Erasmus School of Economics

Master Thesis

MSc Economics & Business

Oil price shocks versus quantitative easing

An analysis of the Eurozone

Author:
Bas van Marle

Supervisor:
Prof. Dr. Casper de Vries

ERASMUS UNIVERSITEIT ROTTERDAM

August 18, 2015

Preface and Acknowledgements

This thesis serves as the completion of my master's degree in Economics and Business with the specialisation Financial Economics. As such, I am very grateful for the guidance of my supervisor Prof. Dr. Casper de Vries during the process of writing this paper. If it would not have been for his help, this thesis probably would have been an endless project. Due to our meetings I was able to make the right methodological steps and produce a thesis of this quality. In addition, I would like to thank all other professors and assistant professors at the Erasmus School of Economics, whose lessons I was able to incorporate in this thesis.

Non-plagiarism Statement

By submitting this thesis the author declares to have written this thesis completely by himself, and not to have used sources or resources other than the ones mentioned. All sources, quotes, and ictations that were literally taken from publications, or that were in close accordance with the meaning of those publications, are indicated as such.

Abstract

This paper explores the effects of an oil price shock and exchange rate movements on the one hand, on the GDP and the unemployment rate of the Eurozone economy. Taking into account the ECB's policy of quantitative easing and various control variables, we construct a vector error correction model to arrive at an estimate of both an oil price shock and the effect of quantitative easing through the exchange rate on the aggregate economy, measured by GDP and the unemployment rate. We observe a J-curve effect from the Euro exchange rate to Eurozone GDP. We find that a negative oil price shock takes effect after three quarters, when its impact on GDP and unemployment rate is larger than the exchange rate effect of quantitative easing. We find no difference in the effect when we use either the real effective exchange rate or the nominal effective exchange rate.

Keywords: oil price, J-curve, output, monetary policy, vector error correction model
JEL codes: C32, E52, Q43

List of Abbreviations

ADF-test:	Augmented Dickey-Fuller test
AIC:	Akaike Information Criterion
ECB:	European Central Bank
ECM:	Error Correction Model
I(p):	Integrated variable of order p
IRF:	Impulse Response Function
KPSS-test:	Kwiatkowski-Phillips-Schmidt-Shin-test
M3:	Money Supply M3
NOPI:	Net Oil Price Increase
OPEC:	Organization for Petroleum Exporting Countries
PP-test:	Phillips-Perron test
QE:	Quantitative Easing
REER:	Real Effective Exchange Rate
SC:	Schwarz Criterion
VAR-model:	Vector Autoregressive model
VEC-model:	Vector Error Correction model
WTI:	West Texas Intermediate

Contents

List of Tables

List of Figures

1 Introduction

Crude oil is by far the most traded commodity in the world. As a non-renewable source of energy that tends to be located in those regions that are most unstable, we have witnessed more frequent price shocks of oil during the past decade (Cohen, 2015). The invasion of Iraq, the Arab spring in Libya, and the sanctions against Iran have all influenced the total supply of oil to the world market and therefore influenced its price significantly over the past fifteen years. In addition, new techniques such as fracking and the global financial crisis have had adverse effects on the oil price leading overall to a much more volatile price of crude oil over the past decade. Most recently, since August 2014, there has been an unprecedented decline in the world price of crude oil. Considering its importance as a resource for industrial growth, it begs the question what the effect of these shocks in the oil price are on the real economy.

Goal of this paper is to identify the link between oil price shocks and the real economy of the Eurozone, thereby estimating the effect of the size of oil price shocks on the economic growth of the Eurozone. As a net-importing region of oil, the Eurozone would in theory benefit from a lower oil price. Following the global decrease in oil prices during the fall of 2014 we now observe the first signs of recovery throughout the Eurozone; a declining oil price is however not the only variable likely to influence Eurozone recovery.

On January 22nd 2015 the European Central Bank (ECB) announced to start its programme of Quantitative Easing (QE) with a size of 1.1 trillion euro's after already cutting its interest rates to near zero (Randow, 2015). The proposed result will be an accelerated recovery of the Eurozone economy by lowering borrowing costs and a depreciation of the Euro exchange rate. In this paper we control for these monetary policy actions when measuring the effects an oil price shock. In addition, we examine whether the J-curve effect is present for the Eurozone following the depreciation of the Euro currency.

Controlling for monetary policy we expect the decline in crude oil prices since August 2014 to have a positive effect on the GDP of the Eurozone, as well as a decreasing effect on the unemployment rate. This effect is expected to have a prolonged effect over multiple time periods. Due to this prolonged effect on the Eurozone economy, it is still too early to precisely quantify the the effects of the oil price shock of August 2014 and the monetary shock of January 2015. We can however, by means of a Vector Autoregressive model (VAR-model), estimate whether the recent oil price shock is likely to have had an effect at all given a sample over the past fifteen years. In particular, we hope to point at the main cause of the 2015 recovery of the Eurozone: was it the decrease in the oil price, or was it the quantitative easing policy of the ECB?

There has been previous empirical research into the relationship between oil price changes, exchange rate effects and economic growth. The vast majority of this research has however been performed prior to the year 2000, when oil prices were relatively stable. In addition, almost all research has focused on the United States and not on the Eurozone. There has been research into some specific developed countries such as Portugal or Greece, but these tend to be the exceptions. To our knowledge this is the first paper that investigates the relative effects of oil price shocks versus the effects of exchange rate movements on the aggregate Eurozone economy.

This research is innovative as we examine the effects of an oil price shock in a geographical area over a time-span where this has not been done before. It is relevant to perform this research as it will provide us with insight into the mechanisms of such an oil price shock on the European economy and its significance. This will contribute to academic research, as it examines whether proven theories for other regions are also relevant to the Eurozone. In addition, it will be useful to policy makers as it will test whether QE was really that necessary. If a low oil price was already capable of rebooting the European economy, then it can be argued that QE in fact came too late.

In order to guide and structure our research we will answer multiple questions in this paper. The main question this paper tries to answer is: was the recovery of the Eurozone economy in 2015 due to the policy of quantitative easing by the ECB, or was it in fact the decreasing oil price that gave a boost to economic growth?

We aim to answer this main question guided by several sub-questions. Each of these questions is aimed at exploring part of the main research question, thereby providing further insight into the economic relationship between oil price shocks and the aggregate economy. The sub-questions are:

1. *How are oil price shocks economically linked to economic growth and unemployment?*

2. *Does monetary policy interfere with the estimation of oil price shocks and what variables must be controlled for to separate these effects?*

3. *Do we observe a J-curve effect due to monetary policy changes in the Eurozone embedded in the exchange rate?*

4. *What model best captures the effects of an oil price change on the aggregate economy, and what is the relation between the short-term and long-term effects of such a shock?*

As mentioned, previous research has been conducted into the relationship between oil price changes and the aggregate economy. The majority of this research focussed however on developed nations or a different timeframe. We expect the general result of our study to coincide with the findings of these papers. This indicates that we expect to find a significant increase in real GDP of the Eurozone in case of an oil price decline, and a significant decrease in the GDP of the Eurozone in case of an oil price increase. In addition, we expect to observe a J-curve effect when the Euro becomes weaker relative to the main trading partners of the Eurozone. We will elaborate on our hypotheses in section 2.5.

Chapter 2 starts with an elaborate discussion of the existing literature. Section 2.1 introduces the prior general research on oil price shocks and its effects on the aggregate economy. Section 2.2

will focus on the transaction mechanism through which an oil price shock translates to economic growth. Section 2.3 will focus on the attribution debate, where we examine the effects of monetary policy combined with an oil price shock on the economy. Section 2.4 thoroughly discusses all previous research on the Eurozone. We conclude our literature research by stating our hypotheses in section 2.5, that we will try to evaluate in the rest of our paper.

Our data and its descriptives are introduced in chapter 3. Subsequently we introduce the employed methodology in chapter 4. In particular the difference between the VAR- and VEC-model and the concept of stationarity are treated in this chapter. The concept of cointegration through either the Engle and Granger method or the Johansen method is discussed in section 4.3.

The empirical results of our analysis are presented in chapter 5. We begin with an estimation of the order of integration of the variables in our model. Next we use the the Engle and Granger method and the Johansen method for cointegration to estimate the cointegrated relations in the model. The empirical results and, in particular, their application to the Eurozone economy today are treated in the discussion chapter. Here we aim to place the results of our analysis into the debate surrounding the Eurozone recovery of today. We conclude in chapter 7.

2 Literature review

2.1 Introduction to the research on oil price shocks

The first interest into examining the relationship between oil price shocks and its macroeconomic impact emerged in 1973. In this year the Organization of Petroleum Exporting Countries (OPEC) proclaimed an embargo on the US following their involvement in the Yom Kippur war, which resulted in a sudden increase in the international price of crude oil. A similar shock occurred in 1979, this time caused by the outbreak of war between Iran and Iraq; both are major exporters of crude oil (U.S. Department of State, 2015).

Previous to these two shocks, the oil price was generally accepted to have an insignificant effect on the aggregate economy (Mork, 1994). Following these two oil price shocks and their observed adverse effects on the economies of developed countries, measuring the inverse relationship between oil price shocks and the aggregate economy became the topic of an extensive field of empirical research (Dias et al., 2013).

Early research was devoted to the impact of the oil price increases of the seventies in the United States. (Darby, 1982) was unable to arrive at a firm estimate of an oil-price coefficient on the effects of real income in the United States shortly after these shocks. He blamed the end of the Bretton Woods era for having an influence at exactly the same time as the oil price shock (Jones et al., 2004). This was the first indication of the challenge that lies in isolating the effect of an oil price change of the other variables that influence the aggregate economy; we return to this issue in section 2.3 which covers the attribution debate.

Hamilton, in 1983, did find a significant relationship between the oil price increase and GNP growth in the US. In his influential paper he was the first to find a convincing effect of a causal relation between the increased oil prices and the aggregate economy. In fact, he was able to show that all but one of the recessions following World War II were the result of rising oil prices. Shortly after the paper from Hamilton, Burbidge and Harrison (1984) found evidence of the relation between oil price shocks and the aggregate economy for the United Kingdom and Japan using a VAR-model.

In section 2.2 we take a closer look at the relationship between oil price shocks and the real economy. Section 2.3 pays attention to the discussion of the effect of oil price changes versus the effect of monetary policy: the so-called attribution debate. Section 2.4 goes into the previous empirical work on the Eurozone and substituent countries. In section 2.5 we present the hypotheses based on the literature that are tested in the remainder of this paper.

2.2 Relationship between oil price shocks and economic growth

The majority of empirical and theoretical papers that have been written on the relationship between oil price shocks and economic growth find that there is indeed a causal relationship between the two. However, not all papers agree on the exact transmission channels through which an oil price shock has an impact on the aggregate economy. The question that we address in this section is how oil price shocks actually affect the aggregate economy.

Hickman et al. (1987) provide an empirical paper that captures the inverse relationship between oil price changes and aggregate economic activity for the United States. A positive oil price shock, which is an increase in the price of crude oil, has a negative effect on a net-importing oil country. On the other hand, we expect that a negative oil price shock, which is a decrease in the price of crude oil, has a positive effect on a net-importing oil country. As the plethora of research has focused on the United States, which is a net-importing country, in particular the negative effects on the aggregate economy following an oil price increase have been researched.

Rasche and Tatom (1977) link rising oil prices to a supply-side shock which has a negative effect on output. Crude oil is a basic input into the production function; when the price of energy rises this increased cost is faced by manufacturers. In turn, this leads to a decline in both productivity and output growth. Consequently, the decline in productivity has a negative effect on the real wage growth. Rotemberg and Woodford (1996) , in a theoretical contribution, estimate using a simulation model that a 10% increase in the price of oil has an output effect of 2.5% six quarters later.

Keane and Prasad (1996) find that the decline in real wage growth is not consistent across the entire labour market. On the individual level an oil price increase depresses the wages of workers. However, the relative employment possibilities of skilled workers in an oil-importing country actually increases following an oil price increase. Skilled labour works as a substitute for energy in the overall production function. The bottom line is, however, that aggregate employment declines in a net-importing country following an oil price increase (Carruth et al., 1998).

Following an oil price change the equilibrium allocation across various industrial sectors will be affected; this is referred to as the dispersion hypothesis (Lilien, 1982). When the oil price changes other resources, such as labour, change across industrial sectors. Oil intensive industries shrink in size, whereas those industries that rely only very little on the increased oil price increase. Overall, the result is a contraction of the overall output and therefore a reduced growth of GDP.

Oil price increases also have their effects on the price level in a country; as it is an essential input for many products there is a link to inflation (Chen, 2009). When monetary authorities observe this increased inflation they may implement restrictive monetary policy, which has a negative effect on economic growth. The opposite reaction, of a central bank executing an expansive monetary policy, might reduce negative growth shocks in the short-term, but has severe adverse effects in the long-run to high inflation levels. We elaborate on this in section 2.3, where we address the attribution debate.

The theoretical impact of an oil price shock on exporting countries is straightforward: a lower oil price results in lower national income. The exact size of this impact is however under discussion.

A large percentage of the total GDP of oil exporting countries usually depends on the oil price. An increase in the oil price therefore, at least in the short-term, has a positive effect on the GDP of oil exporting countries. In the long-run, a sustained higher oil price leads to new exploration of oil fields that are more difficult to extract or a shift towards the use of more alternative energy sources (Ghalayini, 2011).

Over time, since the seventies, researchers found that the original relationship between oil price shocks and the aggregate economy has decreased. This has challenged researchers to alter their models in order to examine whether a relationship still exists. Hamilton (1996) recognized this changing relationship and introduced the notion of 'net oil price increase' (NOPI). This variable produces a number in case of an oil price increase, but take the value zero when the new oil price is not higher than any value over the past twelve months. The NOPI variable therefore ignores price decreases, and positive price changes that are deemed to small. Using this variable Hamilton finds a statistically significant inverse relationship between an oil price increase and GDP over the period 1948-1994.

This asymmetry between the effects of a negative oil price shock versus the effect of a positive oil price shock on the aggregate economy has been under much scrutiny (Brown and Yücel, 2002). Mork (1994) describes that a significant negative elasticity is found when there is an oil price increase, but that there is an insignificant effect in the case of an oil price decrease. Whereas all but one of the post WWII recessions were caused by a sharp rise in oil prices, none of the following oil price declines was followed by a boost in United States' economic activity.

Using data on the US, but also the G-7 countries, Norway and Euro Area as a whole, Jimenez-Rodriguez & Sanchez (2005) find the effects of an increase in the oil price on real GDP to differ significantly from the effects on real GDP following a decrease in the oil price. This is clear evidence that there is no symmetric positive or negative effect of oil price changes. They find that an increasing oil price has a significant negative impact on GDP growth of oil importing countries, with the exception of Japan, and mixed results for oil exporting countries. They conclude that: "oil price shocks are together with monetary shocks the largest source of variation other than the variable itself for most of the countries." (Jiménez-Rodríguez and Sánchez, 2005, p. 203)

The effect of an oil price shock is expected to have a delayed effect on economic growth. Businesses need to adapt their production functions to the new oil price. Some large corporation may not benefit from this lower oil price immediately due to hedged positions against higher oil prices or existing long-term contracts with suppliers (PWC, 2015). It is for this reason that the long-term effect following an oil price change is expected to be larger than the short-term effect. Most empirical papers employ a lag length of at least a year to capture the full effect of an oil price change (Jones et al., 2004).

2.3 The attribution debate

Following the first paper by Darby (1982) , researchers noticed that monetary policy changed during the same time period as the first oil price shocks of the seventies. This raises the question to what extent the oil price changes are responsible for a change in GDP growth or is it monetary policy that has the real effect on aggregate output?

Bernanke et al. (1997) examine monetary policy as the central issue rather than a factor in the oil price to GDP relationship. Using a VAR-model with Hamilton's NOPI measure they conclude that all the recessions that were previously attributed to oil price increases were in fact caused by monetary policy. Using the data from Bernanke et al. the researchers Hamilton and Herrera (2004) reach the exact opposite conclusion. They criticize in particular the far-fetched policy options that the Federal Reserve would have according to Bernanke et al., as well as the limited lags that were included in their model. Balke et al. [2002] confirm the results obtained by Hamilton and Herrera (2004), but do observe that there is indeed a significant effect on the short-term interest rates following both a negative and a positive oil price shock.

Since the start of the financial crisis in Europe, after the fall of Lehman Brothers, the European Central Bank lowered the refinancing rate gradually from a high of 4.25% in 2008 to a low of 0.05% today (European Commission, 2015). Induced by the ECB to lower borrowing cost and thereby stimulate the economy, this is a factor that will need to be controlled for in order to arrive at a correct estimate of the effect of an oil price change on the aggregate economy.

A second, more controversial, policy measure that was implemented by the ECB over the past years has been Quantitative Easing (QE). After months of speculation the ECB officially announced the details of its asset-purchase programme on the 22nd of January 2015. Not only will this policy have the intended effect of decreasing the borrowing costs of European sovereigns, it will do so through substantially increasing the monetary base of the Euro. Joyce et al. (2011) find that QE in the United Kingdom lead to a depreciation of the Sterling exchange rate index; we expect a similar effect to take place for the Euro currency.

This expansionary monetary policy will have a positive effect on the aggregate Eurozone economy in the long-run, as the depreciation of the Euro currency vis-à-vis the main trading partners will improve the position of Eurozone' companies. In the short-run however, we expect the weaker real value of the Euro currency, as captured by the Real Effective Exchange Rate (REER), to have a negative effect on the GDP of the Eurozone.

This expectation is evidence of the so-called J-curve effect: initially the balance of payments of the Eurozone worsens due to a Euro depreciation, before a long-term improvement of the trade balance occurs (Magee, 1973). In the short-run international business contracts are fixed. As such, aggregate imports become more expensive due to the weaker position of the Euro currency. In the long-run, new contracts are be made based on the depreciated currency, which has a positive effect on the Eurozone GDP.

Empirical results of the J-curve effect are ambiguous (Bahmani-Oskooee and Ratha, 2004). Hsing (2008) examines the depreciation of the currencies of seven Latin American countries, and finds evidence of the J-curve only for Chile and Ecuador. The length of the J-curves for these two countries versus the US dollar are 1 quarter and 3 quarters respectively. As in many other empirical studies, evidence of a J-curve effect is found for only a subset of the included countries. Rose and Yellen (1989) find no evidence of a J-curve effect of the G-countries versus the US dollar.

Prior to the formation of the Eurozone, Hacker and Hatemi (2003) found evidence of a J-curve effect for Belgium and the Netherlands in a study of small Northern European countries. Unfortunately no research is available on the J-curve effect of the Euro currency. However, by including both the money supply and the exchange rate of the Eurozone we expect to include the relevant variables in order to tackle the potential J-curve effect on the GDP of the Eurozone. Including these variables allows us to estimate the individual effects of an oil price shock or an exchange rate effect on the Eurozone economy.

2.4 Previous research on the Eurozone

Whereas the sheer majority of research regarding the effects of an oil price shock on the aggregate economy has been focussed on the United States, some research has been performed on the European market. The first paper to include a European country when examining the effect of oil price shocks on the aggregate economy was Burbidge & Harrison (1984) . Using data for West-Germany dating back to 1961 they find that the oil price affects domestic industrial production through the industrial production of other foreign countries. They do, however, suggest that this causality between the domestic production and international production runs both ways. They find that oil price shocks did not affect the real wage in Germany at that time, due to a very elastic supply of foreign labour.

More than twenty years later, Cologni and Manera (2009) examine the effects of a negative oil price shock in the year 1990 within the G7-countries, including the three largest Eurozone countries: Germany, France and Italy. In their VAR-model the inflation level for every country increases following an increase in the oil price. In addition, they find that the higher oil price has a negative impact on the French real GDP of -0.217% four quarters later and a negative impact on the Italian GDP of -0.170%. The direction of the oil price shock for the Eurozone countries is compatible with the effect on the US economy; its impact is however more moderate. This is in line with an earlier observation by Abeysinghe (2001), who finds that in general the effects of an oil price shock on the aggregate economy in the US are larger than the effects of a similar shock in other OECD countries.

Lescaroux and Mignon (2008) use a sample which is most comparable to the sample employed in this paper. They examine a sample of 36 countries including the Eurozone-12, on an individual level, over the period 1960 – 2005 by means of a VAR-model. For eight out of twelve of the Eurozone countries they find a significant Granger-causal relationship which runs from the oil price change to either the GDP or the unemployment rate. A weakness of this paper is the use of annual rather than more frequent data. When using annual data, rather than quarterly or monthly data, the change in the direction and size of the shock per lag period becomes impossible to estimate (Jones et al., 2004). The resulting model will therefore be imprecise in its estimations.

