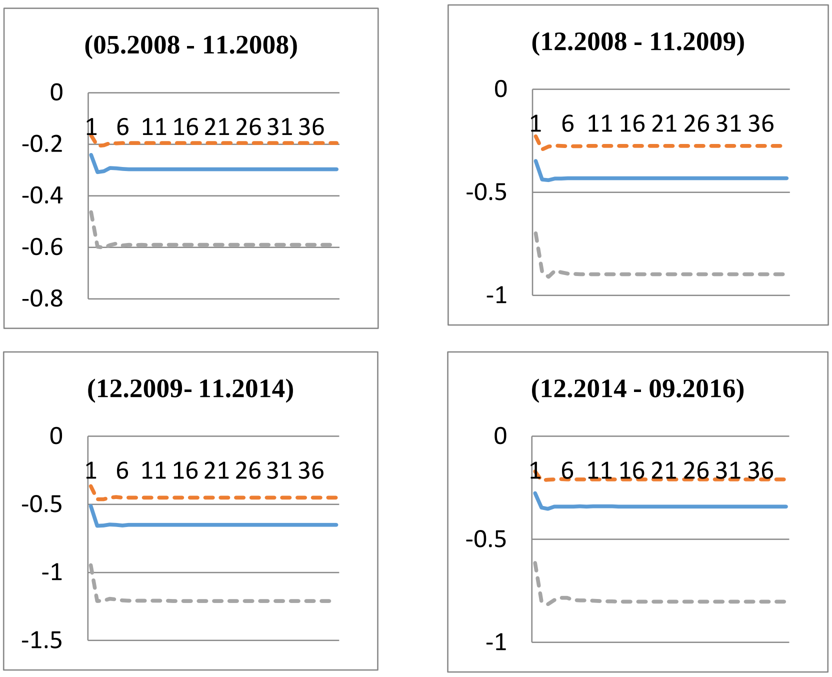


Figure 6 (continued): Impulse Response Analysis for United Arab Emirates

(i) Impulse of Real Effective Exchange Rate on Real Effective Exchange Rate between terms

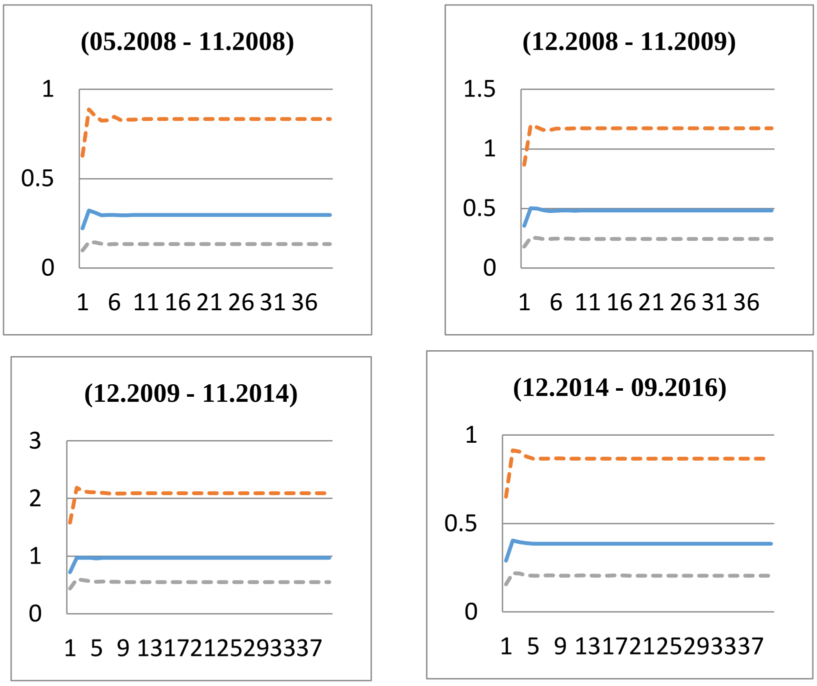


Figure 6 (continued): Impulse Response Analysis for United Arab Emirates

(a) Impulse of Oil Shock on Oil between terms

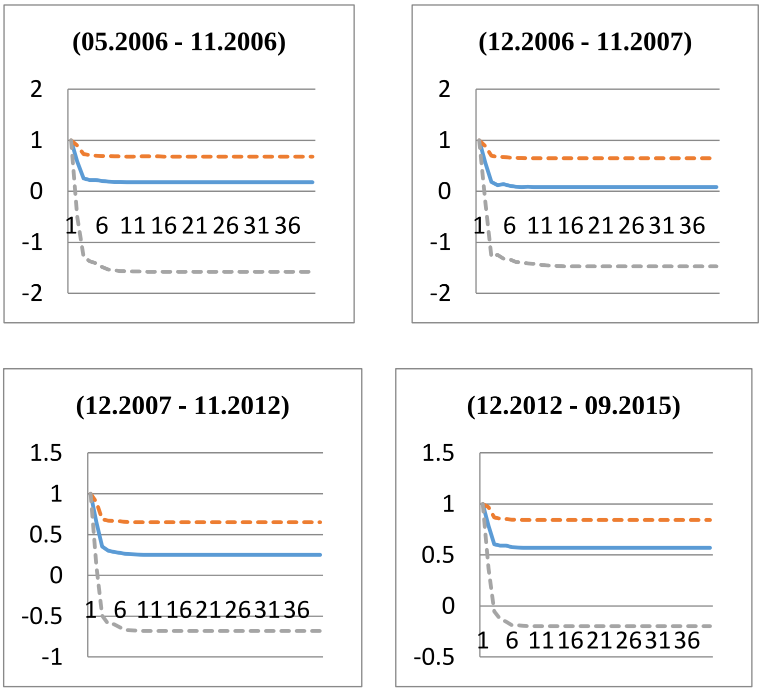
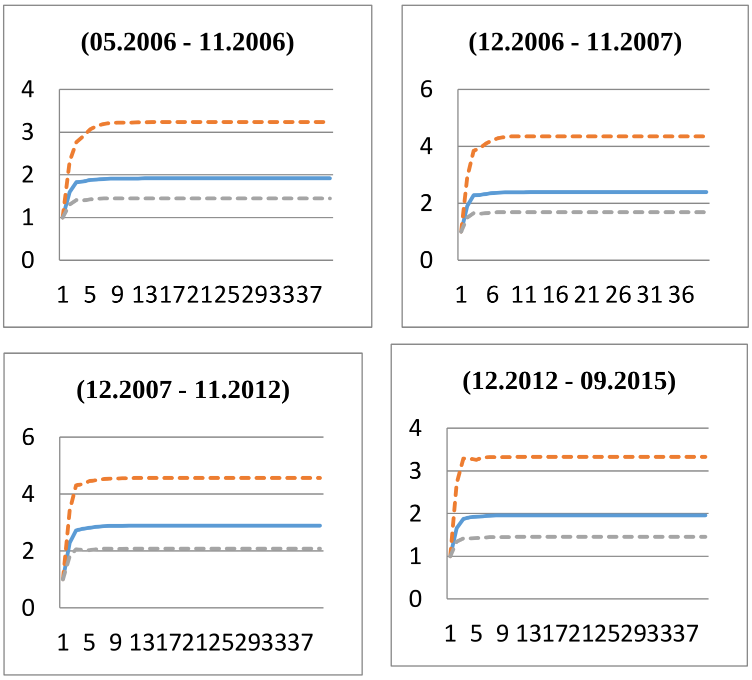


Figure 7: Impulse Response Analysis for Qatar

(b) Impulse of Oil Shock on Stock Exchange between terms



(c) Impulse of Oil Shock on Real Effective Exchange Rate between terms

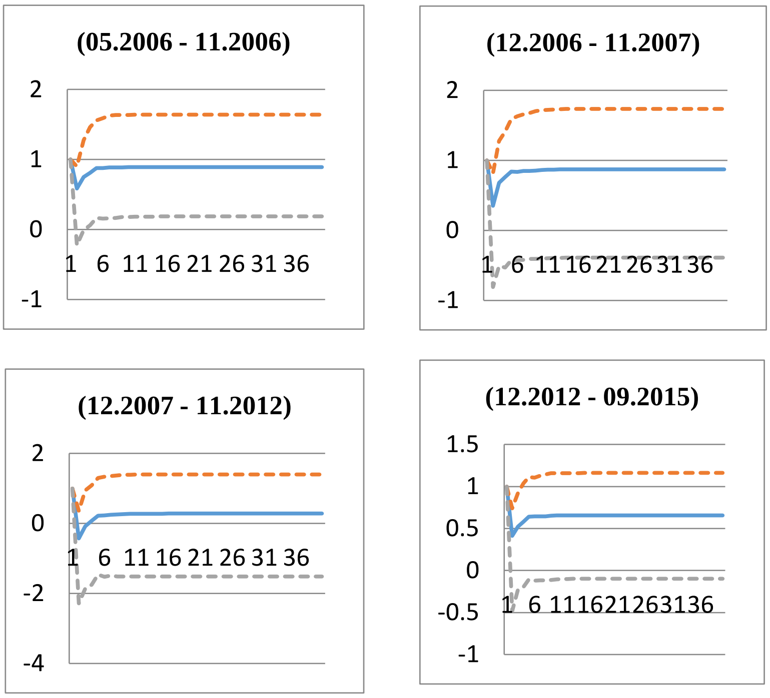
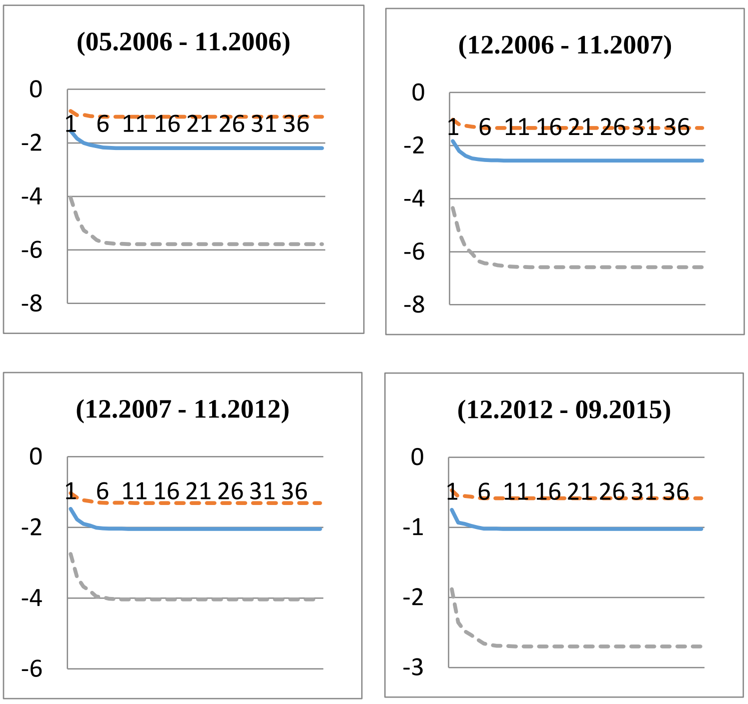


Figure 7 (continued): Impulse Response Analysis for Qatar

(d) Impulse of Stock Exchange on Oil between terms



(e) Impulse of Stock Exchange on Stock Exchange between terms

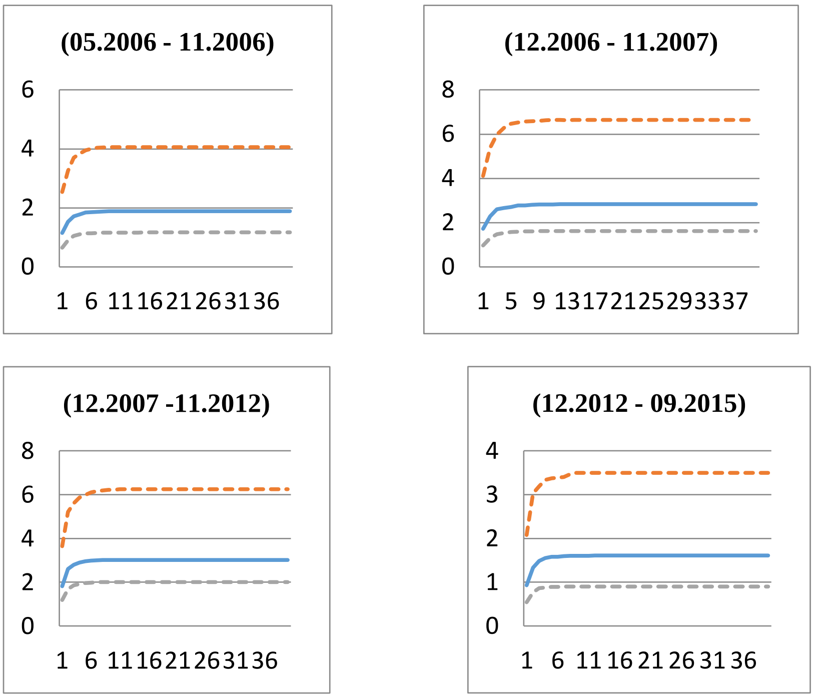
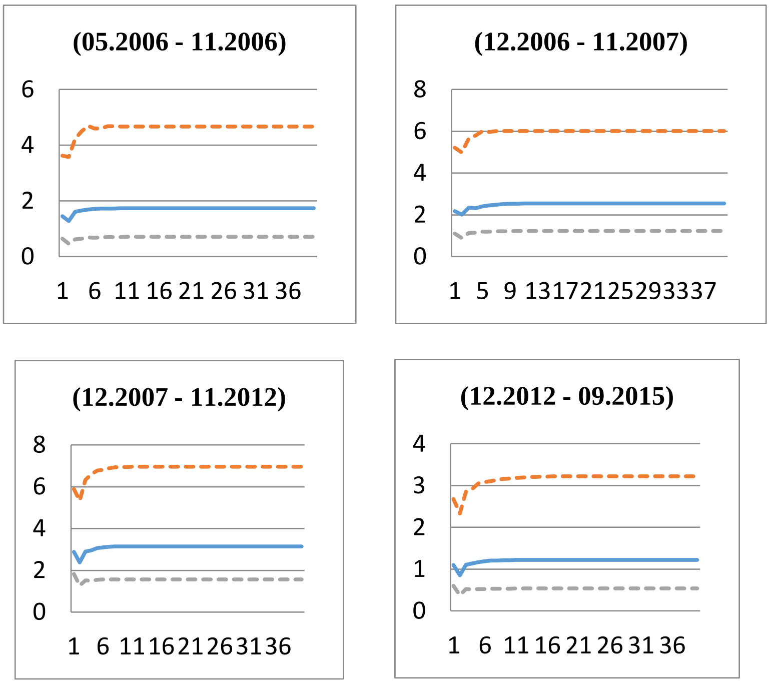


Figure 7 (continued): Impulse Response Analysis for Qatar

(f) Impulse of Stock Exchange on Real Effective Exchange Rate between terms



(g) Impulse of Real Effective Exchange Rate on Oil between terms

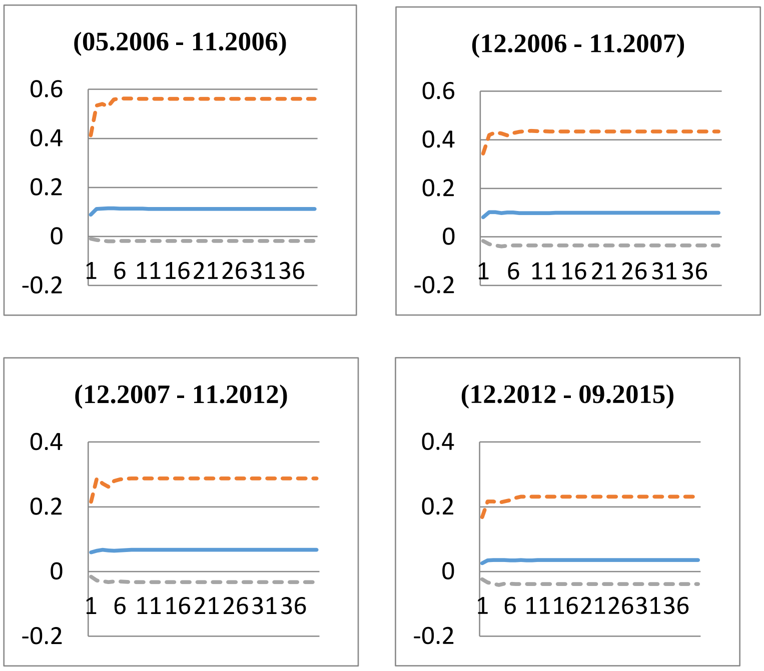
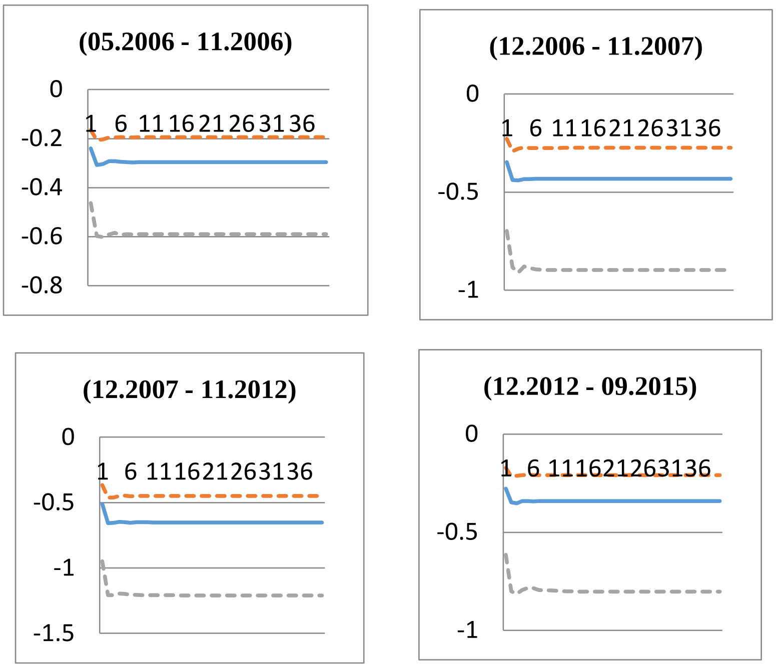


Figure 7 (continued): Impulse Response Analysis for Qatar

(h) Impulse of Real Effective Exchange Rate on Stock Exchange between terms



(i) Impulse of Real Effective Exchange Rate on Real Effective Exchange Rate between terms

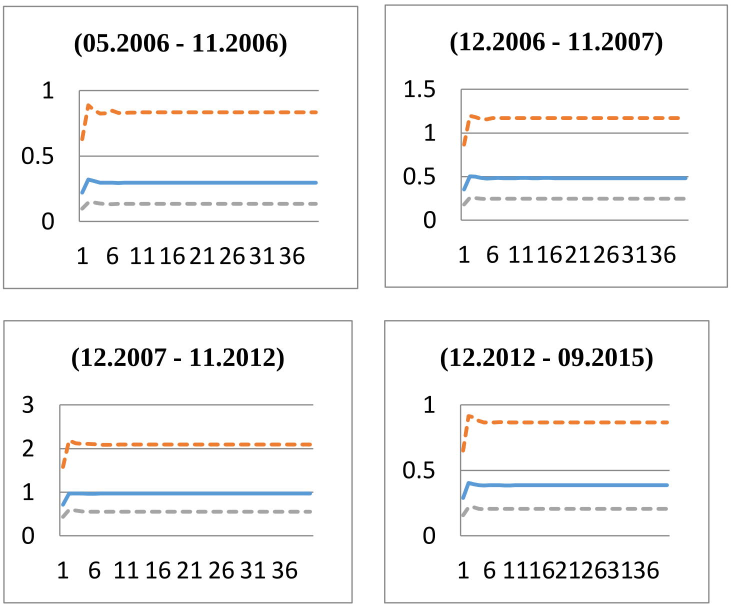
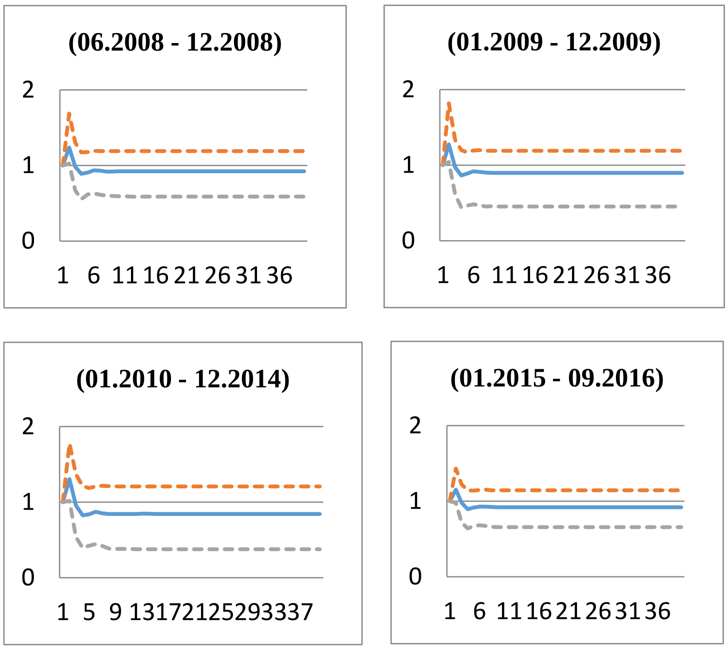


Figure 7 (continued): Impulse Response Analysis for Qatar

(a) Impulse of Oil Shock on Oil between terms



(b) Impulse of Oil Shock on Stock Exchange between terms

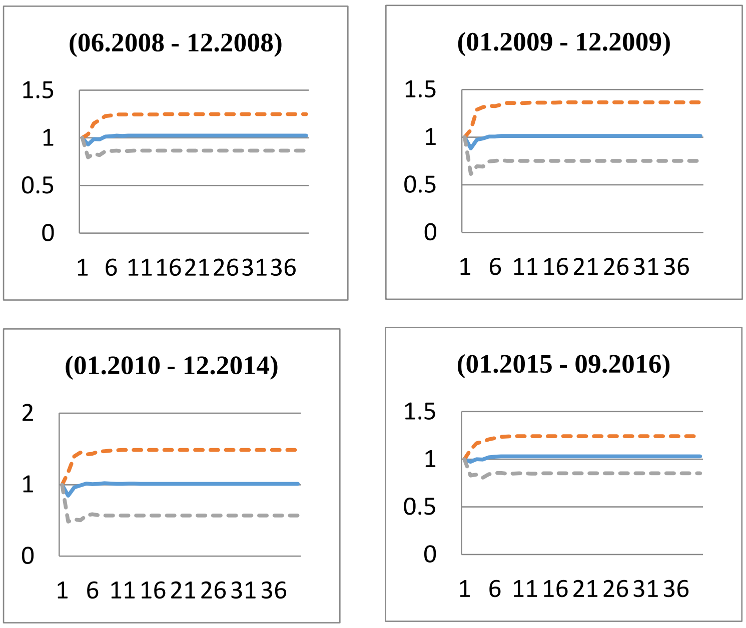
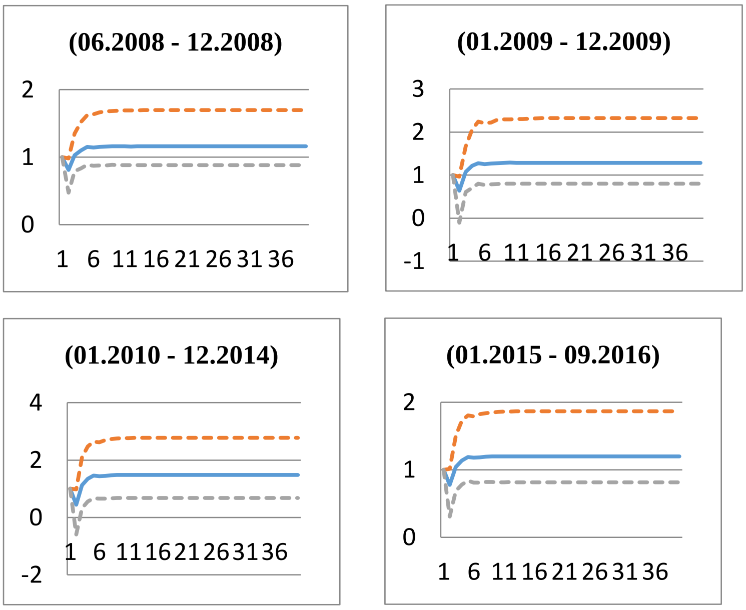


Figure 8: Impulse Response Analysis for Kuwait

(c) Impulse of Oil Shock on Real Effective Exchange Rate between terms



(d) Impulse of Stock Exchange on Oil between terms

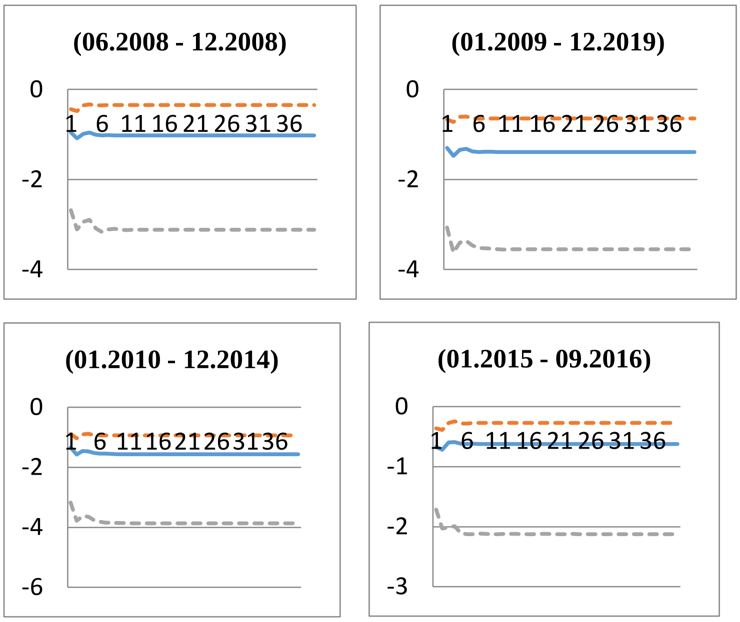
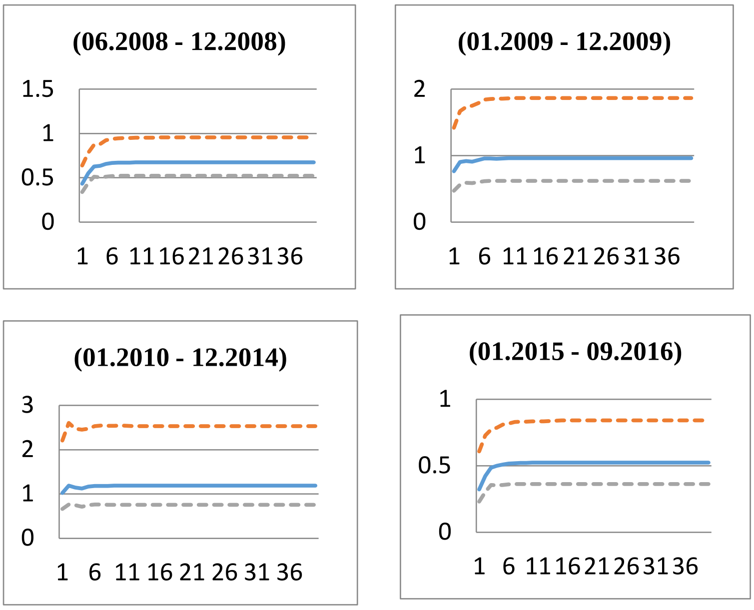


Figure 8 (continued): Impulse Response Analysis for Kuwait

(e) Impulse of Stock Exchange on Stock Exchange between terms



(f) Impulse of Stock Exchange on Real Effective Exchange Rate between terms

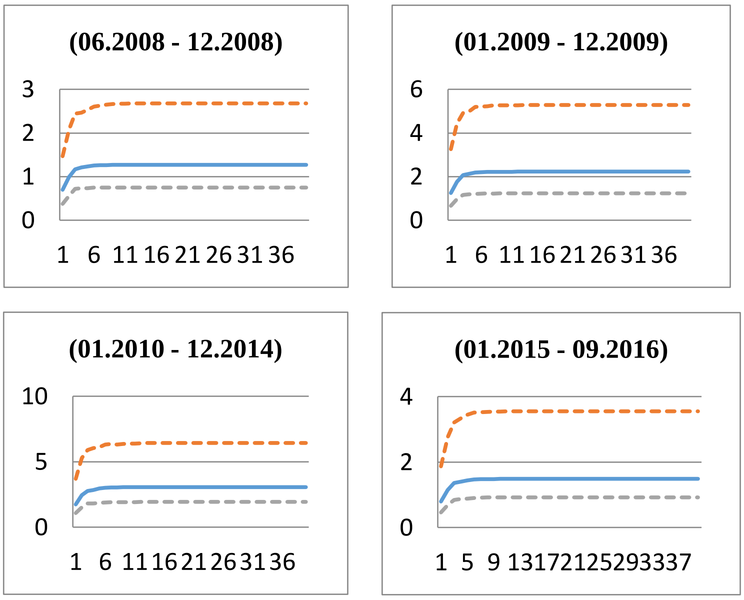
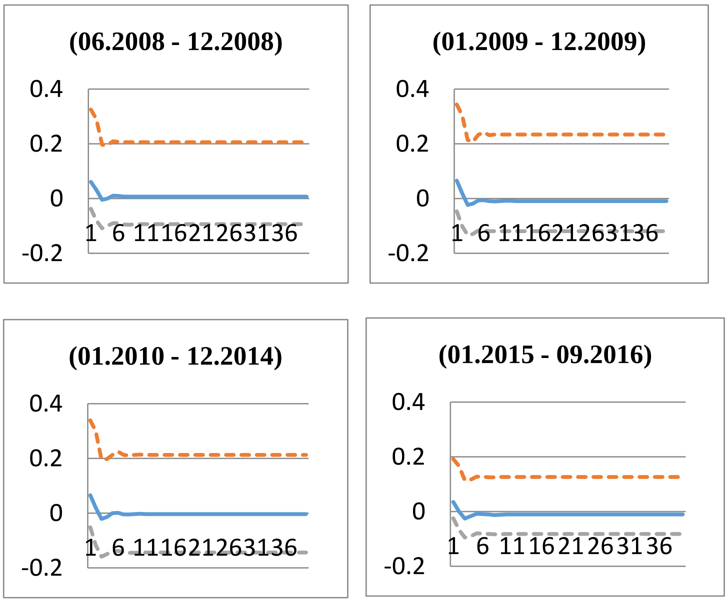


Figure 8 (continued): Impulse Response Analysis for Kuwait

(g) Impulse of Real Effective Exchange Rate on Oil between terms



(h) Impulse of Real Effective Exchange Rate on Stock Exchange between terms

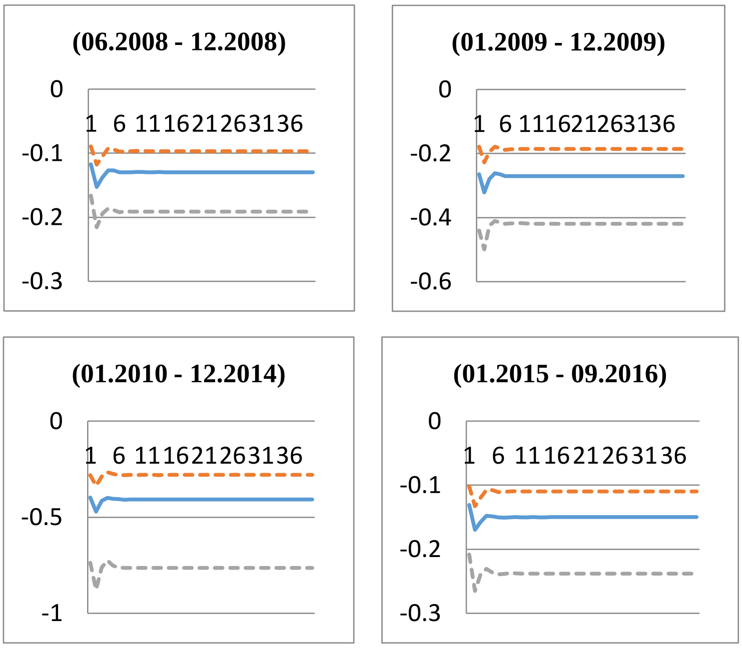


Figure 8 (continued): Impulse Response Analysis for Kuwait

(i) **Impulse of Real Effective Exchange Rate on Real Effective Exchange Rate between terms**

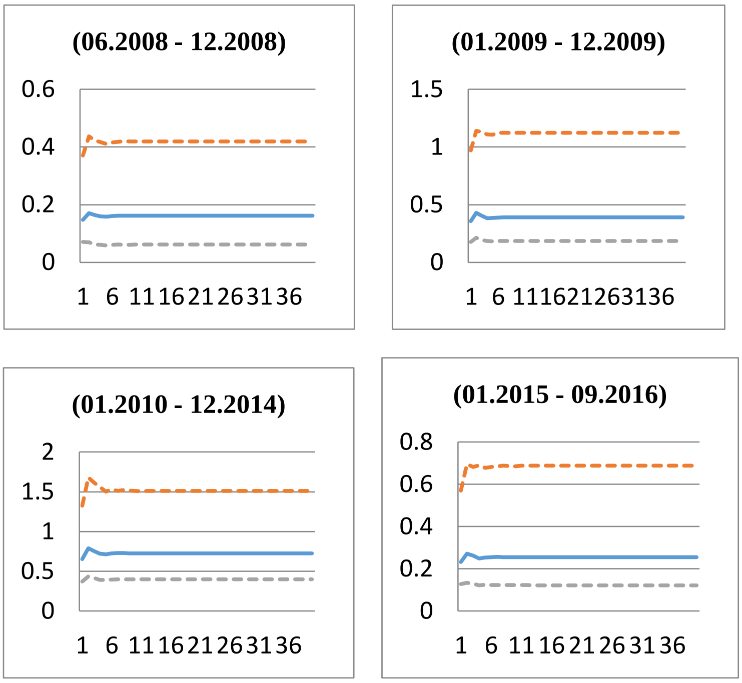


Figure 8 (continued): Impulse Response Analysis for Kuwait

(a) **Impulse of Oil Shock on Oil between terms**

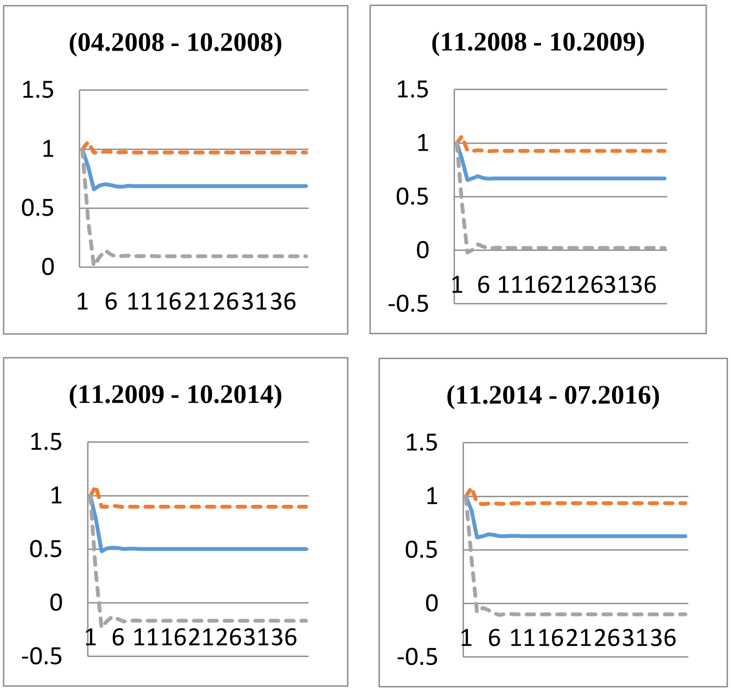
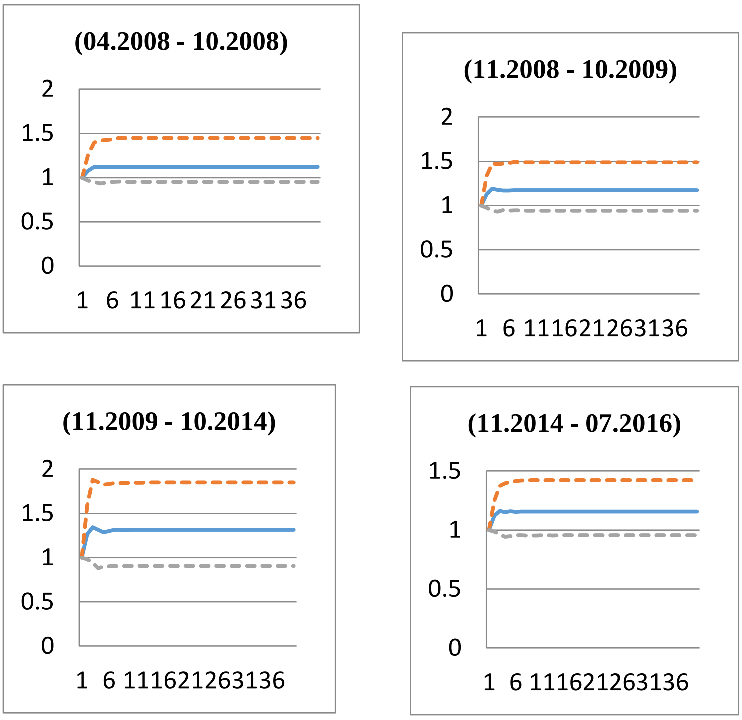


