Empirical analysis of the oil market

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Abstract

The aim of this study, is the modeling of the oil market, the identification of several oil price shocks, and the detection of their effect on the Russian economy. We perform an empirical analysis of the determinants of the oil price. Through the estimation of a SVAR model, we identify three oil price shocks, from the demand and the supply side. Moreover, we model the oil market using different measures for global economic activity. Through some forecasting analysis, we find that the OECD IP is the best indicator for modeling the oil market.

Afterward, we conduct an empirical analysis of the effects of oil price shocks on a developing and oil-exporter country: Russia.

The relationship between oil price shocks and the Russian economy has not been studied as much as the relationship itself, but for other countries (for example United States). We expect the effects of these shocks to be different in oil-exporting countries. We use two different models to detect the effect of the oil price shocks on the Russian GDP Growth and Inflation: the Autoregressive Distributed Lag (ARDL) model and the MIDAS model. We study the effect of two different types of shocks on the Russian economy: temporary shocks and accumulated shocks. Analyzing the IRF we find that the two demand shocks have a positive and significant effect on Russian GDP growth, while the effect of the oil supply shock is more muted and almost non-existent. Moreover, the aggregate demand shock and the oil supply shock have a non-significant effect on Russian inflation, while the oil-specific demand shock has a negative effect on Russian inflation.

We use the ARDL and MIDAS models to forecast the Russian GDP growth and inflation. Based on predictive power, the best model to forecast the Russian main macroeconomic variables is the ARDL model.

Different oil shocks have a different effect on Russia's economic growth and inflation as an oil exporter. As a result, not disentangling oil price shocks based on their underlying source could cause difficulties in estimating the real effect of oil price changes in the main macroeconomic aggregates for Russia.

Contents

Chapter 1

Introduction

This is a study on the dynamics of the oil market, which highlights the importance of this energy source as well as its economic context. Crude oil and all other petroleum products (and derivatives) have long been one of the most important sources of energy and main inputs in production processes. This key role of crude oil has repercussions on its economic scenarios. There is much debate among researchers about the effect that the change in the price of oil has on the main economic variables of different countries. As a result, the concern arises over the identification of the determinants of the price of oil. In this strand of literature, we can cite many articles that exploit the topic. However, the main articles that have changed the way we consider the determinants of the price of oil are:[Kilian, 2009] and [Kilian and Murphy, 2014]. Considering their importance and following their approach, we model the oil market using a SVAR model. We define the determinants of the oil price from the demand and the supply side. The variable that defines the supply of crude oil is the global oil production, while the variable that determines the oil demand is the global economic activity which defines the aggregate demand. In the literature, there is a huge debate on the proxies used for real economic activity. There are many economic activity indices proposed by different authors. The novelty here is that we model the oil market using different indices. We detect how much the results change when we consider all these scenarios. Afterward, we perform some out-of-sample forecasting for the real price of oil using a VAR model. By comparing the forecast performance between the models we consider, we choose the one that has the best forecast indicators. Based on the forecasting performance the OECD IP is the best index to forecast the real price of oil.

For researchers and policymakers, it is very important to quantify the effect that different oil price shocks have on the main macroeconomic aggregates of oil importer and oil exporter countries. In this study, we analyze the relationship between the oil price shocks and the Russian economy for two reasons. First, the relationship between oil price shocks and the Russian economy has not been studied as much as the relationship itself, but for other countries (for example United States). We expect the effects of these shocks to be different in oil-exporting countries. Second, Russia is one of the major oil-exporting countries.

After choosing the best model, in the third chapter, we obtain three original time series for the oil demand and supply shocks. To obtain the oil supply shock, the aggregate demand shock, and the oil-specific demand shock we estimate a SVAR model with three variables using a Cholesky decomposition scheme. Hence, we use these time series as explanatory variables in the models used to detect their effect on the main Russian economic variables: GDP growth and inflation. We estimate three different models to exploit these effects: Monthly ARDL, Quarterly ARDL, and MIDAS (and its versions). Different oil shocks have a different effect on Russia's economic growth and inflation as an oil exporter. More specifically, for oil demand shocks that are driven by changes in global economic activity, the response of Russian GDP growth is positive and significant over time. The effect of oil-specific demand shocks is also positive and significant. Rising world demand for oil drives Russia's oil earnings, as well as its economic growth. The effect of a negative oil supply shock is mostly non-significant for the Russian economic growth. When other oil-producing countries decrease production (so the overall oil supply increase), Russia has more market power. This has positive repercussions for the Russian economy.

Furthermore, the inflation response changes when the different oil price shocks are considered. The specific oil demand shock mostly has a negative effect on Russian inflation. On the other hand, the effect of an aggregate demand shock and the oil supply shock is insignificant.

Besides, we make some predictions on Russian GDP growth and inflation using the models mentioned above. Based on their forecasting performance we can choose the restricted versions of the MIDAS models as the best ones to forecast the Russian GDP growth and inflation.

The remainder of this thesis is organized as follows. In Chapter 2, we give an overview of the oil market, the determinants of the oil price, and its importance for the macroeconomy. Here, you can find refinements about the literature review of the oil price determinants and the effect of oil price shocks on the economy.

In Chapter3, we model the oil market through a SVAR model using different identification strategies, different indexes for the real economic activity, and different sub-samples.

In Chapter4, we analyze the effect of oil price shocks on the Russian GDP growth and inflation. In Chapter 5, we report the conclusions.

Chapter 2

Crude oil market

2.0.1 Importance of crude oil

Crude oil is a commodity that has had a wide range of applications since the 19th century.

Oil has been the world's most important energy source since the mid-1950s. Jones et al. establish that energy expenditure reached 14% of US GDP in 1980. Since a significant part of energy expenditure is concentrated on oil, we can say that it has a large contribution to GDP.

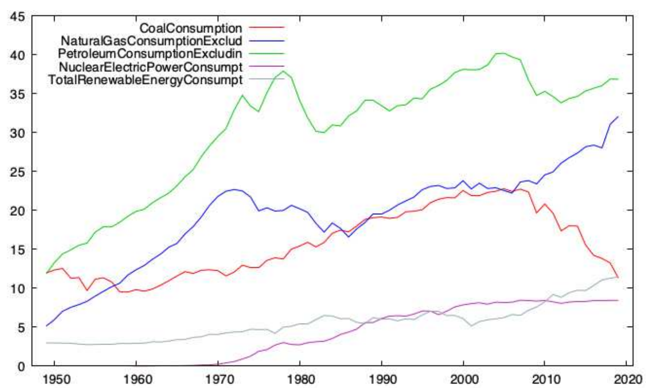


Figure 2.1: Energy Consumption by Source -US

Petroleum is the largest energy source in the United States [1]. Figure 1 shows the different energy sources used in the United States from 1950 to 2020. As we can see there is an increasing trend in the use of these sources over time due to increased energy demand. The most used energy source in the United States is still oil.

Its applications are not limited only to the energy field, but also to other sectors [2].

[1] See: Monthly Review, Table 1.3 Primary Energy Consumption by Source, Eia. Source: https://www.eia.gov/energyexplained/oil-and-petroleum-products/use-of-oil.php

[2] Energy expenditure is a significant percentage of the GDP of industrialized countries. The oil is used as the main energy power for several industry sectors. Petroleum products are used as fuel for vehicles and are the most important input for all forms of transport. Source:https://www.eia.gov/energyexplained/oil-and-petroleum-products/use-of-oil.php. Transportation of goods is important for export and import. Oil satisfies 97 % of the UK transport sector demand. Most of the oil is used for transportation. The transportation sector accounts for the largest share of oil consumption in the United States. Source: https://www.ukogplc.com/page.php?pID=74.

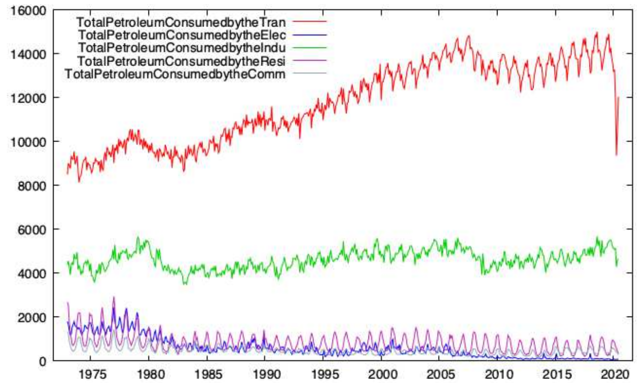


Figure 2.2: US Oil Consumption by Sector

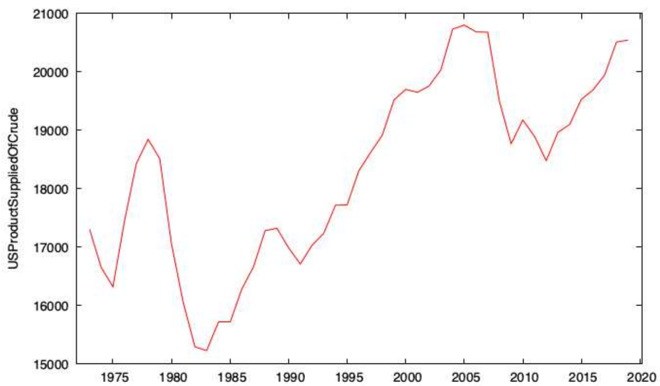


Figure 2.3: U.S. Product Supplied of Crude Oil and Petroleum Products (Thousand Barrels per Day)

Its application expands to produce heating for buildings and to produce other forms of energy such as electricity. In the industrial sector, oil is used as an input for the production of many intermediate and end-user goods. It is very important for the chemical sector for the production of products as plastics, polyurethane, solvents, fertilizers, detergents, paints, and even medicines. Figure 2 shows the total oil consumption in different sectors from 1950 to 2020. Transportation is the main sector in which oil is used.

In 2019, U.S. petroleum consumption averaged about 20.54 million barrels per day (b/d), which included about 1.1 million b/d of bio-fuels [3].

Figure 3 shows the supply of crude oil and its products in the United States over time.

[3]EIA. Source for graphs: Monthly Energy Review, Table 3.7a Petroleum Consumption: Residential and Commercial Sectors; Table 3.7b Petroleum Consumption: Industrial Sector; Table 3.7c Petroleum Consumption: Transportation and Electric Power Sectors- https://www.eia.gov/totalenergy/data/monthly/

2.0.2 A brief review on the evolution of the oil price

So from an economic point of view, what is the reason for the immense interest in oil? As described in the previous section, oil is used in many production processes and consequently, its price has a huge impact on the economy. Therefore, for many years researchers have been interested in understanding the evolution of the oil price over time and its determinants.

The evolution of the oil price and its importance were subject to many theoretical and empirical contributions during the last century. Furthermore, the volatility of oil prices has extensive effects(outcome) on the economy. The researchers' interest, therefore, was not only to study the evolution of oil prices but also to understand the dynamics of its variability. One of the authors who studied the effect of oil price variability on the economy is [Sadorsky, 1999]. The main result of his research was that the volatility of oil prices has different effects on the economy known as asymmetric effects [4].

In past years, the price of crude oil has been assumed to be exogenous to the economy. This was the main reason why the researchers didn't pay much attention to the determinants of the price of oil. It was commonly acknowledged among economists that the price of oil was generally set by OPEC, an external organization, and not determined within the economic system. To better understand the evolution of the oil price back then, it will be useful to retrace the history of the Organization for the Petroleum Exporting Countries (OPEC). The organization was founded in 1960 by the five major oil-exporting countries: Iran, Iraq, Kuwait, Saudi Arabia and Venezuela. Since the organization was created, the price of oil began to rise and the difference between the price paid by consumers and the marginal cost of production was no longer justified by additional marketing and transportation costs. In the 1960s, the price of gasoline (a derivative of crude oil) in many European countries increased by more than dollar 30 per barrel. This increase was attributed to higher excise-taxes on gasoline.

The oil supply from OPEC members can often be in line with their announcements, but that doesn't mean members will produce the exact quote they should have. In reality, the production quotas were rarely respected, while some members produced more and others less [5].

There were many reasons behind the creation of OPEC, which were mainly related to the market power of international oil companies. The objective of the OPEC countries was to steal a portion of the profits - economic rent - from international oil companies. In 1957 there was a downward trend in oil taxes, which resulted in lower profits for oil-producing countries. The explanation for this trend was the decrease in prices due to the strong competition in the oil market during that period. So there were a lot of new companies entering the related market.

In the early 1950s, there were only seven large companies that owned most of the share of the oil market. These companies were the "Seven Sisters" which included Esso (now Exxon), British Petroleum, Shell, Standard Oil of California, Mobil, Texaco, and Gulf which were involved in nearly all oil production destined for international trade. But in 1957 the market share fell from 98% to 89%, due to the entrances of new companies. Due to the continued decline in oil prices, the corporate margin in 1970 felt at a level identified as long-term competition.