Papapetrou (2009) employs a VAR-model for Greece and finds that during periods of accelerated adjustments in the oil price, the negative correlation between oil price changes and the industrial output of Greece strengthens. She observes that this effect is asymmetrical, being only significant for oil price increases. The most significant relationship between these variables is observed when the monthly oil price increase exceeds 3.0% per month.

In a comparable one-country study for Portugal, Dias (2013) finds that an oil price increase of 13% will lead to a reduction in the total level of GDP after five years of 0.7 percentage points. The majority of the adjustments compared to a benchmark case occurs in the second year after the oil price shock. Comparable results are found when comparing the oil price increase and an increase in the unemployment rate. The increased oil price will also have a temporal effect on the inflation rate, which is completely eliminated after three years.

As a comparative study between differences in the effects of an oil-price shock on the aggregate economy of the Eurozone versus the aggregate economy of the US, it is found that there are significant differences between the regions (Peersman and Van Robays, 2009). In particular the transmission channels are different, given the desire of the European Central Bank to keep inflation at a constant rate. Using a VAR-model based on a sample between 1986:Q1 and 2008:Q1, Peersman & Van Robays find that there is a heterogeneous effect following an oil price shock between the Eurozone-12 member states. This is explained by the existence of different labour dynamics within the various Eurozone-12 member states. This heterogeneity is exacerbated by the one-size fits all monetary policy of the ECB.

Chatziantoniou and Filis (2014) investigate both the financial and monetary policy responses following an oil price shock, employing a VAR-model over the period 1991-2010 that includes France, Germany, Italy, Spain, Portugal, and the Netherlands. In both the oil-importing as well as the oil-exporting countries the rate of inflation is significantly affected due to an oil price shock. In addition, they find that the aggregate economy of a larger and more liquid stock market will respond faster to an oil price shock; this response is negative for the Eurozone's net oil-importing countries.

2.5 Hypotheses

Based on the theoretical and empirical papers presented in the literature review, we can now formulate the hypotheses that will be tested in the empirical section of our paper. We summarise our hypotheses as:

- an increase in the oil price will lead to a decline in the GDP of the Eurozone in the long-run;
- an increase in the oil price will lead to an increase in the unemployment rate of the Eurozone in the long-run;
- the short-term effects of an oil price shock on the Eurozone economy will be less significant than the long-term effect;
- the ECB's quantitative easing policy will have a depreciating effect on the Euro exchange rate;
- a depreciating exchange rate will have a negative effect on GDP in the short-run, a positive effect on GDP in the medium-run, and no long-term effect due to the J-curve effect.

3 Data description

3.1 Selection of geographical area and timespan

Before introducing our data we present a clear but brief description of the geographical area and timespan that our research will address in order to avoid confusion. The restricted VAR-model, or VEC-model, that we will implement on the Eurozone will examine the period 1999:Q1 until 2015:Q1 using incremental periods of one quarter. The last observation 2015:Q1 is simply the most recent data published by the ECB. The observation 1999:Q1 is chosen as the first observation of our sample as it was on January 1st, 1999, that the currencies of eleven of the Eurozone countries were virtually fixed. Although physical coins and notes were not introduced until 2002, we do have aggregated and reliable data present for these three intervening years (European Commission, 2015).

With regards to the selection of our geographical area we will examine the Eurozone. As the Eurozone expanded from its initial 11 members in 1999 to 19 members since 2015 it is important to explain which particular Eurozone we mean. In order to be comprehensive we include all 19 Eurozone countries in our analysis. To give a better idea of the relative size of production and consumption of crude oil in the Eurozone per country, we present an overview in appendices A.1 and A.2.

3.2 Selection of variables

First we need to find a variable that captures the price of oil. Whereas the West Texas Intermediate (WTI) is considered the main benchmark for the United States, we will use the Brent price as it is traded in higher volumes. Magyereh (2004) justifies this by pointing out that more than 65% of crude oil trade uses the Brent oil price. WTI serves as an oil benchmark within the US, whereas the Brent price is used as a benchmark in the Eurozone as it is extracted from the North Sea. We use the Brent oil price for the Eurozone in Euro's on a quarterly basis, which is the average price of the closing prices during that period. Data is extracted from the database of the European Central Bank (2015); we will refer to this explanatory variable in our paper as $Oil\,price$.

Second, we need to find a variable that captures the overall activity of the economy. The natural variable to include in this case is the development of real GDP in the Eurozone as is done in the majority of related research. E.g. Dias [2013], Cologni & Manera [2009], Tang et al. (2010) , and Jimenez-Rodriguez et al. (2005) use this variable in their analysis. We use real rather than nominal GDP to correct for the inflation in the Eurozone. The real GDP raw data is extracted from the ECB and collected quarterly; we will refer to this variable in our paper as GDP.

An additional variable to represent economic growth is the unemployment rate. This variable measures job creation and destruction, which is often linked to oil price changes. Davis and Haltiwanger (2001) estimate that 20-25 percent of the variability in employment growth in the United States between 1972 and 1988 was caused by oil price shocks. Unemployment statistics are available from the ECB and are seasonally adjusted to account for seasonal jobs; we refer to this variable in our paper as $Unemployment\,rate$.

Based on our discussions in the literature review of this paper we will incorporate various other variables to account for possible other transmission linkages between oil price shocks and changes in the real economy. As such, we first include a variable to account for the exchange rate. We will use a trade-weighted index of exchange rates, known as the Effective Exchange Rate, that measures the exchange rate of the Euro versus a basket of currencies of the main trading partners of the Eurozone. This leaves us with the choice of either the Real Effective Exchange Rate (REER) or the Nominal Effective Exchange Rate (NEER).

The NEER is simply the nominal exchange rate of the Euro currency versus its main trading partners, whereas the REER is this same nominal exchange rate deflated by the consumer price index. We incorporate the Real Effective Exchange Rate in our main text. Minimal differences between the two series are expected, which will be elaborated upon in the results section. For both series we retrieve quarterly data from the ECB; we refer to these variables as $REER$ and $NEER$. A precise composition of these variables can be found in appendix A.3.

Additional control variables that we include in our analysis are those variables that are likely to have an effect on the growth of the Eurozone GDP. A prime example would be monetary policy, which we can control for by including first the refinancing rate of the ECB, taken as the average rate during the particular quarter. This is the key interest rate that determines what costs a bank will incur when borrowing money from the central bank. We derive our data from the ECB; we refer to this variable in this paper as $Refinancing\,rate$.

Also, we include the money supply of the ECB measured as M3 in our analysis. M3 is the broadest measure of money in the economy. We derive our data from the ECB; we will refer to this variable as $M3$.

The variables $Oil\,price$, GDP, $REER$, $NEER$, and $M3$ will be transformed into their natural logarithmic form as is consistent with the methodology in papers by Burbidge & Harrison (1984) , Rotemberg & Woodford (1996), Papapetrou (2009) and all other leading papers. No transformation will be made to the variables $Unemployment\,rate$ and $Refinancing\,rate$.

3.3 Descriptive statistics and graphs

The next step is to have a look at the descriptives of our variables GDP, $Oil\,price$, $REER$, $NEER$, $M3$, $Refinancing\,rate$ and $Unemployment\,rate$. Figure 1 displays our variables in level over time.

Visual analysis of the series in their levels suggests non-stationarity, as the series tend to drift over time. GDP increased from the start of our data-set until the start of the financial crisis in

Figure 1: Variables in levels

Notes: all variables applicable to the Eurozone 19-fixed set of countries. Range 1999:Q1-2015:Q1.

Figure 2: Variables in first-differences

Notes: all variables in first-differences (Δ). Range 1999:Q2-2015:Q1.

Table 1: Correlation matrix of included variables

	GDP	Oil price	REER	NEER	M3	Ref. rate	Un. rate
GDP	1.0000	0.9041	0.5549	0.6480	0.9458	-0.4390	0.2060
Oil price	0.9041	1.0000	0.3288	0.4498	0.8865	-0.4920	0.4122
REER	0.5549	0.3288	1.0000	0.9821	0.5346	-0.2517	-0.1190
NEER	0.6480	0.4498	0.9821	1.0000	0.6595	-0.3783	0.0255
M3	0.9458	0.8865	0.5346	0.6595	1.0000	-0.6598	0.4449
Refinancing rate	-0.4390	-0.4920	-0.2517	-0.3783	-0.6598	1.0000	-0.8655
Unemployment rate	0.2060	0.4122	-0.1190	0.0255	0.4449	-0.8655	1.0000

Europe during the third quarter of 2008. The price of crude oil in Europe shows the same trend until 2008, when the financial crisis hit. The price of crude oil then soon recovered to its pre-crisis height and even reached an all-time high during the first quarter of 2012. Recently, since August 2014, we have observed a sharp decrease in the oil price.

The graphs show that both the real and nominal value of the Euro currency increased prior to the financial crisis of 2008. Following increased concerns regarding the solvency of certain Eurozone member states, as well as sluggish European recovery, the Euro lost value relative to its main trading partners over the period 2008-2014. We observe a sharp decline in both the real and the nominal value of the Euro currency during the first quarter of 2015 following the anticipated Quantitative Easing by the ECB.

With regards to the monetary policy variables we observe a continuous increase of the monetary supply M3 until the crisis year 2008. Monetary supply fell in the year 2009 and started to increase again in 2010, albeit at a lower growth rate compared to the pre-crisis years. The refinancing rate of the ECB is currently at an all time low, as can be seen in the bottom graph of Figure 1.

When we observe the graphs of our first-differenced variables in the second column of 1 we find that they are oscillating around zero, with downward shocks for all variables around the height of the financial crisis in 2008. This suggests that our series are stationary in first-differences.

Table 1 displays the correlation between the variables in our model. We can, however, not infer any logical conclusion from this table as we do not yet know whether the variables in our model are stationary. To explain the concept of stationarity we continue to an explanation of the methodology in the next chapter. We do, however, find very high correlation in table 1 among the two exchange rate variables REER and NEER of 0.9821, indicating that the differences between the two are likely to be minimal over time.

4 Methodology

In this section we introduce the methodology behind the Vector Autoregressive model (VAR-model) and a specific version of this model referred to as the Vector Error Correction model (VEC-model). We start with an introduction of the VAR-model in section 4.1. This is followed by a discussion on stationarity in section 4.2. In section 4.3 we introduce the concept of cointegration and two tests of cointegration: the Engle and Granger method and the Johansen test. Section 4.4 discusses the selection of the correct lag length, followed by a brief explanation of granger causality in section 4.5. The methodology section concludes with a schematic overview in section 4.6.

4.1 Vector Autoregression

The majority of empirical research exploring the efects of an oil price shock on the aggregate economy has made use of a model belonging to the family of Vector Autoregressive models (VAR-models). The VAR-model was introduced by Sims in 1980 as a solution to allow for a multivariate framework where one variable is explained by both is own lags and the lags of the other included variables in the model. The benefit of such a model is that no a priori restrictions are placed on the structural relationship between the different variables in the model. All variables in the model are treated equally and no a priori difference is made between the endogenous and exogenous variables in the VAR-model.

The VAR multivariate model is a natural extension of the univariate autoregresion model. Rather than analysing a timeseries in isolation, the multivariate model allows for shocks in one variable to proliferate to other variables in the model (Shephard, 2013). In essence, a VAR-model is a system where every variable is explained by its own lags as well as the lags of the other variables in the model. The basic p-lag VAR(p) model has the form (Lütkepohl, 2005):

$$Y_t = c + \sum_{i=1}^{p} A_i Y_{t-i} + u_t \tag{1}$$

where Y_t is the $(n \times 1)$ vector containing the variables in our model, c is the $(n \times 1)$ intercept vector of the VAR, A_i is the $(n \times n)$ matrix of coefficients, and u_t is the vector of error terms. In matrix form this gives (Zivot and Wang, 2007):

$$\begin{bmatrix} Y_{1,t} \\ \vdots \\ Y_{n,t} \end{bmatrix} = \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} + \begin{bmatrix} a^1_{1,1} & \cdots & a^1_{1,n} \\ \vdots & \ddots & \vdots \\ a^1_{n,1} & \cdots & a^1_{n,n} \end{bmatrix} \begin{bmatrix} Y_{1,t-1} \\ \vdots \\ Y_{n,t-1} \end{bmatrix} + \cdots \\ + \begin{bmatrix} a^p_{1,1} & \cdots & a^p_{1,n} \\ \vdots & \ddots & \vdots \\ a^p_{n,1} & \cdots & a^p_{n,n} \end{bmatrix} \begin{bmatrix} Y_{1,t-p} \\ \vdots \\ Y_{n,t-p} \end{bmatrix} + \begin{bmatrix} u_{1,t} \\ \vdots \\ u_{n,t} \end{bmatrix} \tag{2}$$

which are in fact n regressions where each regression contains p lags of each variable in the model. The variables that we will employ in the model for Y_t are GDP, $Oil\,price$, $REER$, $NEER$, $M3$, $Refinancing\,rate$, and $Unemployment\,rate$.

At this point it is vital to check for the stationarity of our variables. When we find all variables to be stationary, or $I(0)$, we can simply run the VAR-model in levels. In practice, however, we find that most timeseries variables are not stationary in levels. They are then integrated of a higher order $N(d)$, where d denotes the number of times we need to first difference the data in order to get a stationary variable. When at least one of our variables is not $I(0)$ we can not run the VAR-model in levels.

4.2 Stationarity

4.2.1 risks of non-stationary regression

A timeseries variable is considered stationary when both the mean, variance and covariances for each lag are constant over time. Empirical research has however shown that most timeseries data contain some form of non-stationary over time (Granger and Newbold, 1974). It is essential to check the stationarity of the series in our model, as working with non-stationary series poses three main problems (Brooks, 2014):

- we would have the risk of running a spurious regression. When we regress two variables that coincidentally trend over time, even though there is no economic relationship, we could end up with a very high explanatory R-squared. If we apply such a regression, we could find a relationship that looks substantial as it would provide a high R-squared and significant coefficient estimates, but which does no reveal a real relationship (Studenmund, 2011).

- If we observe that our timeseries in the model are non-stationary, it can be proven that the t-ratios do not follow a t-distribution and the F-statistic will not follow an F-distribution. A practical consequence is an inflated t-score for our estimated coefficients, which have higher absolute value than the real coefficient. We therefore have a high chance of a Type I error, as we will too often reject the null hypothesis of no significant relation between the variables in the model.

- The third problem of running a regression with non-stationary timeseries is that the persistence of a shock will never die out. In this research we would expect an oil price shock to have an effect on GDP at time $t+1$, than a somewhat smaller effect in period $t+2$, etcetera. Running a regression of non-stationary variables however results in an effect during period $t+n$, where n is infinitely far away, that is not smaller than the effect during time $t+1$. This would clearly contradict economic expectations.

To further clarify the concept of stationarity we consider the simple AR(1) process is defined as (Dickey and Fuller, 1979):

$$Y_t = \gamma Y_{t-1} + \delta t + \epsilon_t \tag{3}$$

Where the value of our timeseries Y at time t is explained by its value in period $t-1$ and the white noise captured by ϵ_t. In addition we can add either a constant, a trend, or both a constant and a trend, which is represented by t. The decision to include this addition depends on the model used. In practice we will run each regression once and check the significance of the included terms to decide whether the inclusion of a constant or trend is necessary. We then pick the model that best represents the underlying timeseries.

To determine on the stationarity of our series we need to examine the value of parameter γ. When our series has value of $|\gamma| < 1$ if will be mean-reverting and therefore stationary. However, when we find that $\gamma = 1$ our series is non-stationary as it will contain a unit root. The variance of the series will approach infinity over time. If we find that $|\gamma| > 1$ our series will also be non-stationary as a shock at time t will explode over time; there is no mean-reversion in the model. We say that a stationary process is integrated of order zero: $I(0)$. When a series is non-stationary in levels we take the first-difference. If the series becomes stationary when put in first differences, the process is integrated of order one: $I(1)$.

4.2.2 Testing for stationarity

In order to eliminate the risk of running a spurious regression, and to aid our choice between the VAR-model and VEC-model in the empirical results section, we will check our variables for stationarity using multiple stationarity tests. There is not one test that is academically regarded to outperform all other tests for stationarity; when our employed tests are in disagreement we will follow the dominating test outcome.

The first test that we use to determine the order of integration of our variables is the Augmented Dickey-Fuller test (ADF-test). This extended version of the Dickey-Fuller test takes into account the possible autocorrelation over more than one lag-length. The DF-test of stationarity subtracts Y_{t-1} on both sides of equation 3, which gives:

$$Y_t - Y_{t-1} = \Delta Y_t = \beta Y_{t-1} + \delta t + \epsilon_t \tag{4}$$

where $\beta = \gamma - 1$. The one-sided null-hypothesis of the DF-test states that our series contains a unit root, which means:

$$\begin{aligned} H_0 &: \beta = 0 \\ H_1 &: \beta < 0 \end{aligned} \tag{5}$$

As stated we will expand the DF-test given in equation 4 to the ADF-test, as we expect our series to be correlated over more than just one lag. This would violate the assumptions of the Gauss-Markov theorem, as our error terms would then be correlated. As a result, we consider an AR(p) process rather than an AR(1) process, where we add p lagged differences to the right-hand side of equation 2. The ADF-regression is then given as:

$$Y_t - Y_{t-1} = \Delta Y_t = c + \beta_1 Y_{t-1} - \sum_{j=1}^{p} a_j \Delta Y_{t-j} + \delta t + \epsilon_t \tag{6}$$

where $\beta_1 = A_1 + ... + A_p - 1$, and $\alpha_j = -A_p$. The included number of lags to include in the ADF-test is determined using the Akaike Information Criterion (AIC), which is further explained in section 4.4. Following the AIC to determine the number of lags we can check if the autocorrelation is indeed removed.

Just as in the DF-test, we include the term δt to include possible exogenous variables. These can be both a constant and a time trend, only a constant, or neither a constant or a time trend. We run all three regressions starting with a model containing both a constant and a time trend, and proceed from here excluding irrelevant variables as they reduce the power of our test (Hamilton, 1994). We decide on the stationarity of our series comparing the t-statistic to the critical value presented by MacKinnon (1996). If our t-statistic has a higher absolute value than the relevant critical value, we reject the null hypothesis concluding our timeseries to be stationary.

If we reject the null hypothesis of a unit root, using the ADF-test at the level series, we conclude the series to be integrated of order 0. If we cannot reject the null hypothesis of a unit root, we run the ADF-test again but this time taking the first-differences of our timeseries variable. Nelson and Plosser (1982) find that most timeseries will be able to reject the null hypothsis of the ADF-test in first-differences, which indicates that the series is I(1).

To confirm and strengthen the results found by the ADF-test we will also use the Phillips-Perron test (PP-test). This variation on the DF-test uses an alternative method to control for serial correlation (Phillips and Perron, 1988). In addition to the choice we already had to make regarding the inclusion of a possible trend or constant in the model, we also need to choose a method for estimating the residual spectrum; we use the Bartlett kernel.

Our third stationarity test is the KPSS-test introduced by Kwiatkowski et al. (1992) . Whereas the ADF-test and PP-test state as the null-hypothesis that the series contains a unit root, the KPSS-test takes the opposite hypothesis. If we are able to reject the null hypothesis of the KPSS-test, this implies that our series contains a unit root. If we find that our series at level contains a unit root the series cannot be I(0), which means that we continue the KPSS-test at the first-differences of the series.

The ADF-test, PP-test and KPSS-test often derive at the same conclusion regarding the order of integration of the series under examination. If there is no shared conclusion, we will follow the conclusion reached by the majority of the employed tests.

4.3 Testing for Cointegration

The usual response to an $I(1)$ series used to be first-differencing of all series in the model and running a new regression based on these first-differences. Even though it removes the risk of running a spurious regression, it is probably not the best approach when dealing with $I(1)$ variables. When all series are first-differenced we give up on information that is contained in the original levels of the variables; which may have a long-run solution opposite to the first-differences of these series.

The preferred method is therefore to estimate whether the $I(1)$ variables in our model are cointegrated. Cointegrated variables are non-stationary by themselves, but the linear combination of the variables is stationary. This removes the risk of running a spurious regression, while keeping the original information of the variables (Brooks, 2014).

An example worth mentioning, which will clarify the idea of a cointegrated relationship, was presented by Murray (1994). Think of a drunk walking on the street: by itself this might be a non-stationary process as the drunk is not able to walk remotely in a straight line. The drunk by himself is performing a random walk, which is $I(1)$. The same would go for an unleashed puppy, who follows its nose and therefore seems to follow a random walk as well, another I(1) process. However, if the puppy belongs to the drunk they will never wander to far from each other. When you find the drunk, it is unlikely that the dog will be very far away. Even though the two series themselves are non-stationary, the distance between the two is stationary, or integrated of order zero.