Figure 9: Impulse Response Analysis for Saudi Arabia

(b) Impulse of Oil Shock on Stock Exchange between terms



(c) Impulse of Oil Shock on Real Effective Exchange Rate between terms

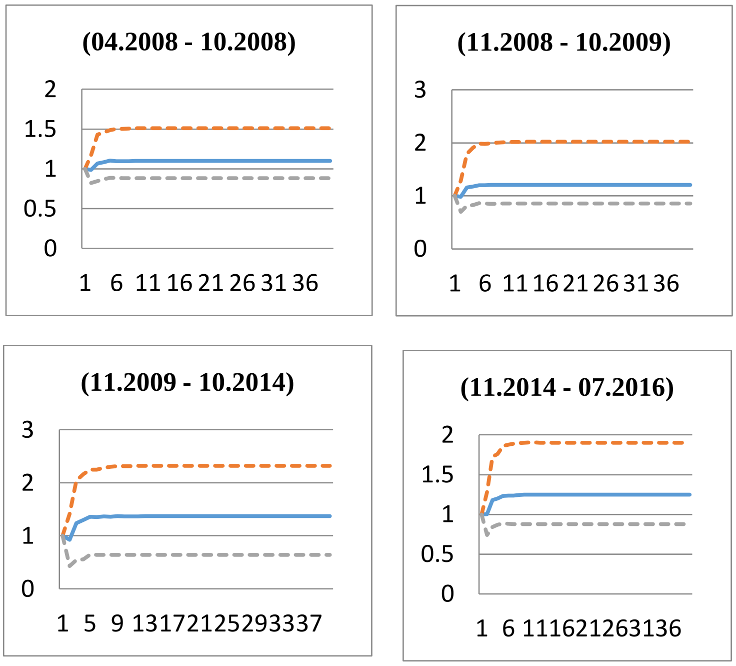
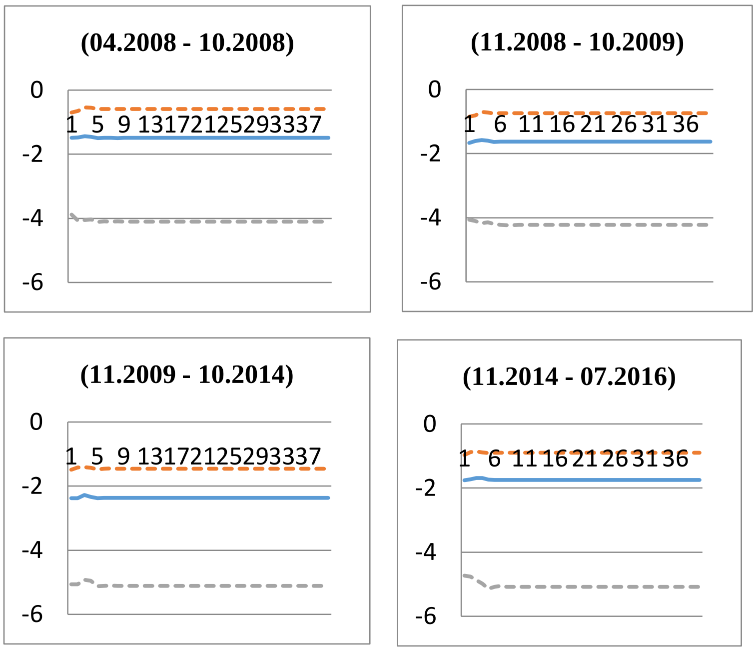


Figure 9 (continued): Impulse Response Analysis for Saudi Arabia

(d) Impulse of Stock Exchange on Oil between terms



(e) Impulse of Stock Exchange on Stock Exchange between terms

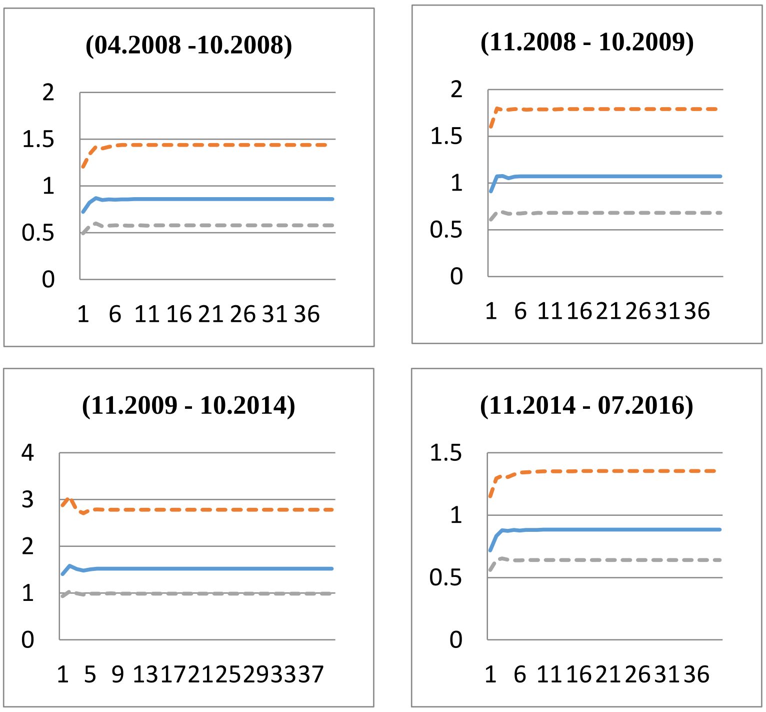
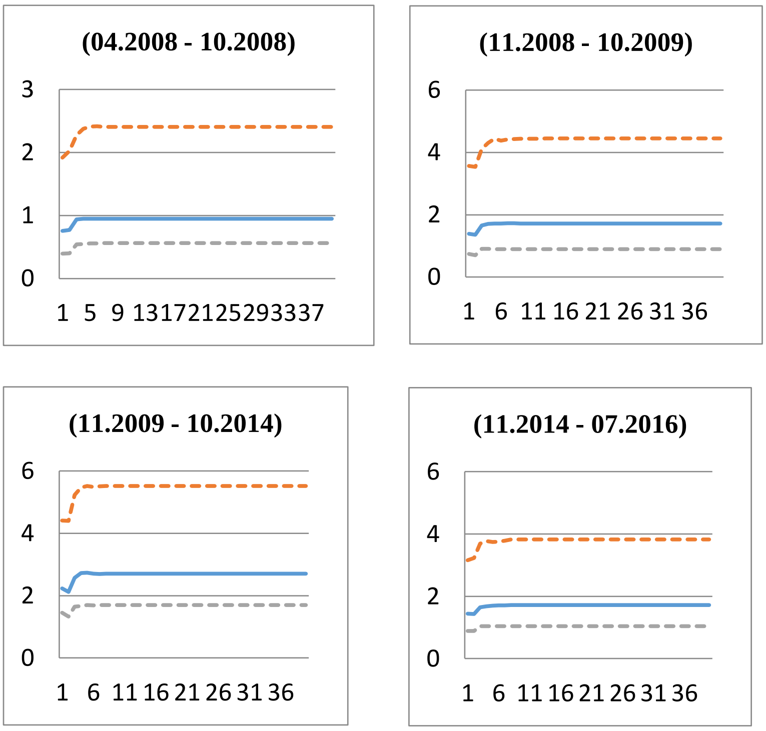


Figure 9 (continued): Impulse Response Analysis for Saudi Arabia

(f) Impulse of Stock Exchange on Real Effective Exchange Rate between terms



(g) Impulse of Real Effective Exchange Rate on Oil between terms

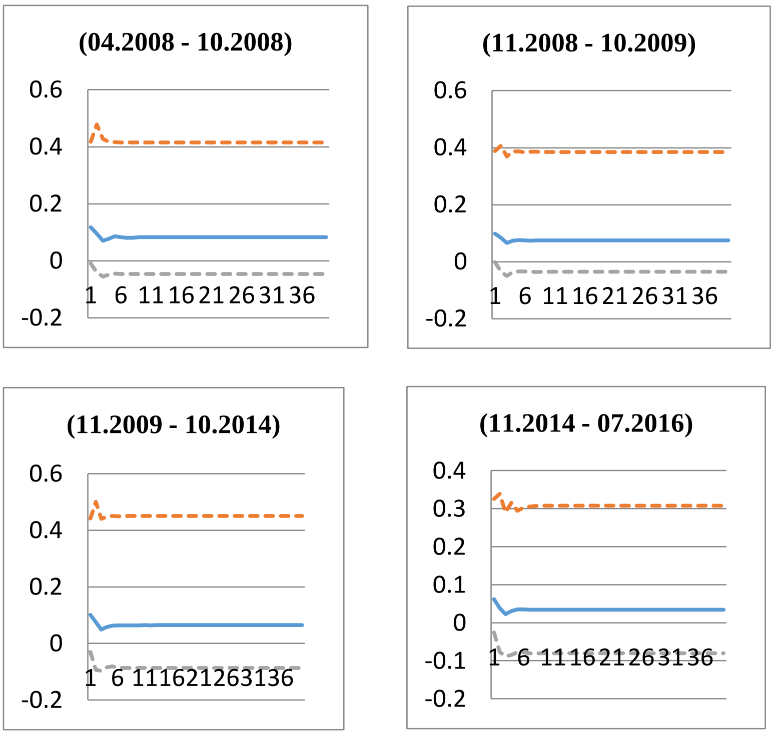
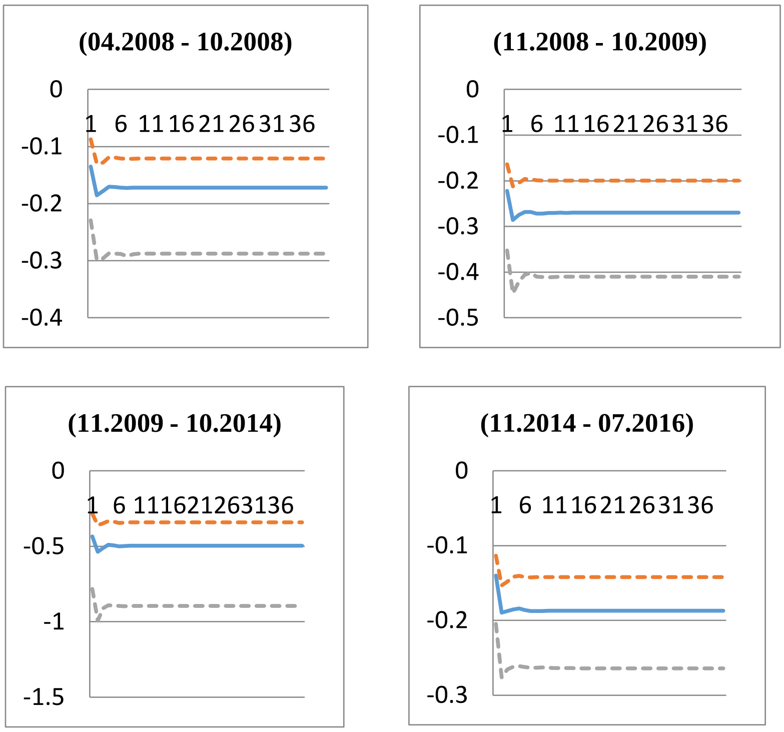


Figure 9 (continued): Impulse Response Analysis for Saudi Arabia

(h) Impulse of Real Effective Exchange Rate on Stock Exchange between terms



(i) Impulse of Real Effective Exchange Rate on Real Effective Exchange Rate between terms

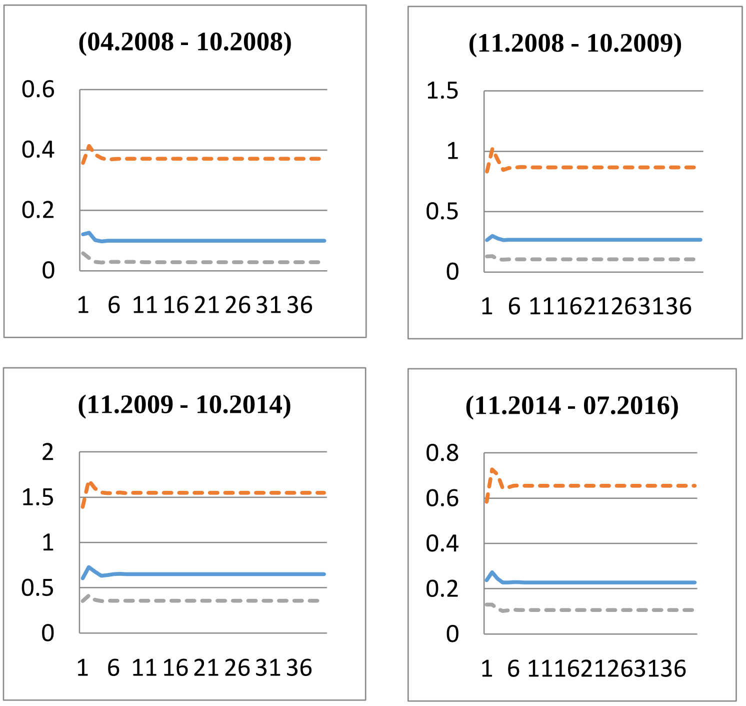


Figure 9 (continued): Impulse Response Analysis for Saudi Arabia

Oil shock is used to see the responses of stock exchange and real effective exchange rate in UAE, Qatar, Kuwait and Saudi Arabia respectively. As it is mentioned above, there are for different time periods and the shocks are given them separately. It can be seen the impulse response of oil shock on Figures 6(a-b-c), 7(a-b-c), 8(a-b-c), and 9(a-b-c). In general, oil shock has positive long lasting and significant impact on the oil itself, stock exchange and real effective exchange rate. As a result, the response of stock exchange to oil is positive and it increases first three months in each period continuously and then continue to increase in the same level after three months in UAE, Qatar and Saudi Arabia. In contrast, although oil shock has positive and long lasting impact on stock exchange, it reduces the stock exchange first two months then starts to increase until the fifth months. After that, it continues to increase in the stable level in each period in Kuwait.

On the other hand, oil has insignificant impact on real effective exchange rate after one month during 12.2009 – 11.2014 in UAE and during 12.2007 – 11.2012 in Qatar which is period three but it has significant and positive long lasting impact on it, but decreases first three months then increases until fifth months and become stable in the rest of the periods. Moreover, real effective exchange rate decreases positively two months then increases until the fifth months and continue to increase in a stable level in each period in Kuwait and Saudi Arabia.

On the other hand, Figures 6(d-e-f), 7(d-e-f), 8(d-e-f) and 9(d-e-f), represent the stock exchange shock on the other variables. When it is given on oil, the response of oil is negative long lasting and significant. In addition, the oil is more responsive to the stock exchange in second periods in Qatar and UAE. In contrast, the impact on real effective exchange rate and also on itself is positive long lasting and significant in each periods. In general, the response of real effective exchange rate is higher in period three in each country. Also, it increases positively first three months and then become stable in UAE, Qatar and Saudi Arabia. However, it increases first five months and become stable in Kuwait.

Lastly, Figures 6(g-h-i), 7(g-h-i), 8(g-h-i) and 9(g-h-i) show the real effective exchange rate shock on the other variables and itself. As it can be seen on the figures, it has positive and long lasting impact on oil but negative long lasting and significant on stock exchange when the shock is given. Moreover, the response of oil to real effective exchange rate is not too much. It is almost close to zero but it is significant during the all periods in each country except Kuwait. It gives response only for a short time which is only one month in each period.

As a result, all of the countries give the same response to the shocks and it is expected to find these results because they have almost same characteristics.

2.5 Conclusion and Policy Recommendations

The association between oil and fundamental shocks which are stock exchange and real effective exchange rate have been changed over time. We estimated these changes by using TVP VAR model. In our estimations, we considered the results of volatility, coherence (joint dependence over business cycle frequencies) and lastly impulse response analysis over time.

We found that, stock exchange is more volitile than oil in UAE, Kuwait and Saudi Arabia but opposite in Qatar. On the other hand, the coherence between oil and stock exchange and oil and real effective exchange rate are at the maximum level in four years time in general. Moreover, the response of stock exchange and real effective exchange rate to the oil shock is positive and long lasting. The response of oil is negative and the response of real effective exchange rate is positive to the stock exchange shock. Moreover, when the the real effective exchange rate shock is given on oil and stock exchange, the responses are positive and negative respectively.

Finally, it is obvious that, oil shock has impact on the stock exchange and real effective exchange rate. Especially, oil shock has more impact on stock exchange. This shows that, these countries are oil dependent countries and the economies of them may be affected from possible oil shocks. So, policy makers could try to find the ways of reducing the oil dependency of the economy.

Chapter 3

THE IMPACT OF UNCERTAINTY SHOCKS ON FOOD PRICES: EVIDENCE FROM G7 COUNTRIES

3.1 Introduction

First of all, we try to estimate the impact of food price volatility on each food prices which are cereals, dairy, fats, meat and sugar. Thus, the meaning of price volatility must be explained before estimating the results. Also, it is not possible to estimate price volatility by excluding the price increases. Otherwise, nobody will understand what is occurred in the international food markets.

Price volatility means that, prices decrease or increase in a specific period of time. In other words, it is the meaning of price movements. The volatility is separated into two which are; 1) low volatility means that, volatility or movement is close to zero or 2) high volatility means that, degrees of magnitude is large. On the other hand, volatility is estimated in the short period of time and period is also important for estimating the volatility. Moreover, it is known that, variations of prices are necessary part of a regular working of the markets.

According to Prakash (2011), when there is a scarcity of any commodities, then the price of commodity increases and this is the essence of the price system. Also, this price increases cause to reduce the consumption. In contrast, this causes to give a signal to producers investing more and increasing the production of scarce commodity.

On the other hand, the reasons of food price volatility are categorized under three sub title.

1) The reason of increases in food prices may be because of the problem of agricultural price volatility. This refers that, high prices are not going to be last and also high prices are the solution for treating the high prices again. Moreover, price volatility is defines as a natural and constant problem of agricultural markets. Also, there are some extra issues which is causing price volatility such as low elasticity of demand and climate shocks which will reduce the supply of commodities.
2) Second important reason for food price volatility is the international food crises which were in 1950, 1970 and present. International food crises may be because of increasing and decreasing of public investment in agriculture.
3) Third explanation is the last reason of food price volatility. Increases in food prices represent the early signal of coming and lasting scarcity on agricultural markets. In addition to this, there is a problem in the equilibrium of demand and supply and this is linked to the price volatility in the food market. On the other hand, all of these explanations increases the pressures on natural resources and try to learn whether these explanations are directly linked to the water, soil, biodiversity, greenhouse gases which is called as agricultural production or indirectly linked like oil.

As a result, some of the researchers suggest that, new sources of demand can be found such as bringing demand and supply together with the diminishing productivity growth in agriculture and also bringing them together in order to have stable prices for a reliable outcome.

Furthermore, all of the three reasons of food price volatility which is explained above are related to three different temporal horizons like short, medium and long term respectively.

In addition, history of food prices is important and it is known from the literature of food price volatility that the international food prices have increased since 2006 and this case is not obvious in the last two decades.

According to World Bank (2011), the food price indexes are observed and checked the price volatilities. Results show that, sugar prices increase 37%, price of rice increases 224% and price of maize increases 77% between January 2007- June 2008 while wheat prices increases %118 between January 2007 – March 2008. As it can be seen from percentages, prices increased sharply. After this period, the price of wheat and rice decreases 55% and also price of maize decreases 64% in the second half of 2008. After more, the food prices start to increase again in the second half of 2010 and price spike exceeded the peak level of 2007 – 2008. Food price index increases more than 30% within seven months (June – December 2010) and cereals price index increase by 57% in the same period. It is obvious that, prices are volatile and it will continue to volatile.

As it can be seen from the history, price of cereals have increased more than they have increased in the international market between January 2006 – December 2011. There is an important point that, the price of food has not turned back to 2007 – 2008 levels and food prices are almost double now when the average of food prices are compared between 1990 – 2006 periods.

On the other hand, recent food price doubling has turned back to 1960 level and food prices are still below the level of 1974. In addition, there was a food crisis in 1974. Also, it is known that, food prices have increased sharply in 1970 and start to decrease during two years and then turn back to the initial level of food prices. Moreover, 2007 – 2008 food price spike occurred after six years of having increases of food prices and also, the prices have decreased just one year and then continue to increase again.

Some of the authors try to investigate the volatility of food prices. For instance, according to Calvo (2008), Gilbert and Morgan (2010), Huchet – Bourdon (2010) and Abbot (2011), food prices are more volatile over time. They do not find any tendency on raised food price volatility starting from 1960 to the recent years. Moreover, food price volatility is higher currently than in the level of 1990 and 2000 while it is lower than the price level of 1970.

On the other hand, increasing food prices or food price volatility has impact on consumption of food. The expectation is about reducing the food consumption, but it is related with the income level of the countries. Generally, food consumption is price inelastic. As an example, consumers who are rich (high and middle income level countries) do not spend too much money for their daily life from their pocket for buying highly processed foods, because food expenditure is a small part of their budget and price volatility does not affect their budget. This shows that, rich consumers are less responsive and more price inelastic to the price changes. In contrast, poor consumers (low income level countries) who buy unprocessed commodities for their daily life spend their large part of budget. So, they become more responsive to price changes than rich countries. Importantly, poor countries face with higher prices before rich countries. This is happened to poor countries in 2007 – 2008 food crises and also in the second half of 2010.

According, to Regmi et. al. (2001), when Tanzania and US are compared, they find that, consumers who live in Tanzania spend 70% of their budget for buying food. In contrast, consumers who live in USA spend 10% of their budget for buying food.
In addition to other reasons of international food price volatility, trade barriers and non tariff measures may be important reasons of volatility. The solution is trade policies for limiting the food price volatility. If countries integrate domestic prices to international prices by using trade policies, then the volatility will be limited.

According to HLPE Report (2011), if the medium term evolution of trade policies will not be able to explain the aspects of higher food price volatility, then it is obvious that, when countries try to reduce the price volatility by using trade policies, it is caused to increase the problem of volatility.

Most of the authors think that, sudden changes in trade policies are caused to have price spikes in 2007 and 2008. Also, it is noted that, export restrictions and export bans become significant factors in food crisis between 2007 – 2008 periods. Another important issue is that, world food crisis is not easy to have it too often. In general, we face with world food crisis three times in a century. However, it looks like a regular issue and it happens like every three decades. For example, food prices have increased starting from World War I such as 1915 – 1917, 1950 – 1957, 1973 – 1974, and 2003 – 2008 periods.

On the other hand, world food stocks are important for the economy, because food prices and price volatility are related to world food stocks as well. Low world stocks were the reason of 1970 food crisis and the increases of food prices in 2010 – 2011 period. It is known that, when world stocks are at high level, the food prices are low and stable.

Gilbert (2010) and Tangerman (2011) say that, when the world stock level is low, there is price volatility. Therefore, world stocks must be at accurate level in order to have food price stability. Also, governments could play a significant role by organizing minimum storage levels.

FAO (2008), Mitchell (2008), and OECD (2008) realize that, production of biofuels was a major factor in the 2007 – 2008 price spikes. First goal of reducing the demand for food is to produce biofuel by limiting the use of food. Also, it is obvious that, if the oil prices increase, production of biofuel will compete with other alternative resources without having any public support. Then, the taxation of biofuel would be a mandatory way to solve and sustain minimum food price stability in the food market.

Lastly, volatility of food prices creates some problems like food security problems. Because, volatility has impact on both purchasing power and income. In order to solve the volatility problem, there are some categories of policies and programs. We will explain them after estimating and interpreting the results.

This study is organized as follows; Section 2 provides an overview of the existing literature on the impact of food price volatility on food prices. Then, it continues with the data and empirical techniques that are used in this paper, respectively. On the other hand, we report the empirical findings from TVP-SVM model. Lastly, provides the final remarks and policy recommendations.

3.2 Literature Review

As it is mentioned above, we focus on the impact of uncertainty shocks on food prices. In other words, this study shows the impact of food price volatility on food prices which is the first study in the literature of economics. There are not published papers about this topic, because they mainly focus on the food price volatility only and also the relationship between food prices and energy prices. Below the studies have provided detailed information about the literature.

Apergis and Rezitis (2003) focus on the agricultural price volatility spillover impacts using GARCH models with a monthly data during January 1989 – December 1999 periods in Greece. Agricultural prices are separated into three parts which are input, output and retail food prices. As a result of estimations, volatility of agricultural input and retail food prices are significant and both of them have positive spillover impacts on the volatility of agricultural output prices. On the other hand, the volatility of agricultural output prices is significant and has positive effect on its own volatility. Also, they seem to be more volatile than agricultural input and retail food prices.

Gilbert (2006) analyses agricultural price volatility in the world. Estimation results show that, volatility was at the lowest level in 1960s and it was higher than this level in 1970s and also first half of the 1980s. In addition, agricultural price volatility reduced again in the second half of 1980s and 1990s. However, the volatility did not reduce below 1960s level.

Gilbert and Morgan (2010) investigate the changes in food price volatility by using monthly data between January 1970 – December 2009 in United States. GARCH model is used for estimating the results and they find that, the food prices are high in the recent years and this is increased the food price volatility. On the other hand, when they compare the previous years with two most recent years, the volatility is lower in the two most recent years. However, variability is high in the recent years except rice and volatility of grain prices increases.

Roache (2010) analyses the reason of increases in food price volatility by using GARCH model of Engle and Rangel. The monthly data is used to measure the low frequency volatility during 1875-2009. The results show that, low frequency food price volatility has positive relation with other food commodities in US. Also, food price volatility increased in last 10 years for the range of different type of commodities.

Huchet-Bourdon (2011) focuses on agricultural commodity price volatility in OECD countries between 1957 – 2009 years which uses monthly data. GARCH model is used to model the volatility in food prices and also try to see if food prices have any relation with oil, fertiliser and exchange rate. Beef, butter, maize, whole milk powder, rice, soybean oil, sugar and wheat prices are the selected agricultural commodities. The results show that, the level of agricultural price volatilities is lower in recent years than in 1970s for beef and sugar respectively. Also, wheat price volatility is found higher in 2007 compare with 1970s. The price volatility of other products is lower than the volatility of wheat in 2007. In contrast, the price volatility of maize, rice and wheat increase in 2008 and it is higher than in 1970s and it gives the same results for each products except sugar when they look at the whole period in 1990s. The price volatility of soybean oil and dairies is found higher at the end of period than in 1990s.

Jacks et al. (2011) investigate the commodity price volatility and the integration of world market since 1700s. They find that, commodity prices play an important role for volatility and poor countries has more volatility than the rich countries and commodity price volatility prevents economic growth of the country. Estimation results show that, the volatility did not increase in time. Moreover, commodity prices are more volatile than manufactures and world market integration causes to have less volatility in commodity prices. On the other hand, the commodity price volatility is higher in the economically isolated countries than the world market integration.

Serra and Gil (2013) estimate the corn price fluctuations in US between January 1990 and December 2010 by using monthly nominal prices of corn. Two dimensional GARCH model is used to measure the volatility. Estimation results show that, corn price volatility can be affected from macroeconomic situations and also there is significant evidence which is stock building decreases the corn price fluctuations.

Minot (2014) focuses on the food price volatility in Sub-Saharan Africa during the period of 1980 – 2010. As it is known from the literature, commodity prices increased sharply in 2010 and 2011. As a result, grain prices volatility have increased in the global market since 2007 and this is found in the estimation results by using monthly price returns. He divided his estimation into two parts. First part is before crisis which includes 27 years (1980 – 2006) and second part is after crisis which is between 2007 – 2010 years and results shows that, unconditional volatility of monthly global prices increased 52 % for maize, 87 % for rice and 102 % for wheat.

Food price volatility may affect developing countries and it may create some critical issues for producers who are farmers and low income consumers. Diaz-Bonilla (2016) investigates the volatile volatility and finds both price levels and volatility has impact on consumers and producers. Especially, consumers who are low income level consume their large amount of salary on food and so they are more tender to food price volatility. For instance, low income consumers who live in Tanzania, Sri Lanka and Vietnam consume more than 60 % of their salary on food. So, food price volatility have high impact on consumers and purchasing power (FAO et al. (2011, a, b, 14)).

Ceballos et al. (2017) search on the source of volatility transmission from international to domestic markets in developing countries by using a multivariate GARCH method in order to estimate the price volatility both in domestic and international markets. Estimation results show that, transmission of volatility is statistically significant in all of the wheat, one quarter of the maize and more than half of the rice markets. Also, when the country's trade volume is large, volatility transmission is more common compare with domestic markets.

According to OECD and FAO (2011) reports, there could not find raised volatility in long run, however there is 'implied volatility' which shows future prices of wheat, maize, and soybeans increases since 1990.

In addition, FAO et al. (2011, a, b, 8) states that, there is only a little bit or no proof about the volatility of food prices has not been increased in the long run in international markets. However, report also says that, they discuss about the extraordinary food price volatility since 2006 in the international market.

On the other hand, international price volatility has a huge impact on both consumers and producers and then it is only transmitted to domestic markets. Moreover, food price volatility is high in Africa compare with other countries in the recent years and it is also known in the world market (Gerard et al. (2011) and G20 (2011)).

Moreover, FAO et al. (2011, 22) show that, volatility of average food prices which are wheat, maize and rice increased in 2008 and decreased in 2009, but there is no test about proofing whether or not the change is statistically significant.

As it can be seen from the literature, most of the studies have used GARCH model in order to measure the food price volatility.

Grier and Perry (2000), Grier et al. (2004), Elder (2004) and Fountas and Karanasos (2008) stated volatility as a GARCH model and define volatility as deterministic. On the other hand, Meddahi and Renault (2004) focus on the Stochastic Volatility (SV) model and they posited that, one merit of the SV model is that, they accommodate room for more uncertainty in the presence of volatility shocks. Therefore, although

GARCH model forces restrictions on conditional moments, SV model does not force. In addition, according to Danielsson (1998) and Kim et al. (1998), SV model has better forecasts than GARCH model both in in-sample fit and out-of sample forecasts.

So, we use Time Varying Parameter Stochastic Volatility in Mean (TVP – SVM) model in order to measure the impact of uncertainty shocks on food prices in G-7 countries. Also, this will be our contribution to the existing literature by allowing time varying impact of food price uncertainty on food price and modeling food price volatility with the SV specification. The estimation results show important evidence of the time variation in the impact of food price uncertainty on food price.

3.3 Data and Methodology

3.3.1 Description of Data

In this chapter, we use six different variables which are food price index, cereal price index, dairy price index, fats price index, meat price index and sugar price index. These are all consumer price indexes and monthly data. The data are taken from Data Stream and the original data were seasonally unadjusted. The dataset is transformed to logarithmic form and then to seasonally adjusted data in order to run the estimations. It is done by using X11 procedure in Eviews9. This is done in many studies which are Mirron (1990), Osborn (1991), Franses (1991), Lee and Siklos (1991) and Apergis (2003). They are all took the data as a seasonally unadjusted and used different techniques to transformed the data to seasonally adjusted. The analyses are done by using Matlab for G7 countries which are Canada, USA, Japan, Germany, UK, Italy and France. Time duration is different in each country because of non-available data. The data is started from 1978M09 to 2017M01 for Canada, from 1967M01 to 2017M01 for USA, from 1970M01 to 2017M01 for Japan and from 1996M01 to 2017M01 for UK. Also, the data is started in 1997M12 end in 2017M01, but the data for sugar price index is not found so this variable is excluded from the data set of Germany. The data is taken between 1997M12 – 2017M01 periods excluding Dairy Price Index in Italy. It is between 1997M12 – 2010M12 years because of non-available data. On the other hand, the data is between 1996M01 – 2017M01 periods in France excluding Dairy Price Index and it is between 1996M01- 2013M12 periods because of non-availability of data.

Below the table shows the descriptive statistics of the data which are all transformed to the logarithmic form and seasonally adjusted.