The period between 1960 and 1973 was characterized by structural changes in the oil market. The economies that were developing a lot during this period increased the consumption of oil

[4] Many researchers have studied the effects of the price of oil and its volatility on macroeconomic variables. The volatility is very important for investors, who are interested in the VAR (value at risk) of this market before making investment decisions.

[5] This happens because even if the marginal cost of the cartel is equal to the marginal revenue, it does not mean that it will be the same also for each member. Thus, it may be that for some members the marginal revenue is greater than the marginal cost, and of course, this is an incentive for them to disregard the quotas and produce more. Marginal revenue is defined as the price minus the profit foregone(lost revenue) from selling a marginal barrel. We can find different estimates on the total production since OPEC has always announced the quantity of production for all members, but in recent years they have limited themselves to declaring only the variations of the previous quotas.

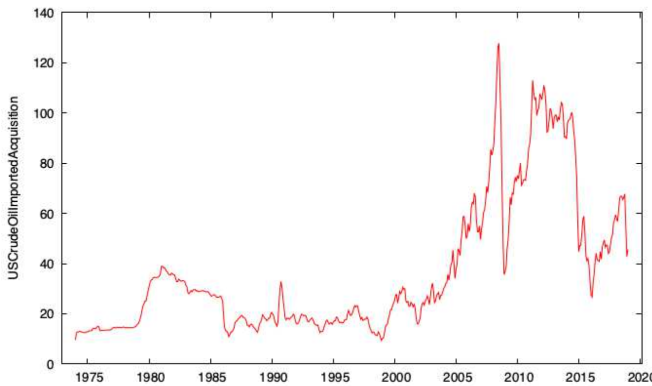


Figure 2.4: Oil Price

and the direct consequence was the increased demand for oil. Therefore, the market was no longer characterized by an excess of supply, but by an excess of demand [6].

In 1960 OPEC saw an increase in taxes on oil, and also on the price per barrel which was the basis for calculating taxes for oil concessionaires. The basic prices for the calculation of taxes were previously the market prices, but afterward, they were fixed and no longer affected by market fluctuations[7].

After the creation of OPEC, conflicts between countries affected the supply side of oil and consequently its price. Oil and its impact on international events have always been at the center of political discussions. One example is the Arab embargo, which began in 1973. During the embargo period, the prices of oil and its derivatives have risen a lot compared to the initial values. This wasn't the only change that lasted for a decade. The volatility of oil prices has also been subject to change. In October 1973, after the Arab-Israeli hostilities, the Arab members of OPEC took some unilateral decisions, such as the increase in tax reference prices, the reduction of the quantity of oil production, and the oil embargo for the United States. and the Netherlands. The result of these decisions was the increase in the price of oil. During this period, the nationalization of the major oil companies took place. The price of oil was published by OPEC as a "given". However, during the period 1975-1978, the OPEC countries disagreed on the exact amount of the oil price change and the oil supply.

In 1980, price increases of up to 32$ per barrel were due to the Iranian revolution and the Iran-Iraq war. During this time there have been huge production cuts in Iran, while other OPEC members were increasing it. Therefore, at many moments in time, there is somehow a compensation between production in some countries and production in others [8].

There are a few other episodes that affected crude oil prices including the period of the Iraqi invasion of Kuwait in 1990. Changes in oil prices also affect the prices of derivatives, which consequently affect the stock markets.

[6] In that period many economists tried to make predictions about the demand, supply, and prices in this market.

[7] [Griffin and Teece, 2016]

[8] Figure 4 shows the evolution of Refiner Acquisition Cost of Crude Oil (Imported) over time. Source: EIA

2.0.3 Determinants of the price of crude oil

Looking at the evolution of the price of oil over the last few decades, we can see substantial fluctuations. There has always been a great deal of interest among researchers, economists, and policymakers in identifying and understanding the factors behind changes in oil prices. Since the 1970s, the evolution of the oil price has been driven by various factors. After the creation of OPEC, there was a common belief among researchers that major oil price fluctuations were driven by exogenous events such as political conflicts and changes within OPEC [9].

According to [Hotelling, 1931], for exhaustible resources, even if their market is perfectly competitive, the price can exceed marginal cost. However, the price of oil is also affected by the scarcity rent which is defined as the difference between the price and the marginal cost. Oil field owners also adjust the quantity produced based on the current price and the expected price for a later period. So in equilibrium, they must receive compensation that makes them indifferent between producing today or in the future. However, the marginal cost to oil producers is obviously affected by technological progress, which may be one of the reasons for the drop in marginal costs and prices. In this market, unexpected resource discoveries can also affect prices. On the other hand, many researchers believe that the price of oil was not much affected by the problem of depletion [10].

Since the early 1970s, there are some episodes we can cite when the price of oil was driven primarily by supply-side factors. There is a consensus in the literature on the explanation for the rise. [Hamilton, 2003] pointed out that the real reason was not war or the destruction of oil fields, but an intentional decrease in oil production (known as an oil supply shock) from Arab countries footnote Arab countries of 'OPEC deliberately cut oil production by 5 percent starting October 16, 1973, ten days into the Arab-Israeli war, by raising the published price of their oil, followed by the announcement of a further 25% production cut November 5, ten days after the war - This note was taken from [Baumeister and Kilian, 2016a] [Baumeister and Kilian, 2016b] [Baumeister and Kilian, 2016c]. The cuts in oil production during this period are known as an Arab oil embargo in Western countries.

Disagreeing with the previous explanation [Barsky and Kilian, 2002] explains the reason for this supply shock by relying on the Tehran / Tripoli agreements between oil companies and the governments of oil-producing countries in the Middle East [11]. The disagreement continues to the extent that according to [Hamilton, 2003] the increase in the price of oil was exogenous concerning macroeconomic conditions but according to[Barsky and Kilian, 2002] it was endogenous. In [Kilian, 2008b] [Kilian, 2008a] the author identifies the increase in global demand for oil as the reason for the rise in oil prices.

Another important episode related to the increase in the price of oil is that of 1979-1980. According to [Hamilton, 2003], the determining factor for this increase in the price of oil is related to the supply side. During this period there was an interruption in oil production from Iran and subsequently the Iranian revolution. [Barsky and Kilian, 2002] argues that the timing of these events does not make the Iranian revolution the main reason for the rise in oil prices.

On the other hand [Kilian and Murphy, 2014] find another reason behind the rise in the price of oil: expectations. Other researchers believe that the main reason was the increase in demand

[9] It shows substantial fluctuations in the real price of oil in recent decades with no obvious long-run trend. The literature has identified several potential determinants of oil price fluctuations, including 1) shocks to global crude oil production arising from political events in oil-producing countries, the discovery of new fields, and improvements in the technology of extracting crude oil; 2) shocks to the demand for crude oil associated with unexpected changes in the global business cycle; and 3) shocks to the demand for above-ground oil inventories, reflecting shifts in expectations about future shortfalls of supply relative to demand in the global oil market —-this paragraph was taken from- see [Baumeister and Kilian, 2015] [Baumeister and Kilian, 2016a] [Baumeister and Kilian, 2016c] [**?**].

[10] See this paragraph in [Hamilton, 2008].

[11] This agreement was signed in 1971 and the main purpose was to fix the price of oil.

for inventories [12]. According to [Kilian and Park, 2009], [Kilian, 2009] and [Kilian and Murphy, 2014] the forces of demand were driving the rise in the price of oil during this period.

The sharp rise in oil prices in the 1980s and 1990s has been attributed to supply shocks [Hamilton, 2003]). The cause was the Iran-Iraq war and consequently the drop in oil production following the destruction of oil fields.

The sharp rise in the price of oil between 2003 and 2008 was attributed to a sharp increase in oil demand due especially to the boom in emerging countries [13]. The high oil price in 2008 was attributed to strong growth in demand from emerging countries (China; Middle Eastern countries) mixed with low price elasticity of demand and followed by the inability of oil-producing countries to shift production for oil demand. [14]. In this strand of literature, elasticity and possible speculation on commodity prices play an important role in explaining the evolution of oil prices. [15].

The decrease in oil prices after 2011 was attributed to shale oil according to [Kilian, 2014].

Between June 2014 and January 2015 the price of Brent oil fell and this decline is attributed to a sharp decline in global economic activity [16].

In the literature exploited so far, we identify supply and demand-side factors as the main drivers of the oil price. But in the oil market literature, other articles provide further explanations for the evolution of the oil price. In [Hamilton, 2008] the author explains the evolution of the oil price over time based on a statistical survey (based on correlations in historical data), on economic theory, and fundamental factors such as supply and demand side. He concludes that changes in the price of oil are permanent and difficult to predict. Furthermore, oil price drivers tend to change over time. Hamilton identifies some new factors underlying the evolution of oil prices such as storage arbitrage, financial futures, and the structural characteristics of oil (exhaustible resource) [17]. According to [Hamilton, 2008], the evolution of the oil price in the period 1970-1997 was mainly determined by low oil demand and supply elasticity and various interruptions in oil supply. In this article, Hamilton discusses the impact that the scarcity rent can have on the evolution of the price of oil.

Elasticity is another very important factor to explore in understanding how oil prices change over time. Therefore, we would like to understand to what extent the oil demand would change if the price changes by a certain amount. The elasticity will be different if we consider the short or the long term. In several studies, researchers have estimated different amounts for the elasticity [18]. The results show that the price elasticity in the short run is greater than in the long run [19].

[12] The empirical models of the oil market that allow both oil demand and supply shocks to influence the price of oil confirm that oil supply shocks played a minor role for the 1979 oil price increase, but suggest that about a third of the cumulative price increase was associated with increased inventory demand in anticipation of future oil shortages, presumably reflecting the geopolitical tensions between the US and Iran and between Iran and its neighbors, but also expectations of high future oil demand from a booming global economy. -taken in [Baumeister and Kilian, 2016a] [Baumeister and Kilian, 2016b] [Baumeister and Kilian, 2016b] [Baumeister and Kilian, 2016c]

[13] [Kilian, 2008b] [Hamilton, 2008] see [Kilian, 2008b] [Kilian, 2008a], [Hamilton, 2009], and [Kilian and Hicks, 2013], [Kilian, 2009], [Baumeister and Peersman, 2013], [Kilian and Murphy, 2014]. Only in the early months of 2008 is there evidence of an increase in the demand for inventory [Kilian and Lee, 2014]

[14] see [Hamilton, 2008]

[15] Variables such as lagged real oil prices, US GDP growth rates, US nominal interest rates were used to forecast oil prices. Although they test predictability, the results show no evidence that these variables can predict changes in oil prices.-[Hamilton, 2008]. However, according to all the tests, the conclusion is that the real price of oil follows a random walk with no drift. Consequently, we can say that the oil price forecast procedure is not simple. The historical series of oil prices is characterized by great changes.

[16] see [Baumeister and Kilian, 2015]

[17] Regarding the oil demand elasticity [Hamilton, 2008] points out (that it is low and has decreased over time - Here we can add something more about the debate on the elasticity of supply and demand

[18] see [Kilian, 2009]

[19] See [Kilian, 2009]. There is another distinction between the elasticity of demand for crude oil and the gasoline

It is very difficult for oil-producing countries to adjust supply in the short term due to the long delivery times that characterize this market. It means that the elasticity of oil supply at the short-run price is very low. A very important factor that has a big impact on the price of oil is the challenge of exhaustion. There is evidence that in many oil-producing countries their production capacity in recent years is much lower. From a geological point of view, there are some problems regarding the new oil production capacities. Political instabilities in countries like Venezuela and Iran have also played a role in the decline of production. Furthermore, geopolitical events in oil-exporting countries also affect the price of oil ([Makin et al., 2014]).

Many theories confirm that the price of oil is mainly driven by fundamentals such as supply and demand ([Kilian, 2009]). On the other hand, oil has been the subject of futures contracts which has been very profitable on the financial markets (hence the oil market has strong financial properties).

Studies have been conducted on oil price drivers, where their downstream could be fundamentals or bubbles. The paths of the bubbles can be explained by the amount of oil ever produced. If in the oil market, noise investors (speculators) have a strong impact on the price, it will take some time for this effect to be reversed by other investors.

All this attention to the evolution of the price of oil is because the change in the price of oil can predict the returns of the stock market ([Driesprong et al., 2008]; [Narayan and Sharma, 2011]; [Phan et al., 2016]. Also, oil price expectations influence the trading strategies of investors investing in the oil-producing and oil-consuming sectors. They can make profits, especially when they look at the information on futures markets ((([Westerlund et al., 2015]; [Narayan et al., 2013]).