Multiple methods were proposed to detect such cointegrated relationships in a model. In this paper we use both the Engle and Granger two-step approach, as well as the Johansen method.

4.3.1 Engle-Granger test

Engle and Granger (1987) propose a two-step method that tests for cointegrated variables in a model, and subsequently develops an Error Correction model that will allow us to run the original relationship in levels without the risk of spurious regression. We will now discuss this two-step method, which actually consists out of four steps, in order to determine whether we will eventually need a VAR-model or a VEC-model.

Suppose we have a simple relationship given by:

$$Y_t = \alpha + \beta_1 X_t + \epsilon_t \tag{7}$$

The first step of the Engle and Granger method is to examine the variables X and Y individually and determine their order of integration. If both series are I(0) we can simply run the regression as it is. If both variables are I(1) this is a spurious regression. The classical solution to variables being I(1) in a regression used to be taking the first differences of both variables, which gives:

$$\Delta Y_t = \alpha + \beta_1 \Delta X_t + \epsilon_t \tag{8}$$

The proposed solution would no longer be spurious, however, it would also lose its potential economic value. Equation 8 only gives the short-term dynamic between the variables Y and X. But if these two variables are in fact cointegrated there is a long-run equilibrium relationship:

$$Y_E = \alpha + \beta_1 X_E + \epsilon_t \tag{9}$$

and using Equation 8 would not provide insight into this long-run relationship, as we expect X to have an effect on Y not only in period t, but also in period t+1, period t+2, etcetera. Engle and Granger find, that if X and Y are cointegrated, a linear combination must be stationary:

$$\epsilon_t = Y_t - \alpha - \beta_1 X_t \tag{10}$$

Which are the residuals from Equation 7. These residuals are in fact a measure of the disequilibrium between X and Y at a specific point in time. We test the residuals using a unit root test: if they are stationary then the variables in our model are cointegrated. To illustrate, for our model Ia including the five variables GDP, $Oil\,price$, $REER$, $M3$, and the $Refinancing\,rate$, we can rewrite equation 7 as:

$$GDP_t = \alpha + \beta_1 Oilprice_t + \beta_2 REER_t + \beta_3 M3_t + \beta_4 Refinancingrate_t + \epsilon_t \tag{11}$$

To determine the cointegration of this model according to the Engle and Granger method we subsequently perform a unit root test on the residual:

$$\epsilon_t = GDP_t - \alpha - \beta_1 Oilprice_t - \beta_2 REER_t - \beta_3 M3_t - \beta_4 Refinancingrate_t \tag{12}$$

If the residuals are found to be stationary according to the unit root test, or I(0), we have a possible cointegrated relationship. We then proceed to the second step of the Engle and Granger method, which is to estimate the Error Correction Model (ECM). Such a model tackles the two initial problems of our model simultaneously: it removes the risk of spurious regression, and is also capable of estimating not only the short-run but also the long-run dynamics of the model. We begin with the Autoregressive Distributed Lag (1,1) model (ADL-model):

$$Y_t = \alpha + \beta_1 X_t + \beta_2 X_{t-1} + \gamma_1 Y_{t-1} + \epsilon_t \tag{13}$$

Note that this equation is similar to Equation 7, with an added term to account for past values of the independent variable X_{t-1} and an added term to account for past values of the dependent variable Y_{t-1}.

Running regression 13 is dangerous, as it could be a spurious regression. Taking the first differences will eliminate the chance of running a spurious regression, but also result in a loss of information on the long-run equilibrium relationship of the variables X_t and Y_t in the model. The Engle and Granger model is capable of preserving the information of the long-term relationship of our variables while simultaneously eliminating the risk of spurious regression when the variables are found to be cointegrated.

To arrive at the Error Correction Model of Engle and Granger after we have found our variables to be cointegrated several steps must be taken. The first is to subtract Y_{t-1} from both sides of Equation 13:

$$Y_t - Y_{t-1} = \Delta Y_t = \alpha + \beta_1 X_t + \beta_2 X_{t-1} - (1 - \gamma_1) Y_{t-1} + \epsilon_t \tag{14}$$

We now have a stationary series on the left hand side, $I(1)$, which is the first-difference of the independent variable Y_t. Next, we subtract $\beta_1 X_{t-1}$ from both sides of Equation 14:

$$\Delta Y_t - \beta_1 X_{t-1} = \alpha + \beta_1 X_t - \beta_1 X_{t-1} + \beta_2 X_{t-1} - (1 - \gamma_1) Y_{t-1} + \epsilon_t \tag{15}$$

$$\Delta Y_t = \alpha + \beta_1 \Delta X_{t-1} + (\beta_1 + \beta_2) X_{t-1} - (1 - \gamma_1) Y_{t-1} + \epsilon_t \tag{16}$$

This can be rewritten as:

$$\Delta Y_t = \beta_1 \Delta X_{t-1} - (1 - \gamma_1) \left[Y_{t-1} - \frac{\alpha}{1 - \gamma_1} - \frac{\beta_1 + \beta_2}{1 - \gamma_1} X_{t-1} \right] + \epsilon_t \tag{17}$$

where $\lambda = 1 - \gamma_1$, $\delta_0 = \frac{\alpha}{1-\gamma_1}$ and $\delta_1 = \frac{\beta_1+\beta_2}{1-\gamma_1}$:

$$\Delta Y_t = \beta_1 \Delta X_{t-1} - \lambda[Y_{t-1} - \delta_0 - \delta_1 X_{t-1}] + \epsilon_t \tag{18}$$

Equation 18 presents the final Error Correction model. Note that: $\epsilon_{t-1} = Y_{t-1} - \delta_0 - \delta_1 X_{t-1}$, which is the error correction mechanism correcting for deviations from the long-run equilibrium. This is a non-spurious regression when the series is cointegrated as $Y_{t-1} - \delta_0 - \delta_1 X_{t-1}$ is $I(0)$, ΔY_t is $I(0)$, and $\beta_1 \Delta X_{t-1}$ is $I(0)$.

Equation 18 is capable of incorporating both the long-term and short-term dynamics of the model. The adjustment speed towards the long-run equilibrium is calculated by the parameter λ. A higher value of λ suggests a faster correction by the error correction term towards long-run equilibrium. Short-term shocks are accounted for by the parameter β_1.

4.3.2 Johansen cointegration method

As with most econometric methods there are multiple available tools to choose from when determining the cointegrated long-term relationship of a model. The Engle and Granger method that was discussed has as a benefit that it is fairly easy to use. However, a drawback of the Engle and Granger method is its lack of detecting multiple cointegrated relations in a multivariate framework. This is where we use the Johansen cointegration test (Johansen, 1988).

The benefit of using the Johansen test is its ability to detect multiple cointegrated relations in a multivariate framework. The purpose of this test is to find maximum likelihood estimators of the cointegration vectors for an autoregressive model, and then apply a likelihood ratio test that there is a give number of such cointegration vectors (Johansen, 1988). As with all tests the Johansen cointegration method also has its pitfalls. It is very susceptible to number of selected lags, which implies we need to carefully weigh the number of lags to include in our model. Gonzalo and Lee (1998) recommend using both the Engle and Granger method as well as the Johansen test for cointegration, as we will do in this paper.

Whereas the Engle and Granger method uses an OLS regression, the Johansen test relies directly on maximum likelihood. Gonzalo (1994) empirically shows that the Johansen method results in better estimates than the Engle and Granger method. Two different likelihood tests are proposed: the trace test and the maximum eigenvalue test. Lutkepohl et al. (2001) compare the maximum eigenvalue and trace test for the cointegrating rank of a VAR process. They find only very small differences between the two procedures. They find that the trace statistic outperforms the maximum eigenvalue when there are two or more cointegrating relations then defined under the null hypothesis. They prefer the trace test, which we will therefore also employ in this paper.

The Johansen method is a maximum likelihood method determining the precise quantity of cointegrating vectors in a non-stationary VAR with imposed restrictions from a VEC-model. The model has as a starting point the VAR(p) (Österholm and Hjalmarsson, 2007):

$$Y_t = c + A_1 Y_{t-1} + ... + A_p Y_{t-p} + \epsilon_t \tag{19}$$

where Y_t is a vector of I(1) variables with size $n \times 1$, and ϵ_t is the vector of error terms. The VAR(p) can be rewritten as:

$$\Delta Y_t = c + \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-1} + \epsilon_t \tag{20}$$

where $\Pi = \sum_{i=1}^{p} A_i - I$ and $\Gamma_i = -\sum_{j=i+1}^{p} A_j$. In the long-run all the ΔY_{t-i} will become zero, and as the expected value of all the error terms is zero, we are left with $\Pi Y t - p$. We then test for cointegration examining the rank of the matrix Π through the eigenvalues. The rank of matrix Π equals the number of eigenvalues that are different from zero, we denote these as λ_i and put them in ascending order $\lambda_1 \geq \lambda_2 \geq ... \geq \lambda_n$. If there are no cointegrated variables, there will be no significance difference from zero of Π. For Π to have a rank of 1, the largest eigenvalue must significantly different from zero, while the other eigenvalues will not be significantly non-zero.

The trace statistic, which tests the null hypothesis of r cointegrating variables against an alternative of n cointegrating variables, is then given by (Brooks, 2014):

$$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} ln(1 - \hat{\lambda}_i) \tag{21}$$

If $\hat{\lambda}_i$ is larger, then $ln(1 - \hat{\lambda}_i)$ will be larger and more negative and therefore the test statistic will be larger. A significantly non-zero eigenvalue indicates a cointegrating vector.

4.4 Lag selection

An issue that is fundamental in employing the VAR- or VEC-model is deciding on the number of lags to include in the model. Granger-causality tests, to which we return in section 4.5, are very sensitive to the lag structure and order selection of the variables of our model (Ghalayini, 2011). Particular variables in the model are likely to have a prolonged effect on the economy. When such a variable is persistent more lags must be included. Jones et al. (2004) state in their review that most empirical studies find the largest impacts of oil price shocks on the aggregate economy in the third and fourth lag; each lag is denoted as a quarter. Most papers even find continued effects after four quarters.

Multiple tests exist to determine the appropriate lag length. The most popular method is the Akaike Information Criterion (AIC), which was presented in Akaike (1977). The AIC is used in important literature on oil price shocks, such as Cologni and Manera (2009) and Bernanke et al. (1997). The AIC compares alternative specifications regarding the number of included lags in the model, by adjusting for the number of independent variables. It is defined as:

$$AIC = log(\frac{RSS}{N}) + 2(K+1)/N \tag{22}$$

where RSS is the residual sum of squares, N represents the sample size, and K is the number of independent variables. The AIC judges whether additional lags in the model are worth the decreasing degrees of freedom. A lower AIC score represents the model with the optimum number of included lags.

A second method that we will use to strengthen our choice of the optimum lag length is the Schwarz Criterion (SC), which was presented in Schwarz (1978) . This model states that the lower a score on the SC, the better the chosen lag length. It is defined as:

$$SC = log(\frac{RSS}{N}) + log(N)(K+1)/N \tag{23}$$

where RSS is the residual sum of squares, N represents the sample size, and K is the number of independent variables.

Alternative methods to approach the optimal lag length are the Bayesian Information Criterion (BIC) and Hannan-Quinn criterion. When the various methods give inconclusive results we will use the lag length suggested by the majority of lag selection criteria. In addition, we believe it is important to keep track of the economic rationale behind the model when incorporating the correct lag length. Incorporating only one lag length when estimating the effects of an oil price shock would clearly be foolish in light of the economic literature.

4.5 Granger Causality

The VEC-model will allow us to separate the short-run and long-run relationships between the variables in our model. In the short-run we can make an even stronger claim between the interdependence of the variables in our model; this is done by determining the Granger Causality between our variables. First introduced in 1969, Granger causality aims to statistically identify whether a particular timeseries variable is useful in explaining another timeseries variable (Granger, 1969).

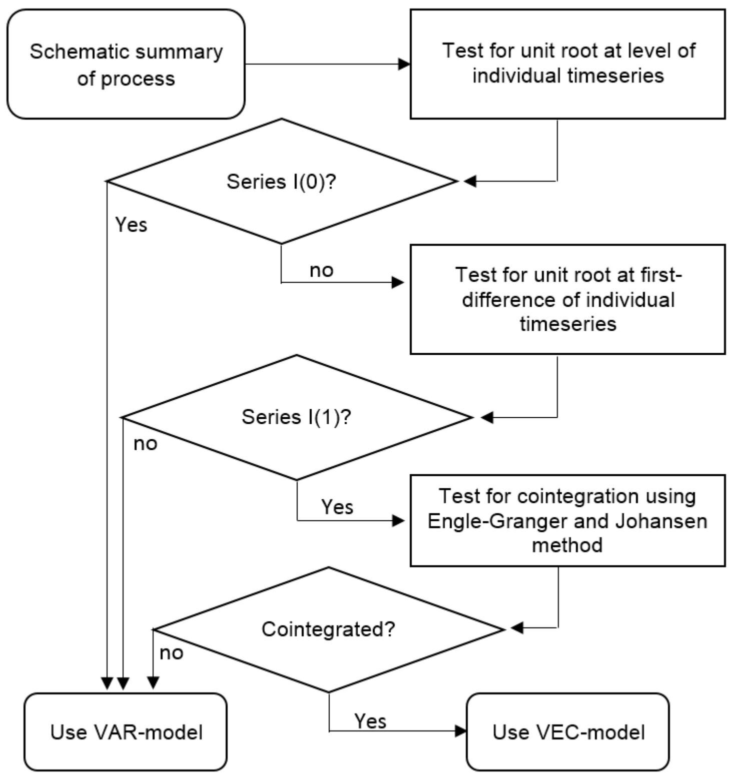
When a variable X is said to 'Granger cause' another variable Y, then the current values of X are helpful in predicting the future values of Y. This causation can run one way, from e.g. X to Y, but can also run both ways. The first is referred to as unidirectional causality; when causality runs both ways we refer to the relationship as bi-directional causality (Brooks, 2014). In fact, Granger causality refers to a correlation between the current values of one variable and the past values of another variable.

We perform bivariate, or pairwise, Granger causality tests on the variables in our final model. In the case that a VEC-model is estimated, we can only test the exclusion of the short-term first-differenced variables. No such test can be performed on the cointegrated relationship, which is the error correction term, in levels itself.

4.6 Schematic summary of methodology

The methodological process described in this section can be summarised schematically by means of Figure 3. We will follow this framework when executing our empirical analysis in section 5.

Figure 3: Schematic overview of methodology



Notes: Schematic representation of the VAR-model decision making process.

5 Empirical results

In this section we introduce the main empirical results of our analysis. We will employ the methodological tools that were introduced in chapter 4, with the purpose of finding the correct impact of an oil price shock or monetary shock on the Eurozone economy over the past fifteen years. In doing so, we will make use of the Eviews software package.

We will follow the same sequence of methodological steps as was done in chapter 4. We will therefore start with examining the stationarity of our variables in section 5.1. Section 5.2 will examine whether there is cointegration between the variables in our model using the Engle and Granger approach. The Johansen method is discussed in section 5.3, including a final presentation of the impulse response functions and granger causality analysis.

5.1 Order of integration

The first step in the empirical part of our research is to find the order of integration of the variables in our model. This is a necessary step as it guides our choice in the use of either the VAR-model or the VEC-model. We follow the methodology presented in section 4.2.2. As such, we use the Augmented Dickey-Fuller test (ADF-test), the Phillips-Perron test (PP-test), and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS-test). We discuss the results from these three tests sequentially in this section. We use the symbol Δ to denote the first-difference of the particular variable.

We first present the results of the ADF-test in Table 2. Recall that the null hypothesis of the ADF-test is that the series tested contains a unit root: rejection of the null hypothesis is therefore a strong sign that this unit root is not present and the series is stationary. The ADF-test finds that our variables GDP, $Oil\,Price$, $REER$, $M3$, and $Unemployment\,Rate$ are not stationary in levels, as we cannot reject the null hypothesis of the ADF-test. We can, however, reject the null hypothesis of a unit root for these series when we take the first difference of these series: they are therefore integrated of order 1.

The exceptions are the variables $NEER$ and $Refinancing\,Rate$; according to the ADF-test we can reject the null hypothesis of a unit root for these variables at the 10%-significance level when the series are considered in levels. This would suggest that both series are I(0). Before we draw any preliminary conclusions, we will first use the PP-test and KPSS-test as robustness checks. If it turns that the series are in fact I(1) according to these two other unit root tests, then following the ADF-test would probably lead to spurious regression.

Table 3 presents the results of the PP unit root test on our series and on the first differences of our series. We find conclusive results with regards to the variables GDP, $REER$, $NEER$, $M3$, $Refinancing\,Rate$, and $Unemployment\,Rate$, which are all found to be integrated of order 1 at the 1%-significance level. The exception here is the variable $Oil\,Price$, for which the PP-test rejects the null hypothesis of a unit root at the 5%-significance level when the series is considered in levels.

Table 2: ADF unit root test

Variable:	Exogenous variables:	Lag length:	Test statistic:
GDP	constant	1	-2.200359
$Oil\ Price$	constant, linear trend	3	-2.535980
$REER$	constant	6	-2.526552
$NEER$	constant	6	-2.606808*
$M3$	constant, linear trend	8	-2.666963
$Refinancing\ Rate$	constant, linear trend	1	-3.250763*
$Unemployment\ Rate$	constant	1	-2.353144
ΔGDP	none	0	-3.192611***
$\Delta Oil\ Price$	none	1	-5.850692***
$\Delta REER$	none	0	-5.637992***
$\Delta NEER$	none	0	-5.830236***
$\Delta M3$	constant	4	-2.713714*
$\Delta Refinancing\ Rate$	none	0	-4.729561***
$\Delta Unemployment\ Rate$	none	3	-3.486764***

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Lag length choice by AIC; Δ denotes the first-difference of the series. ADF critical values without constant or trend are -1.613 (10%), -1.946 (5%), and -2.602 (1%). ADF critical values with only a constant are -2.592 (10%), -2.908 (5%), and -3.538 (1%). ADF critical values with both a constant and a linear trend are -3.171 (10%), -3.485 (5%), and -4.116 (1%).

As a third test of the stationarity of our variables we use the KPSS-test. Recall that this test uses the opposite null hypothesis from the ADF-test and the PP-test: the null hypothesis of the KPSS-test is that the tested series does not contain a unit root. We find that the KPSS-test rejects the null hypothesis for all our variables when considered at levels at either the 5%- or 1%-significance level. This suggests that all series contain a unit root when considered in levels. When we first difference the series, however, we can no longer reject the KPSS null hypothesis for any of the series. The KPSS unit root test therefore concludes that all series are I(1).

When we compare the results of our three stationarity tests, we find disagreement among our tests in three cases. First, the ADF-test rejected the null hypothesis of a unit root at the 10%-significance level when the series $NEER$ and $Refinancing\, rate$ were considered in levels. The PP-test did, however, not reject this same null hypothesis for these two series. The KPSS-test was able to reject the null hypothesis of no unit root in the series $NEER$ and $Refinancing\, rate$ at the 5%-significance level. As two out of three tests conclude that the series are non-stationary in levels, we conclude that they can not be I(0). All three tests however find that the series $NEER$ and

Table 3: PP unit root test

Variable:	Exogenous variables:	Bandwidth:	Test statistic:
GDP	constant	4	-2.538845
$Oil\,Price$	constant	2	-3.071136**
$REER$	none	4	-0.434682
$NEER$	none	3	-0.296411
$M3$	constant	5	-0.902748
$Refinancing\,Rate$	none	3	-1.202033
$Unemployment\,Rate$	none	5	0.190220
ΔGDP	none	1	-3.235935***
$\Delta Oil\,Price$	none	3	-5.878806***
$\Delta REER$	none	3	-5.694219***
$\Delta NEER$	none	2	-5.815195***
$\Delta M3$	constant	2	-5.482581***
$\Delta Refinancing\,Rate$	none	1	-4.764119***
$\Delta Unemployment\,Rate$	none	1	-2.640822***

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Newey-west in Bartlett kernel; Δ denotes the first-difference of the series. PP critical values without constant or trend are -1.613 (10%), -1.946 (5%), and -2.602 (1%). PP critical values with only a constant are -2.592 (10%), -2.908 (5%), and -3.538 (1%).

$Refinancing\,rate$ become stationary when first-differenced: we therefore conclude that both series are in fact integrated or order 1.