Table 2: Descriptive Statistics of the Data for All Countries

	Mean	Standard Deviation	Minimum	Maximum	Number of Observations
Canada					
Food	-3.313	6.368	-37.790	11.965	460
Cereals	-3.815	17.422	-102.936	68.474	460
Dairy	-3.243	6.671	-43.935	35.258	460
Fats	-2.730	10.016	-58.228	44.040	460
Meat	-3.405	12.435	-71.770	45.538	460
Sugar	-3.325	24.389	-203.032	71.903	460
France					
Food	-1.599	4.199	-17.113	10.544	252
Cereals	-0.417	56.310	-222.864	200.633	252
Dairy	-2.348	45.436	-163.902	137.077	215
Fats	-1.623	4.955	-33.697	10.998	252
Meat	-1.956	3.039	-18.393	4.984	252
Sugar	-0.348	5.272	-33.940	12.090	252
Germany					
Food	-1.578	5.875	-30.797	14.849	229
Cereals	-1.641	2.822	-14.028	5.953	229
Dairy	-1.793	12.935	-55.760	42.220	229
Fats	-2.001	19.763	-173.491	54.384	229
Meat	-1.235	4.292	-25.758	5.158	229
US					
Food	-3.925	5.121	-63.208	10.258	600
Cereals	-4.160	6.714	-71.754	10.083	600
Dairy	-3.404	8.722	-74.985	36.589	600
Fats	-3.570	12.232	-101.163	33.914	600
Meat	-3.700	13.931	-186.144	53.789	600
Sugar	-4.203	14.202	-155.524	64.910	600
Italy					
Food	-1.967	2.925	-12.898	5.432	229
Cereals	-1.906	2.957	-21.343	4.086	229
Dairy	-1.611	3.227	-13.315	6.621	156
Fats	-1.770	4.917	-26.023	9.778	229
Meat	-1.722	2.933	-27.839	6.067	229
Sugar	-1.727	2.563	-27.539	6.082	229
Japan					
Food	-2.613	10.299	-72.928	22.384	564
Cereals	-2.314	12.760	-202.066	50.960	564
Dairy	-1.788	10.600	-124.240	22.067	564
Fats	-0.922	12.045	-107.397	34.938	564
Meat	-2.223	6.939	-82.577	10.998	564
Sugar	-1.135	23.447	-266.279	143.900	564
UK					
Food	-1.995	6.865	-28.349	21.762	252
Cereals	-1.754	8.432	-36.765	29.812	252
Dairy	-0.837	12.941	-54.443	49.064	252
Fats	-2.223	25.168	-138.282	120.878	252
Meat	-1.714	9.192	-60.442	31.426	252
Sugar	-3.012	8.109	-32.295	33.708	252

3.3.2 Methodology

Time varying parameter model (TVP) is the suitable in order to estimate the structural instability, given stochastic nature of the parameters over time. In this chapter, we permit the impact of uncertainty shocks on food prices in G7 countries to be time varying and also catching structural instability in the platform of macroeconomics. In addition, this will change the food price uncertainty and food price relationship. On the other hand, Koopman and Hol Uspensky (2002) focus on the stochastic volatility (SVM) model as it gives robust and better estimates in time series analysis with conditional heteroskedasticity. When this model is comparing with the GARCH models, SVM model is mentioned as an inherent stochastic process and it permits volatility shocks. As a result, we bring TVP and SVM models together and then have TVP-SVM model which permits both structural breaks and volatility shocks. In the empirical part of this chapter, efficient Markov Chain Monte Carlo (MCMC) sampler which is developed by Chan (2017) is used to estimate the model rather than conventional Kalman Filter as it is shown below in Equations (13-15).

3.3.2.1 The Model

TVP with stochastic volatility is taken into consideration and it is also added to the equation of conditional mean. In addition, y_t represents the time series of interest. Let's consider;

$$y_t = x_t'\beta_t + \alpha_t e^{h_t} + \varepsilon_t^y, \varepsilon_t^y \sim \mathrm{N}(0, e^{h_t}) \qquad (13)$$

$$h_t = \mu + \phi(h_{t-1} - \mu) + \varepsilon_t^h, \varepsilon_t^h \sim N(0, \sigma^2) \qquad (14)$$

It is known that, x_t is $k \times 1$ which is vector of covariates and then β_t is related $k \times 1$ vector of time varying parameters. Moreover, both ε_t^y and ε_t^h are the mutually and serially uncorrelated disturbances and also the log volatility e^{h_t} following a stationary AR (1) process with $\phi \prec 1$. On the other hand, it is initiated with $h_1 \sim N(\mu, \sigma^2 / (1-\phi^2))$. Both model (13) and (14) are the original setup of Koopman and Hol Uspensky's (2002) research and their study allows the conditional mean of y_t to have time varying parameters. So, parameters α_t and β_t are time varying and also this property is important for macroeconomic applications empirically.

The vector of coefficients which is $\theta_t = (\alpha_t, \beta_t')'$ developed in accordance with the random walk process;

$$\theta_t = \theta_{t-1} + \varepsilon_t^\theta, \varepsilon_t^\theta \sim N(0, \Omega) \quad (15)$$

Ω denotes a $(k+1)x(k+1)$ covariance matrix. In addition, some of the researchers who are Cogley and Sargent (2005), Cogley et al. (2010) study on TVP vector autoregressions. In the model, it is allowed for an inclusive correlation structure between the new findings to the random walk coefficients. As a result, both θ_0 and Ω_0 are constant matrices and random walk in Model (15) is set up with $\theta_1 \sim N(\theta_0, \Omega_0)$. When α_t is zero for all of the $t = 1,...,T$, then the Model in (13)-(15) decreases to the standard TVP regression with stochastic volatility. On the other hand, when $\alpha_t \neq 0$, the model allows an extra channel of persistence and also it is known log volatility pursues an AR (1) process and the shock on h_{t-1} would have impact on h_t. Moreover, it affects the conditional mean of y_t directly. As a note, this channel seems to be important for comparing the model exercise and the forecasting exercise which will be done below. Additionally, model (13)-(15) defining a Gaussian state space model with two different names which are θ_t and h_t. Also, the model is nonlinear in h_t, so it is more difficult to estimate results. In contrast, the model is linear in θ_t and it is much easier to estimate comparing with nonlinear model.

3.3.2.2 Bayesian Estimation

In this part, we explain the MCMC sampler and then try to simulate from the subsequent distribution of the model in (13)-(15). Koopman and Hol Uspensky (2002) simulated the maximum likelihood estimator according to Kalman Filter in order to fit the SVM model by using the original setup with constant coefficient. Especially, the likelihood or integrated likelihood are gained by integrating out h_t and this is measured by using the significance sampling. Also, conditional likelihood is estimated by establishing the conditional density and Gaussian density is used for the conditional density of y_t provided h_t. On the other hand, Carter and Kohn (1994), Fruwirth-Schnatter (1994), de Jong and Shephard (1995), Durbin and Koopman (2002) used Kalman Filter based algorithms for sampling the high dimensional Gaussian density. As an important note, there are some parameters with a constant coefficient SVM model and so one may maximize the likelihood numerically for taking the maximum likelihood estimation. Also, there is disadvantage of this approach which is not easy to generalize to our TVP setup like likelihood evaluation. Because, it includes both θ_t and h_t with Monte Carlo methods. So, this likelihood evaluation stage is nontrival in general, because the states are higher dimensional. In this difficult situation, we accept the Bayesian approach and then enlarge MCMC algorithm to simulate from the joint posterior distribution. Because of the nature of the MCMC algorithm, we may simulate both states once in a time and this decreases dimension of the problem then the estimation becomes easier.

On the other hand, this approach has one more difference than other approaches. It makes this approach more original. This approach builds on the new improvements in band and sparse matrix algorithm rather than using the conventional Kalman filter. New studies which are published recently are used old approach. For example, Rue (2001) used for linear Gaussian Markov fields, Chan and Jeliazkov (2009) and McCausland et al. (2011) used for linear Gaussian state space models, Rue et al. (2009) used for nonlinear Markov random fields, McCausland (2012), Chan et al. (2013), Chan and Strachan (2014), Djegnene and McCausland (2014) used for nonlinear state space models.

Another important point in our new approach is that, it operates the specific structure of the problem and accomplishes the efficiency gains. Also, Hessian of the log conditional density of the log volatilities is band matrix and it includes some nonzero elements only and it manages throughout the diagonal band. Then, this becomes very important for efficient sampling algorithms. Moreover, efficiency has two related concepts which are computational speed and the autocorrelations of the MCMC draws. Computational speed means that, the how much time needed in order to get an exact number of posterior draws. On the other hand, autocorrelations of the MCMC draws means that, when autocorrelation is lower, then they are close to ideal case of independent draws. Also, if draws are produced with a lower autocorrelations, the sampler is going to be efficient and then recommended algorithm is efficient in both concepts. First criteria is that, it is easy to estimate and speed of algorithm is proved at the end of the section. In order to obtain the efficiency in the second concept, the recommended approach illustrates all of the log volatilities $h_1,...,h_T$ jointly. In opposition to this, Mumtaz and Zanetti (2013) illustrate each h_t at a time by using the single move sampler.

Now, assuming the independent priors for σ^2, μ, ϕ and Ω in order to finalize the specification of the model.

$$\begin{aligned} &\mu \sim N(\mu_0, V_\mu), \phi \sim N(\phi_0, V_\phi) 1(|\phi| \prec 1) \\ &\sigma^2 \sim IG(v_{\sigma^2}, S_{\sigma^2}), \Omega \sim IW(v_\Omega, S_\Omega) \end{aligned} \quad (16)$$

Where $IG(v_{\sigma^2}, S_{\sigma^2})$ represents the inverse gamma distribution and $IW(v_\Omega, S_\Omega)$ denotes the inverse Wishart distribution. In addition, $|\phi| \prec 1$ denotes the stationary condition and it is prior for ϕ. Also, x represents the covariates, $y = (y_1,..., y_T)', \theta = (\theta_1',...,\theta_T')', h = (h_1,...,h_T)'$.

Now, below the steps show the posterior draws which is obtained with the order;

$$\begin{aligned} &1. p(h | y, x, \theta, \mu, \phi, \sigma^2, \Omega) = p(h | y, x, \theta, \mu, \phi, \sigma^2); \\ &2. p(\theta | y, x, h, \mu, \phi, \sigma^2, \Omega) = p(\theta | y, x, h, \Omega); \\ &3. p(\Omega, \sigma^2 | y, x, \theta, h, \mu, \phi) = p(\Omega | \theta) p(\sigma^2 | h, \mu, \phi); \\ &4. p(\mu, \phi | y, x, \theta, h, \sigma^2, \Omega) = p(\mu, \phi | h, \sigma^2). \end{aligned}$$

Step 1 shows that, $p(h | y, x, \theta, \mu, \phi, \sigma^2)$ which is joint conditional density is nonstandard and high dimensional. We use the same method of Chan and Strachan

(2014) in order to simulate the joint conditional density and also using the Hessian of log $p(h|y,x,\theta,\mu,\phi,\sigma^2)$ which is a band matrix.

Similarly, Gaussian approximation may be attained and also may be a proposal density for the acceptance or rejection of the Metropolis Hastings algorithm. In addition, it is known that, the Hessian of Gaussian proposal density is band matrix and it is used in Chan and Jeliazkov's (2009) study. They mention this in the study as; it operates the band structure of the inverse covariance matrix of the states and then they get the candidate draws rather than obtaining the Kalman filter based algorithms.

Now, we focus on how to get Gaussian approximation of $p(h|y,x,\theta,\mu,\phi,\sigma^2)$ and then having $p(h|y,x,\theta,\mu,\phi,\sigma^2)\,\alpha\, p(y|x,\theta,h)\, p(y|\mu,\phi,\sigma^2)$ with Bayesian's theorem. On the other hand, the derivation of the explicit expressions is shown on the right hand side for two densities and also as it is shown below, $p(y|\mu,\phi,\sigma^2)$ which shows the prior density is Gaussian. Additionally, we get the Gaussian approximation of $p(h|y,x,\theta,\mu,\phi,\sigma^2)$, if the likelihood $p(y|x,\theta,h)$ is approximated with the Gaussian density in h.

Therefore, $\tilde{h}=(\tilde{h}_1,...,\tilde{h}_T)'\in\mathbb{R}^T$ this is a provided point, in order to approximate the log conditional likelihood $\log p(y|x,\theta,h)=\sum_{t=1}^{T}\log p(y_t|x_t,\theta_t,h_t)$, it is needed to use second order Taylor expansion around $\tilde{h}$ to get the;

$$\log p(y|x,\theta,h)\approx\log p(y|x,\theta,\tilde{h})+(h-\tilde{h})'f-\frac{1}{2}(h-\tilde{h})'G(h-\tilde{h})=-\frac{1}{2}(h'Gh-2h'(f+G\tilde{h}))+c_1 \quad (17)$$

Where c_1 denotes the constant independent of h, $f = (f_1, ..., f_T)'$ and also $G = diag(G_1, ..., G_T)$ by

$$f_t = \frac{\partial}{\partial h_t} \log p(y_t \left| x_t, \theta_t, h_t) \right|_{h_t = \tilde{h}_t},$$

$$G_t = -\frac{\partial^2}{\partial h_t^2} \log p(y_t \left| x_t, \theta_t, h_t) \right|_{h_t = \tilde{h}_t} .$$

Where G denotes diagonal which is a band matrix and also denotes the negative Hessian of the log conditional likelihood which is measured at $\tilde{h}$. Moreover, log conditional density of y_t provided latent variables h_t and $\theta_t = (\alpha_t, \beta_t')'$ is provided with;

$$\log p(y_t \left| x_t, \theta_t, h_t \right.) = -\frac{1}{2}\log(2\pi) - \frac{1}{2}h_t - \frac{1}{2}e^{-h_t}(y_t - x_t'\beta_t - \alpha_t e^{h_t})^2 - \frac{1}{2}\log(2\pi) - \frac{1}{2}h_t - \frac{1}{2}(\alpha_t^2 e^{h_t} + e^{-h_t}(y_t - x_t'\beta_t)^2 - 2\alpha_t(y_t - x_t'\beta_t)),$$

and it is easy to control that,

$$\frac{\partial}{\partial h_t} \log p(y_t \left| x_t, \theta_t, h_t \right.) = -\frac{1}{2} - \frac{1}{2}\alpha_t^2 e^{h_t} + \frac{1}{2}e^{-h_t}(y_t - x_t'\beta_t)^2,$$

$$\frac{\partial^2}{\partial h_t^2} \log p(y_t \left| x_t, \theta_t, h_t \right.) = -\frac{1}{2}\alpha_t^2 e^{h_t} - \frac{1}{2}e^{-h_t}(y_t - x_t'\beta_t)^2.$$

After that, the prior density which $p(h|\mu,\phi,\sigma^2)$ is derived and for this purpose;

$$H_\phi = \begin{pmatrix} 1 & 0 & 0 & \cdots & 0 \\ -\phi & 1 & 0 & \cdots & 0 \\ 0 & -\phi & 1 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \vdots \\ 0 & 0 & \cdots & -\phi & 1 \end{pmatrix}$$

The determinant of H_ϕ is equal to 1. Because of this reason, H_ϕ is invertible irrespective of the value of ϕ. Also, it must be known that, H_ϕ is the lower bi-diagonal matrix so, it means that, nonzero elements of H_ϕ are limited throughout the main diagonal and the diagonal below.

State equation of h_t in (14) is written as following;

$H_\phi h = \tilde{\delta}_h + \varepsilon^h, \varepsilon^h \sim N(0, S_h)$, and then

$\tilde{\delta}_h = (\mu, (1-\phi)\mu, ..., (1-\phi)\mu)', \varepsilon^h = (\varepsilon_1^h, ..., \varepsilon_T^h)'$, and $S_h = diag(\sigma^2 / (1-\phi^2), \sigma^2, ..., \sigma^2)$.

This is the $(h|\mu,\phi,\sigma^2) \sim N(\delta_h, (H_\phi' S_h^{-1} H_\phi)^{-1}$ by log density,

$$\log p(h|\mu,\phi,\sigma^2) = -\frac{1}{2}(h' H_\phi' S_h^{-1} H_\phi h - 2h' H_\phi' S_h^{-1} H_\phi \delta_h) + c_2 \qquad (18)$$

Where c_2 denotes the constant independent of h and $\delta_h = H_\phi^{-1}\tilde{\delta}_h$.

As a result, when equation (17) and (18) are combined to each other then we have

$$\log p(h|y,x,\theta,\mu,\phi,\sigma^2) = \log p(y|x,\theta,h) + \log p(h|\mu,\phi,\sigma^2) + c_3, \approx -\frac{1}{2}(h'K_h h - 2h'k_h) + c_4 \quad (19)$$

Where c_3 and c_4 denote the constant independent of h. Then, $K_h = H'_\phi S_h^{-1} H_\phi + G$ and $k_h = f + G\tilde{h} + H'_\phi S_h^{-1} H_\phi \delta_h$. In addition, log kernel of the density is shown in equation (19) which is $N(\hat{h}, K_h^{-1})$, where $\hat{h} = K_h^{-1} k_h$. On the other hand, Gaussian density with mean vector $\hat{h}$ and precision matrix K_h is used to approximate the $p(h|y,x,\theta,\mu,\phi,\sigma^2)$. In this study, our aim is to notice precision matrix K_h which is tridiagonal. Non-zero elements of K_h show up on the main diagonal and below and above the main one only. As a result, if we want to calculate $\hat{h}$ efficiently, we need to solve the linear system which is $K_h x = k_h$ for x without computing the inverse of K_h^{-1}. Moreover, according to Chan and Jeliazkov (2009), benefits from $N(\hat{h}, K_h^{-1})$ may be get using the precision sampler quickly. On the other hand, we use the Gaussian approximation as a proposal density for accepting or rejecting the Metropolis Hastings step and then there is only one thing remaining which is to choose the point $\tilde{h}$ for Taylor expansion in (17). The aim of selecting $\tilde{h}$ is that, $\tilde{h}$ is the mode of $p(h|y,x,\theta,\mu,\phi,\sigma^2)$ and it is easier to get with the Newton Raphson method.

In order to complete the step 2, step 1 is rewritten again as following;

$$y_t = z_t'\theta_t + \varepsilon_t^y, \varepsilon_t^y \sim N(0, e^{h_t}) \qquad (20)$$

Where $z_t = (\exp(h_t), x_t')'$ and $\theta_t = (\alpha_t, \beta_t')'$. Moreover, Equation (15) and (20) describe the linear Gaussian space model in θ_t. Therefore, benefit from $p(\theta | y, x, h, \Omega)$ can be got by using conventional Kalman filter based algorithms which is used by Carter and Kohn (1994), Durbin and Koopman (2002) or more efficient precision sampler which is used by Chan and Jeliazkov (2009), McCausland et al. (2011).

Additionally, for completing Step 3, both Ω and σ^2 are conditionally independent and provided the latent states which are θ and h. Actually, both of the conditional distributions are standard distributions and they are;

$$(\Omega | \theta) \sim IW\left(v_\Omega + T - 1, S_\Omega + \sum_{t=2}^{T} (\theta_t - \theta_{t-1})(\theta_t - \theta_{t-1})'\right), (\sigma^2 | h, \mu, \phi) \sim IG\left(v_{\sigma^2} + \frac{T}{2}, \tilde{S}_{\sigma^2}\right),$$

Where $\tilde{S}_{\sigma^2} = S_{\sigma^2} + ((1-\phi^2)(h_1 - \mu)^2 + \sum_{t=2}^{T} (h_t - \mu - \phi(h_{t-1} - \mu))^2)/2$.

Finally, both μ and ϕ are sampled jointly in order to develop the efficiency. Also, it must be mentioned that, both step 3 and 4 are standard steps so we that is why we do not explain it longly.

3.3.2.3 Full Sample Estimation

The TVP-SVM model is mentioned as following;

$$y_t = \tau_t + \alpha_t e^{h_t} + \varepsilon_t^y, \varepsilon_t^y \sim \mathrm{N}(0, e^{h_t}) \qquad (21)$$

$$h_t = \mu + \phi(h_{t-1} - \mu) + \beta y_{t-1} + \varepsilon_t^h, \varepsilon_t^h \sim N(0, \sigma^2) \qquad (22)$$

$$\theta_t = \theta_{t-1} + \varepsilon_t^\theta, \varepsilon_t^y \sim N(0, \Omega) \qquad (23)$$

Where $\theta = (\tau_t, \alpha_t)', \Omega$ is 2 x 2 covariance matrix. In the given equations above, $\exp(h_t)$ denotes the variance of the transitory component ε_t^y of y_t. So, the interpretation of α_t is; the impact of the transitory food price volatility on the food prices. On the other hand, β shows the impact of food prices on its volatility.

3.4 Estimation Results

Below the figures show the food, cereals, dairy, fats, meat and sugar price volatilities respectively for G-7 countries.

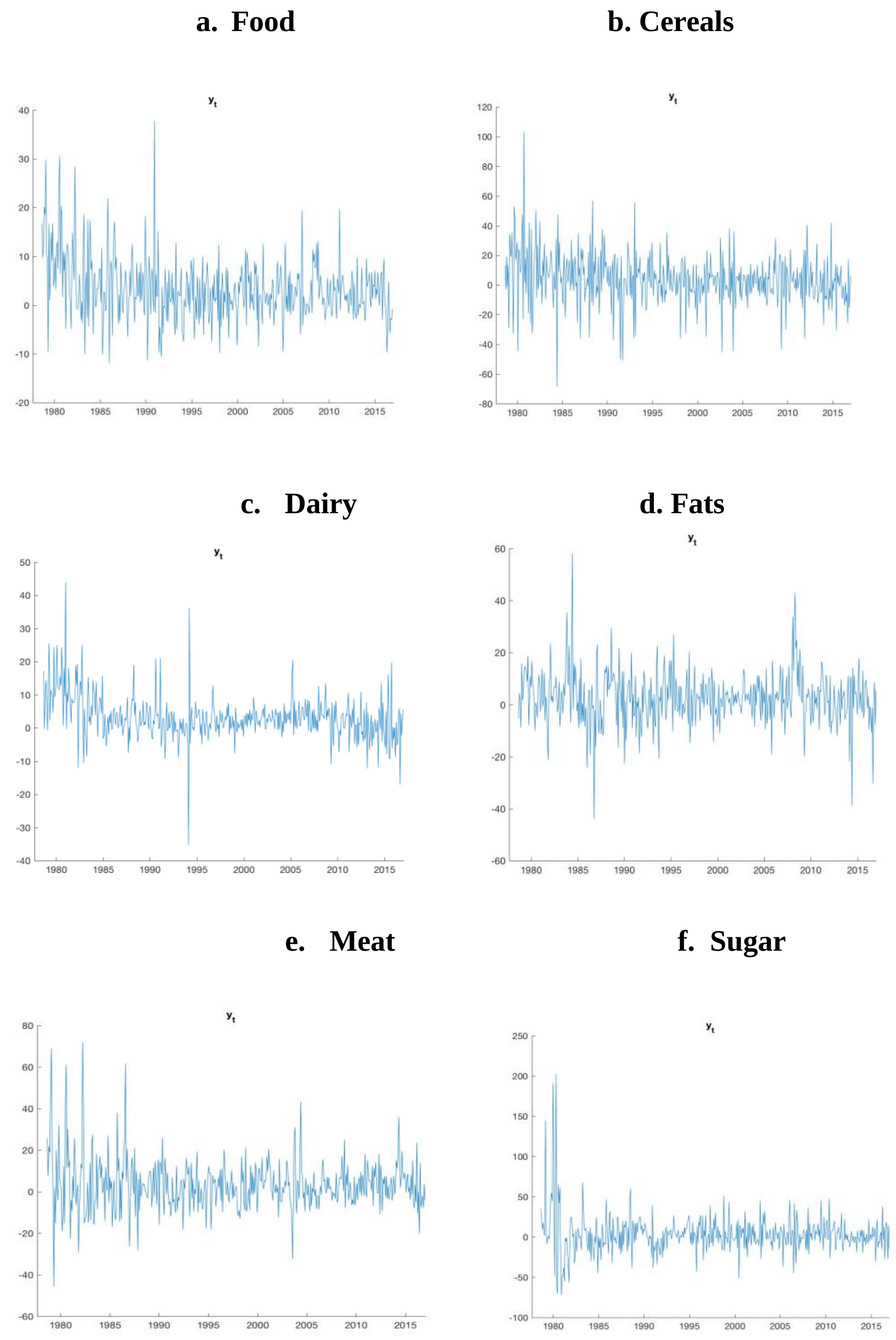
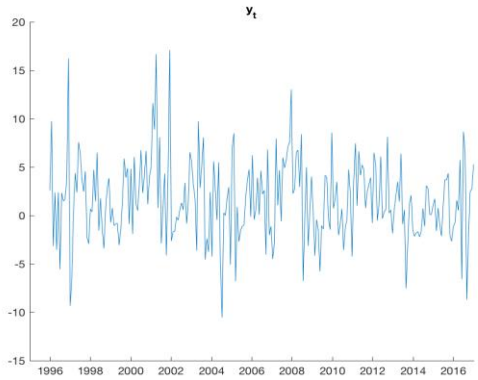
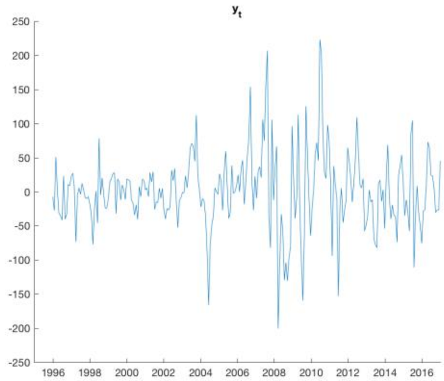


Figure 10a: Time Series of Volatility for Canada

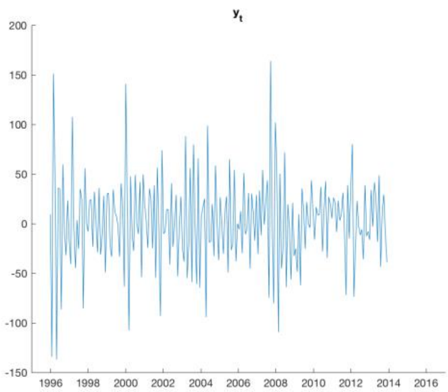
a. Food



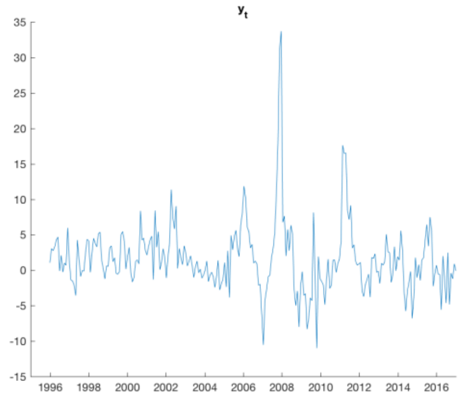
b. Cereals



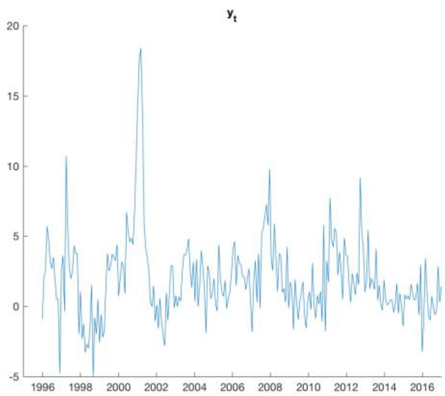
c. Dairy



d. Fats



e. Meat



f. Sugar

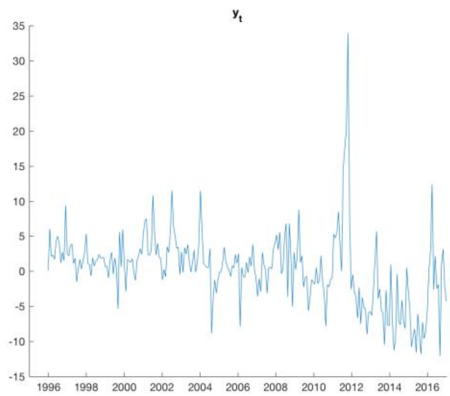
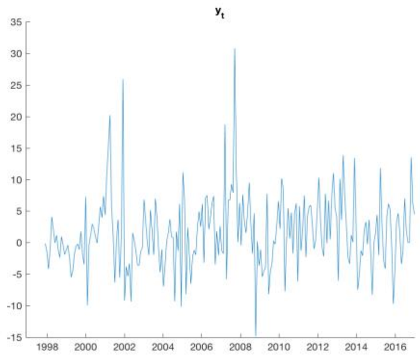
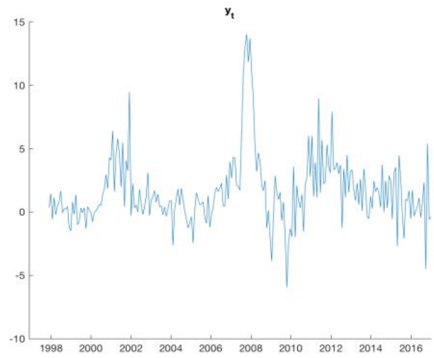


Figure 10b: Time Series of Volatility for France

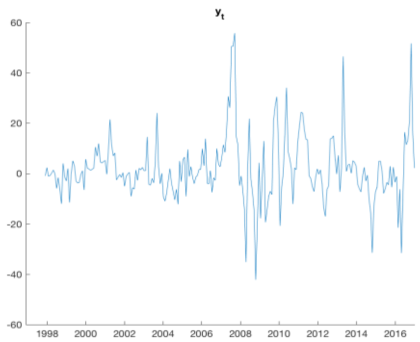
a. Food



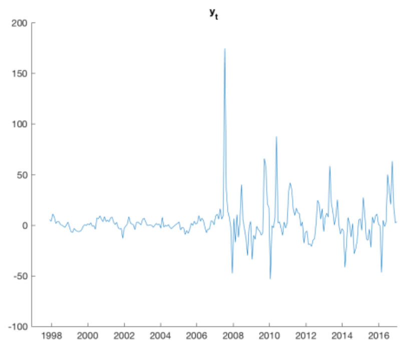
b. Cereals



c. Dairy



d. Fats



e. Meat

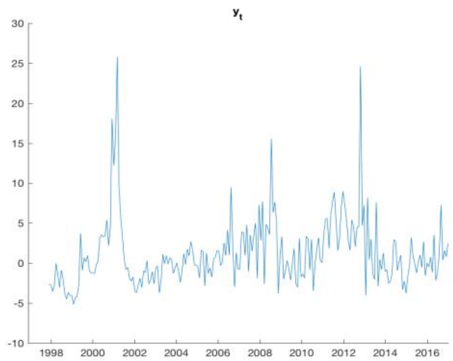
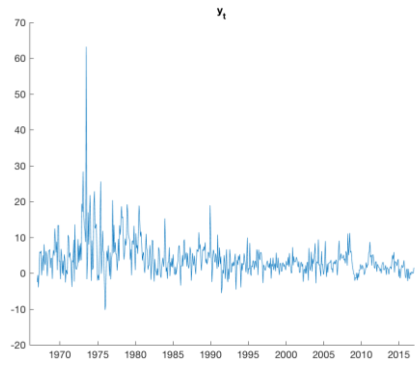
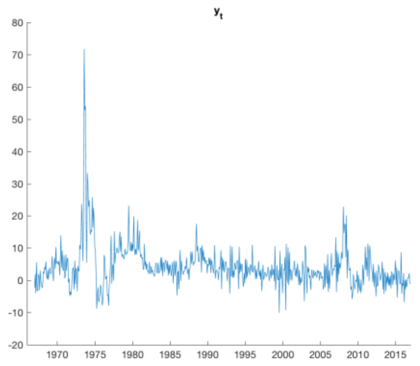


Figure 10c: Time Series of Volatility for Germany

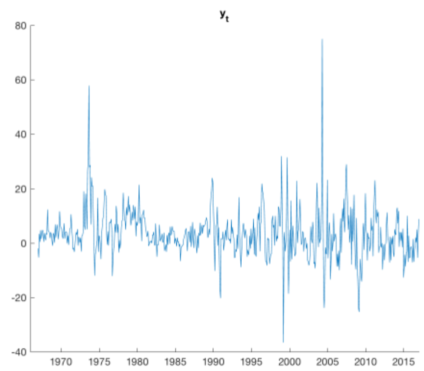
a. Food



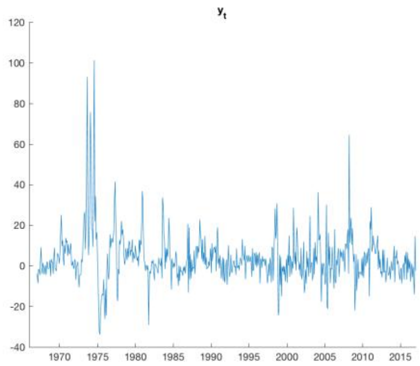
b. Cereals



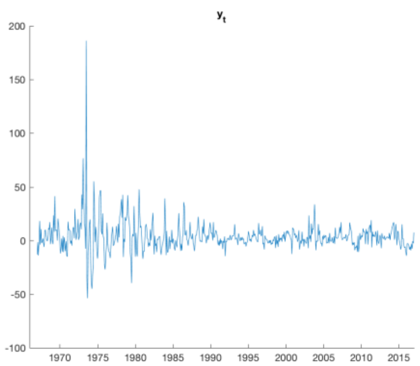
c. Dairy



d. Fats



e. Meat



f. Sugar

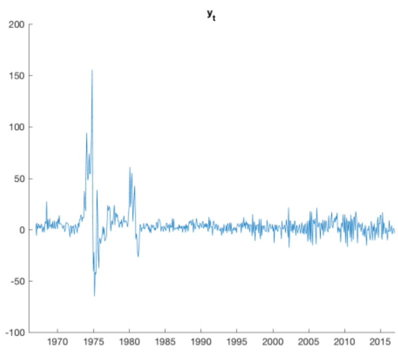
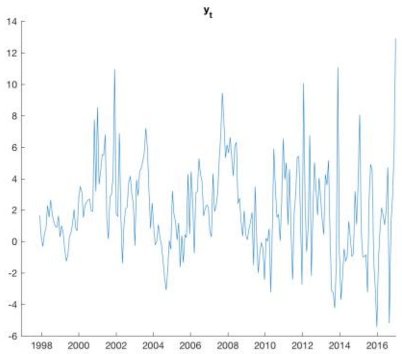
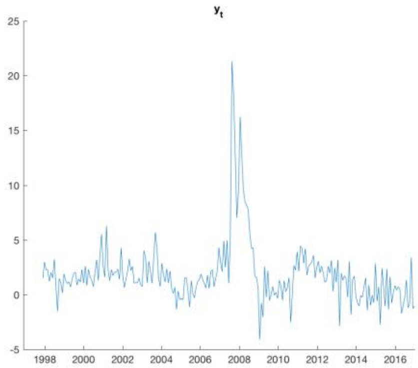