Other authors argue who argue that oil price fluctuations are not only driven by fundamentals, but also by non-fundamental factors. For example, there are some deviations in the price of oil that are not explained by fundamentals, but by other non-fundamental factors such as the US dollar exchange rate, speculation, and geopolitical events [Wang and Wu, 2012]; [Zhang and Wang, 2015]. Therefore, since the oil price deviates from the fundamentals, it means that the market is experiencing the presence of bubbles ([Stiglitz, 1990]).

According to [Kilian, 2009], there are two main groups of drivers for oil price movements: fundamentals and bubbles. The evolution of prices over different time periods is driven by one driver or the other. For example, the evolution of the oil price between 2001 and 2008 was explained in different ways by researchers. Despite the ambiguous results, some experts believe that the changes were driven by fundamentals, especially on the demand side ([Hamilton, 2008] [Hamilton, 2009] ; [Kilian, 2009]; [Kilian and Hicks, 2013]. On the contrary, some research confirms that behind the nominal oil price, the variations are caused by bubbles ([Zhang, 2013]; [Sornette et al., 2009]; [Wu and Zhang, 2014]; [Kesicki, 2010].

According to results in [Lammerding et al., 2013];[Zhang and Wang, 2015]; [Zhang and Yao, 2016], the price dynamics of crude oil and diesel are unsustainable growth processes, so they are driven by bubbles. In the period 2001-2008, the reasons why the price of oil was very high were: speculation, geopolitical event,s and the weakness of the US dollar. According to [Engdahl, 2008], the price of oil in this period was mainly driven by the financial market system and the major Anglo-American oil companies. Meanwhile, up to 60 percent of the crude oil price was pure speculation led by large commercial banks and hedge funds. Some decisions have also been made by the US government to stop or at least reduce speculation on the oil market to reduce the cost of energy. Speculation has increased due to the fear of shortages on the part of OPEC members [Barsky and Kilian, 2004].Furthermore, there have been some geopolitical events that have driven this rise in oil prices such as the US-Iraq war in 2003, the war in Lebanon in 2006,

demand. The price elasticity of crude oil is lower because, despite price increases, the cost of retail gasoline is almost double that of crude oil. Both the demand and supply curves of oil are responding not only to its current price but also to previous prices, as well as to income. In this case, the distinction between the short and the long run cannot be calculated only by including the lagged dependent variable in the OLS regression ([Breunig, 2011].

and the nuclear crisis in Iran. According to ([Narayan and Sharma, 2011] one of the main factors attributed to oil price shocks is the US dollar exchange rate shocks.

2.1 Oil price shocks

2.1.1 Typology of shocks

For many years, oil price changes were assumed to be exogenous, until some researchers proved they were not reasonable (for example [Kilian, 2008b]).

To understand the implications of oil price fluctuations, it is helpful to identify what determines the price of oil. Changes in the nominal price of oil do not cause the same change in size and persistence as the real price of oil. Therefore, studying the shocks that drive nominal oil prices helps us understand the effect on the real oil price, how it will last over time, the magnitude, and when the effect may be visible on the data. Obviously, modeling and decomposing the real price of oil can be very useful for policymakers. The price of oil is not determined solely as a result of changes in oil demand and supply. It also responds to several shocks affecting this market. The real price of oil reacts differently based on the origin of the shock that occurs. It is useful to decompose the price of oil and attribute the right impact that each shock has in its variations. Modeling the oil market by assuming the endogeneity of the oil price, the researchers agree that there is a mix of different shocks that contribute to the formation of the real oil price. The size of this contribution varies according to the shocks.

A key article on this topic is [Kilian, 2009]. For the first time, this article uses a methodology for decomposing the real price of oil into mutually orthogonal components. In this framework, we can find the decomposition of the real oil price into three types of shocks: the oil supply shock, the aggregate demand shock, and the oil-specific demand shock.

Oil supply shocks are defined as unpredictable oil supply innovations and the short-run supply curve for crude oil is assumed to be vertical in [Kilian, 2009] [20]. The underlying reason is that the supply of crude oil does not respond in real-time to demand shocks. Oil producers take time to adjust the amount of production due to costs and uncertainty about the persistence of increased demand. Oil producers adjust their supply according to the trend represented by the demand for oil. It means that changes in oil demand must be persistent and not just temporary to cause major supply-side changes. The analysis in this article highlights some very important conclusions. The author concludes that if the nominal price of oil rises due to an interruption in crude oil production, the effects (increase) on the real price of oil will be small and transitory. The disruptions in the production of oil can be related to the hypothesis that OPEC may have operated as a cartel. On the other hand, some studies that suggest that the effect of cartel activity is not that significant on oil prices [21].An unexpected interruption in the supply of oil causes a sharp decline in world oil production, but in the same year, there will be an increase in production, due to adjustments made by other countries. The effect of these shocks on the real oil price is small, transitory, and partially statistically significant.

A change in the nominal price of oil that is caused by a change in the aggregate demand for all industrial commodities does not have an immediate effect on the real price of oil, instead, the latter is considered a lagging indicator.

The price increase is delayed for six months. In this scenario, the change in the price of oil is delayed but is lasting over time. The unanticipated expansion of aggregate demand causes an

[20] The innovations in the oil supply are caused by wars, conflicts in oil-exporting countries, destruction of oil fields, the discovery of new fields.

[21] [Almoguera et al., 2011]; [Skeet, 1991].

increase in world oil production and a large, persistent, and statistically significant increase in the price of oil.

Furthermore, if the rise in the nominal price of oil is caused by the specific oil demand shock (known as precautionary demand), it will cause an immediate, persistent and substantial increase in the real price of oil. The specific demand for oil is identified as a precautionary demand. The precautionary demand was higher in some periods such as during the Persian Gulf War. In some periods the increase in the price of oil has been caused by uncertainty about the future, fears about possible shortages in oil production which are considered elements of a precautionary demand. An unexpected increase in specific oil market demand causes an immediate, large, persistent, and statistically significant positive effect on the real price of oil.

Analyzing the historical series of oil prices, it is known that at any moment there is more than one shock, which affects the evolution and how the price evolves. For example, there were large positive shocks to global aggregate demand in the years 1978, 1979, and 1980. In 1978 and 1979 there were no interruptions in the supply of oil. On the contrary, in 1980 there were interruptions of the oil supply due to the Iran-Iraq war. In 1979 there was a specific demand for oil on the rise. According to [Kilian, 2008b] and [Kilian, 2008a] oil supply shocks are not very effective in systematically predicting the real price of oil. In [Kilian, 2009] studied the cumulative effect of oil demand and supply on the real oil price. Based on these conclusions, we can say that the cumulative effect of supply shocks has always been very limited. These shocks only amplify the dynamics of real oil prices. The greatest contribution to the real price of oil, also in cumulative terms, is obtained from the aggregate demand and the specific demand of the oil market.

The importance of the role of precautionary demand in the real price of oil is confirmed by episodes such as the collapse of the OPEC cartel in 1985. During this period, the price of oil was affected by the drop in precautionary demand from the oil market, even if the production of oil in Saudi Arabia has increased. For the same reasons the oil price increase in 1990-1991 (Invasion of Kuwait). Due to the fall in precautionary demand in 1997-1998, caused by the Asian crisis, the price of oil has reached its lowest value ever

Another important discovery in [Kilian, 2009] concerns the effects of geopolitical events on the price of oil. In the literature, many articles such as [Hamilton, 2003], [Kilian, 2008b], and [Kilian, 2008a]) have always relate the exogenous variation of oil production to changes in the price of oil.

The novelty in [Kilian, 2009] is that the transmission mechanism of events such as wars and revolutions is not through supply shocks (shortages in production and interruption of supply) but precautionary demand. In times of conflict, the demand for oil increases due to fear of future supply disruption or fear of the possibility of oil fields being destroyed. The shocks related to precautionary demand have very large and immediate effects on the real price of oil.

The results in [Kilian and Murphy, 2014] and [Kim and Vera, 2019] are in line with conclusions in [Kilian, 2009].

In [Lippi and Nobili, 2012], the approach used to explain changes in the real price of oil is somewhat different from [Kilian, 2009]. The evolution of the oil price is explained by three different types of shocks such as oil supply shock, RoW (rest of the world) supply shock, ROW demand shock, US supply shock, US demand shock. One of the most important findings in this paper is that nearly half of the change in the real oil price is attributed to shocks from the RoW business cycle. The price of oil also responds to the US economy, but to a lesser extent. These results are somewhat not in line with those of [Kilian, 2010a] and [Kilian, 2010b], who showed that most of the change in oil prices was explained by precautionary demand. Lippi and Nobili explain this difference by saying that the precautionary demand captures the shock of the RoW demand. So in [Kilian, 2010b], the fact that the model has been structured differently makes the result, not in line with the real world.According to the estimates in this paper, another very important result is that not all the demand shocks are alike. Demand shocks have different implications on the price of oil depending on the country (economy) in which they are generated [22].

2.2 The relationship between oil price shocks and Macroeconomics

2.2.1 Oil price - Macroeconomics

In this section we summarize the existing literature on the relationship between oil price shocks and the main macroeconomic variables in different countries.

For a long time, researchers have focused on identifying the impact of oil price shocks on macroeconomic variables [23].

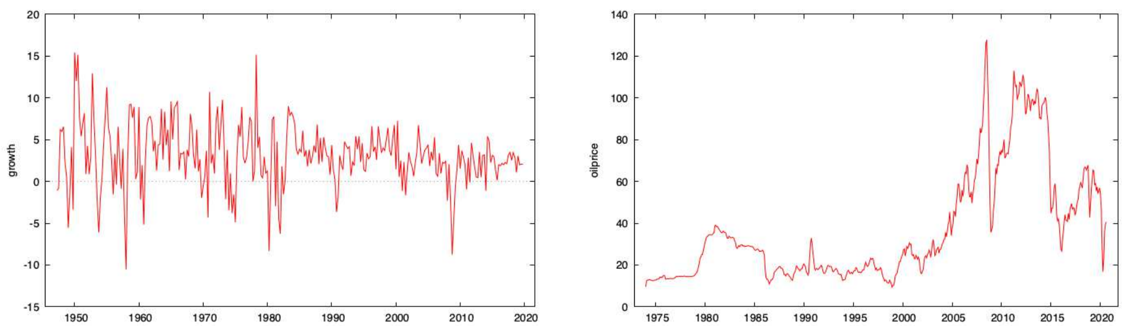


Table 2.1: US growth rate and Oil price

The correlation between oil prices and macroeconomics has not been very clear to economists and policymakers. Many researches have tried to discover not only whether there is a relationship between the two, but also the strength and stability of this relationship over time [25].

Strong increases in the price of oil have always been linked to critical values of macroeconomic variables. One of the most crucial episodes of this large change in the price of oil was in the 1970s when the economy of some of the most industrialized countries was characterized by low growth, high unemployment, and high inflation [26] . Therefore, oil price fluctuations were considered to be the main sources of variation in macroeconomic variables.

[22] The difference is that in the first article 3 shocks are identified (oil supply shock, specific oil demand shock, aggregate demand shock) and the second one identifies 5 types of shock (oil supply shock and oil demand shocks which are decomposed into 4 different shocks known as aggregate supply and demand shocks in the US and ROW-Rest of the world).

[23] According to [Hamilton, 1983], 90% of the US recession was preceded by a peak of the oil price. Authors such as[Barsky and Kilian, 2002] and [Barsky and Kilian, 2004] argue that OPEC drives oil supply by responding to macroeconomic variables that affect oil demand [24].

[25] The seminal paper on analyzing the relationship between oil prices and macroeconomics is the one from [Bruno and Sachs, 1985a] and [Bruno and Sachs, 1985b]. A very important feature is to discover the sheer effect of oil price shocks on macroeconomic variables. An article in which we can find an analysis on this topic is [Rotemberg and Woodford, 1997]. On the relationship between oil price fluctuations and the recession we can find references in the articles of [Hamilton, 1983] and [Hamilton, 1996].