The third case of disagreement between our unit root tests is the variable $Oil\,price$. The PP-test rejects the null hypothesis that the series $Oil\,price$ contains a unit root in levels at the 5%-level. Both the ADF-test and the KPSS-test however find that the series does contain a unit root when considered in levels. When taken in first-difference all three unit root tests find the the variable $Oil\,price$ to be stationary. We therefore conclude that the variable is I(1). The results of our unit root tests are summarized in Table 5.

A first condition that has to be satisfied to construct a VEC-model, is that all variables must be integrated of order 1. As we find that the majority of our unit root tests concludes that all series in our model are I(1), we are now able to look if a cointegrating relationship between the variables exists.

Table 4: KPSS unit root test

Variable:	Exogenous variables:	Bandwidth:	Test statistic:
GDP	constant, linear trend	6	0.217935***
$Oil\,Price$	constant	6	0.946266***
$REER$	constant, linear trend	6	0.202183**
$NEER$	constant, linear trend	6	0.190359**
$M3$	constant	6	1.008362***
$Refinancing\,Rate$	constant	6	0.656487**
$Unemployment\,Rate$	constant, linear trend	6	0.200659**
ΔGDP	constant, linear trend	4	0.050124
$\Delta Oil\,Price$	constant, linear trend	1	0.069565
$\Delta REER$	constant	4	0.167156
$\Delta NEER$	constant	3	0.149244
$\Delta M3$	constant	5	0.171916
$\Delta Refinancing\,Rate$	constant	3	0.087544
$\Delta Unemployment\,Rate$	constant, linear trend	5	0.071626

Notes:* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Newey-west in Bartlett kernel; Δ denotes the first-difference of the series. KPSS critical values with only a constant are 0.347 (10%), 0.463 (5%), and 0.739 (1%). KPSS critical values with both a constant and a linear trend are 0.119 (10%), 0.146 (5%), and 0.216 (1%).

Table 5: Order of integration of variables

Variable	ADF-test:	PP-test:	KPSS-test:
GDP	I(1)	I(1)	I(1)
$Oil\,Price$	I(1)	I(0)	I(1)
$REER$	I(1)	I(1)	I(1)
$NEER$	I(0)	I(1)	I(1)
$M3$	I(1)	I(1)	I(1)
$Refinancing\,rate$	I(0)	I(1)	I(1)
$Unemployment\,rate$	I(1)	I(1)	I(1)

5.2 Engle and Granger method

The Engle and Granger procedure follows the method as described in section 4.3.1. We expect that, over the long-run, our variables are in equilibrium. In the short-run there can, however, be deviations from this long-run equilibrium. The Error Correction model will allow us to separate the long-term equilibrium from the short-term deviations caused by external shocks.

We are interested in the effects of our variables $Oil\,Price$, $REER$, $NEER$, $M3$, and $Refinancing\,Rate$ on the aggregate output of the Eurozone. This is measured by two dependent variables: both GDP and on the $Unemployment\,Rate$. From now on we will distinguish between a model that includes GDP as the dependent variable, which we denote as Model I, and a model that includes $Unemployment\,Rate$ as the dependent variable, to which we refer as Model II.

In addition, we can distinguish between the effects of the Real Effective Exchange Rate (REER) and the effects of the Nominal Effective Exchange Rate (NEER). As such, within both Model I and Model II we run two regressions. Model Ia and Model IIa include REER as an independent variable. Model Ib and Model IIb include NEER as an independent variable.

In total we will therefore examine four separate models using the Engle and Granger procedure. As described in the hypothesis section, we expect our long-run equilibrium of Model Ia to be of the following nature:

$$GDP = -Oil\,price - REER + M3 - Refinancing\,Rate \tag{24}$$

where, in the long-run, an increase in the oil price leads to a reduction in GDP. An increase in the Euro exchange rate vis-a-vis its trading partners will lead to a reduction of GDP. An increase of the money supply M3 will lead to an increase in GDP. Also, an increase of the ECB refinancing rate will lead to a decrease in GDP. Using the Engle and Granger method we will be able to separate our long-term expectations from the short-term deviations that are likely to occur due to effects such as the J-curve effect caused by a depreciating exchange rate. In a similar fashion Model IIb is constructed by changing the Nominal exchange rate (NEER) for the Real exchange rate (REER).

Model II takes the unemployment rate as its dependent variable. Model IIa, which includes the REER, is expected to have the long-run equilibrium form:

$$Unemployment\,Rate = +Oil\,Price + REER - M3 + Refinancing\,Rate \tag{25}$$

where, in the long-run, an increase in the oil price will lead to an increase in the unemployment rate. Also, an increase in the real exchange rate of the Euro currency vis-a-vis its trading partners will lead to increased unemployment in the Eurozone. An increase in the money supply M3 will reduce the unemployment rate, whereas an increase in the refinancing rate will increase the unemployment rate. We can construct a similar Model IIb by changing the REER for the nominal exchange rate NEER.

Using the Engle and Granger methodology we can rewrite Model Ia from Equation 24 as the regression:

$$GDP = \alpha - \beta_1 Oil\,Price - \beta_2 REER + \beta_3 M3 - \beta_4 Refinancing\,Rate + \epsilon_t \tag{26}$$

and Equation 25 to fit our model IIa as:

$$Unemployment\,Rate = \alpha - \beta_1 Oil\,Price - \beta_2 REER + \beta_3 M3 - \beta_4 Refinancing\,Rate + \epsilon_t \quad (27)$$

Model Ib and Model IIb can be constructed in a similar way by changing the variable REER for the variable NEER. Section 5.1 showed that all variables are integrated of order one, which suggests that a possible cointegrating relation exists. Running the level regressions of Equations 26 & 27 and additional regressions for Model Ib Model IIb yields the results presented in Table 6.

Table 6: Level Regressions

	(Ia)	(Ib)	(IIa)	(IIb)
	GDP	GDP	$Un.rate$	$Un.rate$
$Oil\,price$	0.0263***	0.0247	0.8594***	0.9369***
	(0.007)	(0.007)	(0.283)	(0.295)
$REER$	0.0597**		-5.2464***	
	(0.024)		(1.044)	
$NEER$		0.0519*		-5.1830***
		(0.028)		(1.226)
$M3$	0.1749***	0.1783***	-1.7518**	-1.8113**
	(0.016)	(0.017)	(0.682)	(0.741)
$Refinancing\,rate$	0.0108***	0.0112***	-0.9689***	-0.9957***
	(0.001)	(0.001)	(0.060)	(0.061)
$Constant$	22.8837***	22.8239***	84.3941***	85.6705
	(0.392)	(0.406)	(16.906)	(17.976)
observations	65	65	65	65
R-squared	0.9649	0.9635	0.8876	0.8770
Adj. R-squared	0.9625	0.961025	0.8801	0.8688
F-test	412.1345	395.5200	118.4869	106.9338
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000
log likelihood	205.7577	204.4683	-38.9779	-41.9199

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

Table 6 shows that all four models have only significant variables. We therefore continue with all variables included in Models Ia, Ib, IIa, and IIb. We find the size and significance of the real exchange rate and the nominal exchange rate on the aggregate output to be of comparable size. Further interpretation of this model would however be foolish. The extremely high R-squared values suggest that this might be a spurious regression; in fact we know it is a spurious regression as all variables are integrated of order 1.

In line with the Engle and Granger methodology we capture the residuals of Models Ia, Ib, IIa, and IIb and test whether these residuals are stationary using the ADF-, PP-, and KPSS-unit root tests. Results are presented in Table 7.

Table 7: Stationarity of residuals

Model:	Test:	Exogenous variables:	Lag length or Bandwidth:	Test statistic:
(Ia)	ADF-test	none	3	-2.829337***
	PP-test	none	4	-2.276925**
	KPSS-test	constant	5	0.117454
(Ib)	ADF-test	none	3	-2.810693***
	PP-test	none	4	-2.283601**
	KPSS-test	constant	6	0.117586
(IIa)	ADF-test	none	3	-2.863730***
	PP-test	none	4	-4.718908***
	KPSS-test	constant	5	0.149403
(IIb)	ADF-test	none	3	-2.695704***
	PP-test	none	4	-4.655673***
	KPSS-test	constant	5	0.173238

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. ADF-test and PP-test critical values are -1.613 (10%), -1.946 (5%), and -2.603 (1%). KPSS-test critical values are 0.347 (10%), 0.463 (5%), and 0.739(1%).

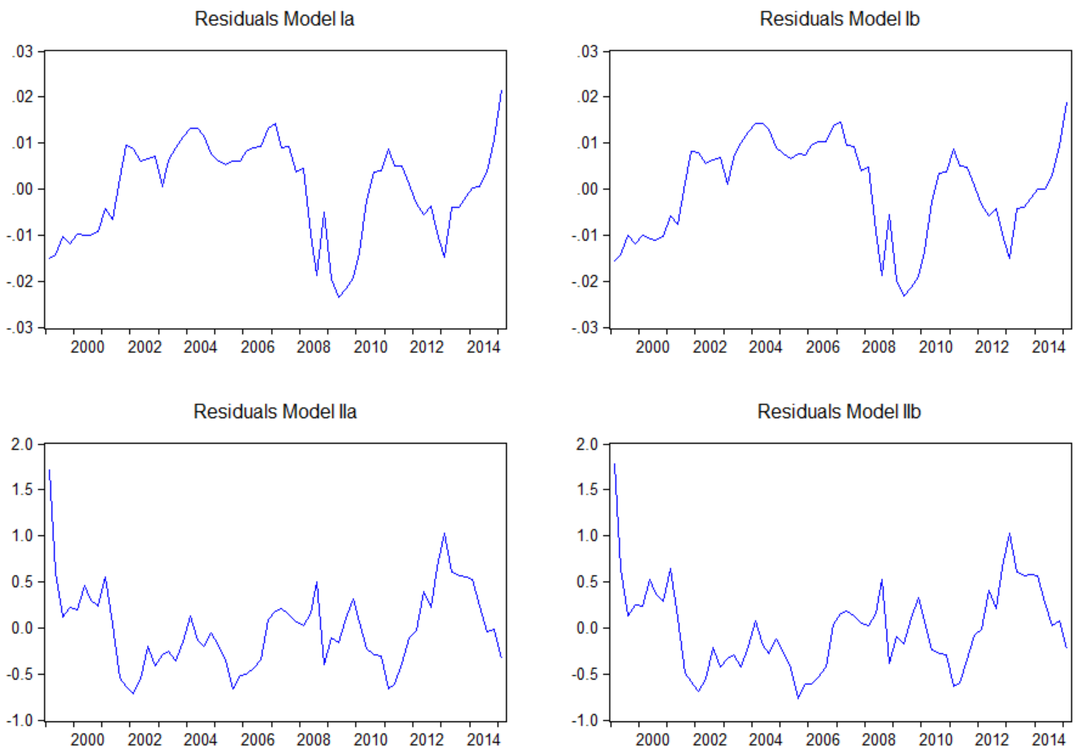
Table 7 shows that both the ADF-test, PP-test and KPSS-test conclude that the residual series from all four models are stationary. We also present the residual series in Figure 4. Observing the residual series, which oscillate around zero, strengthens our conclusion that the residuals of Model Ia, Ib, IIa, and IIb are indeed stationary or integrated or order zero. As such, we can develop the Error Correction Model.

As there is a long-run equilibrium in all four of our models we can set up the regressions of the Error Correction Model. The Error Correction Model, according to Engle and Granger, of Model Ia then takes the form:

$$\begin{aligned} \Delta GDP = c + \gamma_1 \Delta Oil\, price_{t-1} + \gamma_2 \Delta REER_{t-1} + \gamma_3 \Delta M3_{t-1} \\ + \gamma_4 \Delta Refinancing\, rate_{t-1} - \lambda[\epsilon_{t-1}] + u_t \end{aligned} \quad (28)$$

where ϵ_{t-1} is the cointegration term that was derived in the previous step. This cointegration term indicates the long-run relationship between the variables. Short term effects of the variables in Model Ia on the GDP are given by parameters γ_1 to γ_4. A constant and error term u_t are also added.

Figure 4: Residuals of Model Ia, Ib, IIa, and IIb



In a similar fashion we can use the stationary error correction terms of the Models Ib, IIa, and IIb estimated by the regressions in Table 6 to set-up the other Error Correction Models. The ECM of Model IIa takes the form:

$$\begin{aligned} \Delta Unemployment\, rate = c + \gamma_1 \Delta Oil\, price_{t-1} + \gamma_2 \Delta REER_{t-1} + \gamma_3 \Delta M3_{t-1} \\ + \gamma_4 \Delta Refinancing\, rate_{t-1} - \lambda[\epsilon_{t-1}] + u_t \end{aligned} \tag{29}$$

where ϵ_{t-1} is the residual series taken from regression 27. The ECM of Model Ib and IIb can be formed by changing the variable REER in Models Ia and IIa for the variable NEER. The full results of the Error Correction Models Ia, Ib, IIa and IIb are presented in Table 8.

For model Ia and model Ib we find similar results for the Engle and Granger model. The long-run cointegration term, ϵ_{t-1}, has a positive value and is insignificant for both model Ia and model Ib. The positive sign indicates an explosive model, which is not logical. This indicates no long-run significant relationship can be found using the Engle and Granger method for models Ia and Ib.

Table 8: Error Correction Model Regressions

	(Ia) ΔGDP	(Ib) ΔGDP	(IIa) $\Delta Un.rate$	(IIb) $\Delta Un.rate$
$\Delta Oilprice_{t-1}$	0.0179***	0.0177***	-0.2236	-0.2250
	(0.006)	(0.006)	(0.189)	(0.189)
$\Delta REER_{t-1}$	0.0268		-0.0353	
	(0.030)		(1.031)	
$\Delta NEER_{t-1}$		0.0245		-0.0721
		(0.030)		(1.008)
$\Delta M3_{t-1}$	-0.0134	-0.0130	-3.8381**	-3.8315**
	(0.061)	(0.061)	(2.008)	(2.010)
$\Delta Refinancingrate_{t-1}$	0.0063***	0.0063***	-0.3413***	-0.3417***
	(0.002)	(0.002)	(0.074)	(0.074)
ϵ_{t-1}	0.1153	0.1130	-0.0196	-0.0176
	(0.075)	(0.072)	(0.060)	(0.057)
constant	0.0029**	0.0029**	0.0619	0.0619
	(0.001)	(0.001)	(0.037)	(0.037)
observations	63	63	63	63
R-squared	0.4239	0.4230	0.4314	0.4313
Adj. R-squared	0.3733	0.3723	0.3815	0.3814
F-test	8.3867	8.3562	8.6482	8.6458
Prob (F-statistic)	0.0000	0.0000	0.0000	0.0000
log likelihood	245.0691	245.0204	22.2726	22.2683

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

For model Ia and model Ib we find that only the short-term effect of the variables $Oil\, price$ and the $Refinancing\, rate$ are significant at the 1%-significance level. Of these two estimates, neither has the expected sign. Using economic theory, we associate a higher oil price and a higher refinancing rate with a negative effect on GDP. Our estimated coefficients suggest the opposite result. This short term dependency can however be explained, as they trend together in the short-term. High growth levels in the Eurozone push up the price of crude oil in the short-term.

Examining models IIa and IIb we find that the differences between the two are negligible. Both models find the same variables to be significant, and also the found coefficients of these variables display only minor differences between models IIa and IIb. For both models the cointegrating term ϵ_{t-1} has the expected negative sign, but is found to be insignificant. In addition, both models find a higher money supply $M3$ to decrease the unemployment rate in the short-run. Also, a higher ECB

$refinancing\, rate$ will lower unemployment in the short-run. No significant effect of the Oil price or the exchange rate on the unemployment rate is found in either the long-run or the short-run.

The most interesting finding of the Engle and Granger models are not the found coefficients of the oil price and the exchange rate on the aggregate output of the Eurozone. Most estimates are found to be insignificant, most importantly the cointegrating equations themselves are found to be redundant. We do find, however, that there is virtually no difference in the estimated coeffcients when we use either the real exchange rate (REER) or the nominal exchange rate (NEER). Both variables yield the exact same results, as can be seen in Table 8.

Overall, we can not draw any significant conclusions from the Engle and Granger approach that are in line with our hypotheses. Next, we develop the Johansen method to estimate the VEC-models of our variables, which will give us a better idea of the short-term and long-term relationships in our model.

5.3 Johansen method

In addition to the Engle and Granger method we also perform the Johansen test of cointegration. The added advantage of the Johansen test is its ability to identify multiple cointegrated relations between our variables. In this section we continue the logic of section 5.2 by referring to model Ia as the model including the variables GDP and $REER$, model Ib as the model including GDP and $NEER$, model IIa as the model including the $Unemployment\, rate$ and $REER$, and finally model IIb as the model including the variables $Unemployment\, rate$ and $NEER$.

We first estimate the optimal number of lags to include in our model in section 5.3.1. Next, we define the number of cointegrated equations in section 5.3.2. The most interesting results of this paper are presented using impulse response functions in section 5.3.3. We finish this chapter with a test for Granger causality in section 5.3.4.

5.3.1 Lag selection

In section 4.4 we introduced various measures to select the lag order of a VAR- or VEC-model. It is a valid option that all lag order selection criterion arrive at a different optimal lag length, in such a case we must make a deliberate choice in selecting the best possible lag length. This is however a very careful choice as the cointegration among the variables directly depends on the number of included lags (Emerson, 2007). The suggested lag lengths of Models Ia and IIa are presented in Table 9 and 10.

Estimation of the optimal lag length for model Ib finds the exact same results as model Ia in terms of the suggested optimal lag length; estimation of the optimal lag length for model IIb finds the exact same results as model IIa in terms of the suggested optimal lag length. We therefore find it redundant to include these two tables at this point.

Table 9: Lag order selection Model Ia

Lag	LogL	LR	FPE	AIC	SC	HQ
0	200.0153	NA	9.26e-10	-6.610689	-6.434626	-6.541961
1	630.6759	773.7291	9.91e-16	-20.36189	-19.30552*	-19.94953
2	666.7625	58.71726	6.93e-16	-20.73771	-18.80103	-19.98171*
3	688.9956	32.40747	7.99e-16	-20.64392	-17.82692	-19.54427
4	729.9910	52.80770*	5.10e-16*	-21.18614	-17.48882	-19.74285
5	756.6085	29.77549	5.67e-16	-21.24097	-16.66334	-19.45405
6	784.5281	26.50021	6.66e-16	-21.33994*	-15.88201	-19.20939

Notes: * indicates lag order selected by that criterion. LR is sequential modified LR statistic; FPE is final prediction error; AIC is Akaike Information Criterion; SC is Schwarz information Criterion; HQ is Hannan-Quinn information criterion.

Table 10: Lag order selection Model IIa

Lag	LogL	LR	FPE	AIC	SC	HQ
0	-13.08220	NA	1.27e-06	0.612956	0.789019	0.681684
1	406.8509	754.4561	1.96e-12	-12.77461	-11.71823*	-12.36224
2	453.8514	76.47535	9.45e-13*	-13.52039	-11.58370	-12.76438*
3	474.9634	30.77338	1.13e-12	-13.38859	-10.57159	-12.28895
4	504.8245	38.46525*	1.05e-12	-13.55337	-9.856062	-12.11009
5	537.0662	36.06695	9.67e-13	-13.79885	-9.221230	-12.01194
6	567.5914	28.97309	1.04e-12	-13.98615*	-8.528213	-11.85559

Notes: * indicates lag order selected by that criterion. LR is sequential modified LR statistic; FPE is final prediction error; AIC is Akaike Information Criterion; SC is Schwarz information Criterion; HQ is Hannan-Quinn information criterion.

Both model Ia and model IIa find that the various selection criteria propose very different lag lengths for our models. As there is not one suggested optimal lag length, we are now left to choose between the various recommendations. Ivanov and Kilian (2005) conclude that for quarterly VAR-models the Hannan-Quinn (HQ) criterion appears to be most accurate, except when the sample contains less than a 120 observations, then the Schwarz Criterion outperforms the HQ. For Model Ia the suggested lag-lengths for the SC and HQ criteria, are one and two lags respectively. This does not seem correct when reflected by economic reasoning. Based on previous empirical work we find hat it takes at least 7 months, or three quarters, for an oil price shock to have an effect on economic output measured by GDP.

The much criticised paper by Bernanke et al. (1997) used such a short lag length of only seven months. Following this incorrect short lag selection, and the associated incorrect conclusions derived by this paper, lead us to reject the inclusion of only one or two lags in our model. The Akaike Information Criterion (AIC) suggests the longest lag order of 6 lags to be included model Ia. However, as most empirical studies find that the largest impact of an oil price shock occur during the third and fourth quarter after an oil price shock (Jones et al., 2004), we follow the suggested lag length of the LR statistic and the FPE for model Ia: a lag length of 4 quarters. This lag length is equivalent to the selected lag length of much cited papers as Dias (2013) and Papapetrou (2009).