Figure 10d: Time Series of Volatility for USA

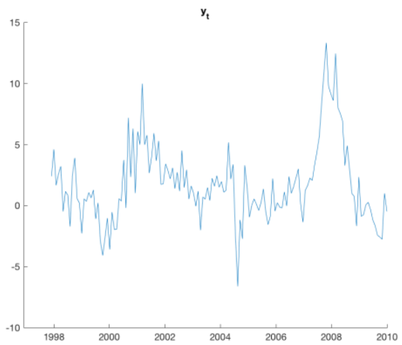
a. Food



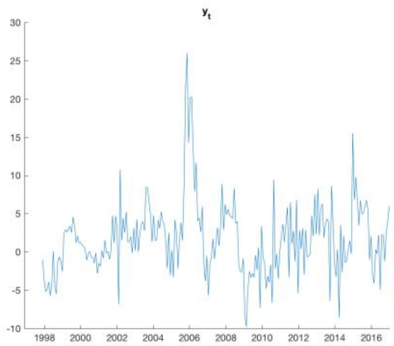
b. Cereals



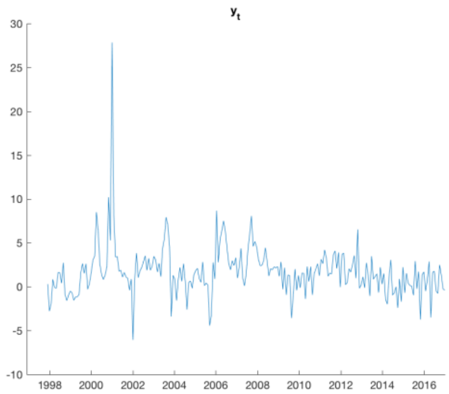
c. Dairy



d. Fats



e. Meat



f. Sugar

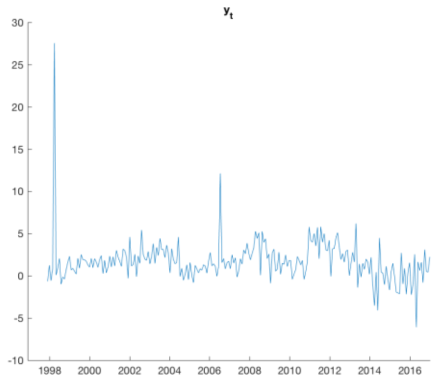
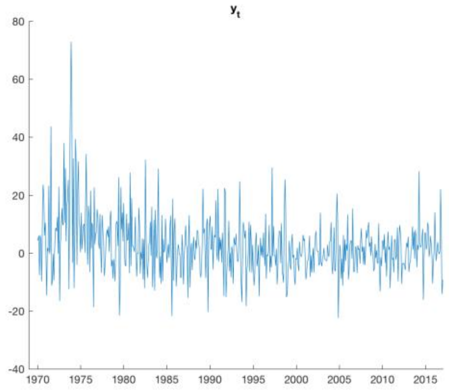
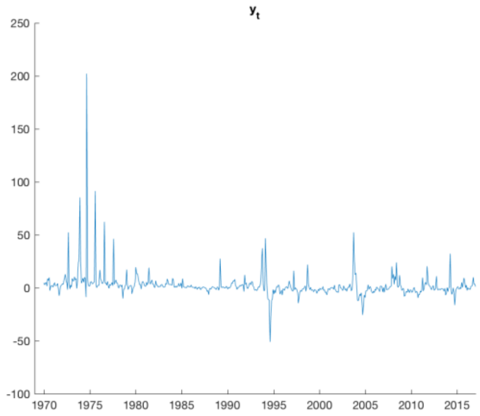


Figure 10e: Time Series of Volatility for Italy

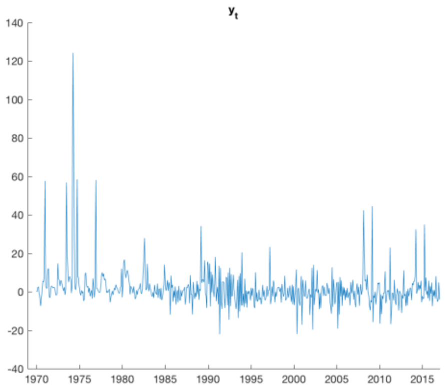
a. Food



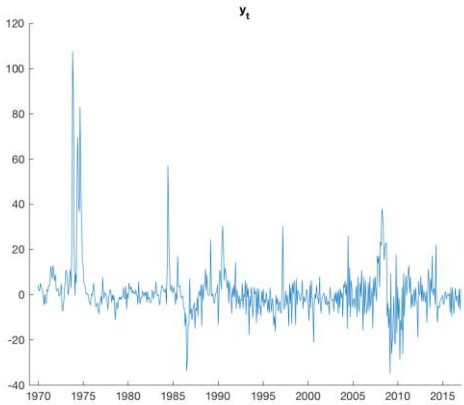
b. Cereals



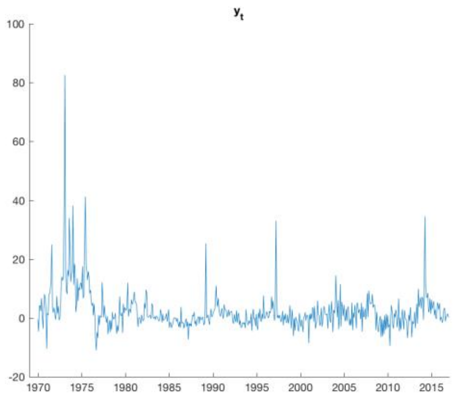
c. Dairy



d. Fats



e. Meat



f. Sugar

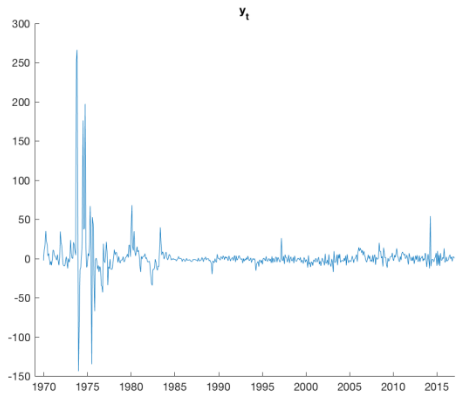
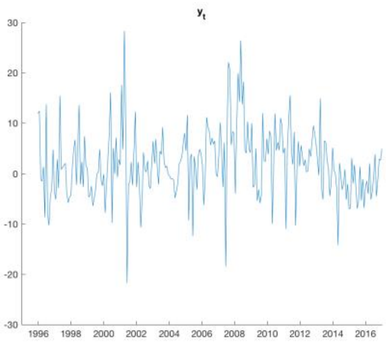
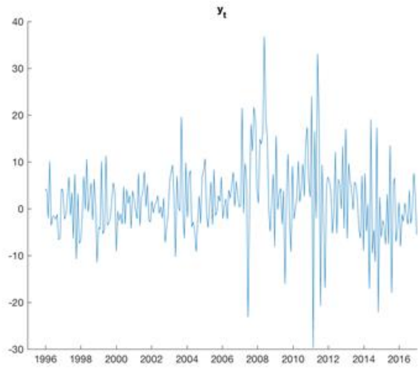


Figure 10f: Time Series of Volatility for Japan

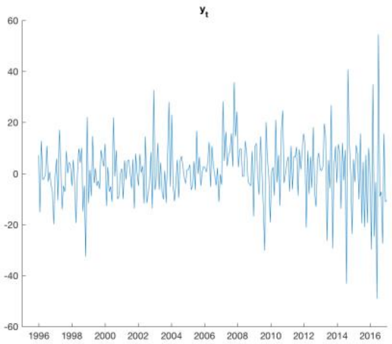
a. Food



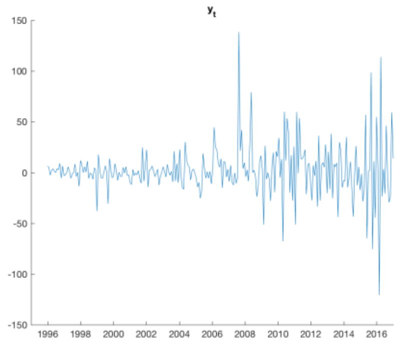
b. Cereals



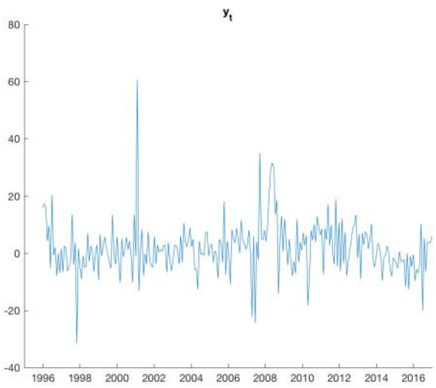
c. Dairy



d. Fats



e. Meat



f. Sugar

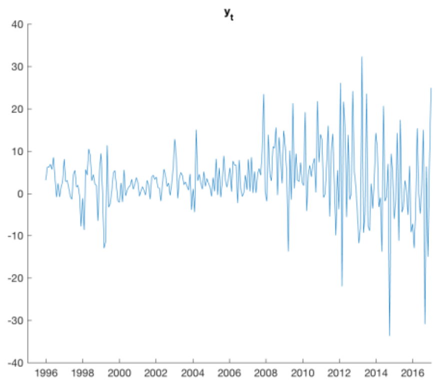


Figure 10g: Time Series of Volatility for UK

Table 3a-b-c-d-e-f-g show the estimation results of posterior moments and quantiles of the stochastic volatility (SV) in mean model parameters for Canada, France, Germany, USA, Italy, Japan and UK respectively.

Table 3a: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in Canada

		Food				**Cereals**	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	3.125	0.325	(2.626, 3.602)	μ	5.206	0.472	(4.730, 5.730)
β	-0.000	0.003	(-0.005, 0.004)	β	-0.002	0.003	(-0.006, 0.003)
ϕ	0.958	0.019	(0.925, 0.987)	ϕ	0.945	0.024	(0.906, 0.988)
σ^2	0.033	0.008	(0.021, 0.048)	σ^2	0.049	0.013	(0.031, 0.074)
ω_α^2	0.004	0.001	(0.003, 0.006)	ω_α^2	0.002	0.000	(0.001, 0.002)
$\omega_{\alpha,\tau}^2$	-0.003	0.004	(-0.010, 0.002)	$\omega_{\alpha,\tau}^2$	-0.001	0.002	(-0.003, 0.002)
ω_τ^2	0.088	0.044	(0.042, 0.167)	ω_τ^2	0.097	0.053	(0.045, 0.189)
		Dairy				**Fats**	
μ	2.880	0.490	(2.180, 3.569)	μ	4.095	0.339	(3.612, 4.565)
β	-0.002	0.003	(-0.007, 0.003)	β	-0.001	0.003	(-0.005, 0.004)
ϕ	0.963	0.018	(0.932, 0.990)	ϕ	0.958	0.018	(0.926, 0.986)
σ^2	0.057	0.015	(0.037, 0.084)	σ^2	0.035	0.008	(0.024, 0.051)
ω_α^2	0.004	0.001	(0.003, 0.006)	ω_α^2	0.003	0.001	(0.002, 0.004)
$\omega_{\alpha,\tau}^2$	-0.003	0.004	(-0.009, 0.002)	$\omega_{\alpha,\tau}^2$	-0.001	0.003	(-0.006, 0.003)
ω_τ^2	0.077	0.035	(0.038, 0.142)	ω_τ^2	0.093	0.049	(0.043, 0.180)
		Meat				**Sugar**	
μ	4.121	0.362	(3.538, 4.679)	μ	5.159	0.397	(4.546, 5.710)
β	-0.003	0.002	(-0.007, 0.001)	β	0.002	0.001	(-0.001, 0.004)
ϕ	0.961	0.017	(0.930, 0.987)	ϕ	0.960	0.017	(0.930, 0.987)
σ^2	0.044	0.011	(0.029, 0.063)	σ^2	0.050	0.014	(0.031, 0.077)
ω_α^2	0.004	0.001	(0.003, 0.005)	ω_α^2	0.002	0.000	(0.002, 0.003)
$\omega_{\alpha,\tau}^2$	-0.001	0.003	(-0.007, 0.003)	$\omega_{\alpha,\tau}^2$	-0.000	0.002	(-0.004, 0.003)
ω_τ^2	0.094	0.046	(0.043, 0.184)	ω_τ^2	0.101	0.055	(0.045, 0.198)

**The results are based on 50,000 posterior with a burn in period of 50,000.

Above the Table 3a shows the estimation results for Canada. All the series which are food, cereals, dairy, fats, meat have negative and sugar has positive and statistically not significant impact on their volatility. In other words, they are statistically not different from zero. On the other hand, volatility persistence is measured in order to see if the volatility is consistent. The results show that, all of the series are highly volatility persistence because ϕ values are greater than 60% and they are approximately 95% for each series.

The results are given in Table 3b for France. The estimation results shows that, food and cereals have positive, dairy, fats and meat have negative and statistically insignificant impact on their volatility. In contrast, sugar has negative and significant impact on its volatility.

On the other hand, all of the series are highly volatility persistence because ϕ values are approximately 95% - 96% for each series in France.

Table 3b: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in France

		Food				**Cereals**	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	2.763	0.815	(2.267, 3.204)	μ	5.080	1.896	(1.386, 6.915)
β	0.005	0.012	(-0.006, 0.016)	β	0.001	0.000	(-0.000, 0.001)
ϕ	0.956	0.031	(0.925, 0.987)	ϕ	0.974	0.023	(0.932, 0.999)
σ^2	0.037	0.010	(0.027, 0.046)	σ^2	0.039	0.012	(0.024, 0.063)
ω_{α}^2	0.008	0.002	(0.005, 0.010)	ω_{α}^2	0.019	0.036	(0.004, 0.082)
$\omega_{\alpha,\tau}^2$	-0.004	0.007	(-0.010, 0.002)	$\omega_{\alpha,\tau}^2$	0.002	0.023	(-0.019, 0.032)
ω_{τ}^2	0.100	0.053	(0.056, 0.143)	ω_{τ}^2	0.114	0.067	(0.048, 0.241)
		Dairy				**Fats**	
μ	7.094	0.651	(6.304, 8.533)	μ	1.694	0.600	(0.826, 2.685)
β	-0.000	0.002	(-0.003, 0.003)	β	-0.007	0.005	(-0.014, 0.001)
ϕ	0.948	0.037	(0.872, 0.986)	ϕ	0.957	0.025	(0.913, 0.993)
σ^2	0.049	0.018	(0.029, 0.081)	σ^2	0.050	0.013	(0.032, 0.075)
ω_{α}^2	0.003	0.001	(0.002, 0.005)	ω_{α}^2	0.027	0.016	(0.011, 0.057)
$\omega_{\alpha,\tau}^2$	-0.000	0.003	(-0.004, 0.004)	$\omega_{\alpha,\tau}^2$	0.001	0.027	(-0.040, 0.038)
ω_{τ}^2	0.106	0.039	(0.052, 0.178)	ω_{τ}^2	0.119	0.072	(0.050, 0.250)
		Meat				**Sugar**	
μ	0.860	0.417	(0.204, 1.509)	μ	1.983	0.554	(1.274, 2.951)
β	-0.004	0.005	(-0.013, 0.005)	β	-0.009	0.004	(-0.016, -0.002)
ϕ	0.945	0.029	(0.894, 0.989)	ϕ	0.951	0.030	(0.895, 0.992)
σ^2	0.039	0.010	(0.025, 0.058)	σ^2	0.057	0.019	(0.033, 0.093)
ω_{α}^2	0.017	0.009	(0.007, 0.034)	ω_{α}^2	0.013	0.006	(0.007, 0.025)
$\omega_{\alpha,\tau}^2$	-0.006	0.013	(-0.028, 0.011)	$\omega_{\alpha,\tau}^2$	-0.010	0.017	(-0.040, 0.011)
ω_{τ}^2	0.081	0.035	(0.041, 0.144)	ω_{τ}^2	0.156	0.086	(0.067, 0.319)

**The results are based on 50,000 posterior with a burn in period of 50,000.

Now, below the Table 3c provides the estimated posterior moments and quantiles of the SV in mean model parameters. The estimations show that, food has positive, cereals, dairy, and meat have negative and statistically not significant effect on their volatility. In contrast, fats have negative and statistically significant impact on its volatility which means it is statistically different from zero. On the other hand, all of the series are highly volatility persistence in Germany like in the other countries.

Table 3c: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in Germany

		Food				**Cereals**	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	3.280	0.884	(2.678, 3.971)	μ	1.032	1.130	(-0.615, 2.937)
β	0.006	0.010	(-0.010, 0.017)	β	-0.001	0.007	(-0.013, 0.011)
ϕ	0.960	0.026	(0.926, 0.990)	ϕ	0.975	0.019	(0.940, 0.998)
σ^2	0.042	0.012	(0.029, 0.057)	σ^2	0.051	0.015	(0.031, 0.078)
ω^2_α	0.007	0.003	(0.004, 0.010)	ω^2_α	0.018	0.009	(0.008, 0.035)
$\omega^2_{\alpha,\tau}$	-0.002	0.007	(-0.010, 0.005)	$\omega^2_{\alpha,\tau}$	-0.004	0.012	(-0.025, 0.013)
ω^2_τ	0.109	0.066	(0.054, 0.178)	ω^2_τ	0.073	0.029	(0.039, 0.127)
		Dairy				**Fats**	
μ	3.777	0.791	(2.632, 5.204)	μ	2.779	1.992	(-1.009, 4.969)
β	-0.003	0.003	(-0.008, 0.002)	β	-0.005	0.002	(-0.008, -0.002)
ϕ	0.963	0.024	(0.919, 0.996)	ϕ	0.978	0.016	(0.947, 0.998)
σ^2	0.068	0.021	(0.040, 0.106)	σ^2	0.097	0.033	(0.056, 0.158)
ω^2_α	0.016	0.008	(0.008, 0.030)	ω^2_α	0.031	0.019	(0.012, 0.069)
$\omega^2_{\alpha,\tau}$	-0.002	0.018	(-0.030, 0.022)	$\omega^2_{\alpha,\tau}$	0.022	0.036	(-0.026, 0.085)
ω^2_τ	0.127	0.081	(0.051, 0.277)	ω^2_τ	0.204	0.196	(0.056, 0.551)
		Meat					
μ	1.473	0.659	(0.479, 2.717)				
β	-0.008	0.008	(-0.021, 0.004)				
ϕ	0.959	0.024	(0.915, 0.992)				
σ^2	0.077	0.020	(0.049, 0.113)				
ω^2_α	0.014	0.006	(0.007, 0.026)				
$\omega^2_{\alpha,\tau}$	-0.008	0.012	(-0.030, 0.008)				
ω^2_τ	0.094	0.043	(0.046, 0.175)				

**The results are based on 50,000 posterior with a burn in period of 50,000.

Below Table 3d shows the estimation results of United States (US). According to estimation results, food, cereals, dairy, fats and meat have negative and statistically insignificant impact on its volatility. In other words, they are all statistically not different from zero. On the other hand sugar has positive and significant impact on its volatility. Moreover, all of the series are highly volatility persistence in US and they are around 96 – 97%.

Table 3d: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in US

		Food				**Cereals**	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	1.020	1.742	(-3.103, 2.531)	μ	2.160	0.387	(1.593, 2.652)
β	-0.003	0.002	(-0.007, 0.001)	β	-0.000	0.002	(-0.003, 0.002)
ϕ	0.982	0.012	(0.962, 0.999)	ϕ	0.963	0.015	(0.938, 0.987)
σ^2	0.054	0.013	(0.036, 0.078)	σ^2	0.048	0.010	(0.033, 0.066)
ω^2_α	0.009	0.003	(0.005, 0.015)	ω^2_α	0.007	0.002	(0.005, 0.011)
$\omega^2_{\alpha,\tau}$	-0.008	0.008	(-0.023, 0.002)	$\omega^2_{\alpha,\tau}$	-0.005	0.006	(-0.015, 0.003)
ω^2_τ	0.088	0.034	(0.046, 0.152)	ω^2_τ	0.073	0.029	(0.038, 0.128)
		Dairy				**Fats**	
μ	2.866	0.478	(2.205, 3.557)	μ	3.564	0.258	(3.156, 3.973)
β	-0.000	0.002	(-0.004, 0.003)	β	0.000	0.001	(-0.002, 0.003)
ϕ	0.971	0.013	(0.949, 0.991)	ϕ	0.949	0.016	(0.921, 0.975)
σ^2	0.048	0.010	(0.033, 0.065)	σ^2	0.071	0.015	(0.049, 0.097)
ω^2_α	0.015	0.006	(0.008, 0.026)	ω^2_α	0.005	0.001	(0.003, 0.007)
$\omega^2_{\alpha,\tau}$	-0.000	0.014	(-0.023, 0.022)	$\omega^2_{\alpha,\tau}$	-0.002	0.004	(-0.009, 0.004)
ω^2_τ	0.113	0.058	(0.050, 0.225)	ω^2_τ	0.083	0.036	(0.041, 0.152)
		Meat				**Sugar**	
μ	3.317	0.456	(2.625, 3.970)	μ	3.146	0.510	(2.295, 3.827)
β	-0.002	0.002	(-0.005, 0.001)	β	0.003	0.001	(0.001, 0.005)
ϕ	0.965	0.015	(0.939, 0.988)	ϕ	0.972	0.012	(0.952, 0.991)
σ^2	0.072	0.017	(0.047, 0.103)	σ^2	0.057	0.012	(0.039, 0.079)
ω^2_α	0.008	0.003	(0.005, 0.013)	ω^2_α	0.004	0.001	(0.003, 0.006)
$\omega^2_{\alpha,\tau}$	-0.003	0.009	(-0.019, 0.010)	$\omega^2_{\alpha,\tau}$	-0.003	0.003	(-0.009, 0.002)
ω^2_τ	0.134	0.092	(0.052, 0.313)	ω^2_τ	0.078	0.031	(0.040, 0.138)

**The results are based on 50,000 posterior with a burn in period of 50,000.

The results are given in Table 3e for Italy. The estimation results show that, food and sugar have negative and significant impact on their volatility. In other words, they are all statistically different from zero. In contrast, dairy, fats and meat have negative and cereals have positive and statistically not significant impact on their volatility.

On the other hand, all of the series are highly volatility persistence because ϕ values are between 93% - 96% for each series in Italy.

Table 3e: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in Italy

		Food				**Cereals**	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	0.547	0.878	(-0.336, 1.946)	μ	0.521	0.682	(-0.541, 1.778)
β	-0.020	0.007	(-0.032, -0.008)	β	0.001	0.007	(-0.010, 0.012)
ϕ	0.940	0.040	(0.865, 0.991)	ϕ	0.964	0.023	(0.922, 0.996)
σ^2	0.056	0.016	(0.034, 0.086)	σ^2	0.058	0.018	(0.035, 0.091)
ω_α^2	0.023	0.032	(0.008, 0.052)	ω_α^2	0.018	0.009	(0.008, 0.035)
$\omega_{\alpha,\tau}^2$	-0.014	0.047	(-0.085, 0.036)	$\omega_{\alpha,\tau}^2$	-0.006	0.012	(-0.029, 0.010)
ω_τ^2	0.225	0.117	(0.088, 0.452)	ω_τ^2	0.077	0.029	(0.041, 0.130)
		Dairy				**Fats**	
μ	1.290	1.181	(-0.424, 3.530)	μ	1.793	1.209	(-0.488, 3.196)
β	-0.005	0.008	(-0.018, 0.007)	β	-0.004	0.005	(-0.012, 0.004)
ϕ	0.959	0.035	(0.891, 0.998)	ϕ	0.969	0.022	(0.928, 0.997)
σ^2	0.043	0.014	(0.026, 0.069)	σ^2	0.048	0.015	(0.029, 0.075)
ω_α^2	0.034	0.022	(0.012, 0.077)	ω_α^2	0.020	0.010	(0.009, 0.038)
$\omega_{\alpha,\tau}^2$	0.015	0.032	(-0.033, 0.064)	$\omega_{\alpha,\tau}^2$	0.009	0.024	(-0.028, 0.046)
ω_τ^2	0.154	0.097	(0.057, 0.331)	ω_τ^2	0.184	0.119	(0.064, 0.404)
		Meat				**Sugar**	
μ	1.177	0.486	(0.517, 1.994)	μ	0.534	0.458	(-0.129, 1.278)
β	-0.006	0.009	(-0.020, 0.990)	β	-0.023	0.013	(-0.044, -0.001)
ϕ	0.940	0.033	(0.880, 0.990)	ϕ	0.930	0.033	(0.873, 0.977)
σ^2	0.056	0.019	(0.032, 0.091)	σ^2	0.109	0.031	(0.065, 0.166)
ω_α^2	0.018	0.010	(0.008, 0.036)	ω_α^2	0.014	0.007	(0.007, 0.026)
$\omega_{\alpha,\tau}^2$	-0.006	0.015	(-0.034, 0.013)	$\omega_{\alpha,\tau}^2$	-0.005	0.010	(-0.024, 0.008)
ω_τ^2	0.093	0.044	(0.044, 0.176)	ω_τ^2	0.077	0.030	(0.039, 0.133)

**The results are based on 50,000 posterior with a burn in period of 50,000.

Below Table 3f shows the estimation results of Japan. According to estimation results, cereals and dairy have negative and statistically significant impact on their volatility. In other words, they are all statistically different from zero. On the other hand, food and sugar have positive, fats and meat have negative and they all have statistically not significant impact on its volatility. Moreover, all of the series are highly volatility persistence in Japan and they are in between 84 – 96%.

Table 3f: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in Japan

		Food				Cereals	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	4.051	0.308	(3.570, 4.518)	μ	1.451	0.233	(1.072, 1.823)
β	0.002	0.002	(-0.002, 0.006)	β	-0.011	0.003	(-0.016, -0.006)
ϕ	0.965	0.015	(0.939, 0.988)	ϕ	0.847	0.026	(0.801, 0.886)
σ^2	0.033	0.008	(0.022, 0.048)	σ^2	0.498	0.067	(0.400, 0.609)
ω_α^2	0.003	0.000	(0.002, 0.003)	ω_α^2	0.054	0.024	(0.023, 0.096)
$\omega_{\alpha,\tau}^2$	-0.001	0.002	(-0.005, 0.002)	$\omega_{\alpha,\tau}^2$	-0.015	0.020	(-0.049, 0.017)
ω_τ^2	0.090	0.044	(0.042, 0.173)	ω_τ^2	0.063	0.017	(0.039, 0.095)
		Dairy				**Fats**	
μ	3.119	0.187	(2.807, 3.422)	μ	3.174	0.314	(2.679, 3.647)
β	-0.010	0.003	(-0.014, -0.005)	β	-0.002	0.002	(-0.004, 0.001)
ϕ	0.884	0.025	(0.841, 0.923)	ϕ	0.948	0.017	(0.919, 0.974)
σ^2	0.200	0.032	(0.149, 0.256)	σ^2	0.101	0.021	(0.071, 0.139)
ω_α^2	0.004	0.001	(0.003, 0.005)	ω_α^2	0.005	0.001	(0.003, 0.007)
$\omega_{\alpha,\tau}^2$	-0.002	0.003	(-0.008, 0.002)	$\omega_{\alpha,\tau}^2$	-0.003	0.004	(-0.010, 0.004)
ω_τ^2	0.081	0.037	(0.038, 0.150)	ω_τ^2	0.088	0.043	(0.041, 0.170)
		Meat				**Sugar**	
μ	1.933	0.290	(1.488, 2.354)	μ	2.837	0.952	(1.540, 4.140)
β	-0.004	0.003	(-0.008, 0.001)	β	0.000	0.001	(-0.002, 0.002)
ϕ	0.940	0.020	(0.905, 0.971)	ϕ	0.968	0.015	(0.942, 0.991)
σ^2	0.095	0.019	(0.066, 0.130)	σ^2	0.142	0.053	(0.041, 0.216)
ω_α^2	0.009	0.003	(0.005, 0.014)	ω_α^2	0.007	0.002	(0.004, 0.011)
$\omega_{\alpha,\tau}^2$	-0.004	0.007	(-0.016, 0.005)	$\omega_{\alpha,\tau}^2$	-0.005	0.006	(-0.016, 0.002)
ω_τ^2	0.076	0.034	(0.038, 0.141)	ω_τ^2	0.083	0.036	(0.041, 0.145)

**The results are based on 50,000 posterior with a burn in period of 50,000.

Lastly, below the Table 3g provides the estimated posterior moments and quantiles of the SV in mean model parameters for UK. The estimations show that, food has positive, fats, meat and sugar have negative and statistically not significant effect on their volatility. In contrast, cereals have positive and dairy has negative and statistically significant impact on their volatility which means it is statistically different from zero. On the other hand, all of the series are highly volatility persistence in United Kingdom like in the other countries.

Table 3g: Estimated Posterior Moments and Quantiles of the SV in Mean Model Parameters in UK

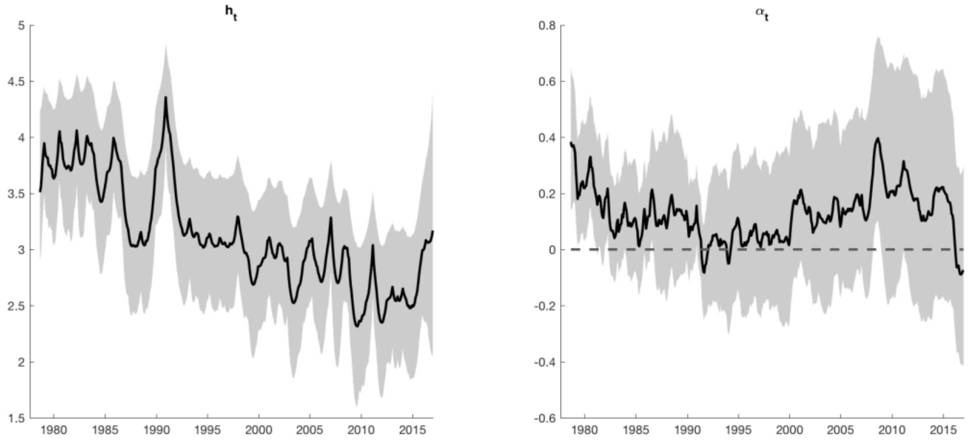
		Food				Cereals	
Parameter	Posterior mean	Standard Error	90% credible interval	Parameter	Posterior mean	Standard Error	90% credible interval
μ	3.092	0.728	(1.085, 3.926)	μ	3.573	0.683	(2.472, 4.309)
β	0.004	0.005	(-0.004, 0.012)	β	0.010	0.005	(0.001, 0.018)
ϕ	0.952	0.028	(0.904, 0.992)	ϕ	0.961	0.021	(0.923, 0.994)
σ^2	0.038	0.011	(0.024, 0.060)	σ^2	0.040	0.012	(0.024, 0.061)
ω_α^2	0.007	0.002	(0.004, 0.011)	ω_α^2	0.005	0.001	(0.003, 0.007)
$\omega_{\alpha,\tau}^2$	-0.002	0.006	(-0.013, 0.007)	$\omega_{\alpha,\tau}^2$	-0.002	0.005	(-0.010, 0.005)
ω_τ^2	0.104	0.063	(0.044, 0.220)	ω_τ^2	0.108	0.058	(0.047, 0.220)
		Dairy				**Fats**	
μ	4.553	0.282	(4.171, 5.028)	μ	5.020	0.396	(4.407, 5.690)
β	-0.020	0.003	(-0.025, -0.015)	β	-0.011	0.002	(-0.014, -0.007)
ϕ	0.923	0.043	(0.825, 0.969)	ϕ	0.951	0.021	(0.912, 0.978)
σ^2	0.046	0.014	(0.028, 0.072)	σ^2	0.076	0.022	(0.045, 0.118)
ω_α^2	0.004	0.001	(0.003, 0.006)	ω_α^2	0.005	0.001	(0.003, 0.007)
$\omega_{\alpha,\tau}^2$	-0.002	0.007	(-0.015, 0.008)	$\omega_{\alpha,\tau}^2$	-0.007	0.018	(-0.037, 0.013)
ω_τ^2	0.355	0.320	(0.081, 0.956)	ω_τ^2	1.099	1.141	(0.101, 3.310)
		Meat				**Sugar**	
μ	3.632	0.837	(2.637, 4.533)	μ	2.736	2.166	(-2.608, 5.407)
β	-0.000	0.005	(-0.009, 0.009)	β	-0.000	0.008	(-0.013, 0.015)
ϕ	0.951	0.029	(0.901, 0.994)	ϕ	0.985	0.013	(0.959, 0.999)
σ^2	0.051	0.016	(0.031, 0.080)	σ^2	0.058	0.019	(0.033, 0.094)
ω_α^2	0.005	0.001	(0.003, 0.008)	ω_α^2	0.006	0.002	(0.004, 0.009)
$\omega_{\alpha,\tau}^2$	-0.002	0.005	(-0.010, 0.006)	$\omega_{\alpha,\tau}^2$	-0.003	0.011	(-0.012, 0.006)
ω_τ^2	0.105	0.058	(0.046, 0.213)	ω_τ^2	0.136	0.249	(0.044, 0.295)

**The results are based on 50,000 posterior with a burn in period of 50,000.

As a result, when it has been summarized as a whole, we see that, the impact of food price volatility on its volatility is negative and statistically significant in Italy, but it is not statistically significant on the rest of the countries. On the other hand, cereals has negative and statistically significant impact on its volatility in Japan and positive and significant in United Kingdom. In contrast, the rest of the countries have insignificant impact. In addition, dairy has negative and significant impact on its volatility both in Japan and UK. However, it is not significant in rest of the countries. Moreover, fats have negative and significant impact on its volatility in UK and Germany while it is statistically insignificant in other countries. When the estimation is done for meat, it has been found that, it does not have any significant impact on its volatility in all of the countries. Lastly, sugar has negative and statistically significant impact in Italy and France while it has positive and significant impact in USA. In contrast, it does not have any significant impact in other countries.