[26] In the graph below is shown US GDP Growth, unemployment rate, and inflation. Source: FRED. https://fred.stlouisfed.org

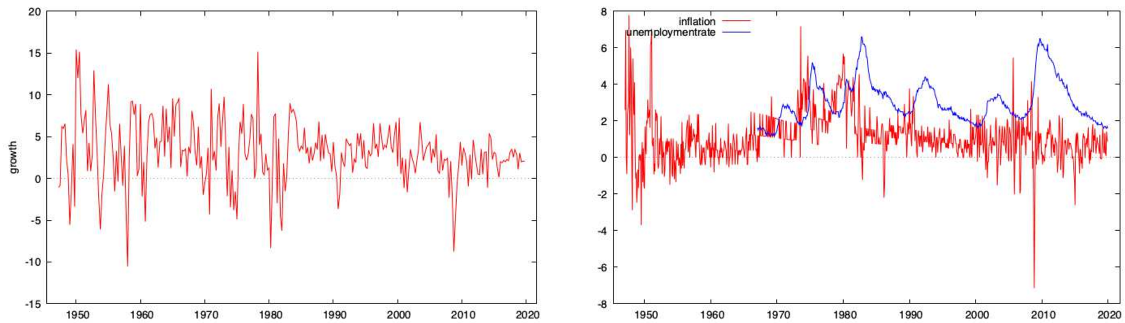


Table 2.2: US growth rate, Inflation and Unemployment

However, according to some studies, this impact has changed over time. For example, during the 1990s and 2000s, we note the presence of large peaks on the historical series of oil prices, but unlike in past years, there was no impact on macroeconomic variables. However, to better understand the relationship between the oil market and the economy, it is necessary to better study the economic context in the different countries. A better analysis must include not only the United States but other countries as well to see if the relationship is the same in all countries.

In the literature, it is shown that the relationship between oil price shocks and macroeconomics has changed over time (eg [Blanchard and Gali, 2007]). They argue that the recession of the 1970s was due in part to fluctuations in oil prices and partially due to other factors. They found that the different impact of oil price shocks on the economy in recent years is due to changes such as decreasing real wage rigidities, more credible monetary policy, and a decrease in the share of oil in production and consumption [27].

Other articles that are in line with the conclusion on the diminishing effects of oil price shocks on the economy are: [Hooker, 2002], [De Gregorio et al., 2007], [Herrera et al., 2007], [Edelstein and Kilian, 2007]. In Hooker (2002) there is evidence of a structural break in 1980, where oil price shocks before this year had a stronger effect on US inflation [De Gregorio et al., 2007] point out that the effect of oil price shocks on inflation has diminished for industrial economies. This decrease is smaller in the case of emerging economies.Some of the reasons behind this conclusion are: economies are less oil-intensive, the inflation environment is more favorable, and oil price shocks in recent years are mostly driven by an increase in world demand.

According to[Lee et al., 1995] and [Ferderer, 1996] the increase in oil price volatility since the 1980s caused the instability of the empirical relationship between oil prices and economic activity.

In [Baumeister et al., 2010b] one of the explanations is based on the decrease in the elasticity of oil demand over time [28].

The impact of oil price shocks on real GDP and inflation decreases over time, according to the results of: [Blanchard and Gali, 2007],[Edelstein and Kilian, 2009], and [Herrera and Pesavento, 2009].

[Bernanke et al., 1997] argue that the recession in the 1970s was mainly due to interest rate changes.

[Barsky and Kilian, 2002] emphasize the role of monetary policy in the 1970 recession. According to the results of this article, the Fed could have avoided the Great Stagflation of the 1970s by following a less expansive monetary policy. They disagree that oil supply shocks caused the Great Stagflation.

[27] Consequently, the cost of firms will depend less on the price of oil.

[28] The steepening of the oil demand curve, as argued by [Baumeister et al., 2010b], skews (distorts) empirical comparisons of macroeconomic effects over time.

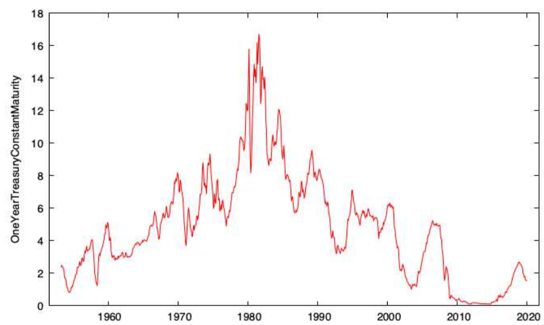


Figure 2.5: OneYearTreasuryConstantMaturity

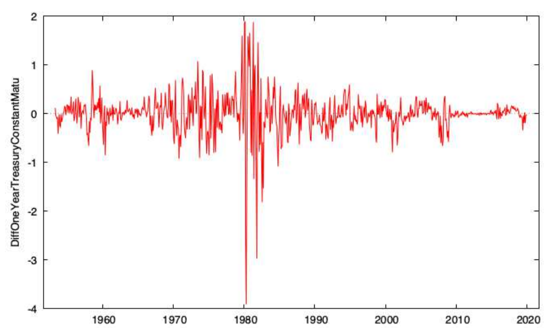


Figure 2.6: DiffOneYearTreasuryConstantMaturity

According to [Blinder and Rudd, 2008], the difference between the 1970s and the 2000s is only due to changes in the link between oil prices and the economy which has tended to fall over time.

[Nordhaus, 2007] attributed this difference to the fact that the US economy has been less dependent on energy in recent years. He highlights another factor: a more flexible labor market. Consequently, the rise in the price of oil is thought to be absorbed by lower wages.

Another explanation concerns the changes in the composition of automotive production and the importance of the automotive sector(eg [Blanchard and Gali, 2007], [Edelstein and Kilian, 2007], [Edelstein and Kilian, 2009], [Kilian, 2008b], and [Kilian, 2008a]) included the automotive sector in his analysis. In recent years, unlike in the past, the demand for this sector increases even if the price of oil increases.Due to the shift from one segment of the industry to another, consumers were buying cars even during episodes of high oil prices, but they only had more incentives to buy small cars.

These theoretical conclusions are in line with other articles such as:[Herrera and Pesavento, 2009], [Blanchard et al., 2010], and [Blanchard and Riggi, 2013]).

According to [Edelstein and Kilian, 2009], the most important channel through which oil price shocks affect the economy is through the demand for motor vehicles. They also show that the strengthening of that relationship between oil prices and the macroeconomy has weakened over time due to the weakening of this channel.

It is very important to understand through which channels oil price shocks are linked to the macroeconomy causing recessions. Oil is present on the consumption side (as a direct consumer good, especially in the automotive industry). So it is a very important consumer good. On the other hand, oil is a crucial input in the production processes of many goods.

Central banks indirectly respond to oil price shocks through monetary tightening. When banks adopt a monetary tightening policy, the level of production is negatively affected. The direct effects mentioned above are not the only ones through which oil price shocks affect the economy. It means that other factors amplify the effect and create a greater impact on macroeconomic variables.

The literature shows that the most important factors influencing the relationship between oil price shocks and macroeconomics are rigidity of real wages ([Blanchard and Sachs, 1982], [Blanchard et al., 2010], and [Blanchard and Riggi, 2013]); imperfect competition ([Rotemberg and Woodford, 1996]); variable utilization rates ([Finn, 2000]; multiplier effects created by externalities across firms([Atkeson and Kehoe, 1999] ([Aguiar-Conraria and Wen, 2007a], and [Aguiar-Conraria and Wen, 2007b]).

In [Hamilton, 2008],[Blanchard et al., 2010], and [Blanchard and Riggi, 2013] agree that there is a very unstable correlation between the oil market and the US economy. [Hooker, 1996] is another article in which the author studies the stability of the relationship between oil price and macroeconomy [29].

To understand the mechanism by which the price of oil affects the macroeconomy, it is important to identify the underlying shocks that drive prices. In studies such as [Kilian, 2009] and [Lippi and Nobili, 2012] we can find a very important contribution in this strand of literature. For example, according to [Kilian, 2009] changes in the price of oil driven by precautionary demand have a more persistent effect on the US economy. The results on the impact of oil price shocks are discussed in [Kilian, 2009] are in line with [Kilian and Murphy, 2014] and [Alquist and Kilian, 2010]. In [Lippi and Nobili, 2012] they conclude that the variance in the oil price is half explained by the shocks on the ROW (rest of the world) economic cycle and also responds to the US economy. This is proof that the oil market variables are not predetermined relative to the US economy. Oil demand shocks are not the same because their implication on the US economy differs depending on whether the shocks originated. It has been shown that the five shocks identified in [Lippi and Nobili, 2012] play a crucial role in the change in oil prices, US activity, and the global economic cycle. In [Lippi and Nobili, 2012], oil prices are not predetermined with respect to the US economy but interact with each other simultaneously. They demonstrate the importance of not having this assumption. On the contrary, in another strand of literature such as [Leduc and Sill, 2004] and [Blanchard et al., 2010] it is assumed that the price of oil is predetermined with respect to the US economy.

Another line of theory regarding this research question argues that the effects of oil price shocks are the same today as they were in the 1970s. The novelty of these papers is that they make a distinction between the published price of oil and the actual cost of oil.The reason for this difference could be the control of the oil price during certain periods [30]. According to [Ramey and Vine, 2011], if the measurement of the cost of oil takes shortages into account, then it can be concluded that the impulse response function of many macroeconomic variables has not changed much over time. This is a conclusion contrary to what has been written in literature for many years.

2.2.2 Different measures of the price of oil

To explain whether the relationship described above is the same over time, it is important to discuss the various measures of the price of oil and whether they coincide with the real cost of oil to firms and households.

[29] Some references about the transmission mechanisms of the oil price shocks to the macroeconomy: [Barsky and Kilian, 2004], [Kilian, 2008b], [Kilian, 2008a], [Kilian, 2014], and [Kilian and Lee, 2014].

[30] [Mork, 1989] was one of the first researchers to pay attention to the contribution of embargoes, price controls, and shortages in the price of oil. After that, there was no particular attention from the authors on this topic for many years.

This topic has been of particular importance in recent years. Authors such as [Hamilton, 2009] and [Kilian and Vigfusson, 2009] have analyzed different measures for the price of oil. The reason why the price of oil differs from the cost of oil is due to the different price control regimes of the United States or European countries and sometimes even consumer sentiment on the price of oil.

According to [Helbling et al., 1975a] and [Helbling et al., 1975b], price controls were imposed by the US national oil industry in response to the OPEC embargo of October 1973. So behind this price control were political reasons. These price controls in the United States have had a major impact on gasoline and diesel fuel. In other countries such as Europe, controls were different: Sunday driving bans (Germany, Italy, Netherlands, Switzerland) and limits on gas purchases (Great Britain, Sweden, Netherlands, Switzerland)[31]. This non-price rationing policy adds additional costs for oil consumers. This phenomenon has been studied in French and Lee (1987).

It is a very problematic question to quantify the exact index of consumer prices for oil. The same problem can be encountered concerning the producer price index.On the producer side, the price of oil is different due to controls on domestic crude oil prices. The measure of the price of oil which is very close to the world price of oil is the refinery purchase cost of imported oil (see [Kilian, 2009]. However, even this measure does not capture all the distortions caused by price controls.

In the literature there are articles such as French and Lee(1987); [Ramey and Vine, 2011] who tried to add the cost of time to the published price of gasoline. Thus, despite the published price of gasoline, we can find even a shortage adjusted index for the real price of gasoline [32].

In the literature, another measure is used to adjusts the price of gasoline. This measure takes into account consumer sentiment about changes in fuel prices. The influence on the consumer was similar during similar periods when shocks hit the price of oil However, consumers are more concerned about long gas lines than high prices, according to CNN.

In the [Ramey and Vine, 2011] is studied the impulse response function of some macroeconomic variables under two different oil price regimes: in the first case it is the standard measure of the nominal price gas and nonlinear Hamilton measurement; in the second case, the real gas price index is taken into account, adjusted for the cost of shortages or the measure of consumer sentiment.

They find that in case they calculate the impulse response function of macroeconomic variables for changes in the oil price (represented by the first two indices), the estimates show that the relationship of the oil price shocks to the macroeconomy has changed. overtime (decreased). However, when the same analysis is made for the second type of indices, the estimates show that this ratio has not changed over time, which means that it is still strong.

They also analyzed the relationship between the shocks to the published CPI for gasoline and consumer sentiments. The results show that the effect has diminished in recent years. On the other hand, the effects of shocks on the shortage-adjusted gasoline price index on consumer sentiment have not changed over time. The second result means that real economic activity is more related to consumers' perceptions of the price of gasoline and its availability than to the price of published fuel. They also show that most of the decrease in consumption after oil price shocks is more due to the decrease in car consumption.

Another interesting feature of oil prices is whether its effect on the economy is symmetric. According to [Edelstein and Kilian, 2009] the effect is symmetric.