For model Ib we find the exact same recommendations regarding the optimal lag length as we did for model Ia. We therefore decide to include four lags in this model as well. For models IIa and IIb we find comparable suggested lag lengths as model Ia and model Ib with the exception of the FPE. Using the same economic reasoning as for model Ia and model Ia, we decide to also include four lags in models IIa and IIb.

5.3.2 number of cointegrated equations

As presented in the methodology, the added value of performing the Johansen method is its ability to find multiple cointegrated relations in the model rather than only one. Table 11 and 12 display the results of the Johansen method for Model Ia, Model Ib, Model IIa, and Model IIb respectively.

Table 11: Cointegration Rank Test Trace statistics Model Ia

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.596103	106.85720	69.81889	0.
At most 1 *	0.359018	52.46158	47.85613	0.0173
At most 2	0.226021	25.77622	29.79707	0.1356
At most 3	0.135259	10.40358	15.49471	0.2510
At most 4	0.027677	1.68404	3.84147	0.1944

Notes: *denotes rejection at the 0.05 level. ** are the Mackinnon-Haug-Michelis (1999) p-values. 4 lags included based on findings in section 5.3.1.

For model Ia the trace statistic rejects at most 1 cointegrated equation, but no rejection of at most 2 cointegrated equations in the model. The trace statistic finds at most 1 cointegrated equation in model IIa. This implies that both models Ia and IIa contain cointegrated equations: we therefore need to use a VEC-model rather than a VAR-model.

We also find that the results of the trace test statistic of model Ib is equal to the result of model Ia: two cointegrated equations in the system. The results of the trace staistic of model IIb is equal to the result of model IIa: one cointegrated equation in the system.

Before we present the final results of our models in section 5.3.3 we check whether the estimated models are in fact correctly specified. We test for autocorrelation in the models in appendix A.4;

Table 12: Cointegration Rank Test Trace statistics Model IIa

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.394536	74.16785	69.81889	0.0215
At most 1	0.280932	44.06229	47.85613	0.1087
At most 2	0.227002	24.27434	29.79707	0.1891
At most 3	0.108283	8.82562	15.49471	0.1891
At most 4	0.031965	1.94924	3.84147	0.1627

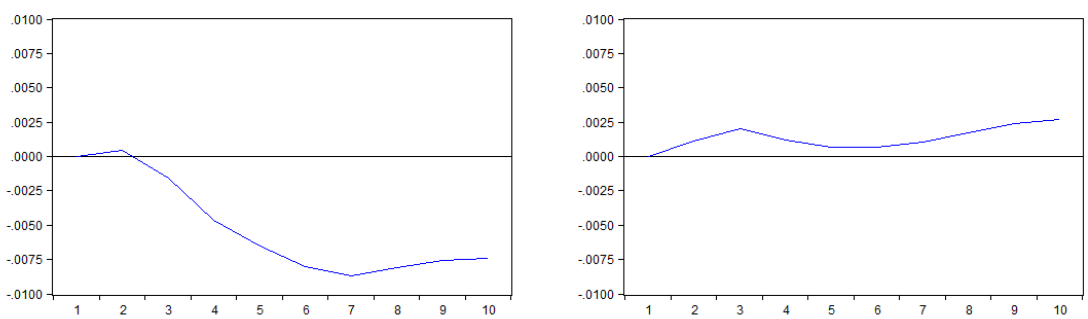
Notes: *denotes rejection at the 0.05 level. ** are the Mackinnon-Haug-Michelis (1999) p-values. 4 lags included based on findings in section 5.3.1.

we find that no autocorrelation is present when we include 4 lags in each model. Subsequently we asses the stability of our models in appendix A.5, where we conclude that all four models are stable.

5.3.3 Impulse response functions

In this section we present the final results of our analysis. Using the obtained results regarding lag selection and optimal number of cointegrated equations we estimate the VEC-models Ia, Ib, IIa and IIb. The resulting estimates can be found in appendices A.6, A.7, A.8 and A.9. Using these estimates we can construct Impulse Response Functions (IRF), which allow us to trace the effect of a one-time shock in one variable on both the current and future values of the other endogenous variables in the model.

Figure 5: Model Ia: response of GDP to Oil price and REER



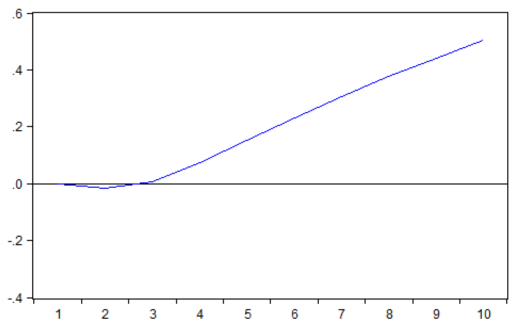
(a) Response of GDP to Oil price

(b) Response of GDP to REER

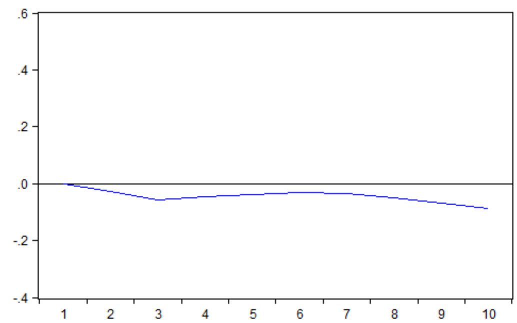
notes: Impulse response functions GDP to Oil price and REER. 10 periods equals 2.5 years (quarterly data). Shock equivalent to cholesky one standard deviation.

The selected impulse response functions regarding a one standard deviation shock of both the oil price and the exchange rate, as measured by REER, are presented in Figures 5 and 6. In these figures we use a cholesky distribution to examine the effects of a one standard deviation shock in all variables of the model. In reality, the shocks in our variables were not all equivalent of one standard deviation over the period 2014Q3 until 2015Q1. In particular, the oil price shock was much larger over this period than its one standard deviation shock.

Figure 6: Model IIa: response of the Unemployment rate to Oil price and REER



(a) Response of unemployment rate to Oil price



(b) Response of unemployment rate to REER

notes: Impulse response functions GDP to Oil price and REER. 10 periods equals 2.5 years (quarterly data). Shock equivalent to cholesky one standard deviation.

Therefore, rather than using the default option of a one standard deviation decomposition method, we are using a customized decomposition method in constructing our IRF. As we are interested in the shocks caused by the exchange rate and the oil price over the period 2014Q3, when the decrease in the oil price first set in, until 2015Q1, the most recent available datapoint, we take the changes in these variables to be on the diagonal of our decomposition matrix. This allows us to trace the effects of the several shocks, taking into account their relative sizes. Table 13 presents the percentage change in our variables over this period.

Table 13: Changes in variables since 2014Q3

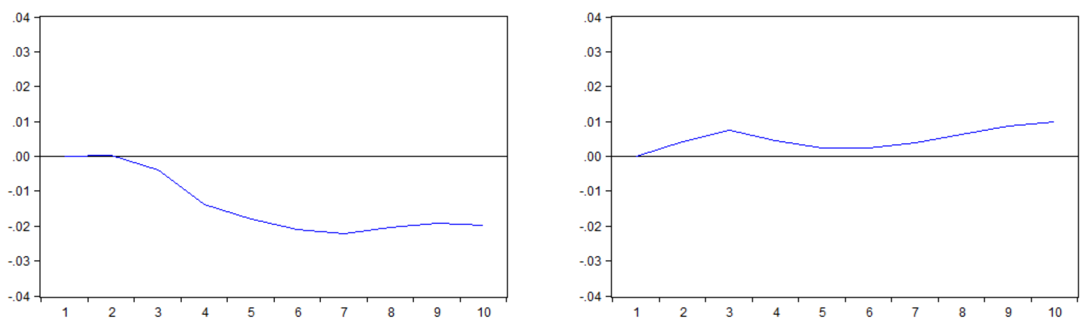
	GDP	$Oil\,price$	$REER$	$NEER$	$M3$	$Ref.rate$	$Un.Rate$
Value 2014Q3:	2417	78.03	98.21	101.71	10079	0.050	11.53
Value 2015Q1:	2435	48.96	90.39	93.74	10470	0.050	11.20
Percentage change:	0.730	-37.249	-7.958	-7.840	3.882	0.000	-0.330

Notes: value of GDP and M3 in billion euros; value of oil price in Euros; REER and NEER indexed; ECB refinancing rate and unemployment rate in percentage points.

Due to their size and the number of impulse response functions estimated by our models, we cannot discuss all the impulse response functions in this section. As such, full IRF graphs have been included in appendices A.10, A.11, A.12, and A.13. We trace the response functions for ten periods, where one period is the equivalent of one quarter. As our VEC-models are stationary we expect the effect of any shock in the long-term to die out to zero.

Figure 8 compares the response of the Eurozone GDP to the change in the oil price and the change in the Real Effective Exchange Rate (REER) over the period 2014Q3 until 2015Q1. In Figure 7a we find that an oil price increase is associated with a GDP decrease in the long-run. Equivalently, the recent oil price decrease is followed by an increase of Eurozone GDP in the long-run. We find that that there is a marginal effect of the oil price shock during the first 2 quarters. During the third quarter the decrease in the oil price starts to have a positive effect on the GDP of the Eurozone. In fact, we find that the effect of a lower crude oil price has a long-term effect on the GDP of the Eurozone.

Figure 7: Model Ia: response of GDP to Oil price and REER



(a) Response of GDP to Oil price

(b) Response of GDP to REER

notes: Impulse response functions GDP to Oil price and REER. 10 periods equals 2.5 years (quarterly data). Shock equivalent to actual changes 2014Q3-2015Q1.

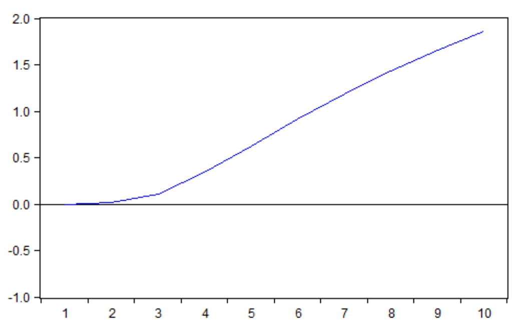
Figure 7b presents the response of Eurozone GDP to the depreciation of the Euro currency following the QE policy of the Cenral Bank. Using a VEC-model, we find that there is a clear J-curve effect present. Following a depreciation in the Euro currency, the GDP of the Eurozone first shrinks. This effect is reversed after the third period, when the GDP displays a positive response to a weakening Euro currency.

Comparing Figures 7a and 7b we find the positive effect of the oil price decrease on Eurozone GDP to be larger than the exchange rate effect caused by QE on Eurozone GDP. Four quarters after the initial oil price shock of August 2014, the price shock is starting have a large positive effect on the GDP of the Eurozone. During this same period, the effect of the weakened Euro exchange rate on the Eurozone aggregate output is ambiguous due to the observed J-curve effect.

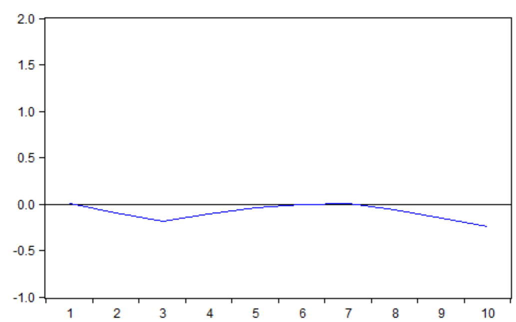
Figure 8 shows the response of the unemployment rate to the 2014Q3-2015Q1 shocks in the oil price and the exchange rate. Unemployment, up to a certain extent, is an indicator of economic growth. As we can conclude from Figure 8a the decrease in the oil price will result in a lower unemployment rate. As with the effect of the oil price on GDP, it takes three quarters for any response to be visible. Four quarters after the 37% decrease in the oil price, the estimated effect on the unemployment rate is already 0.5%.

Whereas the effect of the oil price shock on the unemployment rate is unambiguous, the same can not be said of the effect that an exchange rate shock will have on the unemployment rate of the Eurozone. Figure 8b shows that the effect of either a decrease or an increase in the Euro exchange rate has an ambiguous effect on the unemployment rate of the Eurozone. We do however, examining our VEC-model estimates in appendix A.8 find that a decrease in the real Euro exchange rate has a decreasing effect on the unemployment rate at the 10% significance level; this effect is significant at the 5% level when we consider the nominal Euro exchange rate.

Figure 8: Model IIa: response of Unemployment rate to Oil price and REER



(a) Response of Unemployment rate to Oil price



(b) Response of Unemployment rate to REER

notes: Impulse response functions Unemployment rate to Oil price and REER. 10 periods equals 2.5 years (quarterly data). Shock equivalent to actual changes 2014Q3-2015Q1.

Further examining the impulse response functions of appendices A.10, A.11, A.12, and A.13 we find that there is a negligible differences between models Ia and Ib, or models IIa and IIb. Whereas models Ia and IIa include the real effective exchange rate, the models Ib and IIb include the nominal effective exchange rate. We find that including either of the two series yields the same outcome, even though we could have presumed the NEER to have a faster effect on output than REER as it takes time before prices adjust to purchasing power parity.

5.3.4 Granger Causality

In this section we continue the analysis of the relationship between the variables in our model by estimating the bivariate Granger causality between these variables. Granger causality in the case of two timeseries X and Y is present, when the variable Y can be better predicted using the historical values of both X and Y than the values of Y alone. In this case the variable X is said to Granger cause Y.

We are only able to test the stationary first-differenced short-term relation between our variables and not the causality within the long-run Error Correction Term in levels. Table 14 presents the bivariate granger causality results of model Ia.

Table 14: Granger Causality Model Ia

Dependent variable	Excluded variable					
	Δ GDP	Δ Oil price	Δ REER	Δ M3	Δ Ref. rate	All
Δ GDP	-	5.5834	6.3720*	1.9689	8.4714**	41.056***
Δ Oil price	5.1397	-	8.9160**	2.4994	0.8587	16.3967
Δ REER	3.2369	2.0590	-	3.6630	3.9460	20.6014*
Δ M3	7.1692*	3.5784	2.5678	-	3.7956	14.0843
Δ Ref. rate	11.4492***	6.5601*	5.5391	2.4146	-	21.5872**

notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Value given is chi-square statistic. Degrees of freedom per variable is 3 (4x3 for all variables).

Within model Ia we find that there is no short-term Granger causality running from the oil price to GDP as we cannot reject the null hypothesis of no causality. We do find that the Real Effective Exchange Rate and the Refinancing Rate of the ECB Granger cause GDP in the short-run. We find that GDP also Granger causes the Refinancing rate in the short-run, which leads to a bidirectional relationship. Combined, all variables do Granger cause changes in GDP in the short-run.

We find that, within model Ia, the exchange rate Granger causes changes in the oil price. The exchange rate itself is not Granger caused in the short-run by any of the variables in the model. This is interesting, as we would have expected the money supply M3 to Granger cause the exchange rate REER in the short-run.

We now compare the results of model Ia to the results of the Granger causality tests on model IIa, which are presented in Table 15. In model IIa we observe that none of the variables in the model individually Granger causes the unemployment rate in the short-term; combined they do have a significant effect on the unemployment rate. Similar to model Ia we find that the exchange rate REER is the only variable to have a significant causal relation to the oil price.

The exchange rate REER is Granger caused only by the unemployment rate. The same goes for the money supply M3, which is also Granger caused by the unemployment rate. The refinancing

Table 15: Granger Causality Model IIa

Dependent variable	Excluded variable					
	Δ Un. rate	Δ Oil price	Δ REER	Δ M3	Δ Ref. rate	All
Δ Un. rate	-	2.0992	5.5821	2.1105	5.6766	26.1449**
Δ Oil price	3.4842	-	6.8576*	4.4151	1.5620	14.8635
Δ REER	6.3659*	5.8811	-	0.3789	4.2496	18.9688*
Δ M3	7.3729*	2.3620	4.6523	-	2.5630	19.2423*
Δ Ref. rate	8.5526**	7.0983*	5.2241	2.3776	-	18.3692

notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Value given is chi-square statistic. Degrees of freedom per variable is 3 (4x3 for all variables).

rate is Granger caused according to these results by both the unemployment rate and the oil price. Before we jump to any preliminary conclusions regarding the causal relations in our model, it is important to stress that these are only the one-period causal relations. We know that most variables, in particular oil price shocks, will need more than one lag period of three months to affect other variables in the model.

Changing the real exchange rate of the Euro in the Granger causality tests for the nominal exchange rate of the Euro did not yield any different results. We therefore find it superfluous to include their full tables in this section as no alternative conclusions are derived.

6 Discussion

Following similar policy measures in the United States, the United Kingdom and Japan, the European Central Bank followed suit on the 22nd of January 2015 by implementing quantitative easing. This controversial monetary policy measure, sometimes referred to as a measure of last resort, was considered the last policy option left to the ECB after they had already gradually lowered the refinancing rate to near zero since the start of the financial crisis in 2008. Today, the QE policy of the European Central Bank is praised by the monetary authorities themselves (Black and Speciale, 2015). However, the QE policy is also linked to serious adverse effects, such as potential bubble in the housing market and stock markets (Zabrodzka, 2015).

Whereas the effect of QE in the United States, United Kingdom and Japan can be separated in quite straightforward fashion from other shocks on their national output, the situation in the Eurozone has been much different over the past year. In the fall of 2014 we observed an unprecedented decline in the global price of crude oil. Following decreased demand form emerging economies and the exploration of new shale gas fields the international markets responded: over the past nine months a barrel of crude oil lost 40% of its value.

In this paper we find that both the oil price effect, as well as the quantitative easing policy through the exchange rate, have an effect on the Eurozone output measured by either GDP or the unemployment rate. The real question is: was it a necessity, as the ECB claims, to implement quantitative easing policy in the Eurozone given all the adverse effects it can have? We conclude, even though the exchange rate deprecation will have a positive effect after four quarters, that it is in fact the decreased oil price that gives the largest boost to the Eurozone economy in the second quarter of 2015.

This conclusion undermines the legitimacy of the QE policy implemented by the ECB. In the defence of the central bank, the current oil price decline has been of an unprecedented size and was not expected by most analysts. Critical questions could however certainly be asked, given the possible adverse effects of QE. The international war on currency depreciation, combined by the creation of a potential bubble on the stock markets, challenges the necessity and effectiveness of the QE policy.

We hope that our analysis will encourage the policy makers at the ECB to critically reflect on the continued duration of QE policy. The minimal result of the conclusions derived in this paper is a call for humbleness from the ECB. The boost in output was not caused by their intervention, but it is due in majority to a factor they do not control: the oil price formed on the international commodity markets. Given the lagged effects of the oil price shock, recovery in the Eurozone as a consequence of lower oil prices is just setting off.

7 Conclusion

In this paper we set out to estimate the relative effect of the 2014 oil price shock in combination with the quantitative easing policy of the European Central Bank from January 2015. We used a vector error correction model based on historic data over the period 1999Q1 until 2015Q1 to assess the impact of the oil price shock and the effect of QE through the exchange rate on aggregate output of the Eurozone, measured by the GDP and the unemployment rate. In addition, we control for the effect of other shocks due to a change in the money supply M3 or a change in the refinancing rate of the ECB.

We find that, as there is a time discrepancy between the fall in oil prices and the implementation of QE, the growth of GDP and the decrease in unemployment rate during the second quarter of 2015 is due more to the decrease in the oil price than to the implemented QE policy. This is a robust result, using either the real exchange rate or the nominal exchange rate.

We explain this effect by pointing at the lagged influence of an oil price shock on the real economy. We find that it takes at least three quarters for an oil price shock to have an influence on the Eurozone GDP or the unemployment rate. In addition, we observe that the exchange rate effect of QE has a J-curve effect on the aggregate economy. As such, its effects after two quarters on the aggregate economy are negative, or ambiguous at best.

Our findings have strong policy implications. It turns out that the economic recovery of the second quarter of 2015 is probably due more to the decline in oil prices than the QE policy of the ECB. For this reason, critical questions could be raised regarding the necessity of this controversial monetary policy measure. In addition, our paper adds to the rich field of economic research on oil price shocks. This paper contributes by being the first to research the effect of such a shock on the aggregate Eurozone, in particular controlling specifically for extraordinary monetary policy from the ECB.