Now, Figure 11a-f, 12a-f, 13a-f, 14a-e, 15a-f, 16a-f and 17a-f show the estimations of the h_t and α_t and also associated 90% credible intervals for G-7 countries. Below the figures represent the evolution of food price volatility which is left panel and denotes by using h_t. On the other hand, right panel which is α_t represents the time varying impact of food prices volatility on a specific food price. Moreover, as it can be seen on the figures, shaded regions represent the 90% credible confidence intervals and estimated posterior means are shown by the solid lines. In addition, all of the estimations are based on 50,000 posterior with a burn in the period of 50,000.

a. Food



b. Cereals

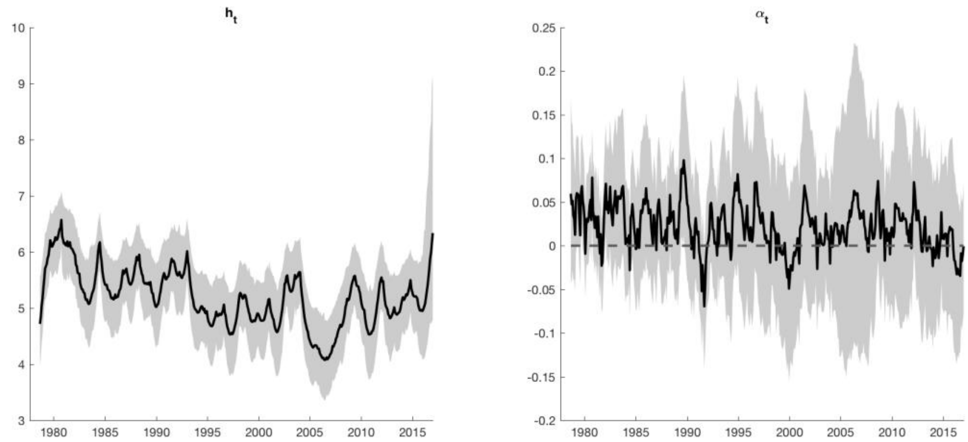
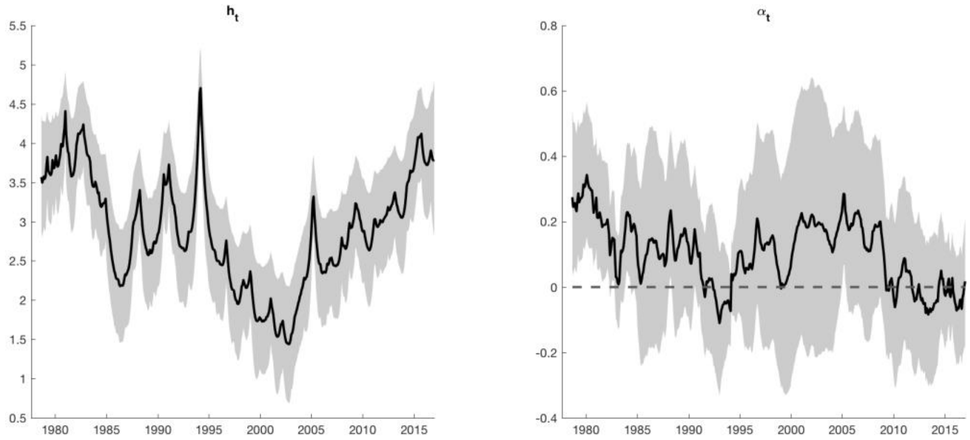
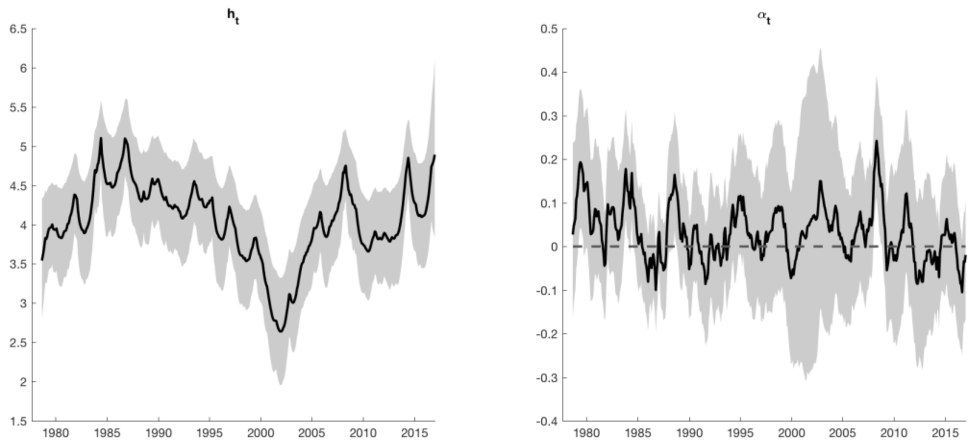


Figure 11: Evolution of Volatility and Impact of Volatility
on Each Food Price in Canada

c. Dairy



d. Fats



e. Meat

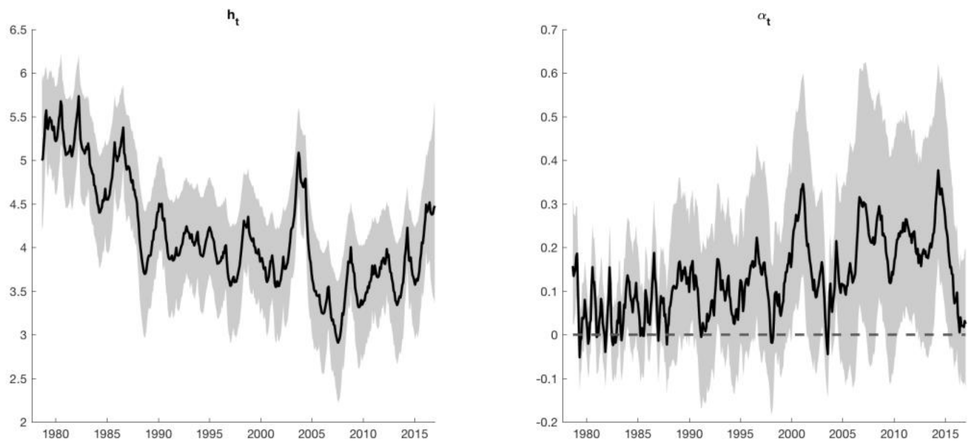


Figure 11 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Canada

f. Sugar

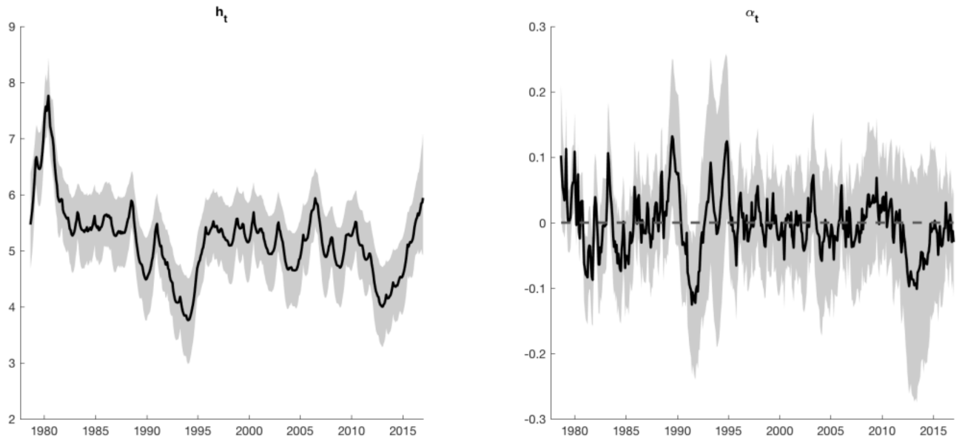


Figure 11 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Canada

Above Figure 11a shows that, food price uncertainty has positive impact on food prices until the end of 1990 and then become negative between 1991-1992 years. Later, the effect become negative in 1994 and then starts to increases positively and the impact of food price uncertainty is at the maximum level in 2009 and it continues to become positive until the middle of 2015. Then, it turns to negative.

On the other hand, the impact of food price volatility is mostly positive on cereals and it is volatile. Also, the impact is negative in 1982, 1985, 1992 and 2000 respectively. Then, it is positive until the end of 2015 and it turns to negative.

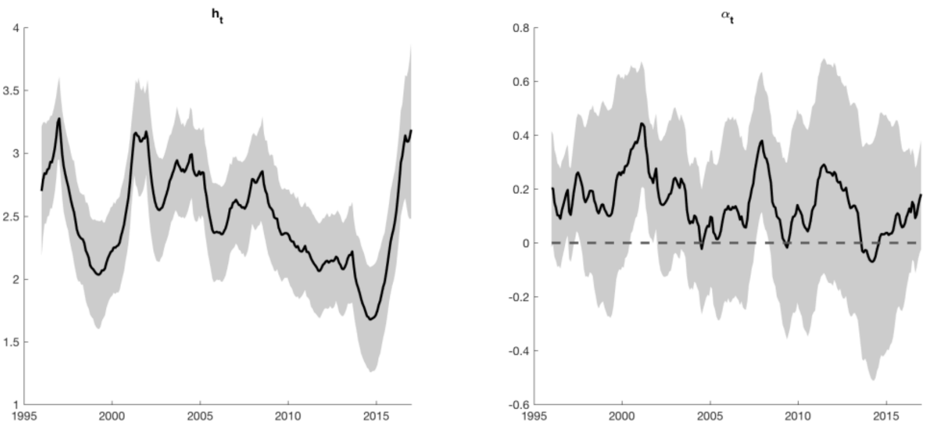
Moreover, as it can be seen in Figure 11c, the effect of food price volatility is positive on dairy prices in general. Even if α_t is close to zero, the impact is positive. In addition, the impact is negative between 1992 – 1993 periods and it is positive until the end of 2010. At the beginning of 2011, the impact turns to negative and become positive and then negative again and continue to volatile.

The effect of food price uncertainty on fats prices are positive in general and the positive effect is at the maximum level in 2009. In contrast, the effect is negative between 1982-1983 year, 1986, 1992 and 2000 respectively. Additionally, the impact becomes negative in 2012 until the beginning of 2015 and then it continues to be negative at the second part of 2015.

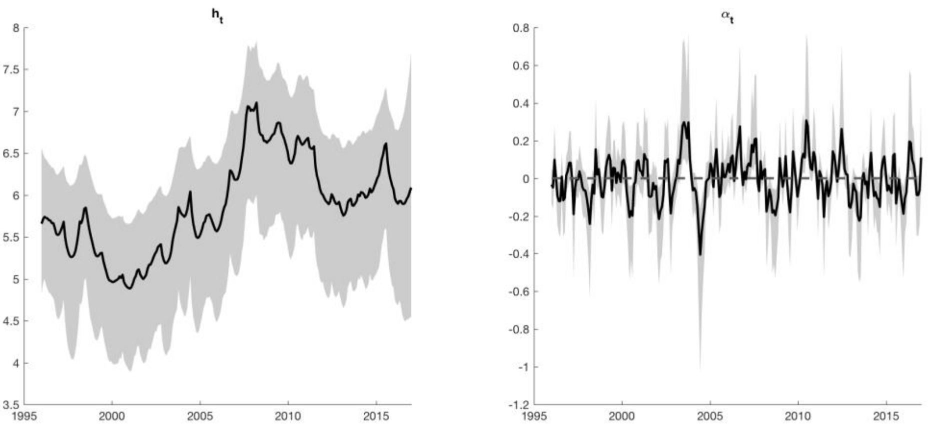
The impact of food price volatility is positive on meat prices almost each year. It is only negative in three years which are 1979, 1981 and 2004 respectively and the impact is all positive in the rest of the years.

Lastly, Figure 11f shows the impact of food price volatility on sugar prices. The impact seems negative between 1992-1993 periods and it is the highest level of negativity. In contrast, the impact is positive in 1990 until the end of 1990. In addition, negative impact has been analysed between 2012- 2015 years.

a. Food



b. Cereals



c. Dairy

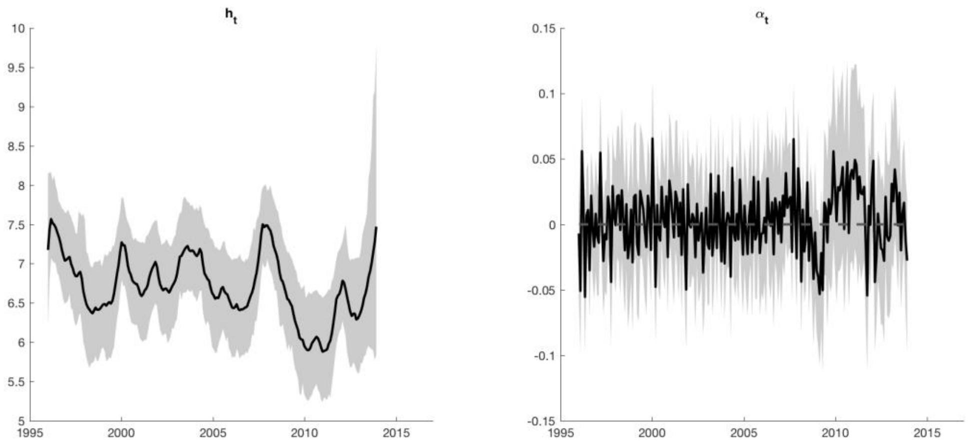
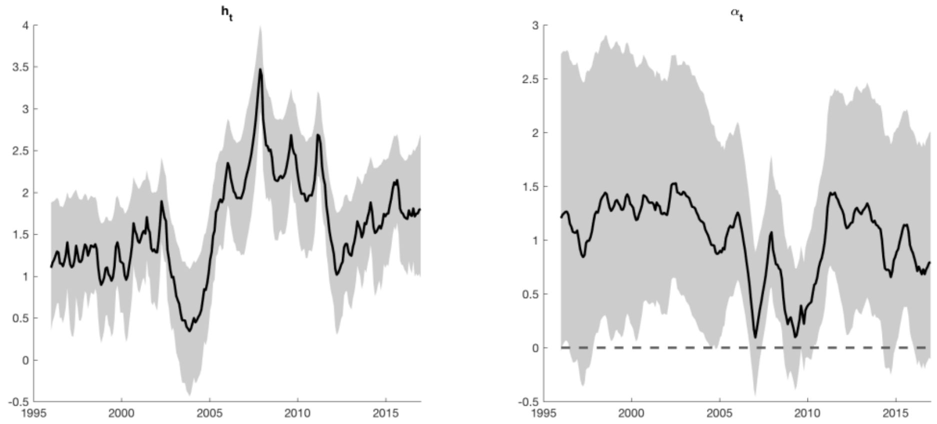
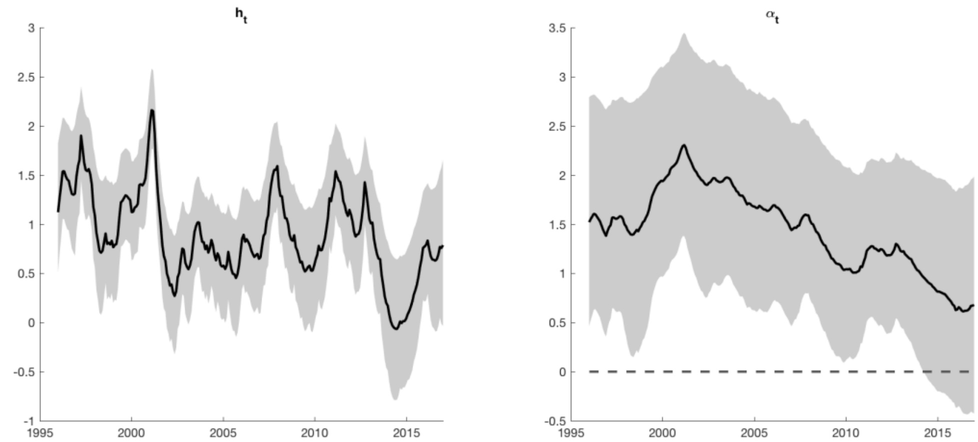


Figure 12: Evolution of Volatility and Impact of Volatility
on Each Food Price in France

d. Fats



e. Meat



f. Sugar

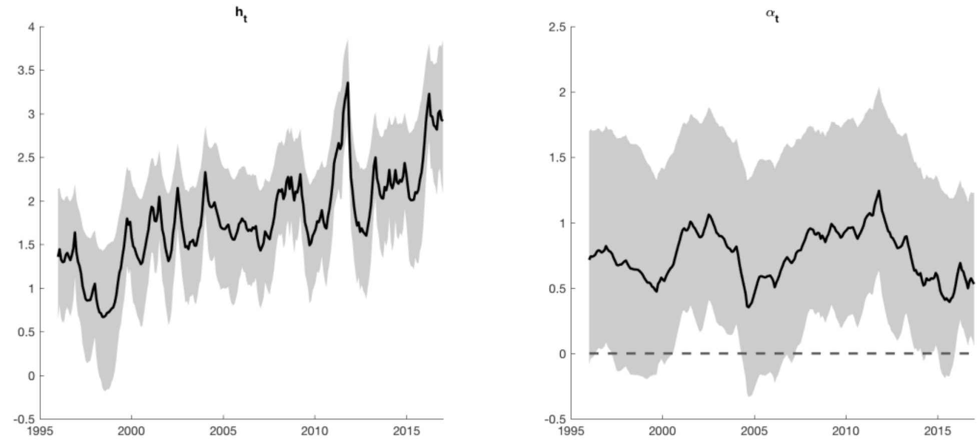


Figure 12 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in France

Now, above the figures represent the estimation results of France. Figure 12a shows the impact of food price volatility on food prices and the results provides a positive impact on food prices following the beginning of the 2014 for France, while it has a negative impact up to the beginning of 2015 and then turns back to the positive impact.

On the other hand, Figure 12b shows the effect of food price volatility on cereals prices. Estimates of α_t are close to zero or positive/negative until the first half of 2004. The effect become negative in the second half of the 2004 and maximum level of negativity in 2005 and then starts to be usually positive in 2006 until 2014. After 2014, it has a negative impact on cereals prices.

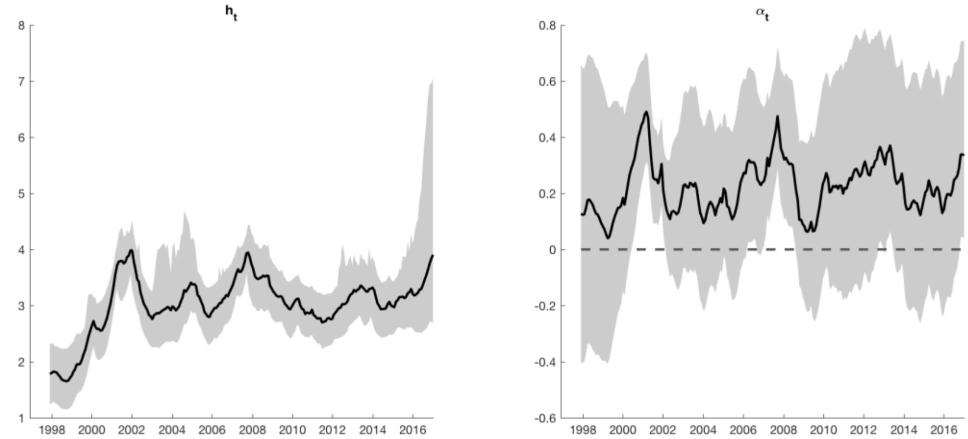
In addition, the impact of food price volatility is estimated on the dairy prices. Estimates of α_t are close to zero or positive/negative until the end of 2010, while it has a positive impact between 2011 – 2012 then it turns to negative.

Figure 12d shows the impact of food price uncertainty on fats prices. Positive impact is found and it fluctuates slowly with small amounts until 2002. Then, the impact is reduced until 2005 and then increased and finally the impact is close to zero in 2007. The impact is increased again at the beginning of 2008 and then started to close to zero in 2010. After 2010, the effect starts to increase and continue to be volatile.

Moreover, the impact of food price volatility is positive on meat prices. The impact increases positively until the end of 2002. Then the impact starts to decrease positively.

Lastly, the impact of food price volatility is positive in sugar prices. The impact is volatile and positive in each years of the dataset in France.

a. Food



b. Cereals

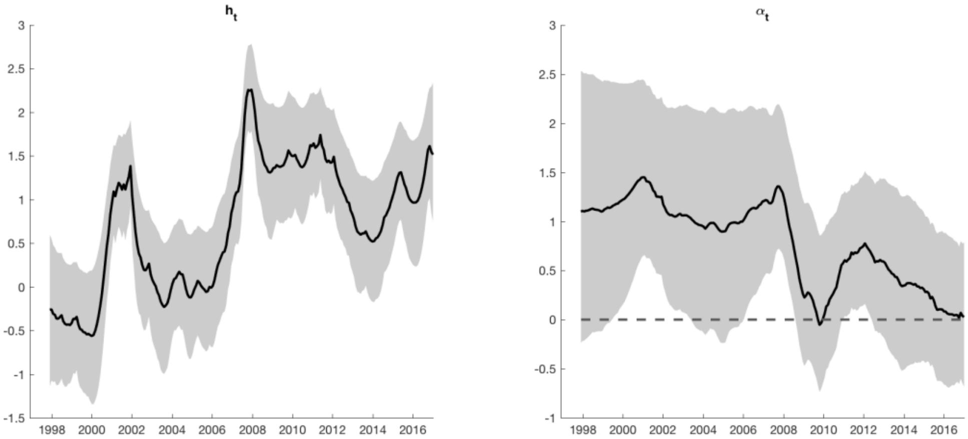
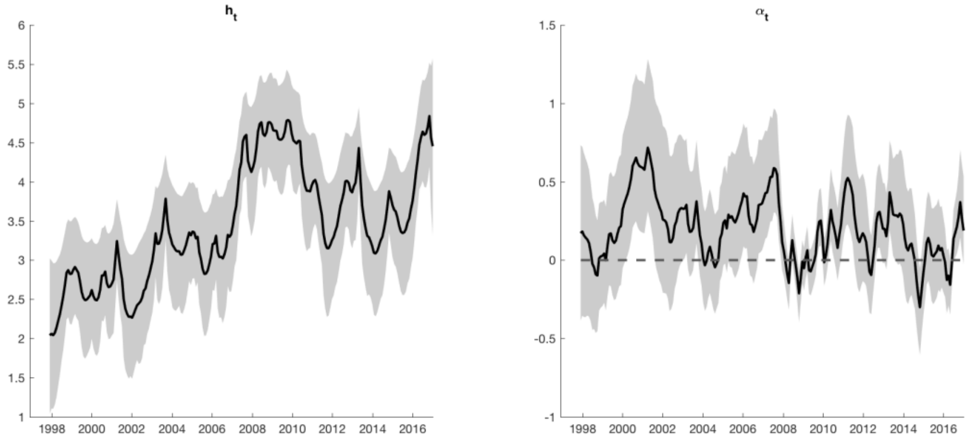
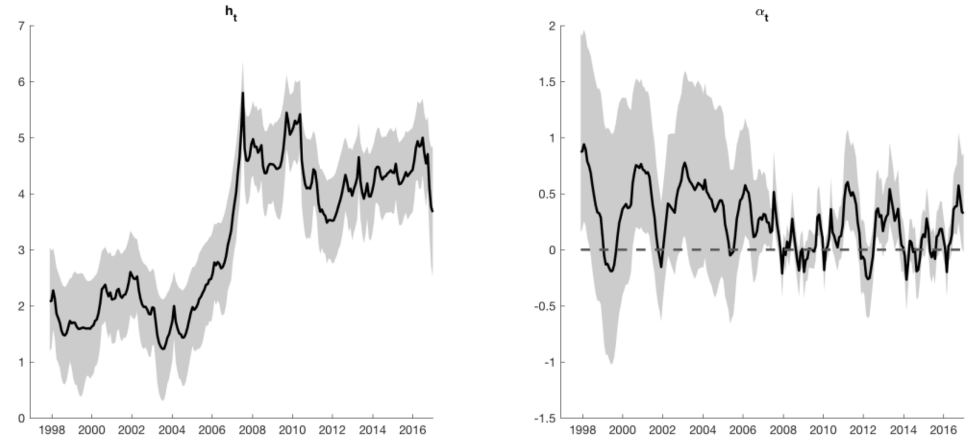


Figure 13: Evolution of Volatility and Impact of Volatility
on Each Food Price in Germany

c. Dairy



d. Fats



e. Meat

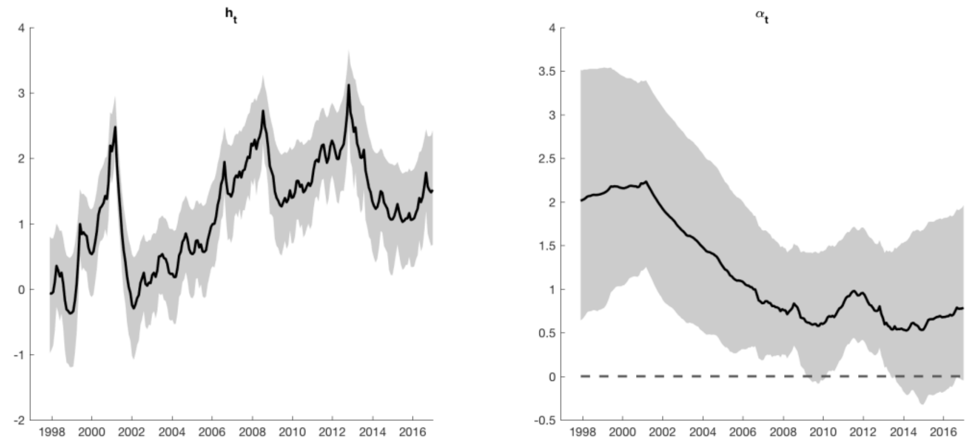


Figure 13 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Germany

When the estimation is done for the general perspective which is shown in Figure 13a, the impact of food price volatility is positive on food prices in each year. In other words, when food price volatility increases, the food prices increase as well. The impact is at the maximum level at the beginning of 2001, while the impact starts to decrease and continue to be volatile until the beginning of 2008. Then, as it can be seen on the figure, it is close to zero at the end of 2009 and later the impact starts to increase and continue to be volatile.

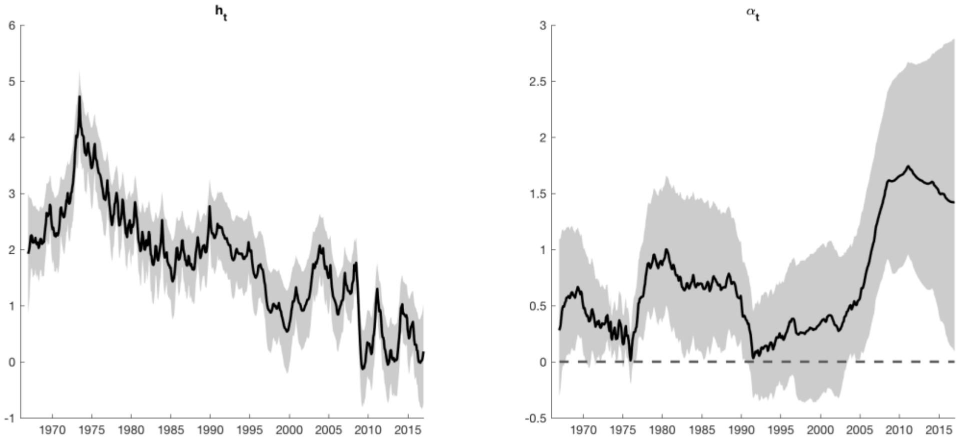
On the other hand, food price volatility has positive impact on cereals prices. The important point is that, the impact of food price volatility decreases suddenly between 2008 - 2010 periods and close to zero which means it loses the impact on cereals prices. Then, it starts increasing until 2012 and decreasing until 2016. Also, it is close to zero again in 2016.

Moreover, there is a positive impact of food price volatility on dairy prices while it is close to zero or even negative after 2008 in Germany.

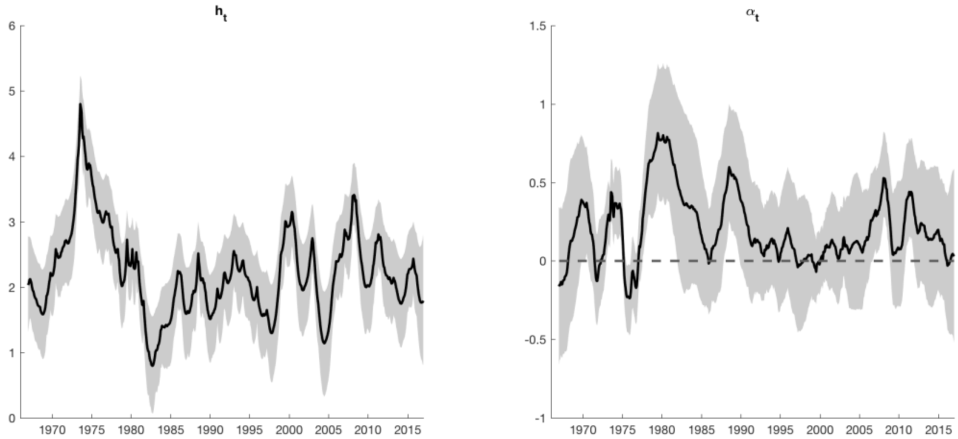
Furthermore, the impact of food price volatility is positive on fats prices while it is close to zero or negative after 2008. Before 2008, it is just negative at the beginning of 2000 and 2002 but the impact is positive between these two years.

Lastly, there has been found a positive impact of food price volatility on meat prices. The impact is reduced starting from 2002 until the beginning of 2010 and then continue to be stable.

a. Food



b. Cereals



c. Dairy

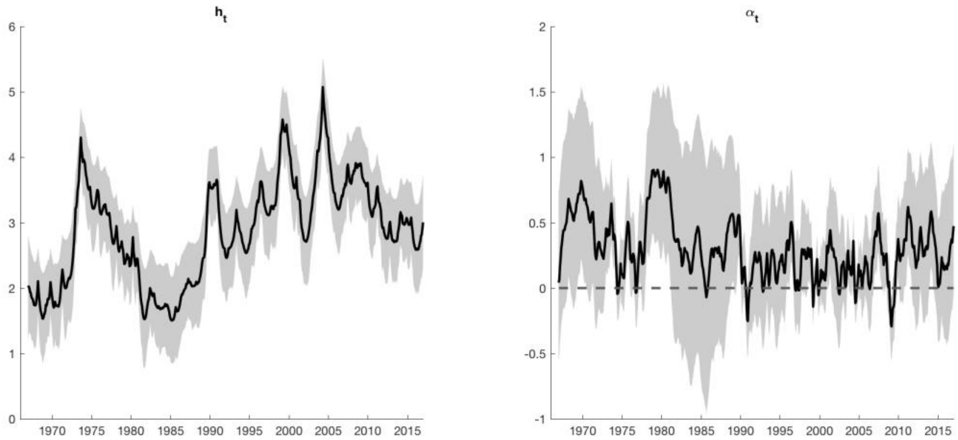
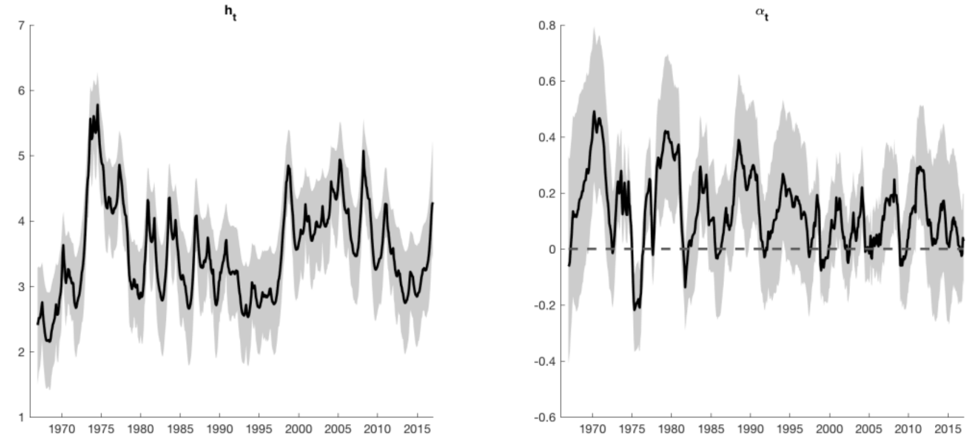
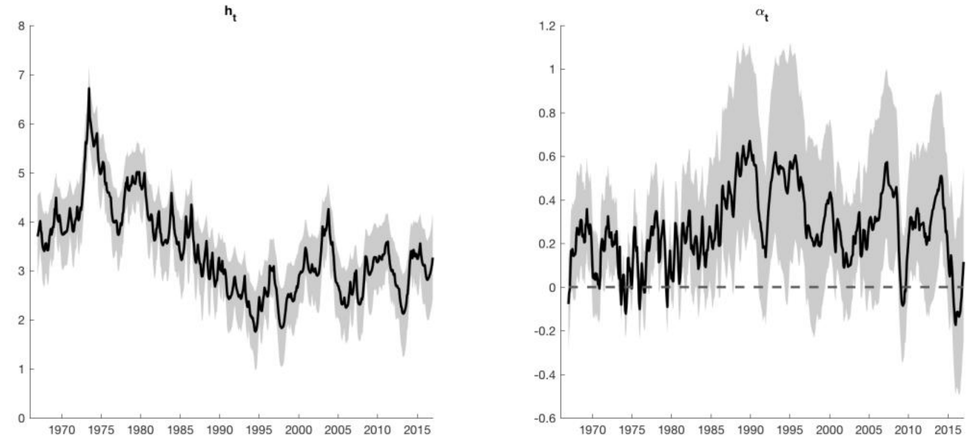


Figure 14: Evolution of Volatility and Impact of Volatility on Each Food Price in US

d. Fats



e. Meat



f. Sugar

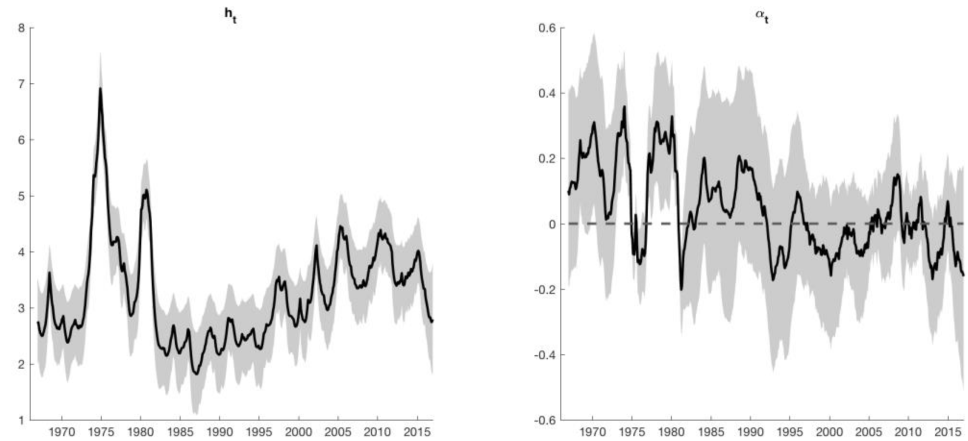


Figure 14 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in US

According to the right panel of Figure 14a, the impact of food price volatility is positive on food prices, while it is close to zero in 1976 and 1991. The positive impact increases slowly until the beginning of 2012 and reach to the maximum level and then the impact reduces a little.

On the other hand, there is a positive impact of food price volatility on cereals in general. Estimates of α_t are close to zero or negative until the end of 1978 then the impact turns to positive. Although it has a positive impact, the impact is close to zero between 1994 – 2005 years. After that, the impact is positive again and it is close to zero at the second part of 2015.

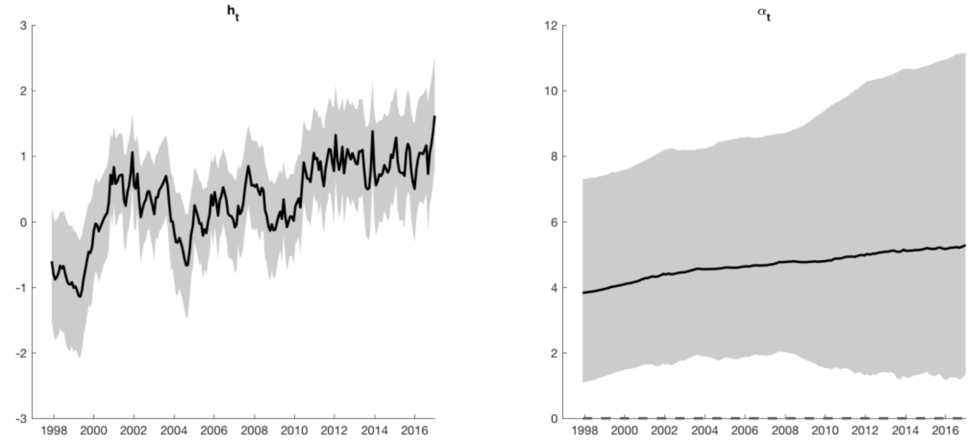
The effect of food price volatility is positive on dairy prices in each year except in 1990 and 2009. The impact is negative in both years.