[31] [Pisarski and De Terra, 1975]

[32] See Figure 7. Source: FRED. https://fred.stlouisfed.org

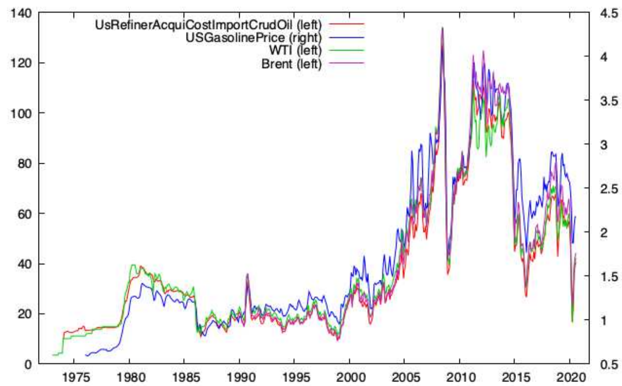


Figure 2.7: Meausures of Oil price

2.2.3 Crude oil: Production and Consumption

Ecological economists have always believed in a connection between the negative effects of oil price shocks in the past and consumption and production. This theory holds because oil prices have been shown to influence the economy on the supply side (production) and on the demand side (consumption). Taking the production side into account, low energy prices are correlated with increased labor productivity [Cleveland et al., 1984]. They are also linked to economic growth ([Ayres and Warr, 2009]. The relationship between the cost of energy and economic growth is negative. So, if the cost of energy decreases, it means that there will be more economic growth and vice versa. However, this is the point of view of ecological economists.

Oil economists do not find evidence of a large relationship in terms of share between the cost of energy and economic growth or business cycle ([Kilian, 2008b] and [Kilian, 2008a]). Oil economists think that oil price shocks affect the economy primarily on the consumption side (Lee and Ni, 2002). On the consumption side, we mean the expenses of households and firms. Furthermore, according to [Kilian and Park, 2009], the stock returns in energy-intensive industries are less affected by oil price shocks than industries that are heavily dependent on final consumer demand.[Edelstein and Kilian, 2009], found that in the period 1970-2006 the effects of oil prices on expenditure were minimal. In contrast, [Hamilton, 2009] analyzed the period 2007-2008 and found that the price of oil was a very important determinant of the consumption path.

Unlike oil economists, macro-economists defended the notion that the negative economic effects of oil price shocks were due to bad policy responses. For example, they conclude that the 1970s recession was not caused by oil price shocks, but by the contraction policy of the Federal Reserve, which raised interest rates to control inflation ([Bernanke et al., 1997]). According to these macro-economists, the effect was not the same in the 2000s due to changes in inflation policy. Another reason was that monetary authorities had more credibility in the 2000s than in the 1970s ([Blanchard and Gali, 2007]). However, the 2008 financial crisis turned out to be contrary to the above claims. The crises have shown that it is no longer true that oil price shocks will no longer affect the economy thanks to improved monetary policy.

Even before the crisis, some authors opposed this theory. For example, Hamilton had supported the idea that during the 1970s, even if the monetary authorities' response to oil price shocks were different, they would still lead to recession. Evidence for this claim can be found in [Hamilton, 2009]. According to [Hamilton and Herrera, 2004], oil price shocks were the main reason for the crises and monetary policy could not be enough to avoid it.

2.2.4 The price of oil and inflation

Inflation is one of the mechanisms by which oil prices can affect the economy. On the contrary, this theory was not valid in 2008 because the initial inflation values were very low and the anti-inflationary monetary policy was very strong. Furthermore, in [Kilian and Lewis, 2011], high oil prices are not inflationary. Moreover in [Kilian, 2014] showed that oil price shocks can also be deflationary due to the negative effects on consumer demand.

The relationship between oil price shocks and inflation has also been studied earlier in [Barsky and Kilian, 2004]. They analyzed several episodes characterized by oil price shocks and tried to find out if high inflation coincides with these periods. The evidence shows very contradictory results. On the one hand, episodes such as the invasion of Kuwait in 1990, the collapse of OPEC in 1986, and the OPEC meeting in 1999 were followed by sharp and short-lived spikes in CPI inflation.On the other hand, some events were followed by a decline in inflation (War in Afghanistan 2001 and Iraq 2003). Other events had very little impact on the level of inflation (Iran-Iraq 1980). According to [Barsky and Kilian, 2002], oil price shocks are unequivocally inflationary for the gross output price. In [Barsky and Kilian, 2004] make a distinction between the effect of an oil shock on the CPI (which will increase it) and on the GDP deflator (there is no evidence for an increase in this variable).

2.2.5 The price of oil and economic growth

One of the most studied effects of the oil price shock is that on economic growth. For many years, oil price shocks have been blamed for low productivity and low economic growth. In many studies, the authors found a very strong relationship between political events in the Middle East and the recession in the United States [33].

Comparing the timing of various political events with recessions, there is some lag between the two. For example, the March 1999 OPEC meeting preceded the March 2001 recession. As you can see, the delay is about two years. Similar delays exist between the Iranian revolution and the January 1980 recession and between the Iran-Iraq war and the July 1981 recession. However, this relationship is contradicted by other events which do not show any delay to the U.S recession. Typical examples of the next case are the October war and the oil embargo that preceded November 1973. On the other hand, it was the recession of July 1990 that preceded the August 1990 invasion of Kuwait. As we can realize, the relationship between political events in the Middle East and recessions in the United States is somewhat irregular.

In [Barsky and Kilian, 2004], the two authors explain through a time series analysis that it is not necessary to define the oil price shocks as the root cause of US recessions. The two authors also studied the relationship between low productivity and oil price shocks, especially in 1973. They found that perhaps the one-to-one ratio wasn't that strong but the environment at the time made it seem that way. In that particular period, productivity growth rates were very low, so the relationship with high oil prices was only causal.

For many years, researchers have tried to discover not only the relationship between oil price shocks and recessions but also the mechanisms by which the effects can be transmitted. For example, the effect of oil shocks on gross output depends on a different number of assumptions we can make. One of the most important is the form of the production function we assume. If gross production depends on labor, capital, and imported oil, it means that a shock in the oil market while holding K and L constant will be very small. If oil consumption decreases, production will also decrease and the amount will coincide with the cost share of oil ([Barsky and Kilian, 2004]). The share of oil in output is also important. The rise in the price of oil causes an increase in

[33] [Hamilton, 1983]

the share of oil in output [34].

The relationship between the price of oil and value-added is less clear and depends on whether the form of the market is assumed to be perfect competition or whether the fixed mark-up is allowed. In the first case, there is no relationship. The next case is studied in [Rotemberg and Woodford, 1996] (model with time-varying markups) through a model that captures an existing relationship even if its magnitude depends on the possibility that the mark-up ratio changes.

When there is an increase in the price of imported oil, obviously the wealth transferred from industrial countries to oil-producing countries will be greater. According to Olson's (1988) estimates, however, the relative share of expenditure in GDP is very small.

[34] [Rotemberg and Woodford, 1997] and [Rotemberg and Woodford, 1996]

Chapter 3

Structural VAR Modeling of the Oil Market

3.1 Introduction

For many years economists have been interested in understanding the determinants of the evolution of the price of crude oil. Crude oil is a commodity whose price fluctuates a lot over time [1].

From a macro perspective, we are interested in understanding the economic forces that cause such fluctuations. What we want to know is to what extent the supply or demand forces contribute to oil price changes. Obviously, supply and demand factors are not the only ones contributing to the formation of the oil price. Apart from these factors, others play an important role in oil price formation such as inventories, expectations, news, shale oil production, and so on [2]. Furthermore, policymakers need to understand the response of macroeconomic aggregates to exogenous changes in the price of oil. To explain economic phenomena, it is important not only to create new models but also to study, replicate and verify the reliability of other frameworks and models used, in particular the papers that have become the "tradition" of modeling in a given field [3].

[Kilian, 2009] for the first time sought to identify changes in the oil price due to various underlying shocks. This article is one of the most important regarding oil market modeling, which uses a Structural Vector Autoregressive (SVAR) model to explain the determinants of oil prices. As is well known among researchers, certain identification restrictions need to be imposed when using SVAR models[4]. This article uses the Cholesky decomposition and Sign restrictions scheme to identify shocks.

Regarding the modeling of the oil market, another important paper is [Kilian, 2014] which uses signs and other restrictions (supply and demand elasticity bounds) for the identification strategy[5].

In the oil market literature, these identification strategies have played an important role in

[1] In Figure 2.4 we show the evolution of the US acquisition cost of crude oil over the period 1973-2020. The US acquisition cost of crude oil is a better proxy for the price of oil when modeling the oil market [Kilian, 2009].

[2] [Kilian and Murphy, 2014]

[3] For some "replications" in the topic of the oil market modeling see: [Kim and Vera, 2019], [Baumeister and Hamilton, 2019], and [Zhou, 2020].

[4] [Kilian and Lütkepohl, 2017]

[5] There are some more papers, among others, that use the later identification scheme: [Baumeister and Peersman, 2013], [Kilian and Zhou, 2019], [Zhou, 2020], and [Theobald and Hohlfeld, 2017]

identifying the determinants of the oil price and how their contribution has changed over time [6].

However, there is a huge debate going on among the authors mentioned above about: the choice of the determinants of the oil price, the choice of the right identification restrictions to use in the SVAR framework, and the choice of the right index used as a proxy for the global economic activity index.

To write this article, we took a cue from this debate and try to better understand how to answer the doubts mentioned above. First of all, we replicate the two articles [Kilian, 2009] and [Kilian and Murphy, 2014] which have a great contribution in the literature of the oil market modeling and have been cited several times. We estimate a SVAR model for the period 1974-2007, using first a Cholesky decomposition scheme [7]. Afterward, we estimate a SVR for the period 1974-2009 using sign and elasticity bounds restrictions to identify shocks[8]. Furthermore, we run the two SVAR models extending the sample period to 2019 and, after re-estimating the SVARs, we compare the IRFs. Some of the results do not change. However, there are some IRFs that behave differently.

Second, we want to understand if the results in [Kilian, 2009] and [Kilian and Murphy, 2014] change when we use different proxies for the global economic activity index. In this article, we explore the variables that could determine the price of oil. We pay more attention to the variables that represent the demand side of the oil market. Real-world economic activity is one of the crucial variables that influence the dynamics of the oil market. The dilemma here is to carefully choose the best index to represent global economic activity. In the literature, studies have identified many indices that can represent this variable in the models used to explain the evolution of the oil price.

We replicate [Kilian, 2009] and [Kilian and Murphy, 2014] by replacing one of the variables (the real economic activity index) in the data-set with other indices. Therefore, instead of using the Kilian index, we replace it with three other indices: OECD IP + IP for six emerging countries, GECON (General Economic Conditions Index), and the WSP(world steel production) index. We re-estimate the SVAR for each of the indices for three sample periods: 1974-2009; 1974-2019; 1990-2019. The first sampling period is the same as that used in the original papers. The second sampling period is basically used to include more recent data in the model. Afterward, we estimate the model for the period 1990-2019 because the world steel production index is only available after 1990. some of the IRFs after the different typologies of estimation change. The response of the real economic activity index to the three oil price shocks differs when using different indexes. Furthermore, to understand which of these indexes has a better predictive power for the real price of oil we perform some forecasting analysis [9]. We estimate a VAR model for each of the indexes used as a proxy for the real economic activity index and four different sub-samples. First, we estimate the VAR for the period from 1974:01 to 2018:12. After, we perform a dynamic out-of-sample forecast for the period from 2019:01 to 2019:12. In this case, the KI has the best forecasting performance for the real price of oil. However, all these models fail to outperform the AR(1) model which is usually used as a benchmark in the forecasting analysis.

Second, we estimate the VAR model for the period from 1990:01 to 2018:12. We choose this sub-sample to start from 1990:01 since the availability of the WSP index starts from that date. After, we perform a dynamic out-of-sample forecast for the period from 2019:01 to 2019:12. In

[6] [Baumeister and Hamilton, 2019].

[7] This replication follows [Kilian, 2009].

[8] The elasticity bounds restrictions are not the same as in [Kilian and Murphy, 2014]. Thus, this estimation is not considered a real replication of the model used in the previously mentioned paper.

[9] The forecasting accuracy statistic that we use to choose between the models is the MRSE(Mean Root Squared Error).

this case, the OECD index followed by the GECON index have the best forecasting performance for the real price of oil. Furthermore, models, where these two indexes are used, are the ones that outperform the AR(1) model. The other models fail to outperform the benchmark.

The forecasting for the other two sub-samples is based on the financial crisis of 2008. We want to analyze if the predictive power of the indexes implied in this analysis changes after this episode. First, we estimate the VAR for the period from 1990:01 to 2006:12. After, we perform a dynamic out-of-sample forecast for the period from 2007:01 to 2007:12. In this case, the OECD index has the best forecasting performance for the real price of oil. Furthermore, all models outperform the benchmark.

Second, we estimate the VAR for the period from 2009:01 to 2018:12. After, we perform a dynamic out-of-sample forecast for the period from 2019:01 to 2019:12. In this case, the OECD index has the best forecasting performance for the real price of oil, and the model that uses this index is the only one that outperforms the benchmark. Based on these results we choose the OECS IP index as the best for forecasting the real price of oil and modeling the oil market.