Future research to assess the combined impact of the 2014Q3 oil price shock and the 2015Q1 QE policy should incorporate data that is not present at this point in time. Preferably at least six quarters after the initial oil price shock should be incorporated, so that the full effect can be captured after all the lagged effects of the initial shock have worked through to the aggregate economy.

A second recommendation to extend this research would be to incorporate more commodity prices into the multivariate model. In praticular the price of natural gas is closely linked to the crude oil price, and might therefore have additional explanatory power.

A Appendices

A.1 Net imports of Crude oil

As explained in the literature we expect an oil price shock to have a different effect on either an oil importing or an oil exporting country. In this paper we examine the Eurozone, and thereby assume that it is a homogenous group: either all countries are importers or all countries are exporters of crude oil.

Table 16 was produced by subtracting the crude oil exports per Eurozone country from its crude oil imports, which leads to the net imports of crude oil per country. We observe that Estonia is the only exporter of crude oil in the Eurozone. In comparison to the rest of the Eurozone, the amount of oil exported by Estonia is however negligible. All other Eurozone countries are net importers of crude oil, with Germany, Italy, the Netherlands and France being the largest importers of crude oil. We can also see that the total import of crude oil by the Eurozone has been declining since its peak in 2005.

Table 16: Annual net import of crude oil (thousands of barrels per day)

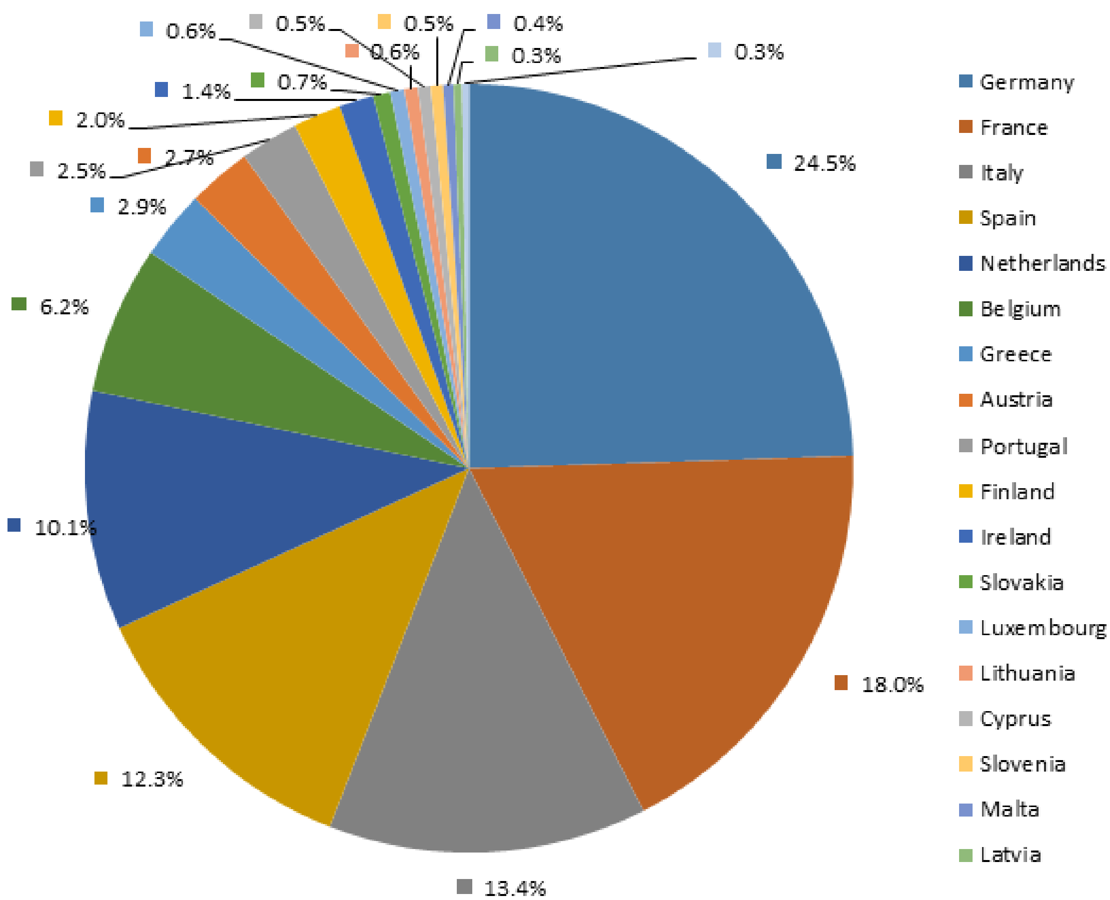
Country	1999	2001	2003	2005	2007	2009	2011	2013
Austria	171.4	170.3	164.4	163.3	161.4	162.5	165	158.8
Belgium	653.6	673.9	731.2	649.3	659.8	595.6	565.6	563.5
Cyprus	23.7	23.1	19.4	NA	NA	NA	NA	NA
Estonia	-1.2	-2.5	-3.3	-3.5	-5.8	-8.3	-8.4	-11.7
Finland	228.5	237.0	247.7	219.7	250.9	232.9	230.5	236.0
France	1649.0	1720.1	1735.1	1714.3	1634.2	1458.7	1303.9	1125.0
Germany	2086.4	2126.6	2147.5	2265.8	2149.0	1978.2	1819.7	1829.0
Greece	344.5	402.7	402.2	406.8	458.5	411.7	368.5	466.2
Ireland	59.6	71.0	65.4	67.3	69.3	54.9	61.9	61.6
Italy	1775.9	1837.7	1847.3	1912.1	1913.4	1624.7	1558.3	1317.6
Lithuania	88.6	148.1	140.5	192.6	154.2	179.4	189.4	NA
Netherlands	1233.9	1278.4	1204.3	1297.1	1239.8	1246.9	1201.0	1155.3
Portugal	287.6	266.9	284.0	289.7	274.8	227.1	217.1	282.4
Slovakia	106.5	109.5	111.5	109.7	122.1	114.3	120.4	117.4
Spain	1181.7	1147.5	1161.7	1205.2	1175.6	1112.7	1120.5	1148.4
Eurozone-19	9896.1	10210.2	10258.8	10489.2	10257.0	9391.3	8913.5	8449.5

Notes: missing data marked by NA; no country data available for Latvia, Luxembourg and Malta. Data retrieved from the US Energy Information Administration .

A.2 Annual Consumption of Crude oil

Figure 9 gives the share of total crude oil consumption per Eurozone member state as a share of total Eurozone consumption over the year 2013. We observe that over half of the crude oil consumption within the Eurozone originates from three countries: Germany, France, and Italy. If we include Spain and the Netherlands we find that these five countries combined consume over 75% of all crude oil within the Eurozone.

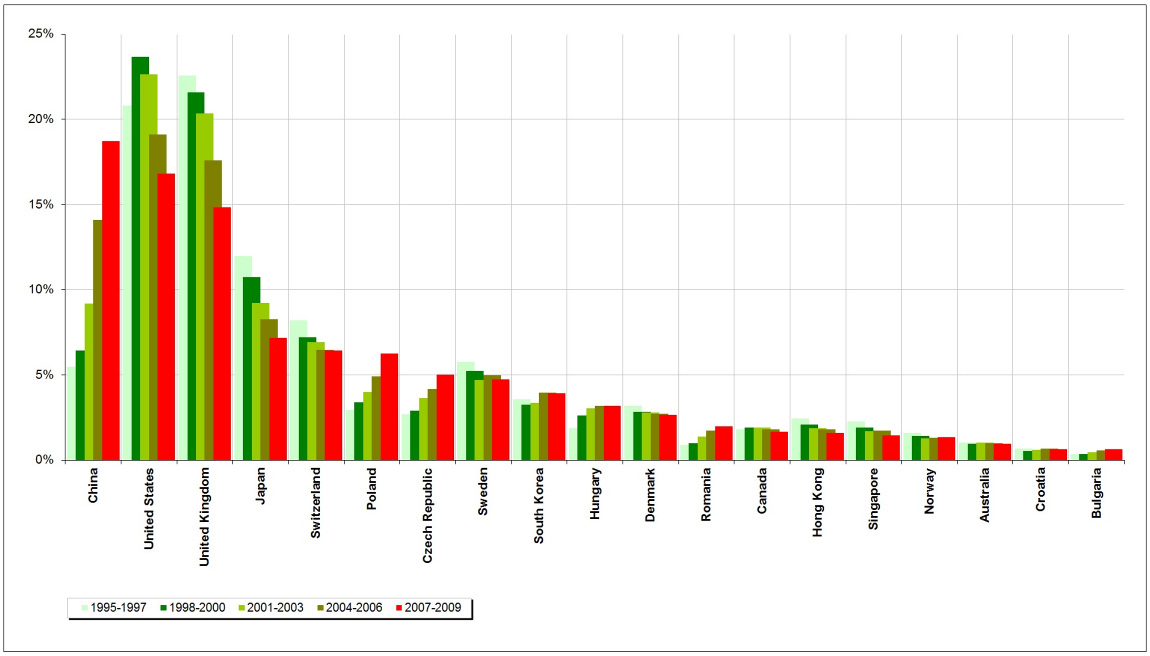
Figure 9: Crude oil consumption as a share of total Eurozone consumption (year 2013)



A.3 Composition of the Real and Nominal Effective Exchange Rate

The Real Effective Exchange Rate (REER) and the Nominal Effective Exchange Rate (NEER) are measures of the Euro exchange rate relative to the currencies of the largest nineteen trading partners of the Eurozone. To arrive at the Effective Exchange Rate we first determine the relative trade weight of the largest trading partners of the Eurozone. Figure 10 below, which was taken from the ECB's statistical Data Warehouse, shows the relative weights of the trading partners of the Eurozone and therefore the relative weight of their currencies in the construction of the Effective Exchange Rate. The country weights are revised on a three-year basis and sum to one.

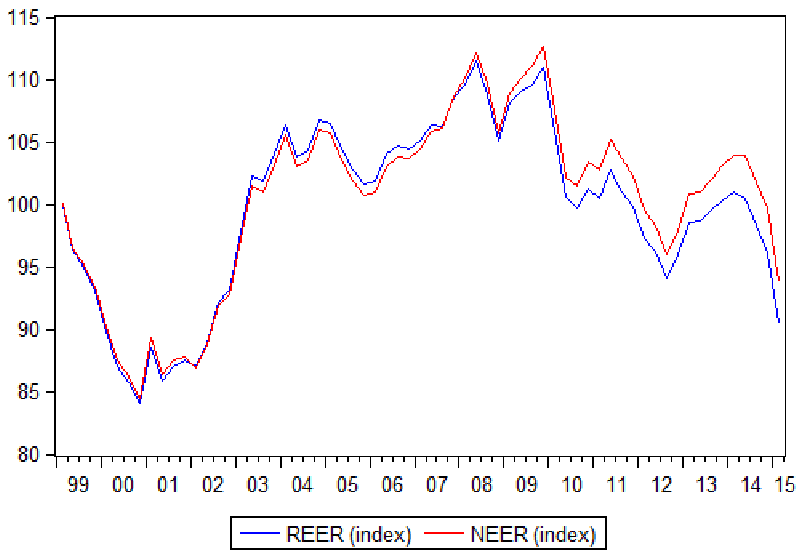
Figure 10: Current trade weights underlying the Effective Exchange Rate



The strength of the Euro currency versus the basket of countries and weights in Figure 10 can then be used to create an index. The intuition behind the Effective Exchange Rate is that when the index goes up, more foreign currency can be obtained for one euro. A higher index therefore corresponds to a stronger international position of the Euro currency. The base year of the index is 1999.

The Effective Exchange Rate comes in two versions: the nominal (NEER) and real effective exchange rate (REER). Whereas the NEER takes the nominal value of the Euro currency versus its trading partners, the REER deflates this by the Consumper Price Index and thereby gives the real buying power of the Euro currency versus the other currency. It equals the price of a similar basket of goods in different countries. The two series are plotted together in Figure 11.

Figure 11: Nominal and Real effective exchange rate



When comparing the REER and NEER over the time period 1999Q1 until 2015Q1 we observe only minimal differences over time. The correlation between the two series is 0.98, which indicates strong comovement over time.

A.4 LM test for autocorrelation

In this appendix we test for the autocorrelation of the estimated VEC-models. Model Ia and model Ib, with GDP as the dependent variable, are estimated with 4 lags and 2 cointegrated equations. Model IIa and model IIb, with the unemployment rate as the dependent variable, are estimated with 4 lags and 1 cointegrated equation.

Table 17: Autocorrelation LM-test VEC-models

	Model Ia		Model Ib		Model IIa		Model IIb	
Lags	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob	LM-Stat	Prob
1	33.80664	0.1121	33.78714	0.1125	28.84891	0.2703	25.78104	0.4194
2	19.40970	0.7771	19.18570	0.7881	18.78126	0.8075	18.50334	0.8203
3	44.75811	0.0089	44.64052	0.0092	33.11613	0.1282	32.37894	0.1473
4	18.33393	0.8279	18.29083	0.8298	20.76829	0.7055	21.83526	0.6452
5	21.48384	0.6653	21.82989	0.6455	24.96640	0.4643	25.44060	0.4379
6	19.48747	0.7732	20.11294	0.7409	14.18072	0.9585	14.26069	0.9570
7	24.70124	0.4792	23.92419	0.5238	25.38822	0.4408	25.64395	0.4268
8	22.95222	0.5804	23.45234	0.5512	23.25355	0.5628	22.88405	0.5843
9	11.69847	0.9888	10.94366	0.9932	18.31129	0.8289	17.58917	0.8593
10	19.75149	0.7597	19.80799	0.7568	11.20010	0.9919	11.79629	0.9881
11	23.66575	0.5387	23.09863	0.5718	26.54836	0.3788	25.47991	0.4358
12	28.82558	0.2713	28.43843	0.2881	30.69489	0.1993	28.65068	0.2788

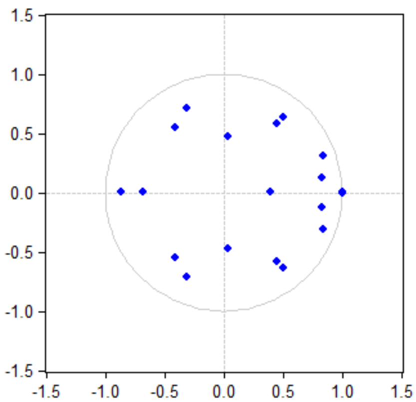
Notes: probabilities from chi-square distribution with 25 degrees of freedom.

Table 17 shows that our VEC-models are free from autocorrelation with the exception of the third lag in model Ia and model Ib. Including more lags will however also result in redundant lags, which is why we keep both models at 4 included lags.

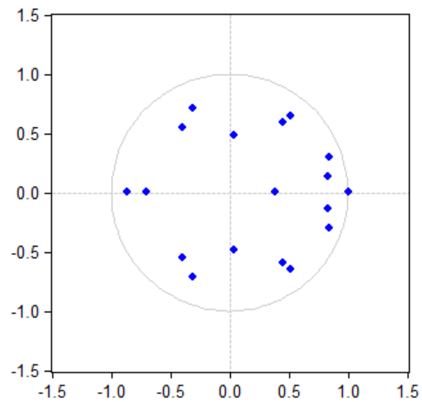
A.5 Stability of VEC-models

Figure 12 shows the stability of our four models. If we have K variables and r cointegrated equations, we find $K - r$ unit moduli. This matches our four models where model Ia and model Ib have 3 unit moduli and model IIa and model IIb have 4 unit moduli. Although there is no universal theory on the necessary distance of the other ranks to one, we find that the distance from one is sufficient for both models (StataCorp., 2013).

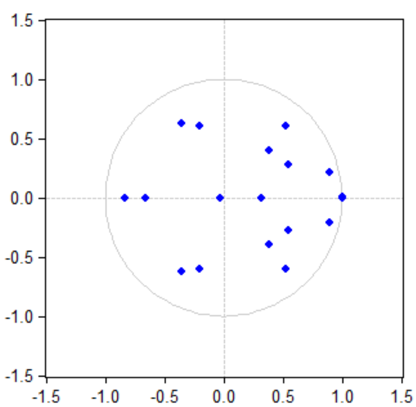
Figure 12: Stability circle of eigenvalues



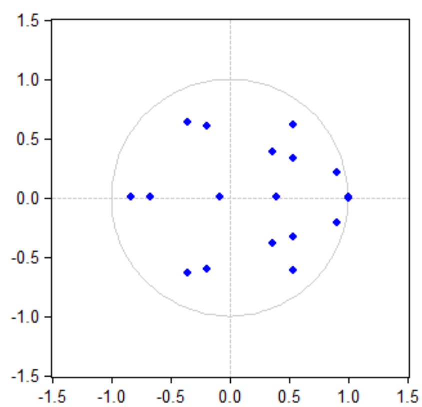
(a) Model Ia



(b) Model Ib



(c) Model IIa



(d) Model IIb

A.6 VEC-model Ia: the effect on GDP including REER

In this section we present the vector error correction estimates of model Ia, including the variables GDP, $Oil\,price$, $REER$, $M3$, and the $Refinancing\,rate$. The cointegrated equations are given in the top part of table 18, indicating the long-run equilibrium relationship. The short-term effects are included up to four lags in the output below.

Table 18: VEC-model Ia

Cointegrating Eq:	CointEq1	CointEq2			
GDP(-1)	1.000000	0.000000			
Oil price(-1)	0.000000	1.000000			
REER(-1)	-0.060514**	-1.163341			
	(0.02308)	(1.21967)			
M3(-1)	-0.202129***	-0.681654			
	(0.00895)	(0.47273)			
Ref. rate(-1)	-0.001472	0.107481			
	(0.00159)	(0.08409)			
Constant	-22.19515	21.47851			
Error Correction:	D(GDP)	D(Oil price)	D(REER)	D(M3)	D(Ref. rate)
CointEq1	-0.151539*	1.550995	1.449403***	0.649382***	-2.571244
	(0.08706)	(2.69468)	(0.49211)	(0.17325)	(6.55609)
CointEq2	-0.003917	-0.200943**	-0.017098	-0.009215*	-0.060840
	(0.00271)	(0.08388)	(0.01532)	(0.00539)	(0.20407)
D(GDP(-1))	0.805782***	4.614685	-0.003978	0.182741	32.22276***
	(0.16949)	(5.24586)	(0.95802)	(0.33727)	(12.7630)
D(GDP(-2))	0.173631	3.686616	-0.018556	-0.940078***	14.88148
	(0.17888)	(5.53638)	(1.01107)	(0.35595)	(13.4699)
D(GDP(-3))	0.075720	-8.282634*	-1.460671*	-0.076856	-12.34221
	(0.14377)	(4.44974)	(0.81263)	(0.28609)	(10.8261)
D(Oil price(-1))	0.004653	0.363744**	0.028754	0.002993	0.481650
	(0.00546)	(0.16906)	(0.03087)	(0.01087)	(0.41131)
D(Oil price(-2))	-0.010627*	-0.454826***	-0.013767	0.019332*	-0.973028**
	(0.00559)	(0.17306)	(0.03160)	(0.01113)	(0.42105)
D(Oil price(-3))	-0.003888	0.317507*	-0.025618	0.003170	0.469159
	(0.00571)	(0.17679)	(0.03229)	(0.01137)	(0.43012)
D(REER(-1))	0.038837	1.349819*	0.115945	0.030811	1.337853
	(0.02618)	(0.81026)	(0.14797)	(0.05209)	(1.97134)

Table 18: continued

D(REER(-2))	-0.015227	-0.675485	0.034708	-0.049288	-3.935725**
	(0.02629)	(0.81379)	(0.14862)	(0.05232)	(1.97994)
D(REER(-3))	-0.048631*	-1.776672**	-0.062002	0.074299	-1.417888
	(0.02653)	(0.82121)	(0.14997)	(0.05280)	(1.99798)
D(M3(-1))	-0.061334	-1.150881	-0.381205	-0.038790	-0.489554
	(0.07289)	(2.25605)	(0.41201)	(0.14505)	(5.48890)
D(M3(-2))	0.044250	-2.157628	-0.599136*	0.305043**	-2.631680
	(0.06395)	(1.97923)	(0.36145)	(0.12725)	(4.81541)
D(M3(-3))	0.080778	2.143847	-0.069538	-0.310936**	6.008838
	(0.06634)	(2.05340)	(0.37500)	(0.13202)	(4.99587)
D(Ref. rate(-1))	0.003613	-0.032980	-0.025601*	0.004275	0.063903
	(0.00248)	(0.07690)	(0.01404)	(0.00494)	(0.18709)
D(Ref. rate(-2))	-0.004829*	0.060725	-0.004954	-0.003151	0.028352
	(0.00257)	(0.07964)	(0.01454)	(0.00512)	(0.19375)
D(Ref. rate(-3))	0.004232*	0.013570	0.011492	0.008208	-0.065279
	(0.00252)	(0.07793)	(0.01423)	(0.00501)	(0.18961)
Constant	-0.000670	0.025334	0.017698*	0.015925***	-0.178578
	(0.00179)	(0.05541)	(0.01012)	(0.00356)	(0.13482)
R-squared	0.753913	0.470990	0.409717	0.706702	0.537574
Adj. R-squared	0.656623	0.261847	0.176349	0.590747	0.354755
Sum sq. resids	0.000621	0.595269	0.019853	0.002461	3.523610
S.E. equation	0.003801	0.117658	0.021487	0.007565	0.286259
F-statistic	7.749114	2.251995	1.755668	6.094620	2.940463
Log likelihood	264.0249	54.64804	158.3682	222.0510	0.412082
Akaike AIC	-8.066389	-1.201575	-4.602236	-6.690196	0.576653
Schwarz SC	-7.443508	-0.578694	-3.979355	-6.067315	1.199534
Mean dependent	0.002612	0.012330	-0.000469	0.013100	-0.048361
S.D. dependent	0.006487	0.136946	0.023676	0.011825	0.356367

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

A.7 VEC-model Ib: the effect on GDP including NEER

In this section we present the vector error correction estimates of model Ib, including the variables GDP, $Oil\,price$, $NEER$, $M3$, and the $Refinancing\,rate$. The cointegrated equations are given in the top part of table 19, indicating the long-run equilibrium relationship. The short-term effects are included up to four lags in the output below.