Furthermore, the effect of food price volatility on fats prices are positive in general. It has negative impact only in 1975 and 1981. After 1981, the impact is close to zero or positive until the end of the years.

The positive impact of food price volatility is found on meat prices. The impact is reached to the maximum level in 1990 and then it decreases sharply until 1991 and then starts to increase. After 2007-2008, the impact reduces and become negative until 2010. On the other hand, as it is shown on the figure 14e, the impact is negative after 2015 and then positive in 2016.

Lastly, food price volatility has positive impact on sugar prices following the beginning of 1975. Then, it has negative impact between 1976 – 1977 years while it has positive impact until the beginning of 1980. After 1980, the impact is positive until 1993 and then the estimation results show both positive and negative impacts.

a. Food



b. Cereals

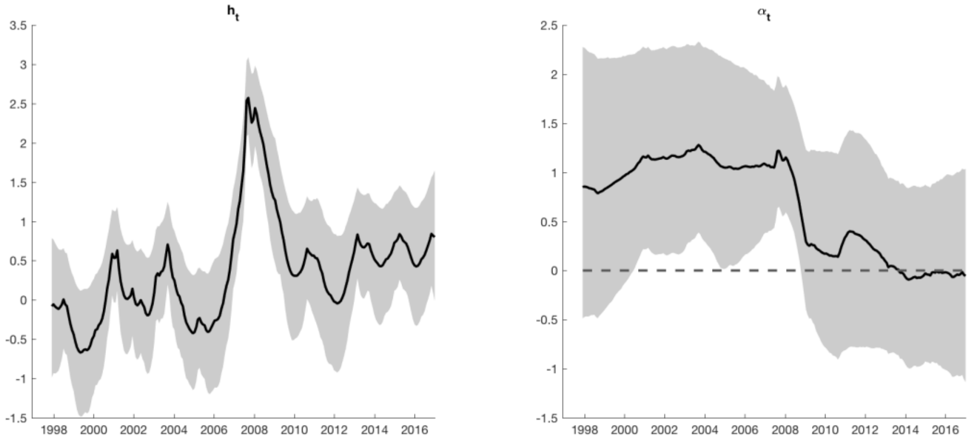
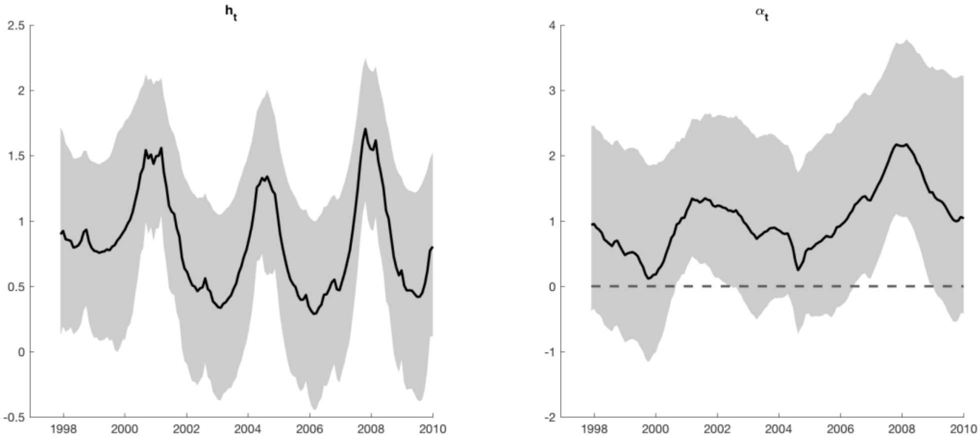


Figure 15: Evolution of Volatility and Impact of Volatility on Each Food Price in Italy

c. Dairy



d. Fats

e. Meat

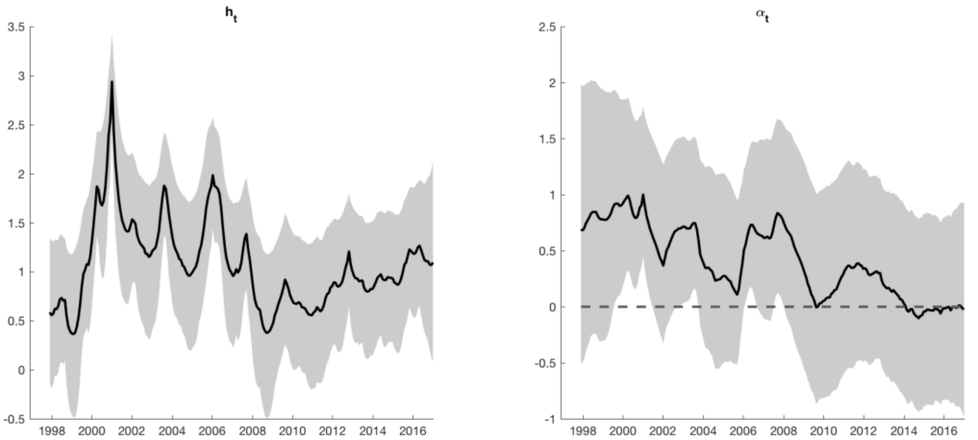


Figure 15 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Italy

f. **Sugar**

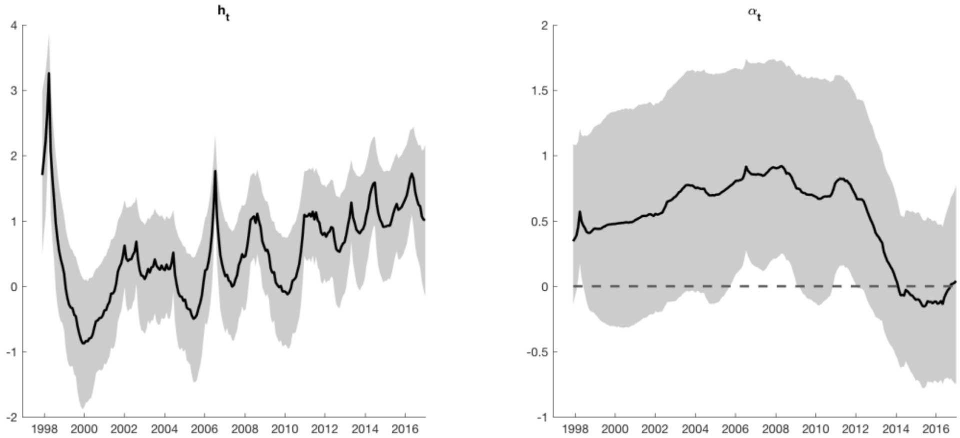


Figure 15 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Italy

Figure 15a represents the impact of food price volatility on food prices. According to estimation result, the impact is positive and stable for the whole dataset.

Moreover, there is positive impact of food price volatility on cereals prices in general. Although it has a stable impact on it, it decreases sharply starting from the beginning of 2008 to the end of 2011. Then, the impact is almost close to zero or negative on cereals prices after 2014.

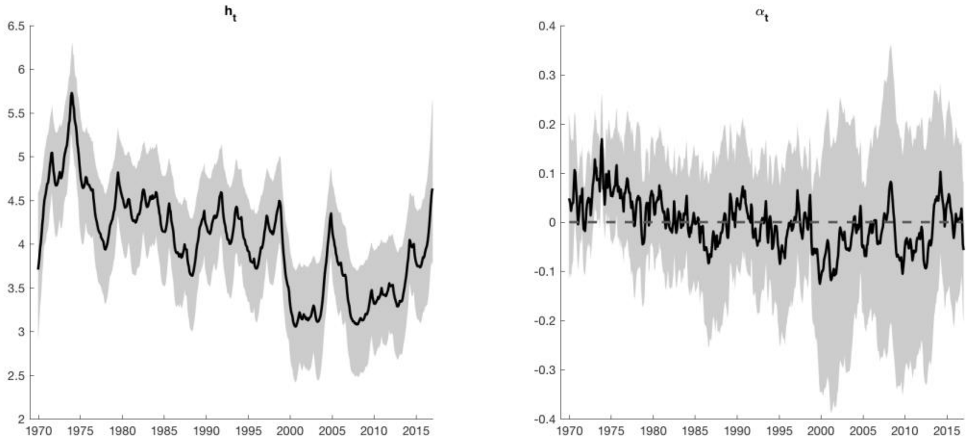
On the other hand, food price volatility provides a positive impact on dairy prices while it is close to zero in 2000 and 2005. Also, the impact is at the maximum level in 2008 then starting to reduce.

The effect of food price volatility is positive on fats prices in general. There is only negative impact between 1998 – 1999 years. Also, the impact is negative in 2009 and then turns to positive.

There is a positive impact of food price volatility on meat prices while it is close to zero in 2006, 2010 and between 2014 – 2016 years. Another important thing is that, although it is a positive impact, the impact decreases suddenly after 2008.

Lastly, estimation results provides positive and stable impact on sugar prices until the beginning of 2012 and then it decreases sharply and close to zero in 2014 then become negative.

a. Food



b. Cereals

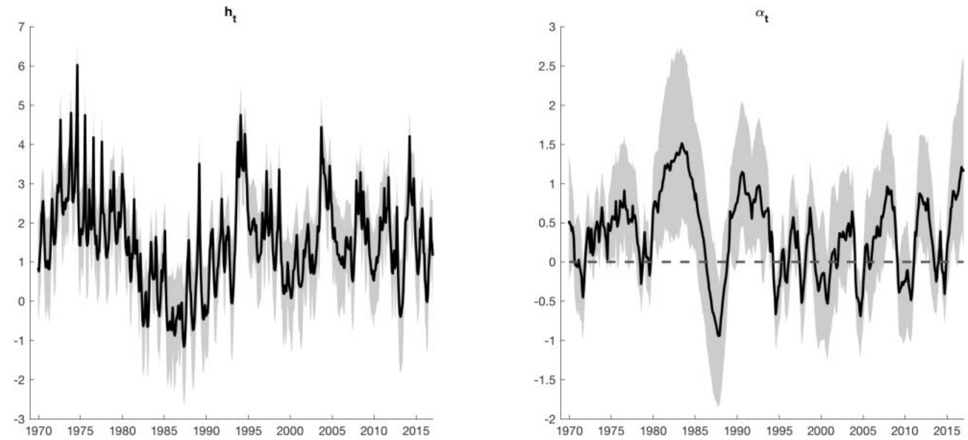
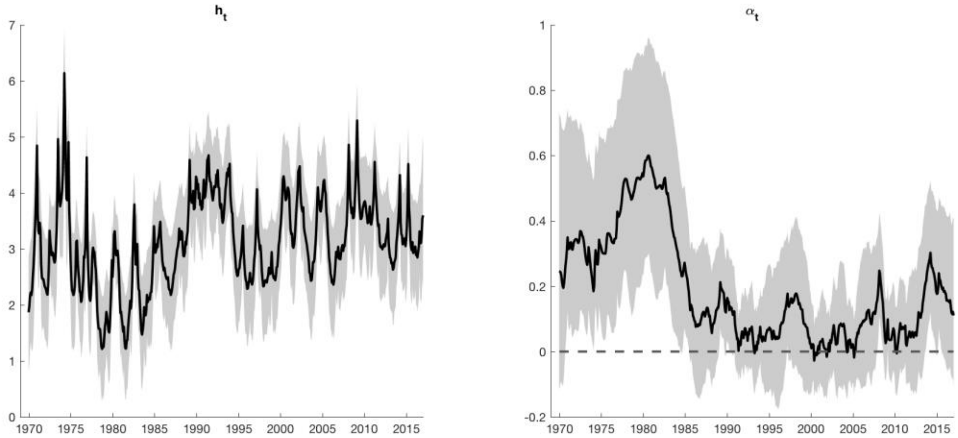
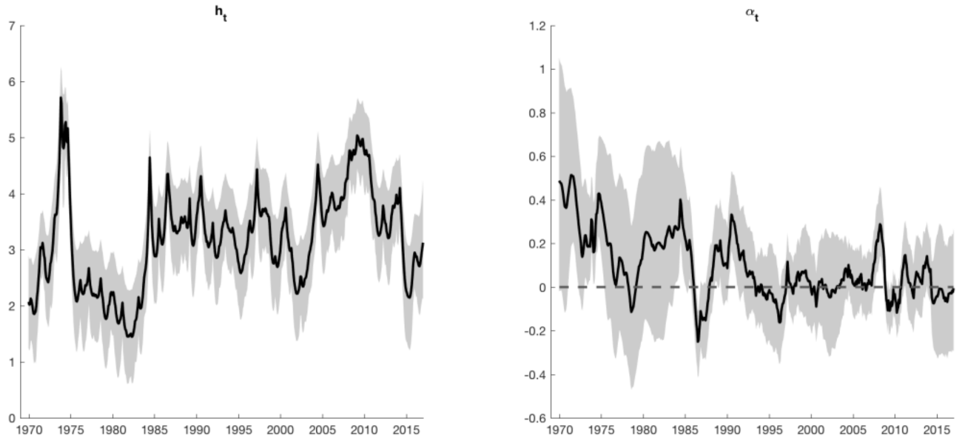


Figure 16: Evolution of Volatility and Impact of Volatility on Each Food Price in Japan

c. Dairy



d. Fats



e. Meat

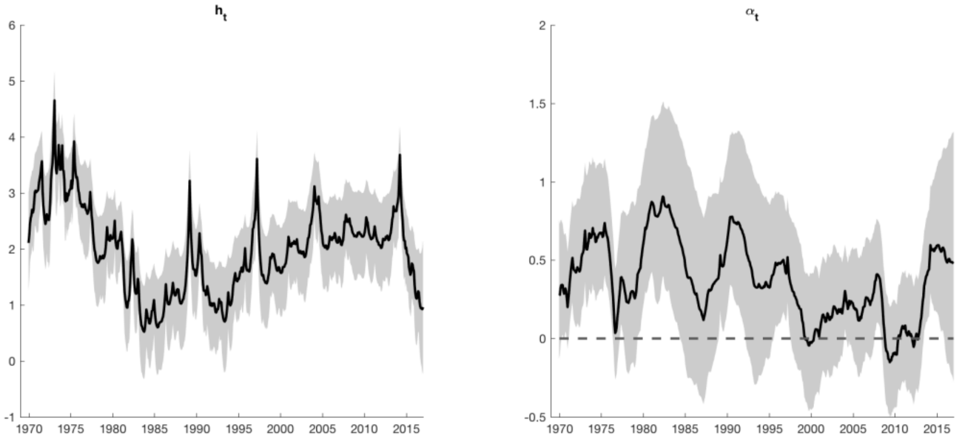


Figure 16 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Japan

f. Sugar

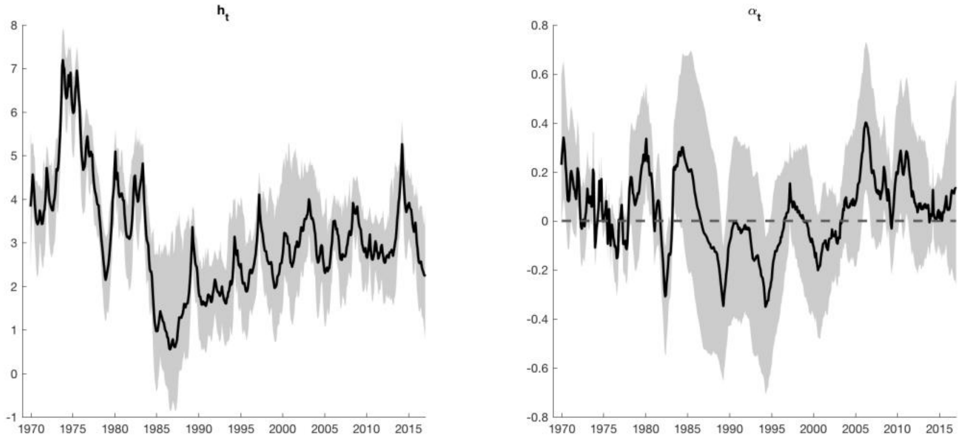


Figure 16 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in Japan

Above the Figure 16a shows the impact of food price volatility on food prices. It has positive impact on food prices until 2000, while it is close to zero or negative effect in 1986. The negative impact is starting from the beginning of 2000 until the end of the periods except 2008 and 2013.

On the other hand, there is a positive impact of food price volatility on cereals prices. However, the impact become negative between 1986 – 1989 years and then become positive until the beginning of 1995. After that, it is volatile which means that, the impact become positive, negative or close to zero.

Moreover, the impact of food price volatility is positive on dairy prices. The impact starts to decrease in 1981 until 1989. After, the impact is close to zero or positive until the end of the periods.

There is a positive effect of food price volatility on fats prices until the end of 1979 while it has negative impact between 1980 – 1981 periods. Then, it turns to positive and become negative in 1986. After 1986, the impact volatile around zero level but it becomes either positive or negative.

When the estimation is done for meat prices, positive impact of food price volatility is found on meat prices. Also, the impact is close to zero in 2000, 2009 and 2012 respectively and then negative in 2010.

Lastly, the impact of food price volatility is positive, close to zero and negative on sugar prices until the 1986. Then, the impact is negative between 1986 – 2005 years while it is positive after 2005.

a. Food

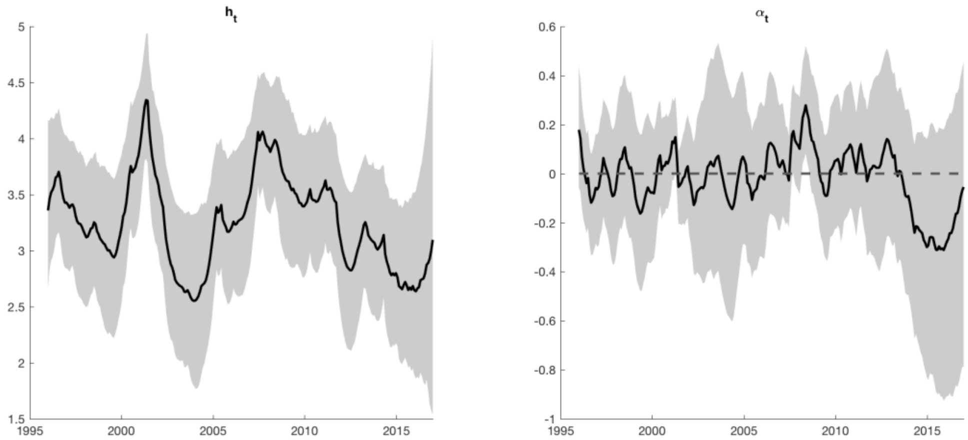
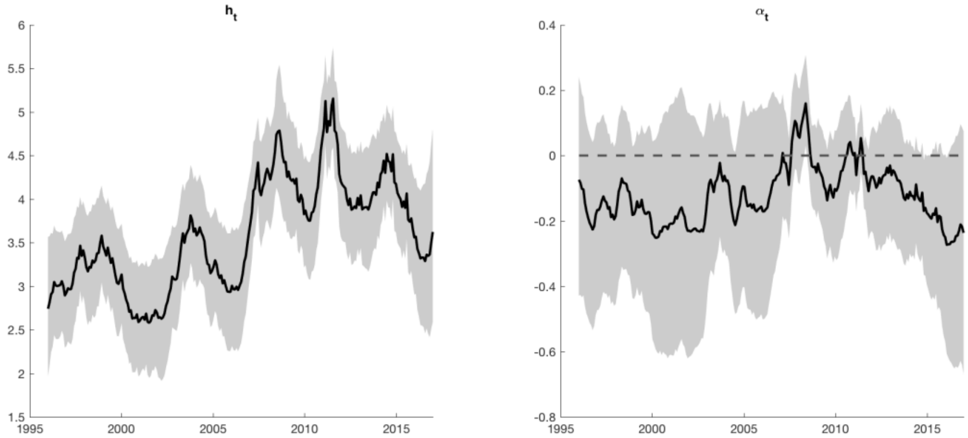
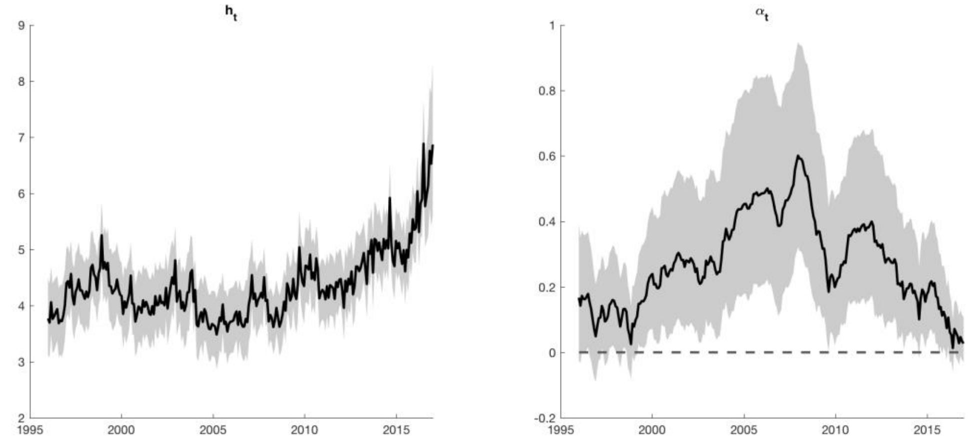


Figure 17: Evolution of Volatility and Impact of Volatility on Each Food Price in UK

b. Cereals



c. Dairy



d. Fats

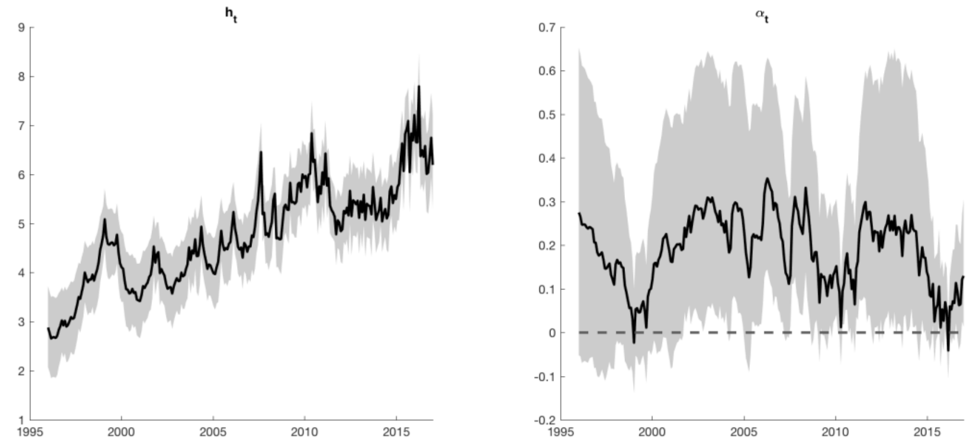
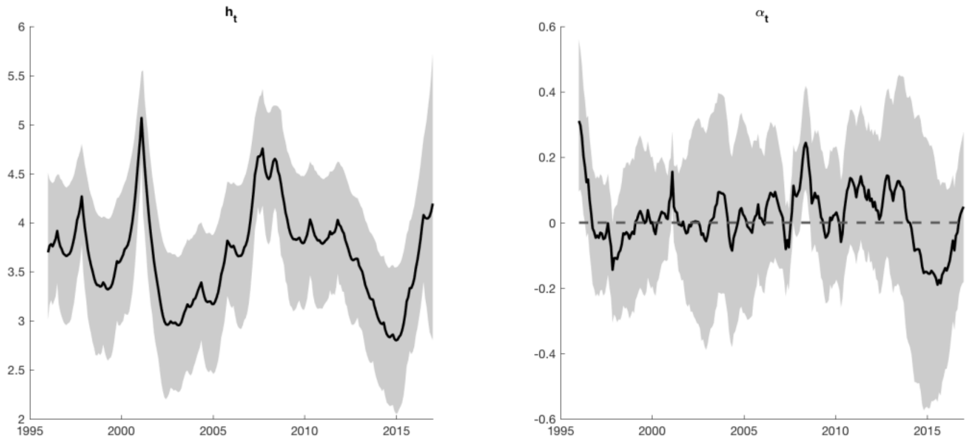


Figure 17 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in UK

e. Meat



f. Sugar

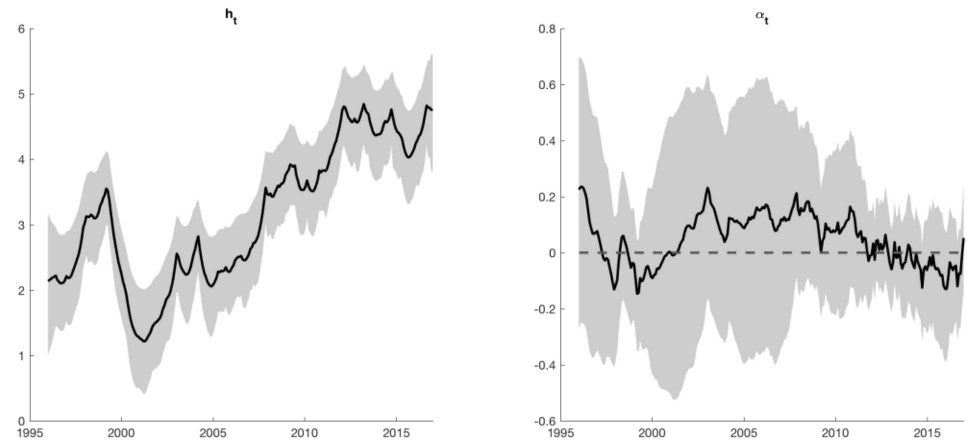


Figure 17 (continued): Evolution of Volatility and Impact of Volatility on Each Food Price in UK

Now, the results are estimated for United Kingdom. Figure 17a shows negative impact of food price volatility on food prices in general, while it is close to zero or positive impact in some years only.

According to estimations, the impact of food price volatility is negative on cereals prices. It is only positive between 2008 – 2009 periods and in 2011.

On the other hand, the impact of food price volatility is positive on dairy prices. The impact decreases suddenly after 2008 until 2010 and then increases until 2013. As it can be seen on the figure, the impact decreases starting from 2013 and it is close to zero at the end.

Positive effect of food price volatility is found on fats prices. As it is shown on the figure 17d, the impact reduces between 1995 – 2000 periods and become negative. Then, it fluctuates positively until the middle of 2015 and turns to negative and positive again.

The impact of food price volatility on meat prices decreases positively and become negative at the beginning of 1997. Then, the impact volatile around zero level and the impact is close to zero, positive either negative.

Lastly, it is almost same as the previous one. So, the impact of food price volatility on sugar prices decreases positively and become negative until 1998. Then, the impact is positive between 2002 – 2011 periods and close to zero or negative until the end of the periods.

As a result of the all estimations, all the countries show the same reaction to the food price volatility. In general, the impact of food price volatility is positive on food prices in six of the G-7 countries which are Canada, France, Germany, US, Italy and Japan. In contrast to them, UK has negative impact of food price volatility on food prices. On the other hand, the food price volatility has positive impact on cereals prices in general in five of the G-7 countries which are Canada, Germany, US, Italy and Japan. At the same time, UK has negative and France has either positive or negative impact on cereals prices. In addition, the effect of food price volatility is positive on dairy prices generally in six of the G-7 countries while it is either positive or negative effect in France. Moreover, there is positive impact of food price volatility on fats prices in each country. Additionally, the impact is same as the previous one on meat prices in six of the G-7 countries, while it is either positive or negative impact in UK. Finally, the impact of food price volatility is negative on sugar prices in Canada, positive in France, Italy and US and then either positive or negative in Japan and UK. Also, the impact is not estimated on sugar because of missing values in the dataset in Germany, so the sugar prices are only excluded from the dataset in Germany.

As it is mentioned before, in order to solve the volatility problem, there are some categories of policies and programs which are ex-ante interventions relative to price shocks and ex-post interventions relative to price shocks. The aim is to stabilize the food prices and decrease the effect of food price volatility on income and purchasing power. First program (which is an instrument) is trying to decrease the food price volatility and the size of price shocks. The aim is to have a better working market over time and space. If consumers, producers and traders who are exporting and importing foods and manufacturers who are buying and selling food products respond fastly and sufficiently, then small food price volatility will be enough to solve the disequilibrium in the market. Information systems, transport and communication infrastructure, decreasing transaction costs on markets, storage capacity, grading and clearing rules for government interventions in markets are also included in the program.

In addition, direct state interventions decreases the food price volatility in domestic markets. Foreign trade, public food reserves and price band schemes are used by interventions.

Aim of the second program is to manage the food price volatility and it can be done by using the managing price risk ex-ante interventions relative to price shocks. Financial products which are weather insurance, forward contracts and options, credit and saving associations and also agricultural investment are included in this program. These are all increases the domestic production and stabilize the production of food with the variety and resilience of food system too.

On the other hand, ex-ante price volatility management instruments are used to increase the efficiency of smallholders and increase the supply in the short run. Also, extension services and provision of subsidized inputs are included in these instruments. These are all performed by using subsidies and increasing the issue of fiscal sustainability. In this part of the program, promotion of employment in rural non-farm economy is used as a policy instrument via decentralization. Moreover, they prepare a program about supporting the small and medium rural enterprises.

Furthermore, civil society organizations play an important role for the interventions. Interventions may not be organized without civil society organization. Because, they manage and account in the social protection programs like minimum wage and right to food. On the other hand, producer organizations play an important role by managing collective actions together with the members and preparing programs like rotating funds, group insurance local buying for social programs.

Lastly, there is a solution for overcoming the food price volatility. So, ex-post interventions relative to price shocks are used as an instrument and program for overcoming the volatility. Emergency loan programs are included, because they reinforce to have a response to the price shocks. Another important instrument is included to the interventions which is large variety of social protection for vulnerable households. Cash and food transfers, school feeding programs, productive safety nets, guaranteed employment schemes are also included in this instrument. Civil society organizations play an important role for overcoming the food price volatility. They try to organize social protection programs in the short term to help the vulnerable households.

3.5 Conclusion

We estimated the impact of food price volatility on each food prices which are cereals, dairy, fats, meat and sugar in G7 countries by using TVP-SVM model. In our estimations, we considered the results of volatility, posterior moments of the stochastic volatility in mean model parameters and finally the evolution of volatility and the impact of volatility on each food price. In general, the impact of food price volatility is positive on food prices in six of the G-7 countries which are Canada, France, Germany, USA, Italy and Japan. In contrast to them, UK has negative impact of food price volatility on food prices.

Also, as it is learnt from the past and recent food crises, the heaviness and the evolution of food crises may decrease with better management of information and learning from the past experiences. In addition to these, the coordination of policy interventions is important for decreasing the impact of food crisis.

Chapter 4

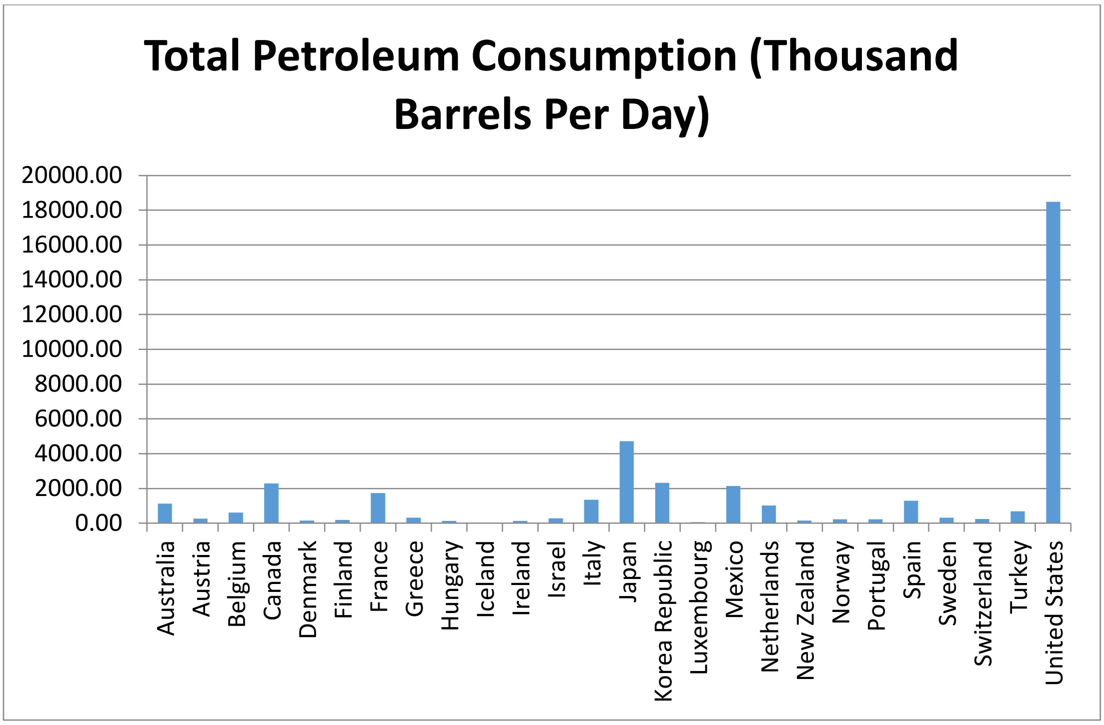
OIL PRICE MOVEMENTS AND MACROECONOMIC PERFORMANCE: EVIDENCE FROM TWENTY-SIX OECD COUNTRIES

4.1 Introduction

The role of oil, which is a very important energy source, in energy markets and the overall economy has been well documented in the energy economics literature. Many studies have investigated the effects of oil and its prices on macroeconomic indicators; however, results are still inconclusive (Chang and Wong, 2003). Oil price movements do not only affect energy markets but also the overall performance of the economy. Oil prices have risen exponentially since 2002 (Cong et al., 2008), leading to fluctuations in international markets. As suggested by Dogrul and Soytas (2010), increases in oil prices lead to increases in the cost of production in many sectors; this might reduce production and increase unemployment while also resulting in inflation (Cavalcanti and Jalles, 2013). Importantly also, increases in oil prices erode export competitiveness (Lee and Chiu, 2011). This is even more critical if an economy is dependent on importing raw materials and intermediate goods.

Since the first oil shock in 1973, there have been many studies on the empirical link between oil prices and macroeconomic fundamentals. Although the empirical relationship between oil prices and macro-economies has been confirmed in previous research, such as Burbidge and Harrison (1984), and Hamilton (1983), it has been argued that this relationship has weakened following the collapse of oil prices in 1986 (Chang and Wong, 2003).

The contribution of the study to the existing literature is by analyzing the relationship between oil prices and the overall performance of twenty-six OECD (Organisation for Economic Co-operation and Development) countries, namely, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Luxembourg, Mexico, the Netherlands, New Zealand, Norway, Portugal, Switzerland, Sweden, Spain, Turkey, and the United States (US). The US is the top oil consumer with 18,949 thousand barrels per day; Japan ranks third with 4,464 thousand barrels per day; Canada comes in ninth with 2,289 thousand barrels per day; South Korea is tenth with 2,230 thousand barrels per day; Mexico ranks eleventh with 2,133 thousand barrels per day; and France consumes 1,792 thousand barrels per day (EIA, 2014) as plotted in Figure 18. Therefore, it is highly likely that oil price changes will have significant effects on the macroeconomic performances of OECD countries. A similar study was carried out by Mark et al. (1994) again in the case of the OECD countries who found asymmetric effects of oil prices on the macroeconomic performances in the seven countries (with only one exception, Norway). However, there is still a room to investigate such relationship using the newest approaches and in the case of the other OECD countries as well.