The remainder of the paper is organized as follows.

In Section 3.2, we investigate the advantages and disadvantages of the Kilian index. In addition, we introduce the main measures of real economic activity used to model the oil market. We examine the similarities and the differences between them.

In sections 3.3 and 3.4 we focus more on the different types of identification strategies used to obtain data on oil price shocks and some concerns related to each. We explain Fry and Pagan's critique and how it relates to the representation of the IRF in [Uhlig, 2005]. In Sections 3.5, we describe the data source and the various transformations applied to the data. Furthermore, in this section we explain in more detail the technical part of this article, relating to the methodology, scripts, and Software.

In Section 3.6, we explain the methodology used in the paper to answer our research question. We introduce the SVAR model and various restrictions used to identify the different oil price shocks.

In section 3.7, we present the results of various model estimations, based on different sample periods, different identification strategies, and different economic activity indexes.

In section 3.8, we report the results of the forecasting analysis for different sub-samples. Concluding remarks are in Section 3.9.

3.2 Alternative measures of the "Real Economic Activity"

To explain and model the evolution of many economic variables (in particular the price of oil), it is necessary to identify a variable that represents global economic activity. In the latest oil market literature, the Kilian index has been widely used as a proxy for global economic activity. As discussed in [Kilian, 2009], this index is the best proxy used to model the oil market.

Advantages of the Kilian index The Kilian index is a measure of dry cargo shipping rates. According to [Kilian, 2009], this is the only index that measures the part of global real economic activity that drives the demand for industrial commodities. The Kilian index captures the magnitude of fluctuations in the volume of shipments in commodity markets better than GDP or industrial production ([Kilian and Zhou, 2018]).

One of the most important advantages of the Kilian index is that it does not need to aggregate the real economic activity of all countries such as for world GDP or world industrial production.

Compared to other indices used to represent global real economic activity (eg GDP), the Kilian index has the advantage of being available since January 1968 on a monthly frequency.

It can, therefore, be used in high-frequency models and has the advantage of being built in real-time (e.g., [Baumeister and Kilian, 2016c]).

[Alquist et al., 2013] and [Baumeister and Kilian, 2012] found that the Kilian index produces good predictions of the US refining acquisition cost (RAC) of crude oil imports[10].

However, there is a huge debate among researchers about the validity of this index and its drawbacks.

Drawbacks of the Kilian index Despite the many advantages of the Kilian index, there are some drawbacks. Since this index is related to maritime transport, the presence of the shipbuilding and demolition cycle can influence its relationship with the real economic activity [11].

Furthermore, many doubts have arisen as to whether the index can capture recent changes in economic activity. Many researchers are concerned about its validity as a good indicator of true global economic activity [12]. One concern relates to the volatility this index has had over time.[Hamilton, 2019] notes that the nominal shipping index series, which was the underlying series for the construction of the Kilian index, after 2008 changes significantly. This was the reason why Kilian started using BDI (Baltic Dry Index) in 2008 to update his index [13]. For the same reason, the results of [Baumeister and Kilian, 2012] are no longer shared by the authors.

Here another problem arises concerning the exogeneity of the Kilian index to the price of oil. The BDI is indirectly dependent on the price of crude oil [14]. The first criticisms are based on the evidence that changes in the real oil price have predictive power for the Kilian index, so it cannot be used to model commodity markets. However, according to Kilian, there is no reason to conclude that predictive evidence implies a causal relationship, so this index can still be used to model commodity markets [15]. [Kilian and Zhou, 2018], to defend its index, argues that all the indices used in the literature, as a proxy for real global economic activity, are not exogenous to the price of oil.

[Hamilton, 2019], reported another problem with this index related to a construction error. Kilian took the log twice to calculate this index, which is very rare for economic data. Hamilton shows how the results reported in [Kilian, 2009] change due to this error [16] . In [Kilian, 2019], we can find the new index of Kilian which has been corrected by taking off one of the log applications. Also in this article, the author explains that even after changing the index the main results do not change.

In [Hamilton, 2019] there are other criticisms of this index relating to the predictive power of oil prices. The reason behind the construction of the Kilian index was to model commodity prices. Hamilton performs a forecasting regression model and applies an F-test bringing to the conclusion that the measure of real economic activity is not useful in predicting the price of commodities. In his conclusions, Hamilton defends the thesis that world industrial production is a better measure than the Kilian index for describing world GDP and predicting the price of raw materials.

To understand whether the proposed monthly measures used as a proxy of world real GDP are suitable, we can check the correlation between GDP and the cyclical component of the proposed monthly measures. [Hamilton, 2019] used the OLS (Ordinary Least Square) estimation to calculate the correlation between the growth rate of world GDP and the various alternative

[10]RAC is the variable used as a proxy of the price of crude oil when modeling the oil market.

[11][Kilian, 2009] and [Kilian and Zhou, 2018]

[12][Baumeister et al., 2020] and [Hamilton, 2019]

[13][Hamilton, 2019]

[14]e.g., [Manescu and Van Robays, 2014] and [Ravazzolo and Vespignani, 2015])

[15] [Kilian and Lütkepohl, 2017]

[16][Hamilton, 2019]

measures used in the literature [17]. [Hamilton, 2019] underlines that the cyclical component of industrial production is strongly correlated with annual GDP growth. Neither the cyclical component of real shipping costs is significantly related to GDP growth, nor is the Kilian index.

The disadvantages of the Kilian index explained so far, are the main reason why an increasing number of articles have recently focused on proposing alternative measures for real economic activity. These measures are mainly based on world industrial production, world steel production, and commodity prices. In the following paragraph, alternative indicators of global economic activity are evaluated.

Other indices World GDP and world industrial production have been widely used in the literature as a proxy for global economic activity. Since a single country's GDP cannot be used as a proxy for global real output ([Kilian and Hicks, 2013]), a quarterly world real GDP is constructed from the PPP-weighted average of single countries real GDPs. The quarterly time series of world GDP is very short to model commodity markets[18]. Furthermore, this index has the disadvantage of being available quarterly. In commodity market modeling, it is more appropriate to use monthly data as the validity of the restrictions used in some models (e.g. SVAR) depends on the frequency of the data.Another important disadvantage of this index is that it cannot be a real-time measure and does not include full sample data for emerging countries[19]. Since real-world GDP at very high frequencies is not available,[Kilian and Zhou, 2018] argue that to estimate the higher frequency models it is necessary to find another index, used as a proxy for the global real economic activity [20].

To overcome the problem of the frequency of data for world GDP, the OECD has constructed a monthly proxy for global real GDP. However, according to [Kilian and Zhou, 2018], this measure is not suitable for modeling commodity markets.

Monthly industrial production is a better measure than GDP to represent global economic activity because it is available on a monthly frequency. However, it cannot be used for real-time forecasting. It also has many drawbacks, similar to those of GDP, as regards the missing data for the whole sample of some emerging countries. To overcome these drawbacks [Baumeister and Hamilton, 2019] propose an alternative index for the global economic activity. They construct a global index for industrial production. The underlying time series is the one obtained from the OECD Main Economic Indicators (MEI). To construct the index, the time series of the individual emerging countries (Brazil, China, India, Indonesia, Russian Federation, and South Africa) are added to the industrial production of OECD countries. [Baumeister et al., 2020] identifies this index as one of the best for predicting the price of oil (the refiner acquisition cost of imported crude oil).

[Hamilton, 2019] propose another monthly index (Hamilton Index) based on dry cargo freight rates.

The real shipping cost factor is another index very close to the Kilian index.[Baumeister et al., 2020] proposes this alternative index based on the unbalanced panel of disaggregated shipping costs(the same data at the base of the Kilian index) and extracts a common factor. It was built based on freight rates for 61 shipping routes for different goods (grain, coal, fertilizers, iron ore, scrap metal, oil seeds). Using the EM algorithm the missing observations are filled in giving a final time series which is available since 1973 [21]. This index somewhat addresses the drawbacks of the Kilian index.

[17] For further explanations on the formula see [Hamilton, 2019].

[18] It is available since 1990.

[19] [Kilian and Zhou, 2018].

[20] Quarterly real GDP has been available since 1990, but the annual frequency index dates back to 1960

[21] To use this as a proxy for the real economic activity index it should be deflated and it is common to calculate the growth rates as the first logarithm difference.

Real commodity price factor. [Alquist et al., 2020], [Delle Chiaie et al., 2017], and [West and Wong, 2014] extract a global factor from a large cross-section of monthly real commodity prices. This index is constructed based on 23 basic industrial and agricultural commodities prices whose markets are sensitive to changes in global economic conditions. The selection of the set of commodities is guided by the same criteria as Alquist et al. (2019).

A very recent measure used as a proxy for real global economic activity is the world steel production proposed by [Ravazzolo and Vespignani, 2015]. This index is available on a monthly frequency since 1990. These data are easily measurable, but the index still has some drawbacks ([Kilian and Zhou, 2018]). This index does not need to be deflated because is based on real values (steel production).

[Baumeister et al., 2020] suggest a new proxy for the real economic activity: the index of global economic conditions (GECON). They use 16 indicators represented by variables that influence energy demand. These variables are related to different categories of data: real economic activity, commodity prices, financial indicators, transportation, uncertainty, expectations, weather, and energy-related measures. The principal component was extracted from the unbalanced panel of 16 variables by recursively applying the EM algorithm and using this estimated factor instead of the measure of economic activity.

3.3 Identification strategies

The SVAR model is widely used in the crude oil market modeling literature. This model is a structural dynamic simultaneous-equation model [22]. By estimating the SVAR model we can derive the time series of structural shocks. The SVAR representation is shown below:

$$A_0 z_t = \alpha + \sum_{i=1}^{j} A_i z_{t-i} + \epsilon_t \tag{3.1}$$

3.3.1 Point-estimate models

In the SVAR framework, an identification scheme for shocks must be used. [23]. To this end, we need to impose some restrictions. So far, several identification methods have been used in the literature: short-term restrictions, long-term restrictions, dynamic restrictions, and sign restrictions.[24].

Sims(1980) originally proposed a recursive identification scheme based on exclusion restrictions (or zero restrictions), the so-called "Cholesky decomposition". This method has been widely used by researchers for its easy interpretation and estimation. However, care must be taken when sorting variables within the SVAR model, as different sorting can lead to different results. Models that use this type of identification strategy are called "point estimation models", which means that after estimation we will get unique values for the parameters. Consequently, we will have unique time series for each shock and unique IRFs(Impulse Response Functions) [25].

[22] [Kilian and Lütkepohl, 2017]

[23] Further information on the issue of identification see [Christiano et al., 1999] and [Taylor, 2004].

[24] [Kilian and Lütkepohl, 2017]

[25] The IRF is a tool through which we can show the effect that a single shock has on the variables included in the SVAR model.

3.3.2 Set-identified models

In addition to Cholesky decomposition, other methods have been used in the literature to identify SVAR models . [Faust, 1998], [Canova and De Nicolo, 2002] and [Uhlig, 2005] introduced "the sign restriction approach". This approach immediately became an alternative to traditional identification approaches based on "exclusion restrictions".

An advantage of the sign restriction identification scheme is that the order of the variables is not important[26]. This is an advantage that the sign restriction identification scheme has over exclusion restrictions. Even though recursive models are much simpler, it is often difficult to justify the order of variables from an economic point of view. The sign-identified models are more general than recursively identified models.
However, this does not mean that subsequent ones are nested to the first. The generality of the sign-identified models is given by the fact that they relax the exclusion restrictions imposed by the point-identified models. On the other hand, the sign-identified models impose sign restrictions on parameters that in the previous case were by no means restricted.
Furthermore, using sign restrictions implies using more information on the direction of the effects that shocks could have on the variables of interest. This information could come from economic theory. Sign restrictions represent inequality restrictions, often considered weak restrictions, which can be imposed on impact (static restrictions) or across horizons (dynamic restrictions).[27]. They are more qualitative than quantitative and show the direction but not the magnitude of the effect that shocks could have on variables.

Models using sign restrictions are called "set-identified models", which implies that after estimation we will obtain several values for each parameter based on the different admissible models [28]. It means that after the estimation we are not going to obtain unique values for the parameters but a set of values. In this case, the parameters of the impact multiplier matrix (A_0) in the sign-identified model are no longer point identified but set identified. This creates complications not only for the estimation procedure but also for the interpretation of the results which can sometimes be contradictory. In the set-identified framework, there can be several models that satisfy the restrictions and consequently, each model implies a set of results. Sometimes the results can be contradictory to each other or the initial economic intuition behind the model. At this stage, it will be difficult to interpret and choose the right model because all these structural models are equally probable. However, there can be cases where the results from different models are in line with each other [29].