Table 19: VEC-model Ib

Cointegrating Eq:	CointEq1	CointEq2			
GDP(-1)	1.000000	0.000000			
Oil price(-1)	0.000000	1.000000			
NEER(-1)	-0.063840**	-0.955813			
	(0.02666)	(1.32309)			
M3(-1)	-0.200394***	-0.767815			
	(0.00980)	(0.48647)			
Ref. rate(-1)	-0.001477	0.092854			
	(0.00158)	(0.07862)			
Constant	-22.23079	23.11779			
Error Correction:	D(GDP)	D(Oil price)	D(NEER)	D(M3)	D(Ref. rate)
CointEq1	-0.144121*	1.344206	1.434675***	0.634111***	-3.115661
	(0.08479)	(2.61109)	(0.48701)	(0.16752)	(6.34462)
CointEq2	-0.004244	-0.207564**	-0.016186	-0.009023	-0.034022
	(0.00288)	(0.08871)	(0.01654)	(0.00569)	(0.21554)
D(GDP(-1))	0.806171***	4.822125	-0.035428	0.184406	32.73135**
	(0.17016)	(5.24034)	(0.97740)	(0.33620)	(12.7334)
D(GDP(-2))	0.173635	3.537588	0.120074	-0.929625***	15.33265
	(0.17960)	(5.53116)	(1.03164)	(0.35486)	(13.4400)
D(GDP(-3))	0.068248	-8.113693*	-1.552212*	-0.065981	-12.27959
	(0.14311)	(4.40721)	(0.82201)	(0.28275)	(10.7090)
D(Oil price(-1))	0.004985	0.378815**	0.032796	0.003175	0.490798
	(0.00553)	(0.17017)	(0.03174)	(0.01092)	(0.41349)
D(Oil price(-2))	-0.010527*	-0.453872***	-0.017909	0.019104*	-0.987673**
	(0.00566)	(0.17433)	(0.03252)	(0.01118)	(0.42360)
D(Oil price(-3))	-0.003518	0.336552*	-0.028849	0.003371	0.490389
	(0.00575)	(0.17710)	(0.03303)	(0.01136)	(0.43034)
D(NEER(-1))	0.035079	1.385973*	0.104940	0.032061	1.339923
	(0.02545)	(0.78364)	(0.14616)	(0.05028)	(1.90413)

Table 19: continued

D(NEER(-2))	-0.015622	-0.678262	0.016301	-0.047521	-3.885817**
	(0.02545)	(0.78372)	(0.14618)	(0.05028)	(1.90435)
D(NEER(-3))	-0.047840*	-1.625297**	-0.074892	0.076636	-1.261722
	(0.02577)	(0.79370)	(0.14804)	(0.05092)	(1.92859)
D(M3(-1))	-0.062081	-1.128675	-0.367336	-0.034151	-0.313863
	(0.07334)	(2.25876)	(0.42129)	(0.14491)	(5.48850)
D(M3(-2))	0.044831	-2.118397	-0.652098*	0.300489**	-2.469902
	(0.06458)	(1.98872)	(0.37092)	(0.12759)	(4.83234)
D(M3(-3))	0.083668	2.222763	-0.085908	-0.318616**	6.194809
	(0.06711)	(2.06683)	(0.38549)	(0.13260)	(5.02212)
D(Ref. rate(-1))	0.003525	-0.035580	-0.025944*	0.004235	0.054043
	(0.00251)	(0.07728)	(0.01441)	(0.00496)	(0.18777)
D(Ref. rate(-2))	-0.004954*	0.061715	-0.005520	-0.003095	0.028631
	(0.00260)	(0.07992)	(0.01491)	(0.00513)	(0.19420)
D(Ref. rate(-3))	0.004267*	0.016953	0.012219	0.007984	-0.066445
	(0.00254)	(0.07832)	(0.01461)	(0.00502)	(0.19031)
Constant	-0.000697	0.022459	0.019034*	0.015909***	-0.187286
	(0.00180)	(0.05542)	(0.01034)	(0.00356)	(0.13467)
R-squared	0.751063	0.470189	0.407573	0.707502	0.538053
Adj. R-squared	0.652645	0.260729	0.173358	0.591863	0.355423
Sum sq. resids	0.000629	0.596170	0.020739	0.002454	3.519957
S.E. equation	0.003823	0.117747	0.021962	0.007554	0.286111
F-statistic	7.631420	2.244765	1.740166	6.118202	2.946139
Log likelihood	263.6736	54.60189	157.0361	222.1343	0.443714
Akaike AIC	-8.054872	-1.200062	-4.558559	-6.692926	0.575616
Schwarz SC	-7.431991	-0.577181	-3.935678	-6.070046	1.198497
Mean dependent	0.002612	0.012330	6.16E-05	0.013100	-0.048361
S.D. dependent	0.006487	0.136946	0.024155	0.011825	0.356367

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

A.8 VEC-model IIa: the effect on unemployment including REER

In this section we present the vector error correction estimates of model IIa, including the variables $Unemployment\,rate$, $Oil\,price$, $REER$, $M3$, and the $Refinancing\,rate$. The cointegrated equations are given in the top part of table 20, indicating the long-run equilibrium relationship. The short-term effects are included up to four lags in the output below.

Table 20: VEC-model IIa

Cointegrating Eq:	CointEq1				
Un. rate(-1)	1.000000				
Oil price(-1)	-3.284618**				
	(1.27638)				
REER(-1)	4.499882				
	(3.87903)				
M3(-1)	4.661867				
	(3.00734)				
Ref. rate(-1)	0.392011**				
	(0.17386)				
Constant	-156.6136				
Error Correction:	**D(Un. rate)**	**D(Oil price)**	**D(REER)**	**D(M3)**	**D(Ref. rate)**
CointEq1	-0.091729***	0.052392	-0.012591**	-0.003039	0.080360
	(0.02846)	(0.03209)	(0.00557)	(0.00206)	(0.07651)
D(Un. rate(-1))	0.886200***	0.051348	-0.036817	-0.015376	-0.520039
	(0.14385)	(0.16223)	(0.02816)	(0.01043)	(0.38676)
D(Un. rate(-2))	-0.009810	-0.299941	-0.003715	0.018472	-0.582502
	(0.18561)	(0.20932)	(0.03633)	(0.01346)	(0.49904)
D(Un. rate(-3))	0.016709	0.280328**	0.057468**	-0.021698**	0.460427
	(0.14134)	(0.15940)	(0.02767)	(0.01025)	(0.38003)
D(Oil price(-1))	-0.238448	0.500849***	0.005567	-0.003105	0.927462**
	(0.16562)	(0.18678)	(0.03242)	(0.01201)	(0.44530)
D(Oil price(-2))	0.017865	-0.394177**	-0.037609	0.016970	-0.691469
	(0.17061)	(0.19242)	(0.03340)	(0.01237)	(0.45873)
D(Oil price(-3))	-0.015274	0.276851*	-0.050520*	-0.009498	0.429583
	(0.14142)	(0.15949)	(0.02768)	(0.01025)	(0.38024)
D(REER(-1))	-0.769883	1.260751	0.173264	0.072934	0.700336
	(0.74933)	(0.84507)	(0.14668)	(0.05433)	(2.01471)
D(REER(-2))	0.463248	-0.787172	0.048532	-0.033271	-4.242084**

Table 20: continued

	(0.77049)	(0.86895)	(0.15082)	(0.05586)	(2.07162)
D(REER(-3))	1.482365*	-1.589343*	0.015437	0.096803*	-1.223845
	(0.77091)	(0.86941)	(0.15090)	(0.05589)	(2.07273)
D(M3(-1))	0.289233	1.803888	0.160203	0.039031	3.232774
	(2.00934)	(2.26610)	(0.39333)	(0.14569)	(5.40252)
D(M3(-2))	-1.264997	0.542590	-0.138639	0.399306***	-1.556776
	(1.69113)	(1.90722)	(0.33104)	(0.12261)	(4.54692)
D(M3(-3))	-2.104997	2.391807	-0.041867	-0.241906*	3.831026
	(1.84691)	(2.08290)	(0.36153)	(0.13391)	(4.96577)
D(Ref. rate(-1))	-0.124840*	-0.026411	-0.022284*	0.001369	0.153634
	(0.06641)	(0.07490)	(0.01300)	(0.00482)	(0.17856)
D(Ref. rate(-2))	0.096626	0.074837	-0.002126	-0.005343	0.081519
	(0.06859)	(0.07736)	(0.01343)	(0.00497)	(0.18442)
D(Ref. rate(-3))	-0.069084	-0.068925	0.014099	0.006432	-0.280674*
	(0.06268)	(0.07069)	(0.01227)	(0.00454)	(0.16853)
Constant	0.042886	-0.060316	0.001614	0.011132***	-0.118943
	(0.03903)	(0.04401)	(0.00764)	(0.00283)	(0.10493)
R-squared	0.826602	0.390547	0.385702	0.662134	0.488460
Adj. R-squared	0.763548	0.168927	0.162321	0.539274	0.302445
Sum sq. resids	0.539190	0.685788	0.020661	0.002834	3.897853
S.E. equation	0.110699	0.124844	0.021669	0.008026	0.297637
F-statistic	13.10947	1.762240	1.726653	5.389332	2.625921
Log likelihood	57.66588	50.33061	157.1519	217.7365	-2.666588
Akaike AIC	-1.333308	-1.092807	-4.595145	-6.581524	0.644806
Schwarz SC	-0.745031	-0.504530	-4.006869	-5.993248	1.233082
Mean dependent	0.027760	0.012330	-0.000469	0.013100	-0.048361
S.D. dependent	0.227653	0.136946	0.023676	0.011825	0.356367

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

A.9 VEC-model IIb: the effect on unemployment including NEER

In this section we present the vector error correction estimates of model IIb, including the variables *Unemployment rate*, *Oil price*, *NEER*, *M3*, and the *Refinancing rate*. The cointegrated equations are given in the top part of table 21, indicating the long-run equilibrium relationship. The short-term effects are included up to four lags in the output below.

Table 21: VEC-model IIb

Cointegrating Eq:	CointEq1				
Un. rate(-1)	1.000000				
Oil price(-1)	-3.223689**				
	(1.35018)				
NEER(-1)	5.166186				
	(4.71323)				
M3(-1)	4.211454				
	(3.38500)				
Ref. rate(-1)	0.359265*				
	(0.18168)				
Constant	-146.5245				
Error Correction:	D(Un. rate)	D(Oil price)	D(NEER)	D(M3)	D(Ref. rate)
CointEq1	-0.087879***	0.048486	-0.012057**	-0.003096	0.080622
	(0.02737)	(0.03098)	(0.00550)	(0.00199)	(0.07351)
D(Un. rate(-1))	0.888537***	0.046988	-0.038840	-0.015431	-0.519807
	(0.14338)	(0.16229)	(0.02881)	(0.01043)	(0.38511)
D(Un. rate(-2))	-0.004265	-0.294796	-0.007186	0.018104	-0.590945
	(0.18497)	(0.20936)	(0.03717)	(0.01345)	(0.49681)
D(Un. rate(-3))	0.001456	0.283967*	0.059943**	-0.021169**	0.467440
	(0.13953)	(0.15793)	(0.02804)	(0.01015)	(0.37476)
D(Oil price(-1))	-0.225814	0.495441***	0.011313	-0.002860	0.933997**
	(0.16434)	(0.18601)	(0.03302)	(0.01195)	(0.44139)
D(Oil price(-2))	0.021830	-0.406867**	-0.039595	0.016500	-0.692710
	(0.16954)	(0.19190)	(0.03407)	(0.01233)	(0.45537)
D(Oil price(-3))	-0.007029	0.284329*	-0.053733*	-0.009393	0.428831
	(0.14163)	(0.16030)	(0.02846)	(0.01030)	(0.38039)
D(NEER(-1))	-0.650769	1.212698	0.155026	0.069569	0.528726
	(0.72737)	(0.82328)	(0.14616)	(0.05289)	(1.95363)
D(NEER(-2))	0.426842	-0.814430	0.024514	-0.036237	-4.223967**

Table 21: continued

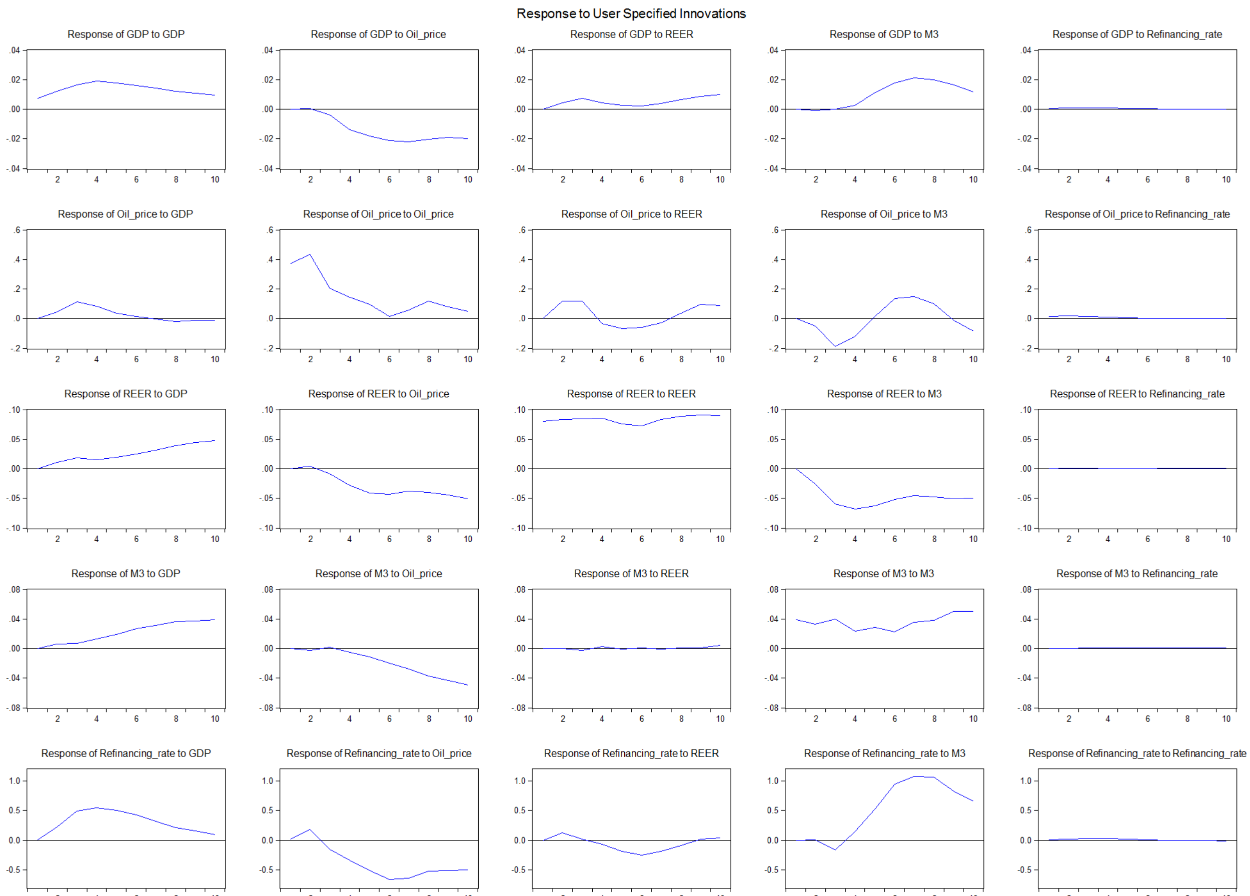
	(0.74077)	(0.83845)	(0.14885)	(0.05386)	(1.98962)
D(NEER(-3))	1.569771**	-1.504201*	-0.010741	0.092684*	-1.264696
	(0.74805)	(0.84669)	(0.15031)	(0.05439)	(2.00918)
D(M3(-1))	0.274242	1.813039	0.163117	0.043291	3.322247
	(2.00573)	(2.27019)	(0.40303)	(0.14584)	(5.38712)
D(M3(-2))	-1.406809	0.509278	-0.166380	0.398083***	-1.418980
	(1.69621)	(1.91986)	(0.34084)	(0.12334)	(4.55579)
D(M3(-3))	-2.253609	2.431322	-0.052858	-0.246736*	3.907101
	(1.85325)	(2.09761)	(0.37239)	(0.13475)	(4.97758)
D(Ref. rate(-1))	-0.123222*	-0.027628	-0.023583*	0.001243	0.147608
	(0.06637)	(0.07512)	(0.01334)	(0.00483)	(0.17826)
D(Ref. rate(-2))	0.098674	0.074370	-0.003177	-0.005332	0.085003
	(0.06854)	(0.07758)	(0.01377)	(0.00498)	(0.18410)
D(Ref. rate(-3))	-0.072915	-0.067948	0.014737	0.006113	-0.277599
	(0.06267)	(0.07094)	(0.01259)	(0.00456)	(0.16834)
Constant	0.045685	-0.059864	0.002609	0.011070***	-0.120226
	(0.03900)	(0.04415)	(0.00784)	(0.00284)	(0.10476)
R-squared	0.827507	0.389338	0.381356	0.661963	0.492200
Adj. R-squared	0.764782	0.167279	0.156394	0.539041	0.307546
Sum sq. resids	0.536376	0.687148	0.021657	0.002836	3.869350
S.E. equation	0.110410	0.124968	0.022186	0.008028	0.296546
F-statistic	13.19268	1.753311	1.695203	5.385209	2.665522
Log likelihood	57.82549	50.27019	155.7153	217.7210	-2.442736
Akaike AIC	-1.338541	-1.090826	-4.548043	-6.581017	0.637467
Schwarz SC	-0.750264	-0.502550	-3.959766	-5.992741	1.225743
Mean dependent	0.027760	0.012330	6.16E-05	0.013100	-0.048361
S.D. dependent	0.227653	0.136946	0.024155	0.011825	0.356367

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors in brackets.

A.10 Impulse response functions model Ia

In this section we present all the impulse response functions of model Ia. Figure 13 presents the response of the variables to the percentage change of the other variables in the model over the period 2014Q3 until 2015Q1; these relative changes are presented in Table 13. These changes are fitted on the diagonal axis of the Covariance matrix of the VEC-model.