Source: Energy Information Administration (2014), USA.

Figure 18: Total Petroleum Consumption in the OECD Countries (2012)

Another contribution of this study to the existing literature is that it employs the latest econometric procedures in a panel setting by using GAUSS and STATA softwares; therefore, consideration of OECD countries will signal important policy messages. This is enhanced by the fact that new methods, including the second generation econometric procedures employed in the study, generate more confident and robust results (Silvestre et al., 2005).

The study is organized as follows: a literature survey is provided in section 2; section 3 defines the data and methodology; section 4 presents and discusses the results; and section 5 concludes the study.

4.2 Literature review

Papapetrou (2001) investigate the relationship between oil price fluctuations, the stock market, economic activity, and employment in Greece The results show that, oil price has a significant impact on economic activity and employment. Also, it is obvious that, when oil price increases or decreases, price of output and employment increases or decreases significantly.

Using quarterly data, Cunado et al. (2003) focus on the impact of oil price fluctuations on macroeconomic variables like inflation and industrial production indices for many European countries. They found short-run impacts on inflation while oil prices exhibited opposite impacts on production growth rates in the short run.

Jimenez-Rodriguez and Sanchez (2005) analyze the impact of oil price movements on real economic activity in some major industrialized OECD countries. According to estimation results, the impact of oil prices are non-linear on real GDP, but increases of oil prices has more impact on economic growth than decreases of oil prices. They also find that in most cases, oil price increases are not statistically significant. Moreover, they divided the countries into two groups, namely, oil-importing and -exporting countries. Oil price increases has a negative effect on economic activity among oil-importing countries except Japan in both linear and non-linear models. On the other hand, they focus on two oil-exporting countries, namely, the United Kingdom and Norway. An increase in the price of oil price negatively and significantly affects economic activity in the UK. In contrast, Norway incurred some benefits from an increase in the price of oil.

Lardic and Mignon (2006) conduct their research on the effect of oil prices on GDP in 12 European countries using the asymmetric co-integration approach. According to their estimation results, there is an asymmetric co-integration between the price of oil and GDP in the 12 European countries; however, there is no standard co-integration between them. Also, an increase in oil prices affect economic activity more than a decrease in oil prices. Moreover, an increase in oil prices causes inflation and affects the unemployment rate in the long run.

Mellquist and Femermo (2007) analyze the impact of oil price movements on unemployment in Sweden. They apply linear regression analysis and use Granger causality tests to examine whether there is a direct relationship between them. According to the linear regression analysis, there is a positive relationship between changes in the price of oil and unemployment; however, it is inconclusive whether the impact of oil price changes on unemployment is both positive and negative in Sweden because the coefficients of the Granger causality are sometimes positive and sometimes negative.

Using the co-integration approach for the economies of the US, the G7, Europe, and the Euro zone, Lardic and Mignon (2008) focus on the long term relations between oil prices and economic activity. On the other hand, increases of oil prices cause to have more impact on GDP comparing with the decreases of oil prices. As a result, standard co-integration is rejected while asymmetric co-integration is accepted and they conclude that, there is asymmetric co-integration between oil prices and GDP in all countries.

In a study by Alvarez et al. (2009) on the effect of oil price movements on consumer price inflation in Spain, in particular, and the Euro zone, in general, the authors find that the effect of oil price changes on inflation is limited and the effect of oil price changes on inflation is higher in Spain than in the Euro zone. Another important finding from this study is that crude oil price movements played an important role in inflation. Moreover, they find both direct and indirect effects. Direct effects cause an increase in spending on refined oil products by households, and indirect effects lost importance.

Chen (2009) investigates the effect of oil prices on inflation in 19 industrialized countries over time and concludes that oil prices had negative effects on inflation. Also, by increasing the value of the domestic currency of a country, monetary policy is more responsive as a reaction to inflation, and trade openness was highly effective in explaining the decrease in oil prices.

Using the efficiency wage model of Carruth et al. (1998), Dogrul and Soytas (2010) investigate the relationship between oil prices, interest rates, and unemployment in an emerging market, namely, Turkey. The contribution of the study is that it shows causality between unemployment, crude oil prices, and real interest rates in an emerging market. The researchers employed the Toda-Yamamoto procedure, which is a new technique. According to the findings from this new technique, both interest rates and real oil prices improve unemployment estimations in the long run in Turkey. Also, oil price movements and interest rate movements have negative and insignificant effects on unemployment. On the other hand, unemployment movements have negative and significant effects on the price of oil; however, it later has an insignificant effect on the price of oil in Turkey. Also, based on the results from the Toda-Yamamoto procedure, both real oil price and real interest rate have an effect on unemployment in the long run in Turkey.

Korhonen and Ledyaeva (2010) conduct a study on the impact of oil price movements on oil-producing and oil-consuming countries. They use data on Russia, an important oil producer in the world. They find that direct impacts from a positive oil price movement are positive and large; there is also a negative indirect impact, but this is very small. The net effect in the case of Russia is therefore positive. "However, the evidence for oil importing countries is mixed. The direct effects of positive oil price shocks are negative for Japan, the US, China, Finland, Germany, Switzerland and UK" (Korhonen and Ledyaeva (2010). There are also negative indirect impacts for Russia, Finland, Germany, and Netherlands. As a result, they find that oil price increases raised Russia's GDP.

Chang et al. (2011) study on the effect of oil prices on macroeconomic variables which are GDP, inflation, and unemployment for 17 countries. Vector error correction model (VECM) is used to estimate the co-integration, impulse response functions (IRF) and variance decomposition (VDC). In addition, the variance auto regression (VAR) is used to estimate non-co-integrated series and see the relationship between the price of oil and macroeconomic variables. Increases in oil prices show an increasing and positive effect on GDP for oil-exporting countries. On the other hand, oil price fluctuations have a negative impact on GDP in the short run for small open economies. Also, they find an uncertain effect of oil price fluctuations on faster GDP growth in large economies. In contrast, when oil price fluctuation is positive, then the effect on CPI is marginal in oil-exporting countries.

Loscos et al. (2011) analyze the effect of oil price movements on GDP growth and inflation in Spain's economy and that of its seventeen regions. They use Qu and Perron's (2007) and Bai and Perron's (1998, 2003a, and 2003b) methodology and procedure to examine structural breaks and the relationship between oil prices, GDP, and CPI inflation. Estimation results provide that, the effects of oil price fluctuations are not statistically significant on GDP and/or CPI inflation. Moreover, non-linear relationship has been found between oil prices and macroeconomic variables namely, CPI and GDP. For the Spanish economy, after 1970, there is a reduced impact of oil price movements on macroeconomic fluctuations. For instance, there is a reduction in the impact of oil price movements on GDP between 1980 and 1990. After 1986, the impacts of oil price movements regain significance in the context of inflation. On the other hand, the results for Spain's 17 regions show that the inflationary impacts of oil price movements reduce in importance and have a positive and significant effect. Also, the GDP effects of oil price movements are important at the level of disaggregation.

Mehrara and Mohaghegh (2011) study on the impact of oil price fluctuations on economic output, money supply, price indices, GDP and etc. for oil-exporting countries by using the panel VAR approach. They find that oil price movements are not an essential reason for inflation. Acording to estimation results, although the money is unbiased in these countries, the macroeconomic fluctuations ensued because of money. In addition, there is a significant impact of oil price fluctuations on economic output and a positive and significant impact on money supply. Lastly, money shocks are one of the important reasons for GDP fluctuations.

Ashley and Tsang (2012) investigate the relationship between oil prices, real output growth, and growth rates on six net oil-importing countries. They use a new technique for estimating and interpreting the estimation results better. The results provide that, there is a statistically significant impact of oil price growth rates on future output growth and the impact continue more than four years. Conversely, the impact of oil price growth rates is not statistically significant on output growth when the change of persistency is less. This shows that, the impact does not continue more than four years and it is less than four years but more than a year. Additionally, there is a statistically significant impact of oil prices on output growth if the persistency is a year or less than a year in some of these net oil-importing countries.

Loscos et al. (2012) investigate the effect of oil price movements on the macroeconomic evolution in G7 countries. They use Qu and Perron's (2007) methodology to examine structural breaks and find that there are three breaks with a non-linear relationship between 1970 and 2008. In addition, they find that, long run multipliers are found and the effects of oil price fluctuations are at the highest level in 1970 on output and inflation. On the other hand, the impact is ended at the end of the 1990s but the effect is high on output and especially on inflation in 2000. The effect of oil price fluctuations on output and inflation is lower in 2000 compared with 1970. This shows that oil price movements lost some of its control of the economy. As a result, according to estimation results, the impact of oil price fluctuations which is seen in 1970 is significant on inflation and GDP. Also, it has almost the same impact in G7 countries in the twenty-first century.

Cavalcanti and Jalles (2013) investigate the impact of oil price fluctuations on macroeconomic variables for Brazil and United States for the last 30 years. They find that, oil price increases have a negative impact on economic growth and a positive impact on inflation in the US. However, the importance of these impacts lessened over time. Conversely, oil price increases have a positive effect on inflation, but oil price movements do not impact on real output growth. They summarize that, negative oil movements generate decreases in consumption and aggregate demand. The movements also cause an increase in prices, a reduction in employment, and an appreciation of the exchange rate. Appreciation of exchange rate affects the competitiveness negatively.

4.3 Methodology

We use the dataset of twenty-six OECD countries for estimating the results. We use yearly data which starts from 1980 to 2011. Oil prices and three macroeconomic variables which are GDP per capita in USD (2005 = 100), CPI (2005 = 100), and the unemployment rate (as a percentage of the total labor force) are used to estimate the results. The data was obtained from the World Bank (2014) and BP (2014) for oil price data. These macroeconomic variables were used to examine the relationship between oil prices and the macroeconomic variables of study sample. Moreover, Dubai's oil prices were used as an oil price variable throughout the models; we divided Dubai's oil prices (in USD) by the CPI of each country as a proxy for their oil prices. In order to capture growth effects, all of the variables were at their natural logarithms.

In this study, the Lagrange multiplier (LM) test, which was developed by Breusch-Pagan (1980), and the bias-adjusted cross-sectional dependence Lagrange multiplier (LM_{adj}) test, which was developed by Pesaran et al. (2008), were used to examine whether there was a cross-sectional dependence between the countries. Secondly, the cross-sectionally augmented Dickey-Fuller (CADF)—developed by Pearson (2006)—unit root test was used as a second generation test for cross-sectional dependency and structural breaks. The Durbin Hausman (Durbin-H) test—a second generation econometric estimation test developed by Westerlund (2008)—was used to measure whether there was co-integration between the series. Finally, in order to test for the possibility of a long-run relationship between the variables, the Common Correlated Effects Mean Group Estimator (CCE Full Robust) developed by Pesaran (2006) and the Augmented Mean Group Estimator (AUG Full) developed by Bond and Eberhardt (2009) and Eberhardt and Teal (2010) were used.

Moreover, in this study, all tests were conducted with three regression types, namely, single, double, and multiple regressions in order to compare the results and to observe for the robustness of the results. Chang and Wong (2003) utilized a similar approach in their study on the impact of oil price fluctuations on Singapore's economy. In our study, by using the second generation econometric methods, the relationship between oil price and macroeconomic variables was analyzed for all twenty-six OECD countries.

4.3.1 Cross-section Dependency Test

According to Breusch and Pagan (1980) and Pesaran (2004), in a series, cross-section dependency needs to be considered; otherwise, the results might be biased. That is, econometric procedures such as panel unit root tests need to be carried out by taking any cross-section dependency (if available) into consideration. Therefore, cross-section dependency needs to be tested in both series and in the co-integration equation.

There are two approaches in this respect: The first approach is the Lagrange multiplier (LM) test developed by Breusch and Pagan (1980), and it is used if the panel's time dimension (T) is greater than the cross-sectional dimension (N). The second test is Pesaran's (2004) CD test, which is used if both T > N or N > T. In these tests, if the ensemble average is zero, but the individual average is different from zero, then the results will be biased. The LM test statistic is obtained as below:

$$CDLM1 = T\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2 \sim \chi^2_{\frac{N(N-1)}{2}} \quad (24)$$

Where the LM statistic is derived from sum of squared residuals from correlation coefficients. This statistic follows the χ^2 (chi-square) asymptotic distribution whose parameter is N (N-1)/2. The sign "~" suggest that LM test statistic has χ^2 asymptotic distribution while N is the number of observations and ε stands for residuals. Then after, $\hat{\rho}_{ij}$ is computed as below:

$$\hat{\rho}_{ij} = \hat{\rho}_{ji} = \frac{\sum_{t=1}^{T}\hat{\varepsilon}_{it}\hat{\varepsilon}_{jt}}{(\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2)^{1/2}\ (\sum_{t=1}^{T}\hat{\varepsilon}_{jt}^2)^{1/2}}$$

In order to solve and fix the problem of bias, Pesaran et al. (2008) modified the LM test statistics, which then became the bias-adjusted cross-sectional dependence Lagrange multiplier (LM_{adj}) test. The LM_{adj} test is presented below;

$$LM_{adj} = \left(\frac{2}{N(N-1)}\right)^{1/2}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}^2\frac{(T-K-1)\hat{\rho}_{ij}-\hat{\mu}_{Tij}}{\upsilon_{Tij}} \sim N(0,1) \quad (25)$$

where $\hat{\mu}_{Tij}$ is average, υ_{Tij} is variance, T is sample size and K is the number of regressors in the i^{th} individual regression.

In the case of the LM_{adj} test, whose procedure follows the standard normal distribution, the null hypothesis, H0, suggests that there is no cross-section dependency. The cross-section dependency tests will enable researchers to investigate if there is any dependency among different cross section units (i.e. among OECD countries with respect to oil prices in this case). Furthermore, panel unit root tests should be carried out based on the test results from cross-section dependency.

4.3.2 Panel Unit Root Tests

As it can be seen from the literature, panel unit root tests are statistically more powerful than the time series unit root tests. The reason is that, panel unit root tests consider both the panel's time dimension and its cross-sectional dimension. In contrast, time series unit root tests take into consideration the time dimension. As a result, when cross-sectional dimension is added to tests, the data become more variable.

However, there is one problem with the panel unit root test, that is, it is unclear whether the relationships among the cross sections that create the panel are independent. As such, the panel unit root tests were separated into two categories, namely, first and second generation tests. Moreover, the first generation tests were further separated into homogenous and heterogeneous sub-categories. In addition, Hadri (2000), Levin et al. (2002), and Breitung (2005) support homogenous models. In contrast, Maddala and Wu (1999), Choi (2001), and Im et al. (2003) support heterogeneous models.

Importantly also, in first generation unit root tests, the cross sections that create the panel are accepted as independent, and if one unit of cross sections has a shock, the impact of the shock is accepted for all units with the same level. However, the impact of the shock should affect each unit of cross sections with different levels. Therefore, second generation unit root tests were developed in order to solve this problem. In addition, the multivariate ADF (MADF) test by Taylor and Sarno (1998), the panel Seemingly Unrelated Regression Augmented Dickey Fuller (SURADF) test (Breuer et al. 2002), (Bai and Ng, 2004), CADF (Pesaran, 2006) and Carrion-i Silvestre et al.'s (2005) test (PANKPSS) are most popular second generation unit root tests.

If there is cross-section dependency between countries, Pesaran's (2006) CADF unit root test is suitable. For example, in this study, as there was cross-section dependency, the CADF unit root test was used to examine whether or not the series were stationary. Panel unit root tests can be conducted for each of the countries using CADF. This test is used when T > N and N > T. Therefore, for stationary tests, CADF critical values are used with Pesaran's (2006) table. If the computed CADF value is greater than the CADF critical value, it means than, H_0 will be rejected. In other words, the series are stationary. The CADF test statistics is generated below:

$$Y_{i,t} = (1 - \emptyset_i)\mu_i + \emptyset_i y_{i,t-1} + u_{i,t} \qquad i = 1,2, \ldots\ldots, N \;\; ve \; t = 1,2, \ldots., T \tag{26}$$

$$u_{it} = \gamma_i f_t + \varepsilon_{it} \tag{27}$$

Where γ_i and $\emptyset_i$ are coefficients, $u_{i,t}$ is error term, f_t is common effect for each cross section (country), ε_{it} : individual specific error term in equation (27).

By using equation (26) and (27), the unit root hypothesis is written as:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{it} \qquad i = 1,2,\ldots.,N \ \ ve \ t = 1,2,\ldots.,T \tag{28}$$

H_0: $\beta_i = 0$

H_1: $\beta_i < 0$ i=1, 2,…., N_1, $\beta_i = 0$ i=N_1+1, N_1+2,…, N.

Also, the panel unit root test was conducted for each of the countries by using the CADF test, and the panel unit root test was used for all countries by taking the average of the unit root tests in order to obtain the CIPS (cross-sectionally augmented panel unit root test). The CIPS is the general unit root test statistic for the panel developed by Pesaran (2006).

The CIPS test statistics is generated below:

$$CIPS = N^{-1} \sum_{i=1}^{N} CADF_i \tag{29}$$

4.3.3 Durbin-H Panel Co-integration Test

Pedroni (1999, 2004), Westerlund (2007, 2008) and Westerlund and Edgerton (2007) investigated the long-run relationship between variables by using panel co-integration analysis. In this study, the Durbin-H panel co-integration analysis, which was developed by Westerlund (2008), was used. Panel co-integration relations with variables (oil prices, GDP, CPI, and unemployment rate) were examined, and cross-section dependencies were found between the series. In order to measure the existence of co-integration, the Durbin-H panel co-integration method was used. Moreover, the dependent variable should be I(1) and independent variables should be I(1) or I(0) in order to use the panel co-integration method (Westerlund, 2008).

In order to decide whether to reject the hypothesis, we looked at the computed test statistics and compared them with the critical value of the normal distribution table. When the computed test statistic was greater than 1.645 (5% significance level), the H_0 was rejected, thereby suggesting the existence of co-integration. According to Westerlund (2008), there are two ways to test for the existence of a co-integration relation in the Durbin-H method, namely, with the Durbin-H group statistic and the Durbin-H panel statistic. In the Durbin-H group statistic, differentiation between the cross sections of the autoregressive parameter is allowed. Conversely, in the Durbin-H panel co-integration analysis, the autoregressive parameter is the same for all cross sections.

4.3.4 Estimation of Long-term Co-integration Coefficients

After finding the co-integration relations among the series, the long-term co-integration coefficients were estimated by using the Common Correlated Effects Mean Group Estimator (CCE Full Robust) developed by Pesaran (2006) and the Augmented Mean Group Estimator (AUG Full) developed by Bond and Eberhardt (2009) and Eberhardt and Teal (2010). The aim of this test is to investigate whether there is a relationship between variables in the long run.

4.4 Estimation Results

4.4.1 Cross-section Dependency in the Panel Data

Firstly, we checked the existence of cross-section dependency in the co-integration equation and among the variables by using the LM_{adj} test. The results are given in Table 4.

Table 4: Results of the cross section dependency (LM_{adj}) test

Variables & co-integration equation CD tests	**OIL**	**GDP**	CPI	UR
		Test Stat. & Prob.		
CD LM1 (Breusch, Pagan 1980)	6401.02* (0.00)	2293.13* (0.00)	1849.87* (0.00)	881.08* (0.00)
CD LM2 (Pesaran 2004 CDLM)	238.32 (0.00)	77.19 (0.00)	59.81 (0.00)	21.81 (0.00)
CD LM (Pesaran 2004 CD)	77.10 (0.00)	41.61 (0.00)	33.46 (0.00)	20.61 (0.00)
Bias-adjusted CD test (Pesaran et al. 2008)	256.41 (0.00)	232.93 (0.00)	250.36 (0.00)	227.76 (0.00)
Bias-adjusted CD test for co-integration equation	29.78 (0.00)	70.93 (0.00)	60.27 (0.00)	70.93 (0.00)

*Note: *: Although the estimated coefficients seem larger, some estimates in the different articles provide the same coefficients in terms of magnitude.*

According to the results in Table 4, the null hypothesis of no cross-section dependency was rejected at $\alpha = 0.01$; therefore, it was concluded that there was cross-section dependency between the series and the co-integration equation. Furthermore, there was cross-section dependency among the countries which creates the panel. This suggests that if a shock were assigned to the oil price, GDP, CPI, and UR of a specific country, then these same variables would be affected in another country. The results of the LM_{adj} test in Table 4 suggest that these macroeconomic variables were interrelated across countries. This is because the null of no cross-section dependency can be rejected and cross-correlation can be confirmed in the cases of the OIL, GDP, CPI, UR variables according to the results of the LM_{adj} tests. This technical finding can be justified by the reality that macroeconomic performances of countries (and trade partners) are interrelated owing to international trade and financial interactions.

4.4.2 Panel Unit Root Tests

In the second step, the second generation unit root tests and panel co-integration analyses were conducted. The results of the CIPS panel unit root tests are presented in Table 5a.

Table 5a: Results of CADF panel unit root test (without difference)

Countries and Variables		**Test Statistics**				**Critical Values**	
	OIL	**GDP**	**CPI**	**UR**	**1%**	**5%**	**10%**
Australia	-1.06	-1.48	-2.95	-3.67	-4.69	-3.88	-3.49
Austria	-0.29	-2.65	-2.31	-2.82	-4.69	-3.88	-3.49
Belgium	-0.29	-1.66	-3.38	-2.42	-4.69	-3.88	-3.49
Canada	-0.28	-1.46	-3.30	-4.67**	-4.69	-3.88	-3.49
Denmark	-0.32	-3.80***	-3.19	-3.44	-4.69	-3.88	-3.49
Finland	-0.24	-1.25	-1.59	-1.52	-4.69	-3.88	-3.49
France	-0.20	-2.47	-3.06	-2.42	-4.69	-3.88	-3.49
Greece	-1.01	-1.68	-1.97	-1.33	-4.69	-3.88	-3.49
Hungary	-2.09	-0.90	-1.66	-2.18	-4.69	-3.88	-3.49
Iceland	-2.24	-1.27	-1.62	-3.90**	-4.69	-3.88	-3.49
Ireland	-0.61	-1.52	-3.02	-1.35	-4.69	-3.88	-3.49
Israel	-9.76*	-3.01	-1.41	-2.46	-4.69	-3.88	-3.49
Italy	-0.29	-1.03	-2.00	-2.90	-4.69	-3.88	-3.49
Japan	0.05	-1.73	-1.74	-1.39	-4.69	-3.88	-3.49
Korea Rep.	-1.10	-1.23	-2.41	-2.68	-4.69	-3.88	-3.49
Luxembourg	-0.35	-1.40	-4.58**	-1.82	-4.69	-3.88	-3.49
Mexico	-2.92	-2.52	-2.18	-2.68	-4.69	-3.88	-3.49
The Netherlands	-0.26	-2.59	-1.84	-1.41	-4.69	-3.88	-3.49
New Zealand	-0.56	-1.90	-2.13	-2.69	-4.69	-3.88	-3.49
Norway	-0.35	-2.32	-2.18	-2.09	-4.69	-3.88	-3.49
Portugal	-0.79	-1.85	-2.69	-1.00	-4.69	-3.88	-3.49
Spain	-0.89	-1.59	-2.51	-2.32	-4.69	-3.88	-3.49
Sweden	-0.20	-0.31	-1.81	-1.97	-4.69	-3.88	-3.49
Switzerland	-0.10	-0.87	-1.42	-0.59	-4.69	-3.88	-3.49
Turkey	-25.93*	-2.40	-1.58	-2.85	-4.69	-3.88	-3.49
US	-0.99	-2.00	-4.52**	0.72	-4.69	-3.88	-3.49
CIPS stat. for all countries (Panel)	-2.04	-1.80	-2.43	-2.22	-2.81	-2.66	-2.58

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. This shows whether the series are stationary.*

Table 5b: Results of CADF panel unit root test (with difference)

Countries and Variables	Test Statistics				Critical Values		
	OIL	GDP	CPI	UR	1%	5%	10%
Australia	-2.90	-5.30*	-6.03*	-6.31*	-4.69	-3.88	-3.49
Austria	-3.41	-4.01**	-3.21	-3.28	-4.69	-3.88	-3.49
Belgium	-3.41	-3.12	-3.05	-1.66	-4.69	-3.88	-3.49
Canada	-3.39	-3.74***	-3.11	-4.22**	-4.69	-3.88	-3.49
Denmark	-3.32	-3.25	-2.04	-3.57***	-4.69	-3.88	-3.49
Finland	-3.42	-4.24**	-2.39	-3.51***	-4.69	-3.88	-3.49
France	-3.49	-3.46	-3.43	-3.09	-4.69	-3.88	-3.49
Greece	-2.23	-2.34	-4.16**	-0.98	-4.69	-3.88	-3.49
Hungary	-1.17	-3.14	-5.21***	-2.62	-4.69	-3.88	-3.49
Iceland	-4.30**	-4.29**	-3.46	-4.20**	-4.69	-3.88	-3.49
Ireland	-3.63***	-1.39	-4.22**	-1.57	-4.69	-3.88	-3.49
Israel	-7.53*	-3.36	-4.46**	-3.41	-4.69	-3.88	-3.49
Italy	-3.36	-4.22**	-2.59	-2.25	-4.69	-3.88	-3.49
Japan	-3.54***	-2.00	-3.29	-2.56	-4.69	-3.88	-3.49
Korea Rep.	-3.60***	-4.11**	-4.03**	-4.23**	-4.69	-3.88	-3.49
Luxembourg	-3.40	-3.13	-2.82	-3.72***	-4.69	-3.88	-3.49
Mexico	-5.66*	-3.85***	-4.21**	-4.95*	-4.69	-3.88	-3.49
The Netherlands	-3.43	-3.50***	-2.49	-2.84	-4.69	-3.88	-3.49
New Zealand	-2.95	-2.48	-3.80***	-3.45	-4.69	-3.88	-3.49
Norway	-3.22	-3.55***	-4.93*	-3.76***	-4.69	-3.88	-3.49
Portugal	-3.10	-3.19	-3.40	-3.61***	-4.69	-3.88	-3.49
Spain	-3.09	-3.56***	-3.92**	-2.97	-4.69	-3.88	-3.49
Sweden	-3.44	-2.94	-5.35*	-2.34	-4.69	-3.88	-3.49
Switzerland	-3.51***	-2.57	-3.45	-1.05	-4.69	-3.88	-3.49
Turkey	-5.89*	-3.92**	-3.78***	-4.25**	-4.69	-3.88	-3.49
US	-3.31	-6.28*	-3.65***	-7.96*	-4.69	-3.88	-3.49
CIPS stat. for all countries (Panel)	-3.60*	-3.50*	-3.71*	-3.40*	-2.81	-2.66	-2.58

*Note: *, ** and ***denote significance levels respectively at 1%, 5%, and 10%. This shows whether the series are stationary.*

The CIPS test statistics for individual countries presented in Table 5a were less than Pesaran's (2007) critical values, with four exceptions; however, the CIPS test statistics for the overall panel was less than the critical values, and the null hypothesis of a unit root could not be rejected at level forms of series. This therefore shows that OIL, GDP, CPI, and UR were non-stationary at levels and in panel settings. CIPS unit root tests were also conducted for the first differences in the series. The results are presented in Table 5b.

Although the CIPS unit root tests provided mixed results, the CIPS test statistics for the overall panel were greater than the critical values, thereby leading to the rejection of the null hypothesis of a unit root for OIL, GDP, CPI, and UR; it was therefore concluded that all of these series were stationary at the first differences in the panel setting. To conclude, the CIPS panel unit root tests for the present study suggest that OIL, GDP, CPI, and UR in the OECD countries were integrated to the order of one, I (1).

4.4.3 Panel Co-integration Tests

In the subsequent step, Durbin-H panel co-integration tests were conducted under three options to check for the robustness of the results: models with a single regressor, models with two regressors; and models with three regressors. The results of the Durbin-H panel co-integration tests for the models with the single regressor are given in Table 6a.

Table 6a: Single regression: results of Durbin-H panel co-integration test

	Durbin-H Group Stats. & Prob. Values	**Durbin-H Panel Stats. & Prob. Values**	**Critical Value (5% significance level)**	**Decision**
Model 1 GDP=f(OIL)	3.01* (0.00)	3.22* (0.00)	1.645	There is co-integration.
Model 2 CPI=f(OIL)	6.10* (0.00)	8.25* (0.00)	1.645	There is co-integration.
Model 3 UR=f(OIL)	3.46* (0.00)	6.67* (0.00)	1.645	There is co-integration.

*Note: * denotes significance level at 1%.*

When OIL was the independent variable, the null hypothesis of no co-integration was rejected according to both the Durbin-H group statistics and the panel statistics. This is so because test statistics are greater than critical values. It was concluded that there was a co-integrating vector in all three models presented in Table 6a. This finding supports the existence of a long-term economic relationship between oil prices and GDP, CPI, and UR in the selected countries when a single regression is adapted.

In the second stage of the co-integration tests, models with two independent variables were evaluated. The results are given in Table 6b.

Table 6b: Double regression: results of Durbin-H panel co-integration test

	Durbin-H Group Stats. & Prob. Values	**Durbin-H Panel Stats. & Prob. Values**	**Critical Value (5% significance level)**	**Decision**
Model 1 GDP=f(CPI, OIL)	2.13** (0.016)	4.67* (0.00)	1.645	There is co-integration.
Model 2 GDP=f(UR, OIL)	0.41 (0.338)	2.62* (0.004)	1.645	There is no co-integration in the Durbin-H group, and there is co-integration in the Durbin H-panel.
Model 3 CPI=f(UR, OIL)	4.61* (0.00)	11.63* (0.00)	1.645	There is co-integration.
Model 4 CPI=f(GDP, OIL)	11.24* (0.00)	19.16* (0.00)	1.645	There is co-integration.
Model 5 UR=f(GDP, OIL)	0.78 (0.215)	2.83* (0.002)	1.645	There is no co-integration in the Durbin-H group, and there is co-integration in the Durbin H-panel.
Model 6 UR=f(CPI, OIL)	-0.86 (0.805)	0.59 (0.275)	1.645	There is no co-integration in either test.

*Note: * and ** denote significance levels respectively at 1% and 5%.*

In the case of Models 1, 3, and 4, the null hypothesis of no co-integration was rejected according to both the Durbin-H group and panel statistics. In the case of Model 2, when GDP was the dependent variable and UR and OIL were the regressors, only the Durbin-H panel statistics allowed the rejection of no co-integration. The same results were obtained in Model 5 when UR was the dependent variable and GDP and OIL were the regressors. The null hypothesis of no co-integration could never be rejected in Model 6 when UR was the dependent variable and CPI and OIL were the regressors. This reveals that a long-term relationship could not be inferred from movements in inflation and oil prices towards unemployment rates in the OECD countries studied.

In the last stage of the panel co-integration tests, the models with three regressors were evaluated. The results are given in Table 6c. Here, when GDP was the dependent variable, the null hypothesis of no co-integration could be rejected at the $\alpha = 0.10$ level in accordance with the Durbin-H group statistics. On the other hand, when UR was the dependent variable, the null hypothesis of no co-integration could not be rejected neither according to group statistics nor panel statistics. Therefore the results of Model 6 in Table 6b and Model 3 in Table 6c are consistent.

Table 6c: Multiple regression: results of Durbin-H panel co-integration test

	Durbin-H Group Stats. & Prob. Values	Durbin-H Panel Stats. & Prob. Values	Critical Value (5% significance level)	Decision
Model 1 **GDP=f(UR, CPI, OIL)**	1.35*** (0.08)	0.60 (0.27)	1.645	There is co-integration.
Model 2 **CPI=f(GDP, UR, OIL)**	6.36* (0.00)	15.06* (0.00)	1.645	There is co-integration.
Model 3 **UR=f(CPI, GDP, OIL)**	-1.82 (0.96)	-0.56 (0.71)	1.645	There is no co-integration in either the group or the panel.

*Note: * and *** denote significance levels respectively at 1% and 10%.*

4.4.4 Estimating Long-term Coefficients

In the step that followed, long-term coefficients were estimated through the Augmented Mean Group Estimator (AUG Full), which was developed by Bond and Eberhardt (2009) and Eberhardt and Teal (2010). Like the Durbin-H panel co-integration tests, the AUG FULL tests were carried out for the three model options with (1) a single regressor, (2) two regressors, and (3) three regressors to check for the robustness of the results.

Table 7a: Single regressions: results of long-term coefficients (AUG Full)

	Coefficients &computed t- stat.
	OIL
Model 1	-0.0088
GDP=f(OIL)	(-1.36***)
Model 2	-4.4524
CPI=f(OIL)	(-3.21*)
Model 3	-0.1623
UR=f(OIL)	(-0.42)

*Note: * and *** denote significance levels respectively 1% and 10%.*
The computed t-statistics are in parentheses.

In the case of the models with a single regressor, as presented in Table 7a, OIL exerted statistically significant but negative effects on GDP (b= -0.0088, $p < 0.10$) and CPI (b= -4.4524, $p < 0.01$). The long-term elasticity coefficient of OIL with respect to UR was not statistically significant. In single regressions, it can be seen that although oil prices led to decreases in real income in OECD countries, it moved again in the negative direction along with consumer prices.

In the second stage, the models with two regressors were evaluated. The results are similar to those in Table 7a and are presented in Table 7b. It is important to note that the long-term coefficients in Model 6 in Table 6b were not estimated since no co-integration was detected in this model.

Table 7b: Double regressions: results of long-term coefficients (AUG Full)

		Coefficients & computed t-stat.		
	GDP	**CPI**	**UR**	**OIL**
Model 1 **GDP=f(CPI, OIL)**	-	-0.0001 (-0.39)	-	-0.009 (-1.52***)
Model 2 **GDP=f(UR, OIL)**	-	-	-0.006 (-6.15*)	-0.008 (-1.71**)
Model 3 **CPI=f(UR, OIL)**	-	-	0.91 (2.10**)	-3.99 (-3.22*)
Model 4 **CPI=f(GDP, OIL)**	-4.53 (-0.21)	-	-	-4.17 (-3.43*)
Model 5 **UR=f(GDP, OIL)**	-51.12 (-7.41*)	-	-	-0.19 (-0.47)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Oil prices again exerted statistically significant and negative effects (at very low levels) on real GDP and CPI. The effect of OIL on CPI was elastic in two different models. Again, the long-term coefficient of OIL with respect to UR was not statistically significant.

Table 7c: Multiple regressions: results of long-term coefficients (AUG Full)

	Coefficients & computed t- stat.			
	GDP	**CPI**	**UR**	**OIL**
Model 1		-0.00004	-0.0068	-0.0088
GDP=f(UR, CPI, OIL)	-	(-0.15)	(-6.47*)	(-1.70**)
Model 2	17.38		0.97	-3.71
CPI=f(GDP, UR, OIL)	(0.53)	-	(1.81**)	(-2.96*)
Model 3	-54.31	0.053		-0.058
UR=f(CPI, GDP, OIL)	(-7.61*)	(2.52*)	-	(-1.52***)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

In the final step of estimating the long-term coefficients for the overall panel, the models with three regressors were evaluated. The results are presented in Table 7c. The results are again consistent with the earlier results where OIL exerted negatively significant effects on GDP, CPI, and UR. To summarize, when the overall panel is considered, it can be seen that oil prices exerted highly inelastic but negatively significant effects on real income and unemployment rates in the OECD countries where their effect on consumer prices were highly elastic and again negatively significant.