The credible sets(or admissible models) in sign-identified VAR models reflect both the uncertainty about the model identification and the estimation. There are several ways to deal with the uncertainty arising from the presence of multiple admissible models. One approach to this problem, exemplified by [Faust, 1998], has been to focus on the admissible model most favorable to the hypothesis of interest.

The narrative approach based on historical decomposition has often been used to choose among the admissible models [30].

However, there is no conventional way to test the validity of the sign restrictions. If they are incorrect, we would expect the number of admissible draws to be zero or very small. [Fry and Pagan, 2011] suggest that in this case, the data or/and the model specification is incompatible with the sign restrictions.

In addition to the identification schemes explained above, in the set identification framework, it may be possible to have a combination of sign restrictions and zero restrictions.

[26] e.g., [Baumeister and Hamilton, 2015]
[27] [Fry and Pagan, 2011]
[28] [Kilian and Lütkepohl, 2017]
[29] [Kilian and Murphy, 2012]
[30] [Kilian and Murphy, 2014]

As we can understand, it is impossible to tell a priory that one approach is better than the other. The choice simply depends on the case study and the convenience of researchers in choosing one or the other approach.

Partially identified models

We refer to models as set-identified models when the constrains imposed are inequalities. Usually, in micro-econometrics, the set-identified models are also known as partially identified models. However, the two models are different from each other. Partially identified models are not always set-identified and vice versa.

The partially identified models may be set-identified models, where the number of identified shocks is lower than the total ones[31]. The partial identification framework arises when researchers are unable to identify all shocks (because they do not have enough information about the signs) or when they are interested in only one or some of the shocks but not all of them[32].

Even when we do not impose the sign of the effect that shocks can have on variables, we still impose that the sign is different from that of other shocks to distinguish them. Conversely, when fully identified models are used, all structural shocks are identified individually.

Other restrictions

When using the sign-identified models, additional restrictions are often necessary to obtain a more meaningful picture and to somehow reduce the uncertainty. The additional restrictions tend to reduce the set of admissible models. Some additional restrictions that can be used are dynamic sign restrictions, elasticity bounds, shape restrictions.

When we impose dynamic sign restrictions, this implies that the restrictions on signs will be valid not only on impact but beyond. However, it is not straightforward to decide the signs of structural impulse responses over longer horizons (e.g., [Canova and Paustian, 2011]).

There are some topics, like oil market modeling, where it is not enough to just impose the sign restrictions. According to [Kilian and Murphy, 2012], these are minimal identifying hypotheses that can allow maintaining problematic structural models in the admissible set. [Kilian and Murphy, 2014] add some bounds for the oil supply and oil demand elasticity. Models that do not constrain the elasticity values are not credible from an economic point of view. It is not consistent to think that the elasticity of oil demand and supply is unlimited and very large (e.g.,[Anderson et al., 2018], [Kilian and Murphy, 2012]).

Shape restrictions are other types of restrictions, which restrict the shape of structural impulse response functions. They consist in changing the impulse response coefficients across the horizon.[33].

3.4 Fry - Pagan Critique

The set-identified models are useful for conducting policy analysis in macroeconomic topics. However, there has been a lot of criticism about the way these models have been used [34].

Applying sign restrictions as an identification method for shocks offers us not a single model that satisfies the restrictions, but many admissible models. It means that for each admissible

[31] e.g.,[Rubio-Ramirez et al., 2010], [Inoue and Kilian, 2013], and [Uhlig, 2005]

[32] [Uhlig, 2005] ,[Fry and Pagan, 2011], and [Canova and Paustian, 2011]

[33] (e.g.,[Blanchard Olivier and Quah, 1989],[Inoue and Kilian, 2016], [Christiano et al., 2005] and[Scholl and Uhlig, 2008]

[34] [Fry et al., 2005], [Fry et al., 2007], and [Fry and Pagan, 2011].

model we will have different values for the parameter matrices and consequently no unique impulse response functions (IRFs). Sometimes the interpretation of the IRF derived from different models can be similar, but on the other hand, nothing guarantees it. Having a large number of models can be a problem for obtaining unique results. In the literature, the authors refer to this issue as multiple models problem [35].

The impulse response function and historical decomposition are very important tools in macroeconomic analysis. The difference between the IRFs in a point-identified model and those in a set-identified model is that in the former case we have a unique IRF while in the latter case we have a set of IRFs derived from different models. In the set-identified framework, having more than one admissible model implies having more than one IRF. On the one hand, this has the advantage of giving us a clearer idea of how much IRF derived from different models differs from each other. On the other hand, in empirical works, researchers would like to have more synthetic results to give a better explanation of economic phenomena. The uncertainty that emerges here is between the models, which implies that we are unable to say which model is right because they all fit the data and meet the previously imposed restrictions.[36]

The solution to this problem so far has been to try to summarize the information contained in the IRFs. One of the most popular ways to do this has been to represent the "median" of IRFs as a summary measure [37] [38]. In this case, we will end up with a unique IRF calculated as the median of all IRFs at each point. The problem that arises here is that the median calculated at one point and the median derived at another point may come from two different models. Therefore, the final IRF does not derive from a single model. Since the final IRF of the shocks comes from different models, we cannot guarantee that the shocks of different models are not yet correlated [39]. This can cause problems when we want to compute the historical decomposition of the shocks. It is possible to compute it, but the results can be ambiguous or even wrong or unreliable.

Other approaches to choosing the best model have been based on the magnitude of the impulse responses [40]. [Uhlig, 2005] choose to give more weight to "large" standardized impulses than to "small" ones[41]. [Peersman, 2005] follows [Uhlig, 2005] on the representation of the IRFs.

Another approach to this problem, exemplified by [Faust, 1998], has been to focus on the admissible model most favorable to the hypothesis of interest. The narrative approach based on the historical decomposition has often been used to choose among the admissible models.[42].

[Fry et al., 2005] follow another strategy, choosing an IRF as close as possible to the median values. This methodology is known as the median target (MT) [43] The IRF in this approach comes from a unique model in contrast to [Uhlig, 2005]. This method has been used by many authors and they conclude that the results obtained using this method do not differ much from those obtained using other methods [44].

[Kilian and Murphy, 2012] and [Kilian and Murphy, 2014] shows the IRF that derives for the

[35] [Fry and Pagan, 2011].

[36] In the set-identified models it is wrong to interpret the extreme lines of IRF as part of a confidence interval (here all the lines are IRFs). In these plots (which in our example will be called "Spaghetti plots"), what we will see is how much the responses vary as the models vary.

[37] see [Uhlig, 2005]

[38] The popularity of this approach is the central argument in the critics exploit in [Fry and Pagan, 2011]

[39] The only certainty we have is that by construction the shocks of a single model are not correlated.

[40] [Faust, 1998] and[Uhlig, 2005])

[41] Thus says "Given a choice among many candidate monetary impulse vectors... It may therefore be desirable to choose the one that generates a more decisive answer than variables " ([Uhlig, 2005]); see penalty function in [Kilian and Lütkepohl, 2017].

[42] [Kilian and Murphy, 2014]

[43] IRFs are standardized and unit-less.

[44] [Fry et al., 2005]- where they applied the MT method to the data in[Blanchard Olivier and Quah, 1989], [Rüffer et al., 2007], and [Canova et al., 2010].

model with an impact price elasticity of oil demand in use closest to the posterior median of that elasticity among the admissible structural models obtained conditional on the least-squares estimate of the reduced-form VAR model.

3.5 Data

The variables used in this SVAR model when following[Kilian, 2009] are: the world oil production, the index of global real economic activity, the real price of oil [45]. When estimating the SVAR model following [Kilian and Murphy, 2014] we add another variable: the oil inventories.

World crude oil production is measured in thousands of barrels per day and it is available in monthly frequency. We transform the data applying the percent change. The resulting time series is cov-stationary [46].

The refiner acquisition cost of imported crude oil is the variable we use as a proxy for the price of oil. Data is available monthly since 1974: 01. We deflate this time series by the US CPI and after apply the log operator. The US CPI data is retrieved from the FRED website.

Kilian Index is one of the proxies used for real-world economic activity index. Data for the Kilian index can be found on the Lutz Kilian website [47].

Another measure of global economic activity is the Industrial Production Index for OECD countries and the six major non-member economies (Brazil, China, India, Indonesia, the Russian Federation, and South Africa). Since 2011 the index has been updated by Baumeister and Hamilton [48]. In order to use this series as an index of economic activity in our model, we apply the logarithm, and then we de-trend it using a simple regression of the data on the time index [49].

Data for the world steel production index are obtained upon request from Francesco Ravazzolo [50]. This index is available monthly frequency from 1990:01 to 2019:05. This index must not be deflated, because steel production is already a real measure We applied the logarithm and then de-trend this series using a simple regression of the data on the time index.

The GECON (Generalized economic condition) index is a monthly indicator [51]. We use the data as reported by Christiane Baumeister without further transformations. All global real economic activity indices have been standardized.

The data for the inventories are obtained from the Christiane Baumeister website [52]. Before inserting this variable into the model we calculate the percentage change.

All data are monthly and are available for the period from 1974:01 to 2019:12. For world steel production we have fewer data available because this time series starts in 1990:01.

[45] EIA: the source for the data regarding the world oil production and the oil price: https://www.eia.gov, changes in oil inventories.

[46] See [Kilian and Lütkepohl, 2017]

[47] https://sites.google.com/site/lkilian2019/research/data-sets. The construction of the index is explained in [Kilian, 2009]

[48] The description for the construction of the index can be found in [Baumeister and Hamilton, 2019]. For more information see Appendix E which is available on the American Economic Association website - https://www.aeaweb.org/articles?id=10.1257/aer.20151569.

[49] This index is available on Christiane Baumeister website. https://sites.google.com/site/cjsbaumeister/home

[50] See [Ravazzolo and Vespignani, 2015]

[51] It is available on the Christiane Baumeister website. https://sites.google.com/site/cjsbaumeister/home

[52] https://sites.google.com/site/cjsbaumeister/home

3.6 Methodology

A Structural Vector Autoregressive regression (SVAR) model is used to explain the dynamics of the real price of crude oil [53]. The SVAR representation is shown below:

$$A_0 z_t = \alpha + \sum_{i=1}^{j} A_i z_{t-i} + \epsilon_t \tag{3.2}$$

where:

$$z_t = \Delta prod_t, rea_t, rpo_t \tag{3.3}$$

[Kilian, 2009] The variables used in this model are: world oil production ($prod_t$), the real economic activity index (rea_t) and the real price of oil (rpo_t). The vector ϵ_t denotes the serially and mutually uncorrelated structural innovations. The matrix A_0^{-1} has a recursive structure such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1}\epsilon_t$.

Through the SVAR model, we compute the structural decomposition of the real price of oil into three different types of shocks: oil supply shocks, aggregate demand shocks, oil specific-demand shocks. To identify the shocks we need to impose some restrictions on the A_0^{-1} matrix. Here we use a recursive identification scheme based on exclusion restrictions, the so-called Cholesky decomposition [54]. The restrictions based on a Cholesky decomposition scheme are plausible from an economic point of view.

Through the Cholesky decomposition it is possible to identify the three oil price shocks as follows:

$$e_t = \begin{bmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \epsilon_t^{oilsupplyshock} \\ \epsilon_t^{aggregatedemandshock} \\ \epsilon_t^{oilspecific-demandshock} \end{bmatrix} \tag{3.4}$$

The three different types of shocks that have been identified are interpreted as follow: oil supply shock (interpreted as unexpected innovations to oil production); aggregate demand shock or shock to global demand for industrial commodities (interpreted as innovations in global real economic activity that cannot be explained by oil supply shocks); oil-specific demand shocks (interpreted as oil price innovations that cannot be explained by oil supply shocks and aggregate demand shocks). Oil-specific demand shocks are related to oil demand which is caused by uncertainty about the future oil supply.

One of the restrictions in this model assumes a short-run vertical supply curve for crude oil (which means that the short-run supply elasticity is zero). Crude oil production is assumed not to respond to innovations in oil demand (both aggregate demand and specific oil demand) within the same month. Furthermore, the idea behind this exclusion restriction is that oil-producing countries do not increase oil production in response to demand shocks within one month given the costs of adjusting the production level. Oil production (which is the model's first variable) responds only to innovations in oil supply within the same month.

Global real economic activity index responds only to the oil supply shock and aggregate demand shock within one month. It is assumed that the oil-specific demand does not affect the

[53] See [Kilian, 2009]

[54] This identification scheme was originally proposed by [Sims, 1980]. The same methodology was also used in[Kilian, 2009]. The Cholesky decomposition scheme implies a recursive form for the equations. It is a special case of the C model, where the C matrix is lower triangular. For more information see [Kilian and Lütkepohl, 2017]

global economic activity within one month. The real oil price responds to the oil supply shock, aggregate demand shock, and oil-specific demand shocks within one month [55].