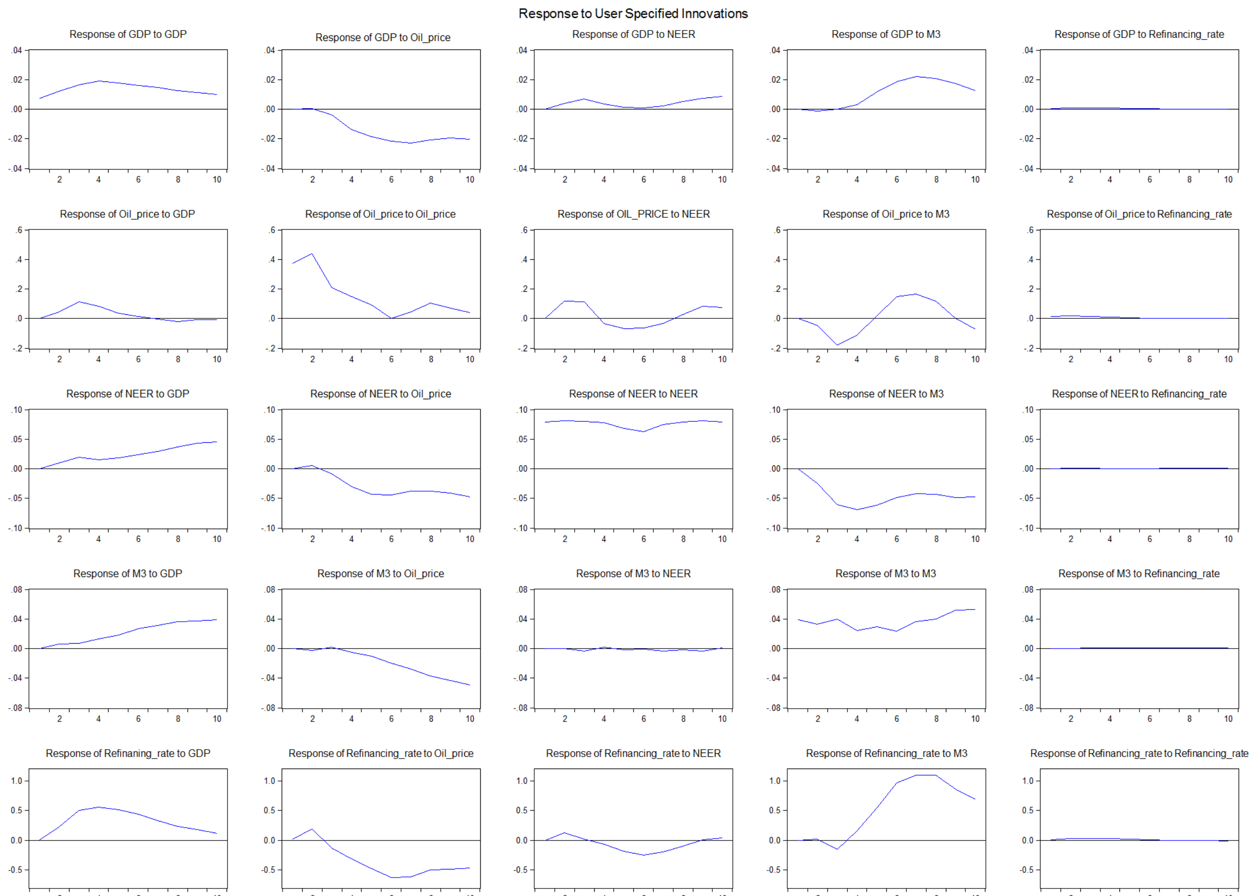
Figure 13: Impulse Response of variables in model Ia



A.11 Impulse response functions model Ib

In this section we present all the impulse response functions of model Ib. Figure 14 presents the response of the variables to the percentage change of the other variables in the model over the period 2014Q3 until 2015Q1; these relative changes are presented in Table 13. These changes are fitted on the diagonal axis of the Covariance matrix of the VEC-model.

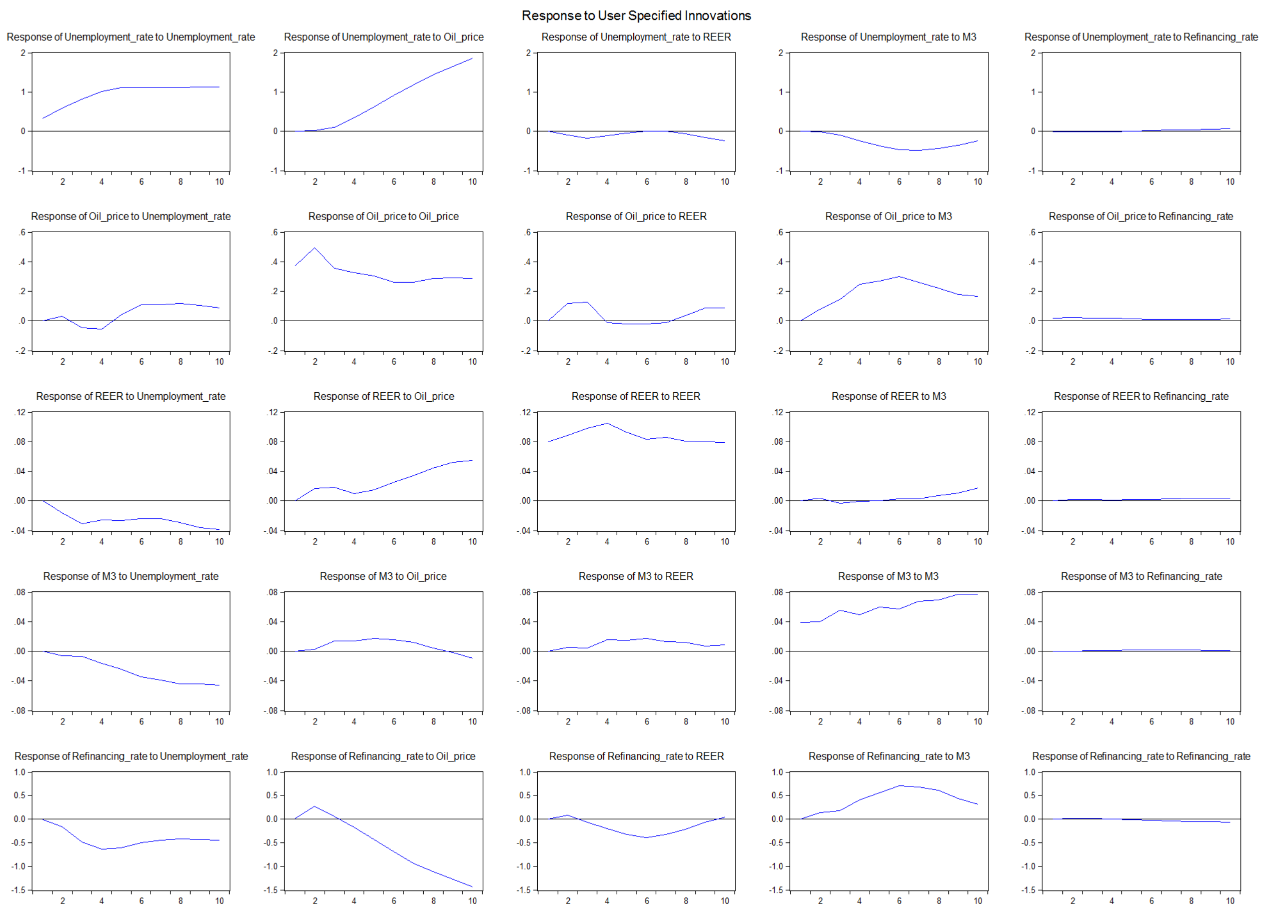
Figure 14: Impulse Response of variables in model Ib



A.12 Impulse response functions model IIa

In this section we present all the impulse response functions of model IIa. Figure 15 presents the response of the variables to the percentage change of the other variables in the model over the period 2014Q3 until 2015Q1; these relative changes are presented in Table 13. These changes are fitted on the diagonal axis of the Covariance matrix of the VEC-model.

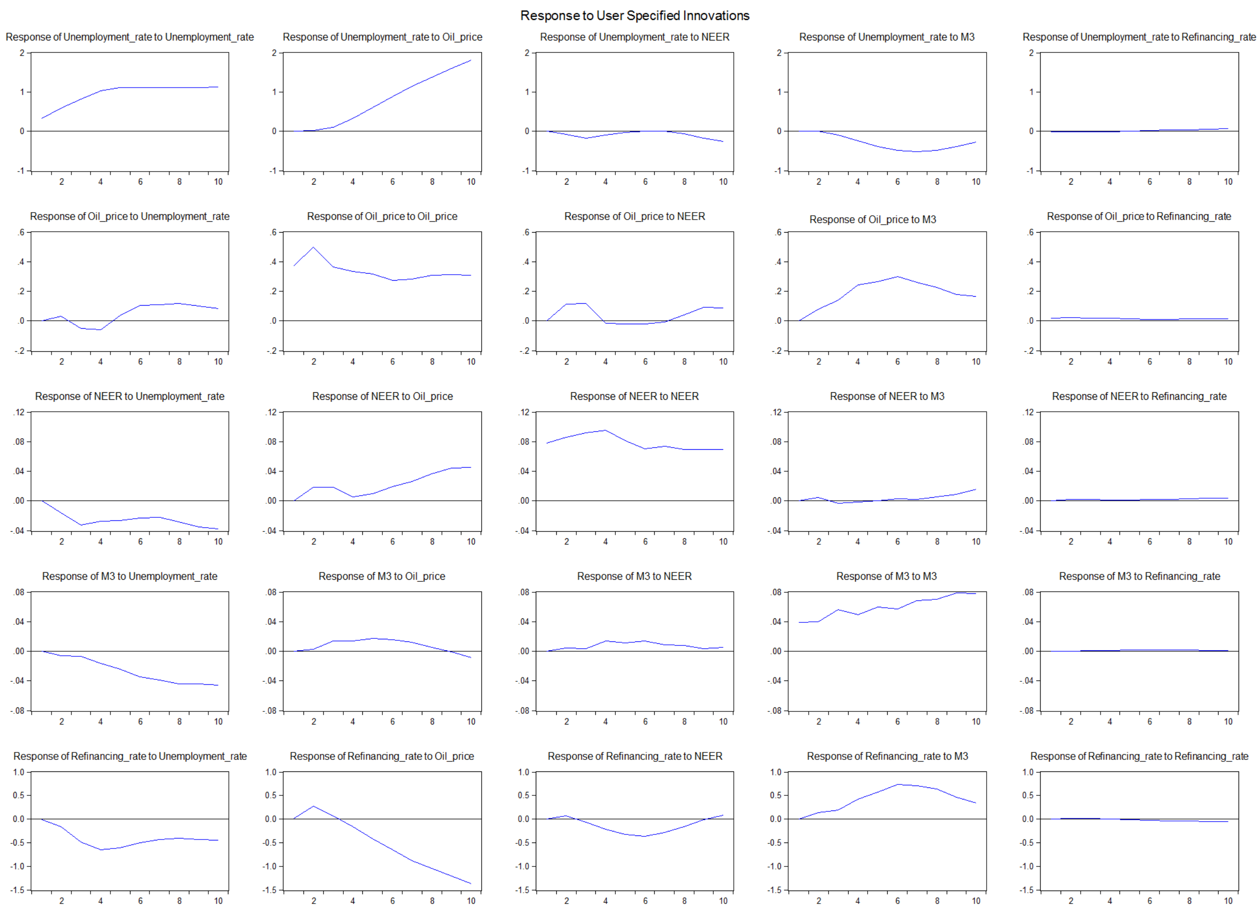
Figure 15: Impulse Response of variables in model IIa



A.13 Impulse response functions model IIb

In this section we present all the impulse response functions of model IIb. Figure 16 presents the response of the variables to the percentage change of the other variables in the model over the period 2014Q3 until 2015Q1; these relative changes are presented in Table 13. These changes are fitted on the diagonal axis of the Covariance matrix of the VEC-model.

Figure 16: Impulse Response of variables in model IIb



References

Abeysinghe, T. (2001). Estimation of direct and indirect impact of oil price on growth. *Economics letters*, 73(2):147–153.

Akaike, H. (1977). Canonical correlation analysis of time series and the use of an information criterion. *Computational Methods for Modeling of Nonlinear Systems*, 126:27.

Bahmani-Oskooee, M. and Ratha, A. (2004). The j-curve: a literature review. *Applied economics*, 36(13):1377–1398.

Balke, N. S., Brown, S. P., and Yücel, M. K. (2002). Oil price shocks and the us economy: where does the asymmetry originate? *The Energy Journal*, pages 27–52.

Bernanke, B. S., Gertler, M., Watson, M., Sims, C. A., and Friedman, B. M. (1997). Systematic monetary policy and the effects of oil price shocks. *Brookings papers on economic activity*, pages 91–157.

Black, J. and Speciale, A. (2015). Draghi says qe working well; seeks 'full implementation'. `http://tinyurl.com/pscnatv`. accessed: 17-08-2015.

Brooks, C. (2014). *Introductory econometrics for finance*. Cambridge university press.

Brown, S. P. and Yücel, M. K. (2002). Energy prices and aggregate economic activity: an interpretative survey. *The Quarterly Review of Economics and Finance*, 42(2):193–208.

Burbidge, J. and Harrison, A. (1984). Testing for the effects of oil-price rises using vector autoregressions. *International Economic Review*, pages 459–484.

Carruth, A. A., Hooker, M. A., and Oswald, A. J. (1998). Unemployment equilibria and input prices: Theory and evidence from the united states. *Review of economics and Statistics*, 80(4):621–628.

Chen, S.-S. (2009). Oil price pass-through into inflation. *Energy Economics*, 31(1):126–133.

Cohen, A. (2015). Systemic violence threatens middle east outlook. `http://www.ensec.org/`. accessed: 11-06-2015.

Cologni, A. and Manera, M. (2009). The asymmetric effects of oil shocks on output growth: A markov–switching analysis for the g-7 countries. *Economic Modelling*, 26(1):1–29.

Darby, M. R. (1982). The price of oil and world inflation and recession. *The American Economic Review*, pages 738–751.

Davis, S. J. and Haltiwanger, J. (2001). Sectoral job creation and destruction responses to oil price changes. *Journal of monetary economics*, 48(3):465–512.

Dias, F. C. et al. (2013). Oil price shocks and their effects on economic acivity and prices: an application for portugal. *Volume 19, Number 2*.

Dickey, D. A. and Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, 74(366a):427–431.

Emerson, J. (2007). Cointegration analysis and the choice of lag length. *Applied Economics Letters*, 14(12):881–885.

Engle, R. F. and Granger, C. W. (1987). Co-integration and error correction: representation, estimation, and testing. *Econometrica: journal of the Econometric Society*, pages 251–276.

European Commission (2015). Economic and financial affairs: the euro. accessed: 20-05-2015.

Filis, G. and Chatziantoniou, I. (2014). Financial and monetary policy responses to oil price shocks: evidence from oil-importing and oil-exporting countries. *Review of Quantitative Finance and Accounting*, 42(4):709–729.

Ghalayini, L. (2011). The interaction between oil price and economic growth. *Middle Eastern Finance and Economics*, 13:127–141.

Gonzalo, J. (1994). Five alternative methods of estimating long-run equilibrium relationships. *Journal of econometrics*, 60(1):203–233.

Gonzalo, J. and Lee, T.-H. (1998). Pitfalls in testing for long run relationships. *Journal of Econometrics*, 86(1):129–154.

Granger, C. W. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, pages 424–438.

Granger, C. W. and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of econometrics*, 2(2):111–120.

Hacker, R. S. and Hatemi-J, A. (2003). Is the j-curve effect observable for small north european economies? *Open economies review*, 14(2):119–134.

Hamilton, J. D. (1994). *Time series analysis*, volume 2. Princeton university press Princeton.

Hamilton, J. D. (1996). This is what happened to the oil price-macroeconomy relationship. *Journal of Monetary Economics*, 38(2):215–220.

Hamilton, J. D. and Herrera, A. M. (2004). Comment: oil shocks and aggregate macroeconomic behavior: the role of monetary policy. *Journal of Money, Credit and Banking*, pages 265–286.

Hickman, B. G., Huntington, H. G., and Sweeney, J. L. (1987). Macroeconomic impacts of energy shocks.

Hsing, Y. (2008). A study of the j-curve for seven selected latin american countries. *Global Economy Journal*, 8(4).

Ivanov, V. and Kilian, L. (2005). A practitioner's guide to lag order selection for var impulse response analysis. *Studies in Nonlinear Dynamics & Econometrics*, 9(1).

Jiménez-Rodríguez, R. and Sánchez, M. (2005). Oil price shocks and real gdp growth: empirical evidence for some oecd countries. *Applied economics*, 37(2):201–228.

Johansen, S. (1988). Statistical analysis of cointegration vectors. *Journal of economic dynamics and control*, 12(2):231–254.

Jones, D. W., Leiby, P. N., and Paik, I. K. (2004). Oil price shocks and the macroeconomy: what has been learned since 1996. *The Energy Journal*, pages 1–32.

Joyce, M., Lasaosa, A., Stevens, I., Tong, M., et al. (2011). The financial market impact of quantitative easing in the united kingdom. *International Journal of Central Banking*, 7(3):113–161.

Keane, M. P. and Prasad, E. S. (1996). The employment and wage effects of oil price changes: a sectoral analysis. *The Review of Economics and Statistics*, pages 389–400.

Kwiatkowski, D., Phillips, P. C., Schmidt, P., and Shin, Y. (1992). Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root? *Journal of econometrics*, 54(1):159–178.

Lescaroux, F. and Mignon, V. (2008). On the influence of oil prices on economic activity and other macroeconomic and financial variables. *OPEC Energy Review*, 32(4):343–380.

Lilien, D. M. (1982). Sectoral shifts and cyclical unemployment. *The Journal of Political Economy*, pages 777–793.

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media.

Lütkepohl, H., Saikkonen, P., and Trenkler, C. (2001). Maximum eigenvalue versus trace tests for the cointegrating rank of a var process. *The Econometrics Journal*, pages 287–310.

MacKinnon, J. (1996). Numerical distribution functions for unit root and cointegration tests. *Journal of applied econometrics*, 11:601–618.

Magee, S. P. (1973). Currency contracts, pass-through, and devaluation. *Brookings Papers on Economic Activity*, pages 303–325.

Magyereh, A. Oil price shocks and emerging stock markets: a generalized var approach.

Mork, K. A. (1994). Business cycles and the oil market. *The Energy Journal*, pages 15–38.

Murray, M. P. (1994). A drunk and her dog: an illustration of cointegration and error correction. *The American Statistician*, 48(1):37–39.

Nelson, C. R. and Plosser, C. R. (1982). Trends and random walks in macroeconmic time series: some evidence and implications. *Journal of monetary economics*, 10(2):139–162.

Österholm, P. and Hjalmarsson, E. (2007). *Testing for cointegration using the Johansen methodology when variables are near-integrated*. Number 7-141. International Monetary Fund.

Papapetrou, E. (2009). Oil price asymmetric shocks and economic activity: The case of greece. In *Austrian Association for Energy Economics 10th IAEE European Energy Conference from 7-10 September 2009 in Vienna*.

Peersman, G. and Van Robays, I. (2009). Oil and the euro area economy. *Economic Policy*, 24(60):603–651.

Phillips, P. C. and Perron, P. (1988). Testing for a unit root in time series regression. *Biometrika*, 75(2):335–346.

PWC (February 2015). Cheap oil, qe and greece - what does it all mean? `http://preview.thenewsmarket.com/Previews/PWC/DocumentAssets/366848.pdf`. accessed: 01-06-2015.

Randow, J. (2015). Europe's qe quandary, why the ecb is finally buying bonds. `http://www.bloombergview.com/quicktake/europes-qe-quandary`. accessed: 03-06-2015.

Rasche, R. H. and Tatom, J. A. (1977). Energy resources and potential gnp. *Federal Reserve Bank of St. Louis Review*, (Jun):10–24.

Rose, A. K. and Yellen, J. L. (1989). Is there a j-curve? *Journal of Monetary economics*, 24(1):53–68.

Rotemberg, J. J. and Woodford, M. (1996). Imperfect competition and the effects of energy price increases on economic activity. Technical report, National Bureau of Economic Research.

Schwarz, G. et al. (1978). Estimating the dimension of a model. *The annals of statistics*, 6(2):461–464.

Shephard, K. (2013). Financial econometrics notes. https://goo.gl/xhPSR3. accessed: 23-06-2015.

Sims, C. A. (1980). Macroeconomics and reality. *Econometrica: Journal of the Econometric Society*, pages 1–48.

StataCorp. (2013). *Stata: Release 13*. Statacorp LP.

Studenmund, A. H. (2011). Using econometrics: A practical guide.

Tang, W., Wu, L., and Zhang, Z. (2010). Oil price shocks and their short-and long-term effects on the chinese economy. *Energy Economics*, 32:S3–S14.

U.S. Department of State (2015). Milestones 1969-1976. https://history.state.gov/milestones/1969-1976/oil-embargo. accessed: 12-06-2015.

U.S. Energy Information Administration. International energy statistics. http://www.eia.gov. accessed: 14-06-2015.

Zabrodzka, A. (2015). Qe could fuel housing bubbles in europe. https://www.economy.com/dismal/analysis/free/255221. accessed: 17-08-2015.

Zivot, E. and Wang, J. (2007). *Modeling financial time series with S-Plus®*, volume 191. Springer Science & Business Media.