After analyzing the long-term coefficients using the overall panel, the long-term coefficients for each OECD country were also analyzed through the AUG Full approach. Table 8a presents the long-term coefficients of OIL with respect to GDP, CPI, and UR for each country through models with a single regressor.

Table 8a: Single regressions: results of long-term coefficients (AUG Full)

	Model 1 GDP=f(OIL)	Model 2 CPI=f(OIL)	Model 3 UR=f(OIL)
	Coefficients & computed t-stats		
Australia	0.018 (4.32*)	-4.04 (-2.75*)	-1.86 (-1.67**)
Austria	0.002 (0.51)	-1.30 (-1.63***)	0.51 (0.92)
Belgium	-0.007 (-2.05**)	-2.27 (-1.72**)	-0.52 (-0.38)
Canada	0.014 (1.91**)	-6.52 (-5.39*)	-0.95 (-0.83)
Denmark	-0.034 (-5.47*)	-5.80 (-5.39*)	-0.39 (-0.30)
Finland	0.037 (3.00*)	-13.91 (-8.45*)	- 3.30 (-1.55***)
France	-0.013 (-3.72*)	-11.71 (-7.25*)	-3.36 (-5.08*)
Greece	0.019 (6.16*)	0.87 (1.01)	-0.96 (-3.17*)
Hungary	0.017 (4.47*)	7.18 (11.05*)	-1.03 (-4.58*)
Iceland	0.003 (1.67**)	-0.15 (-0.21)	-0.03 (-0.23)
Ireland	0.004 (0.21)	-1.75 (-0.79)	1.26 (0.37)
Israel	0.00000036 (0.14)	0.007 (0.50)	-0.008 (-2.59*)
Italy	-0.044 (-8.44*)	-8.73 (-11.77*)	-3.01 (-3.91*)
Japan	-0.086 (-4.56*)	-17.23 (-8.92*)	1.64 (2.06**)
Korea Rep.	-0.088 (-4.23*)	5.65 (3.64*)	0.45 (0.59)
Luxembourg	-0.066 (-5.46*)	0.30 (0.22)	3.39 (3.78*)
Mexico	0.0002 (5.65*)	0.11 (6.18*)	-0.001 (-0.40)
The Netherlands	0.003 (0.46)	5.39 (3.39*)	-2.56 (-1.22)
New Zealand	0.021 (2.37*)	-12.90 (-6.22*)	-1.55 (-1.56***)
Norway	-0.029 (-3.71*)	-11.29 (-10.75*)	-1.86 (-2.76*)
Portugal	-0.015 (-2.45*)	-5.21 (-4.94*)	1.46 (2.85*)
Spain	-0.013 (-2.67*)	-3.60 (-6.14*)	1.75 (1.03)
Sweden	0.036 (4.44*)	-18.36 (-8.11*)	0.79 (0.51)
Switzerland	0.014 (1.87**)	-13.00 (-7.16*)	1.02 (0.97)
Turkey	0.00000013 (-0.88)	0.006 (4.62*)	-0.0001 (-1.77**)
US	-0.023 (-5.57*)	2.55 (4.83*)	4.93 (4.77*)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Table 8a shows that an increase in oil prices did not lead to a significant impact on GDP in the cases of Austria, Ireland, Israel, the Netherlands, and Turkey. Oil price movements exerted statistically significant effects on GDP in the remaining twenty-one OECD countries. Positive coefficients of oil prices with respect to GDP were obtained in the cases of Australia, Canada, Finland, Greece, Hungary, Iceland, Mexico, New Zealand, and Sweden whereas negative coefficients were obtained in the cases of Belgium, Denmark, France, Italy, Japan, South Korea, Luxembourg, Norway, Portugal, Spain, and the US. Table 5-A shows that oil prices exerted mixed effects on CPI and UR whereas in some countries, these coefficients were not statistically significant.

Table 8b presents the estimated coefficients of "OIL" with respect to GDP, CPI, and UR through multiple regression analyses with two independent variables:

Table 8b: Double regressions: results of long-term coefficients (AUG Full)

	Model 1 GDP=f(CPI, OIL)	Model 2 GDP=f(UR , OIL)	Model 3 CPI= f(UR, OIL)	Model 4 CPI=f(GDP, OIL)	Model 5 UR=f(GDP , OIL)	Model 6 UR=f(CP I, OIL)
			Coefficients & computed t-stats of oil price			
	OIL	**OIL**	**OIL**	**OIL**	**OIL**	**OIL**
Australia	0.01 (4.31*)	0.008 (2.09**)	-3.41 (-1.79**)	-3.20 (-2.32*)	-0.81 (-1.76**)	-1.91 (-3.29*)
Austria	-0.0008 (-0.20)	0.007 (1.86**)	-1.12 (-1.28)	-1.86 (-2.36*)	0.06 (0.17)	-0.32 (-0.75)
Belgium	-0.008 (-2.24**)	-0.0004 (-0.15)	-2.75 (-2.15**)	-4.33 (-3.92*)	0.87 (0.97)	1.35 (1.23)
Canada	0.009 (1.33***)	0.008 (1.25)	-6.02 (-5.01*)	-6.24 (-5.42*)	0.23 (0.40)	0.45 (0.72)
Denmark	-0.03 (-5.69*)	-0.034 (-7.05*)	-5.62 (-5.53*)	-6.78 (-4.94*)	-2.42 (-4.31*)	1.10 (1.26)
Finland	0.01 (1.26)	0.003 (0.67)	-13.09 (-6.68*)	-12.96 (-7.96*)	-1.12 (-0.80)	-2.84 (-1.30***)
France	-0.01 (-4.06*)	-0.023 (-4.43*)	-8.37 (-3.77*)	-13.44 (-7.66*)	-4.27 (-7.02*)	-3.01 (-4.21*)
Greece	0.02 (8.23*)	0.017 (6.03*)	0.92 (0.99)	1.99 (1.89**)	0.57 (1.74**)	-0.24 (-0.86)
Hungary	0.01 (2.76*)	0.012 (4.34*)	6.48 (10.50*)	6.84 (8.89*)	0.87 (4.18*)	-0.68 (-2.95*)
Iceland	0.002 (1.52***)	0.003 (2.28**)	-0.09 (-0.17)	0.26 (0.36)	0.32 (3.41*)	0.30 (6.36*)
Ireland	0.008 (0.57)	-0.005 (-0.80)	-1.60 (-0.72)	-1.85 (-0.83)	0.96 (1.07)	2.90 (1.25)
Israel	0.0000004 (0.20)	0.0000006 (0.35)	0.01 (1.28)	-0.0004 (-0.04)	0.001 (0.53)	-0.004 (-1.51***)
Italy	-0.05 (-8.44*)	-0.04 (-3.87*)	-7.07 (-6.27*)	-6.86 (-6.98*)	-4.52 (-6.75*)	-3.36 (-5.24*)
Japan	0.001 (0.10)	-0.09 (-11.28*)	-18.60 (-10.91*)	-8.93 (-3.78*)	-1.73 (-3.23*)	0.54 (0.93)
Korea Rep.	-0.12 (-6.82*)	-0.05 (-4.56*)	4.06 (3.36*)	3.36 (1.16)	0.75 (1.00)	0.62 (0.80)
Luxembourg	-0.06 (-5.48*)	-0.03 (-3.05*)	-2.10 (-1.78**)	-3.50 (-2.13**)	1.81 (3.61*)	1.95 (3.31*)
Mexico	0.0001 (2.77*)	0.0002 (5.47*)	0.11 (5.61*)	0.06 (2.67*)	-0.003 (-0.59)	-0.001 (-0.71)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Table 8b: Double regressions: results of long-term coefficients (AUG Full) (Continued)

	Model 1 GDP=f(CPI, OIL)	Model 2 GDP=f(UR, OIL)	Model 3 CPI=f(UR, OIL)	Model 4 CPI=f(GDP, OIL)	Model 5 UR=f(GDP, OIL)	Model 6 UR=f(CPI, OIL)
	Coefficients & computed t-stats of oil price					
	OIL	**OIL**	**OIL**	**OIL**	**OIL**	**OIL**
The Netherlands	0.004 (0.54)	0.006 (1.50***)	5.20 (3.25*)	5.48 (3.32*)	-1.19 (1.06)	1.80 (1.20)
New Zealand	0.006 (0.68)	-0.0003 (-0.07)	-10.42 (-4.73*)	-11.14 (-6.07*)	-0.40 (-0.73)	-1.19 (-1.16)
Norway	-0.039 (-4.45*)	-0.041 (-5.37*)	-9.53 (-8.20*)	-13.56 (-13.64*)	-2.46 (-4.68*)	-1.63 (-2.33*)
Portugal	-0.007 (-1.11)	0.002 (0.83)	-3.77 (-3.79*)	-3.43 (-4.31*)	-1.60 (8.09*)	-2.28 (3.84*)
Spain	-0.01 (-3.36*)	-0.018 (-4.42*)	-3.66) (-5.71*)	-3.44 (-5.52*)	-3.24 (-3.52*)	-0.82 (0.68)
Sweden	0.01 (1.64***)	0.033 (7.19*)	-16.56 (-8.32*)	-14.96 (-8.14*)	-3.21 (3.75*)	-1.93 (1.63***)
Switzerland	0.01 (1.35***)	0.007 (1.00)	-9.34 (-5.42*)	-12.53 (-6.97*)	-0.38 (-0.80)	-0.35 (-0.71)
Turkey	0.0000003 (-2.14**)	0.000000001 (0.01)	0.005 (5.39*)	0.006 (4.55*)	-0.0001 (0.89)	-0.000024 (-0.38)
US	-0.01 (-4.23*)	0.0007 (0.18)	2.59 (3.95*)	2.45 (3.97*)	-4.00 (6.00*)	-5.62 (6.46*)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Again, there was no consensus on the effects of oil prices on GDP, CPI, and UR of the OECD countries; the coefficients are negative in some while they are positive in others. There are again insignificant coefficients of OIL in some OECD countries.

Finally, Table 8c presents the estimated coefficients of OIL with respect to GDP, CPI, and UR through multiple regression analyses with three independent variables:

Table 8c: Multiple regressions: results of long-term coefficients (AUG Full)

	Model 1 GDP=f(UR, CPI, OIL)	**Model 2 CPI=f(GDP, UR, OIL)**	**Model 3 UR=f(CPI, GDP, OIL)**
	Coefficients & computed t-stats of oil price		
	OIL	**OIL**	**OIL**
Australia	0.007 (1.75**)	-9.89 (-5.81*)	-0.52 (-1.03)
Austria	0.007 (1.61***)	-1.95 (-2.16**)	0.58 (0.75)
Belgium	0.002 (1.18)	-4.70 (-4.01*)	0.54 (0.39)
Canada	0.008 (1.26)	-6.22 (-4.87*)	0.29 (0.46)
Denmark	-0.034 (-6.98*)	-3.73 (-1.98**)	-2.46 (-3.64*)
Finland	-0.004 (-0.93)	-14.70 (-7.48*)	-1.26 (-0.83)
France	-0.024 (-4.86*)	-10.75 (-3.54*)	-4.06 (-6.81*)
Greece	0.024 (8.95*)	2.10 (1.93**)	0.51 (1.11)
Hungary	0.009 (1.47***)	7.82 (12.76*)	1.19 (3.42*)
Iceland	0.003 (2.51*)	-0.55 (-1.02)	0.17 (2.80*)
Ireland	-0.006 (-0.85)	1.88 (0.48)	-0.25 (-0.32)
Israel	-0.00001 (-1.04)	0.014 (1.70**)	-0.003 (-1.08)
Italy	-0.040 (-4.54*)	-4.59 (-3.65*)	-4.43 (-4.34*)
Japan	-0.048 (-4.42*)	-5.88 (-1.12)	-1.64 (-2.02**)
Korea Rep.	-0.090 (-7.53*)	6.22 (2.68*)	-4.05 (-4.00*)
Luxembourg	-0.034 (-2.95*)	-3.61 (-2.50*)	0.56 (0.63)
Mexico	0.00009 (1.31***)	0.066 (2.67*)	-0.003 (-0.64)
The Netherlands	0.013 (2.14**)	4.92 (2.81*)	1.37 (0.79)
New Zealand	-0.0019 (-0.33)	-12.75 (-5.70*)	-0.20 (-0.36)
Norway	-0.047 (-7.54*)	-12.78 (-8.70*)	-2.26 (-4.20*)
Portugal	0.009 (3.48*)	-3.94 (-5.15*)	1.61 (6.43*)
Spain	-0.019 (-3.23*)	-1.39 (-1.25)	-4.00 (-2.56*)
Sweden	0.020 (4.03*)	-15.32 (-8.19*)	3.33 (3.58*)
Switzerland	0.009 (1.18)	-9.18 (-5.15*)	0.20 (0.42)
Turkey	-0.0000003 (-2.35*)	0.006 (5.86*)	-0.0002 (-2.31*)
US	0.008 (1.81**)	2.47 (4.64*)	-0.30 (-0.21)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Table 8c shows the multiple regressions and the long-term coefficients of macroeconomic variables.

Since there was no consensus on the effects of oil prices on GDP, CPI, and UR of the OECD countries in Table 8c, it can be concluded that the results of the estimated coefficients of OIL on GDP, CPI, and UR in the OECD countries were robust, regardless of how many independent variables were included. The results suggest that oil price movements exerted mixed effects on real income, consumer prices, and unemployment in the OECD area depending on the nature and degree of dependence of these economies on external economic events and oil price movements. In order to provide further idea about the stability of our estimates in Table 7c, line plots of these long term relationships have also been provided in Figures 19 through 21. It is clearly seen that those models in Table 7c have been successfully estimated since estimated and actual values of dependent variables in Table 7c are very closer to each other.

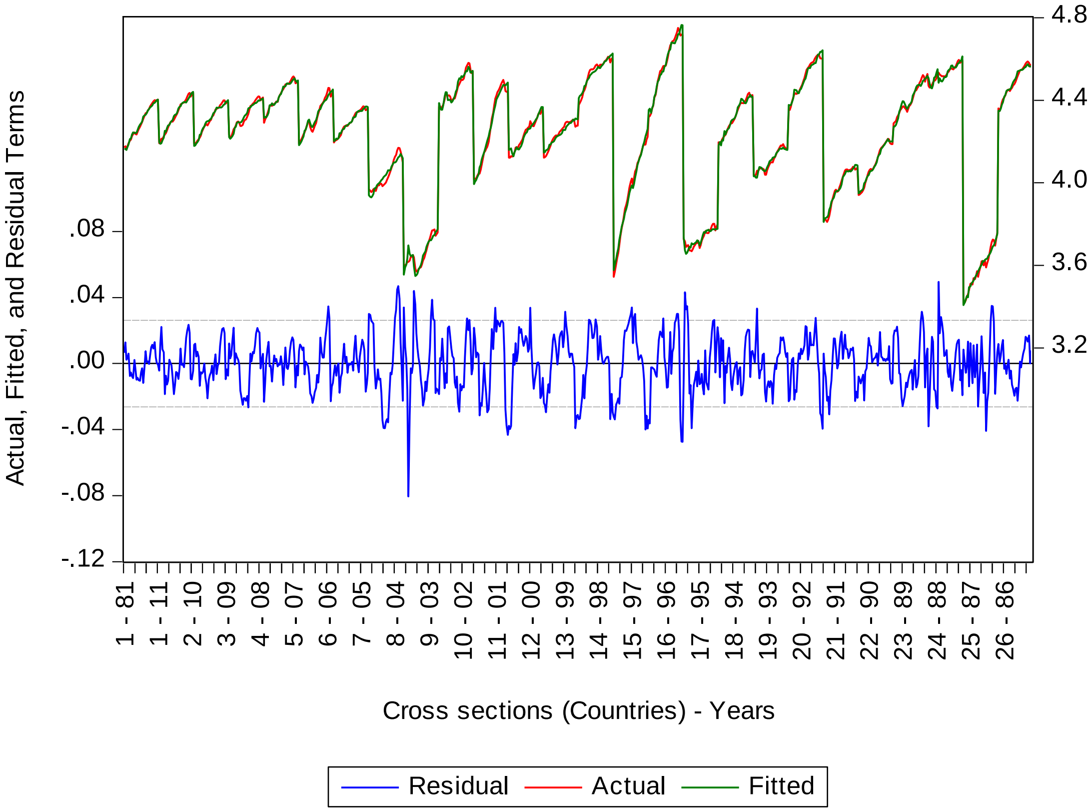


Figure 19: Estimated and Actual GDP by GDP = f (OIL, UNEMP, CPI)

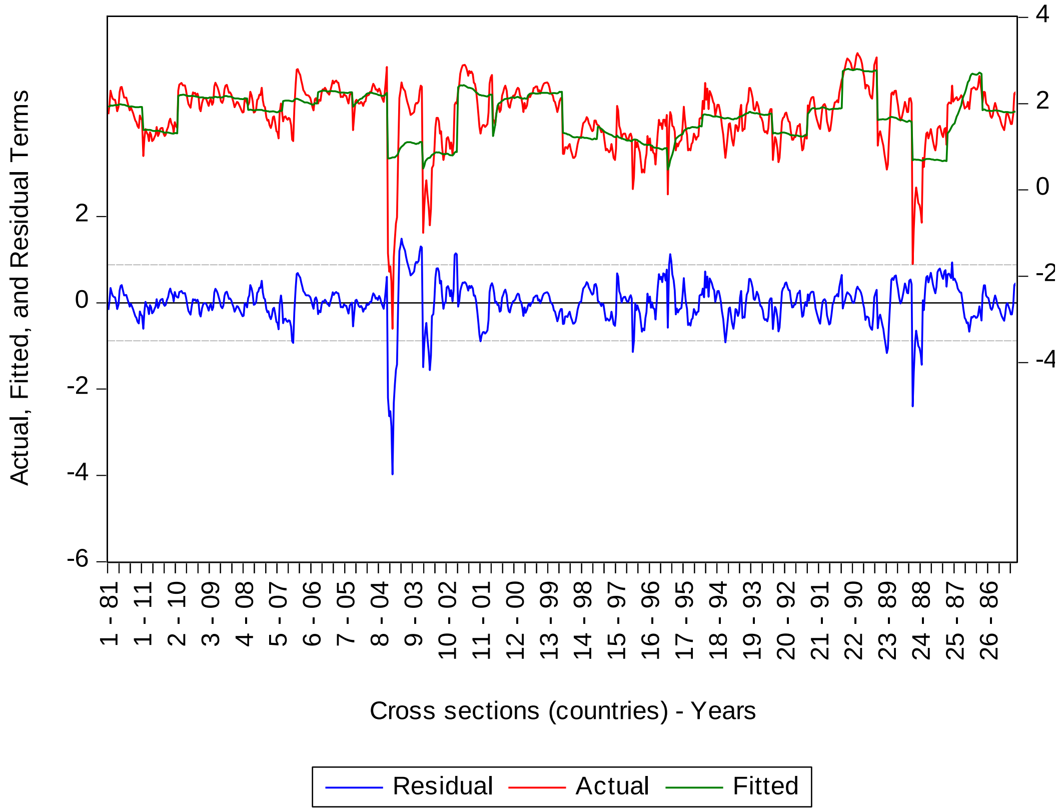


Figure 20: Estimated and Actual UNEMP by UNEMP = f (OIL, GDP, CPI)

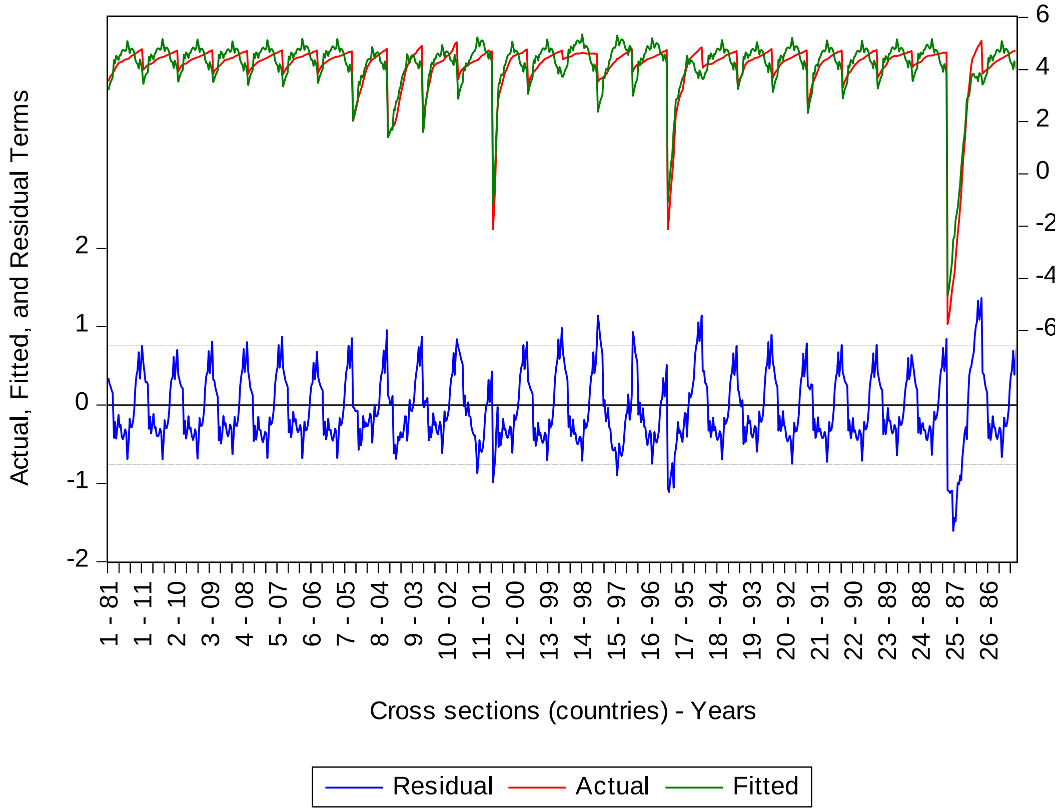


Figure 21: Estimated and Actual CPI by CPI = f (OIL, GDP, UNEMP)

4.4.5 Cross-regional Comparison Through Multiple Regression Models

This section covers a comparison across different regions where the selected OECD countries are situated. The main reason is that sample of the present study is heterogeneous especially in the currencies used. Therefore, such comparison would be needed in order to compare with the main results in the previous section. Initially, the comparison will be made by assigning dummy variables for three major groups: (1) Eurozone (Austria, Belgium, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain), (2) European countries out of Eurozone (Denmark, Hungary, Iceland, Norway, Switzerland, and Sweden), (3) Rest of the countries (USA, Turkey, South Korea, Australia, Canada, Israel, Japan, Mexico, New Zealand). And then, models will be estimated separately for each group.

Tables 9a through 9c presents long run models for these groups. When GDP is dependent variable, oil prices exerts positively significant effect in the case of “Eurozone” countries while significant effects have not been obtained in the cases of “European countries” and the other countries of OECD. Tables 9b and 9c also show that oil prices exerts negatively significant effects on consumer prices in the case of “European countries” and the other countries of OECD. Results across countries are generally similar to those in the whole OECD countries with only one exception which is the effect of oil price on GDP in the case of “Eurozone” countries.

Table 9a: Multiple regressions: results of long-term coefficients (AUG Full) (EUROZONE Countries)

		Coefficients & computed t- stat.		
	GDP	**CPI**	**UR**	**OIL**
Model 1 **GDP=f(CPI, UR, OIL)**	-	-0.0001 (-0.34)	-0.0036 (-3.69*)	0.0103 (1.98**)
Model 2 **CPI=f(GDP, UR, OIL)**	-21.84 (-0.99)	-	0.0743 (0.49)	1.5129 (0.89)
Model 3 **UR=f(GDP, CPI, OIL)**	-58.09 (-3.92*)	-0.0334 (-0.75)	-	0.3828 (0.63)

*Note: *, and ** denote significance levels respectively at 1% and 5%. The computed t-statistics are in parentheses.*

Table 9b: Multiple regressions: results of long-term coefficients (AUG Full) (EUROPEAN countries other than EUROZONE)

	Coefficients & computed t- stat.			
	GDP	**CPI**	**UR**	**OIL**
Model 1 **GDP=f(CPI, UR, OIL)**	-	0.0002 (1.05)	-0.0073 (-5.32*)	-0.0084 (-0.68)
Model 2 **CPI=f(GDP, UR, OIL)**	13.27 (0.40)	-	1.3878 (1.37***)	-4.3949 (-1.35***)
Model 3 **UR=f(GDP, CPI, OIL)**	-47.0403 (-5.07*)	0.0351 (1.63***)	-	-0.7589 (-0.98)

*Note: * and *** denote significance levels respectively at 1% and 10%. The computed t-statistics are in parentheses.*

Table 9c: Multiple regressions: results of long-term coefficients (AUG Full) (The rest of OECD Countries)

	Coefficients & computed t- stat.			
	GDP	**CPI**	**UR**	**OIL**
Model 1 **GDP=f(CPI, UR, OIL)**	-	0.0002 (0.65)	-0.0086 (-4.40*)	-0.0101 (-0.94)
Model 2 **CPI=f(GDP, UR, OIL)**	59.78 (0.82)	-	1.7396 (1.57***)	-4.9163 (-1.75**)
Model 3 **UR=f(GDP, CPI, OIL)**	-46.7734 (-5.04*)	0.0500 (1.48***)	-	-0.1880 (-0.31)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

Finally, Tables 10a through 10c presents results of ECMs and short term coefficients. Still there are some minor differences similar to long run models across country groups as compared to the whole dataset. In the short-term period, oil prices exert negatively significant effects on unemployment rates except “European countries” but positive effects on consumer prices except “Eurozone countries”. The signs of coefficient of oil prices with respect to CPI are all positive in the whole OECD countries and groups of countries. The short-term effects of oil prices on GDP in the groups (Eurozone, European countries, and the other countries) have not been found statistically significant while oil prices exerted positively significant effect on GDP in the short term and in the case of the whole dataset.

Table 10a: Multiple regressions: results of long-term coefficients (AUG Full) (EUROZONE Countries)

	Coefficients & computed t- stat.				
	ECT(-1)	**ΔGDP**	**ΔCPI**	**ΔUR**	**ΔOIL**
Model 1					
ΔGDP=f(ECT(-1), ΔCPI, ΔUR, ΔOIL)	-0.0132 (-0.81)	-	-0.0009 (-4.06*)	-0.0028 (-3.30*)	-0.0032 (-0.69)
Model 2					
ΔCPI=f(ECT(-1), ΔGDP, ΔUR, ΔOIL)	-0.0908 (-7.46*)	-22.1377 (-2.36*)	-	0.0522 (0.96)	-1.4474 (-1.11)
Model 3					
ΔUR=f(ECT(-1), ΔGDP, ΔCPI, ΔOIL)	-0.2202 (-3.59*)	-56.6556 (-4.41*)	-0.1350 (-2.53*)	-	-1.0657 (-2.00**)

*Note: * and ** denote significance levels respectively at 1% and 5%. The computed t-statistics are in parentheses.*

Table 10b: Multiple regressions: results of long-term coefficients (AUG Full) (EUROPEAN countries other than EUROZONE)

	Coefficients & computed t- stat.				
	ECT(-1)	**ΔGDP**	**ΔCPI**	**ΔUR**	**ΔOIL**
Model 1					
ΔGDP=f(ECT(-1), ΔCPI, ΔUR, ΔOIL)	0.0057 (0.31)	-	-0.0005 (-6.62*)	-0.0042 (-4.54*)	0.0051 (1.16)
Model 2					
ΔCPI=f(ECT(-1), ΔGDP, ΔUR, ΔOIL)	-0.1474 (-5.56*)	-55.7779 (-3.36*)	-	0.1728 (0.51)	2.9344 (2.03**)
Model 3					
ΔUR=f(ECT(-1), ΔGDP, ΔCPI, ΔOIL)	-0.2519 (-3.07*)	-41.4104 (-3.88*)	0.1025 (1.17)	-	-0.5350 (-1.27)

*Note: * and ** denote significance levels respectively at 1% and 5%. The computed t-statistics are in parentheses.*

Table 10c: Multiple regressions: results of long-term coefficients (AUG Full)
(The rest of OECD Countries)

			Coefficients & computed t- stat.		
	ECT(-1)	**ΔGDP**	**ΔCPI**	**ΔUR**	**ΔOIL**
Model 1					
ΔGDP=f(ECT(-1), ΔCPI, ΔUR, ΔOIL)	-0.0278 (-1.33***)	-	-0.0012 (-2.92*)	-0.0078 (-5.23*)	0.0017 (0.71)
Model 2					
ΔCPI=f(ECT(-1), ΔGDP, ΔUR, ΔOIL)	-0.1055 (-6.25*)	-38.9022 (-3.03)	-	-0.0706 (-0.48)	1.3801 (1.86**)
Model 3					
ΔUR=f(ECT(-1), ΔGDP, ΔCPI, ΔOIL)	-0.2125 (-5.81*)	-56.3730 (-6.18*)	-0.0243 (-0.63)	-	-0.6989 (-3.60*)

*Note: *, ** and *** denote significance levels respectively at 1%, 5%, and 10%. The computed t-statistics are in parentheses.*

4.5 Conclusion

4.5.1 Summary of the Findings

The aim of this study was to examine the impact of oil price movements on macroeconomic variables. Using panel tests in both Gauss and Stata package programs for the period 1980–2011, we focused on twenty-six OECD countries. We analyzed these countries as a general group and found the impacts of oil prices on macroeconomic variables, such as GDP, CPI, and UR. We conducted cross-section dependency tests, CADF panel unit root tests, and Durbin-H panel co-integration tests to measure whether there was a relation between the variables in the long term; finally, we estimated long-term co-integration coefficients. These tests are all second generation methods and therefore enabled more robust estimation results. When we looked at the long-term coefficients, the oil price had a statistically significant impact in all of the regressions except on the unemployment rate in single and double regression models. This suggests that an increase in the price of oil negatively affected macroeconomic variables, but it had a low impact on UR and GDP and a greater impact on CPI in the long term, in general, on the twenty-six OECD countries.

Moreover, as mentioned above, the impact of oil prices on the unemployment rate was low in the long term because the unemployment rate of a country may increase in the short term. Therefore, the relationship between the unemployment rate and oil prices may not be quite visible in the long run, but perhaps in a future study, the relationship between oil prices and the unemployment rate in the short term could be observed more significantly.

Also, when we compared our results with those of other studies on other countries (non-OECD countries) (Barsky & Kilian, 2004), our estimation results were confirmed. In most of these studies, oil price movements affected macroeconomic variables, such as the unemployment rate, inflation, GDP, economic growth, investment, stock exchange prices, etc. both positively and negatively. For instance, some studies found that oil price increases caused inflation and affected the unemployment rate in the long term. Our findings are therefore equivalent to those of other studies. However, the novel contribution of this study is that it studies 26 OECD countries both in panel and time series settings through employing the latest econometric procedures. Also, when we focused on the long-term coefficients of the individual countries, we found that oil price movements had either a positive or negative long-term impact on macroeconomic variables. In general, we found a negative impact of oil price movements on GDP, CPI, and UR.

4.5.2 Conclusion and Policy Implications

In general, the results of this study show that the impact of oil prices is negative and does exert a statistically significant impact on macroeconomic variables. Therefore, oil price increases generally generate a decrease in GDP, CPI, and the unemployment rate. However, in some cases, there is no statistically significant impact on the unemployment rate. It can be inferred that movements in unemployment are not solely depending on the movements in oil prices in those countries but on the other factors which are not included in this study. We find that unemployment rates in the OECD countries are mainly determined by real GDP. Also, the impact of oil price movements is marginal on GDP and the unemployment rate, but greater on CPI. This was true for all twenty-six OECD countries. This result might signify for successful energy efficiency policies adapted in the OECD countries. Conversely, in the other findings, which focused on individual countries, oil price movements exerted mixed impacts in the long term. The expected impact was negative in general, but for country-specific analyses, both negative and positive impacts were unexpected. The main point is that the impact of oil price movements on macroeconomic variables depends on the country's oil dependency. If oil is used as a main source of industry, it affects everything in the country; but if this is not the case, it does not impact too heavily on the country's macroeconomic variables. Also, nowadays, the use of more fuel efficient vehicles and transportation services is now more widespread.

Moreover, renewable energy resources like biofuels can be used as alternatives to oil; in this way, the demand for oil will decrease and countries' oil dependency will reduce. This will also reduce the impact of oil price movements on macroeconomic variables. For instance, if a country reduces its use of oil and increases its use of alternative energy sources like biofuels, solar energy, and wind energy, then GDP, inflation, the unemployment rate, economic growth, and other macroeconomic variables will be less affected when oil prices increase since this country will be less dependent on oil. On the other hand, we saw both positive and negative impacts of oil price movements while estimating the impacts on each country, and as mentioned above, the impact can be positive if oil is not a major source of a country's economic growth. However, if it is a major source, it will negatively affect GDP, CPI, and the rate of unemployment.

For instance, because of oil price increases in the world, the demand for oil in OECD countries decreased between 2000 and 2010 while it increased in non-OECD countries. Also, most of the OECD countries increased taxes on fuel, promoted the use of biofuels and more efficient vehicles, and increased the usage of optimized transportation. As the price of oil continues to increase, people will consume less and will start to approach towards renewable energy resources more; this means that oil dependency will be reduced as a result of such happening.

Chapter 5

CONCLUSION

As it is mentioned in previous chapters, both oil prices and food price volatility plays an important role in the economy as a whole.

In Chapter 2, we found that, stock exchange is more volitile than oil in UAE, Kuwait and Saudi Arabia but opposite in Qatar. On the other hand, the coherence between oil and stock exchange and oil and real effective exchange rate are at the maximum level in four years time in general. Moreover, the response of stock exchange and real effective exchange rate to the oil shock is positive and long lasting. The response of oil is negative and the response of real effective exchange rate is positive to the stock exchange shock. Moreover, when the the real effective exchange rate shock is given on oil and stock exchange, the responses are positive and negative respectively.

On the other hand, estimation of TVP – SVM in the impact of uncertainty shocks on food prices are covered in Chapter 3. The estimation results shows that, the impact of food price volatility is positive on food prices in six of the G-7 countries which are Canada, France, Germany, USA, Italy and Japan. In contrast to them, UK has negative impact of food price volatility on food prices.

Finally, Chapter 4 attempts to contribute to the literature on the impact of oil price movements on macroeconomic variables. The results of this study show that the impact of oil prices is negative and does exert a statistically significant impact on macroeconomic variables. Therefore, oil price increases generally generate a decrease in GDP, CPI, and the unemployment rate. However, in some cases, there is no statistically significant impact on the unemployment rate. It can be inferred that movements in unemployment are not solely depending on the movements in oil prices in those countries but on the other factors which are not included in this study.

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