[Kilian and Murphy, 2014] In this section, we will conduct the same analysis following [Kilian and Murphy, 2014] [56]. In contrast to the previous model, here we add the variable corresponding to changes in oil inventories. We estimate a SVAR model by imposing sign restrictions, dynamic restrictions, and elasticity bounds restrictions.

The SVAR representation is the same as above [57].

The matrix representation of the reduced form shocks is [58]:

$$e_t = \begin{bmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \\ e_t^{inv} \end{bmatrix} = \begin{bmatrix} - & + & + & a_{14} \\ - & + & - & a_{24} \\ + & + & + & a_{34} \\ a_{41} & a_{42} & + & a_{44} \end{bmatrix} \begin{bmatrix} \epsilon_t^{oilsupplyshock} \\ \epsilon_t^{aggregatedemandshock} \\ \epsilon_t^{oilspecific-demandshock} \\ \epsilon_t^{otherdemandshocks} \end{bmatrix} \tag{3.5}$$

Sign restrictions Here to identify the shocks instead of using a point-identified model we use a set identified model. The restrictions are nothing more than the information we have from economic theory. Generally, the restrictions we impose can be based on formal or informal information.The restrictions we use here are classified in: sign restrictions, dynamic restrictions, and the elasticity bounds restrictions.

Sign restrictions indicate the direction of a given variable's response to a given shock. This type of restriction may arise from economic theory, previous beliefs, or the results of various simulations computed on the topic.

Following the sign restrictions that we impose here, a negative flow supply shock has a negative effect on oil production and the real economic activity index, and a positive effect on the real price of oil on impact. There are no restrictions on the effect of the supply shock on inventories.

A positive flow demand shock is limited to have a positive effect on oil production, the real economic activity index, and the real oil price upon impact. The effect of the flow demand shock on inventories has not been restricted.

A positive speculative demand shock has a positive effect on oil production, real oil price, on inventories, and a negative effect on real economic activity.

Elasticity bounds The elasticity bounds are related to some limited values impose for the demand and supply elasticity. As for the elasticity bounds, in addition to those used in KM, there are many other values for the elasticity of supply and demand derived from empirical results of various articles [59]. In the Bayesian framework, this information about the elasticity bound can be interpreted as a prior [60]. We impose the price elasticity of oil supply to be positive and the price elasticity of oil demand to be positive.

Some literature in the elasticity bounds There is a consensus in the literature that the short-run price elasticity of oil supply is close to zero or even zero. In [Kilian, 2009] a short-term vertical oil supply curve is assumed which implies a supply elasticity equal to zero. In KM

[55] The restrictions explained so far are part of the recursive model explained in [Kilian, 2009].

[56] We will refer to this paper as KM.

[57] Equation3.6

[58] The latest shock is not identified.

[59] [Caldara et al., 2019], [Baumeister and Hamilton, 2019], and [Bjørnland et al., 2019]

[60] [Baumeister and Hamilton, 2019]

the supply elasticity is assumed to be 0≤ elasticity≥0.025 [61]. It seems that the value of 0.025 derives from a calculation relating to the episode of August 1990 when Iraq invaded Kuwait. This episode corresponds to a decrease in oil production in Iraq and Kuwait, an increase in oil production in other countries, and an increase in the price of oil. This supply elasticity is calculated as the ratio of the increase in oil production in other countries (1.17%) to the increase in oil prices (45.3%).

In other articles, we find different values attributed to the elasticity of supply.

In [Caldara et al., 2019] the authors found a short-term supply elasticity of 0.077.

In [Bjørnland et al., 2019] the authors analyze monthly crude oil production from 15,000 individual wells in North Dakota from 1986 to 2015. They estimate a short-term elasticity of supply of 0.2, higher than in the two previous papers. In [Baumeister and Hamilton, 2019] the authors estimate a short-term supply elasticity of 0.15.

In the literature, we also find references on the elasticity of demand. Many authors have studied the price elasticity of oil demand using different data sources and methods.

In [Hausman and Newey, 1995] the authors use cross-country data for the US and provide a long-run elasticity of demand for gasoline of -0.81. These bounds for the elasticity of demand are the same as used in KM. In [Yatchew and No, 2001] the authors use a cross-section of Canadian households and present a long-run elasticity of demand of -0.9. [Baumeister and Hamilton, 2019] estimate a long-run elasticity of demand of -0.51. [Dahl and Sterner, 1991] come up with an average long-run demand elasticity of -0.86. [Espey, 1998] estimate a demand elasticity of -0.58.

[Graham and Glaister, 2004] estimate an elasticity of -0.77. [Brons et al., 2008] proposed an elasticity of demand of -0.84. There is a consensus in the literature that the short-run elasticity of demand is lower than the long-run elasticity.

Good draws When using the sign restrictions we will have a set identified model, which means that in the end, we will not get a single solution[62].

This is why the number of good draws (or solutions, or models that meet all the restrictions) can be high and consequently, the uncertainty about the results will also increase. So, we impose the restrictions using all the information we have from economic theory or empirical results. By adding more information (through the restrictions we impose), we expect to reduce the range of good draws. In principle, we would say that when the number of good draws is reduced after adding a restriction, it means that this restriction is very informative and helps us reduce uncertainty.

However, we can say that adding new restrictions reduces uncertainty if and only if the restrictions we impose are the real ones, otherwise we could have biased results.

Hence, we must be careful to interpret the reduction in the number of good draws after adding a restriction.

To understand this better, let's say that after adding a block of restrictions to the model the number of good draws is zero (this is an extreme case). This means that there is no model that meets these restrictions. So the restrictions individually or their combination may be wrong and what we need to do is use other restrictions. When the number of good draws is very low, we are very close to the borderline case, which means that we must pay attention to the restrictions we are imposing and their validity. Having imposed restrictions and if the number of good draws decreases, it means that the restriction is very informative or even very restrictive as there is a very small number of models that satisfy it. This is one of the reasons we need to be careful when interpreting the results.

[61] In the online Appendix related to [Kilian and Murphy, 2012], we find the explanation of the choice for the supply elasticity bounds.

[62] see [Kilian and Lütkepohl, 2017]

[Kilian and Murphy, 2012] argued why it was not enough to use only the sign restriction to model the oil market. Basically, researchers want to use more restrictions in order to reduce the number of eligible draws.

Empirical evidence We estimate a SVAR model using two different identifications schemes for the shocks: the Cholesky decomposition and the sign restrictions. In the former case three variables are entering the model: the percentage change in oil production, an index for global economic activity, the real price of oil. Through the Cholesky decomposition, we identify three oil shocks: oil supply shock, aggregate demand shock, oil specific demand shocks. The SVAR is estimated for the period 1974:01-2007:12 following [Kilian, 2009]. Afterwards, the same model is estimated but for the extended sample 1974:01-2019:12. Then, we estimate the SVAR for the period 1974:01-2019:12 using several variables as a proxy for the global economic activity. We compare the results obtain after each estimation.

When estimating the SVAR model using the sign restrictions for the identification of shocks, four variables are entering the model: the percentage change in oil production, an index for global economic activity, the real price of oil, and the change in inventories (which somewhat captures shifts in the expectations of forward-looking traders). We rebuilt the data-set by getting the data from the same sources as KM and transforming it accordingly. Through a combination of sign restrictions, dynamic restrictions, and elasticity bounds we identify the three oil shocks interpreted as in the previous model. We estimate a SVAR model for the period 1974:01-2009:08. Afterwards, the same model is estimated for the extended sample 1974:01-2019:12. Then, we estimate the SVAR for the period 1974:01-2019:12 and 1990:01-2019:05 using several variables as a proxy for the global economic activity. The alternative indices despite the Kilian index are the OECD IP index, GECON index and the WSP (World Steel Production)index. We compare the results obtain after each estimation.

3.6.1 IRFs plots

Another important aspect is how we decide to show the IRF. In the case of point estimation, we do not have to concern because the solution is unique, so the IRF derives from a single model and what we can do is decide to add error bands for the graphical representation.

But when it comes to the set identified models, we are left with many models, and we can derive IRF corresponding to each model. The main point is to choose the right IRF to display in a chart Having a large number of models usually increases the uncertainty about the results. For example, different models can provide different IRFs (in sign and magnitude). In this case, we may have problems of interpretation because we do not know which is the "right" model.

Usually, when computing the IRF, the econometric software calculates them as the median at each point [63]. But at any point, the medians could be coming from a different model. So the final IRF is not the one corresponding to a single model but the union between these different points. There has been a lot of criticism of this methodology.[64].

In KM the authors use the estimates of the impulse response for the model with an impact price elasticity of oil demand in use closest to the posterior median of that elasticity among the admissible structural models obtained conditional on the least-squares estimation of the reduced-form VAR model.

Taking into account the whole debate on this [65], we have decided to represent the IRF as

[63] For example, when we have a set identified model, Gretl calculates the IRF in this way. For more information see the SVAR documentation in Gretl

[64] [Fry and Pagan, 2011], and [Baumeister and Hamilton, 2019])

[65] [Fry et al., 2005], [Fry et al., 2007], and [Fry and Pagan, 2011]

a "Spaghetti plot" [66]. In the Spaghetti plot, all the IRFs corresponding to all good draws are visible. In this way, we will have a much clearer vision and we will not go wrong in having to make a choice.

3.7 Results

3.7.1 SVAR with Cholesky identification

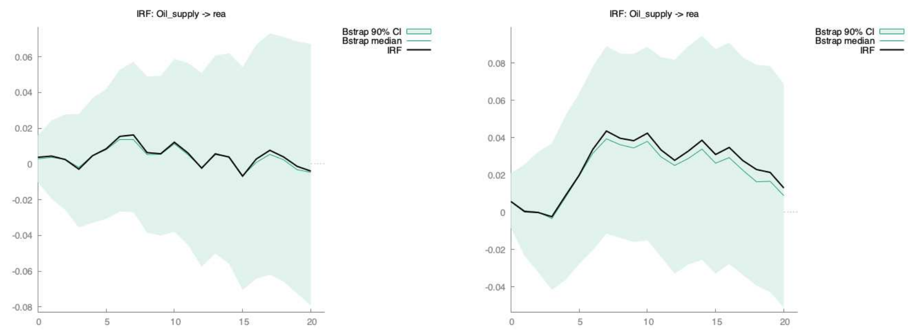


Table 3.1: The response of the Kilian index to the oil supply shock

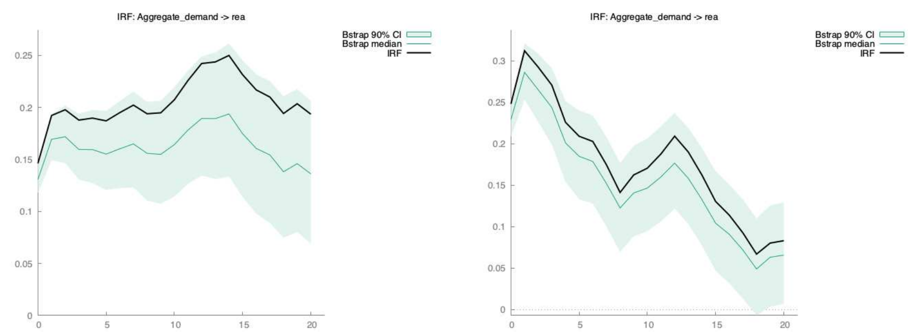


Table 3.2: The response of the Kilian index to the aggregate demand shock

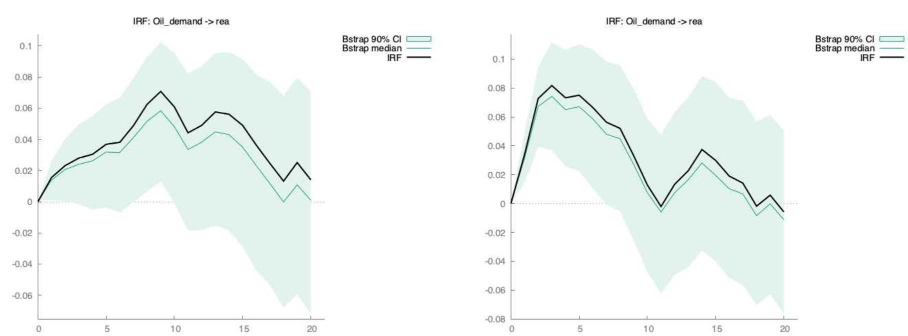


Table 3.3: The response of the Kilian index to the oil-specific demand shock

[66] The notation "Spaghetti Plot" is taken from the documentation relating to the sign restrictions in Gretl written by Riccardo(Jack)Lucchetti

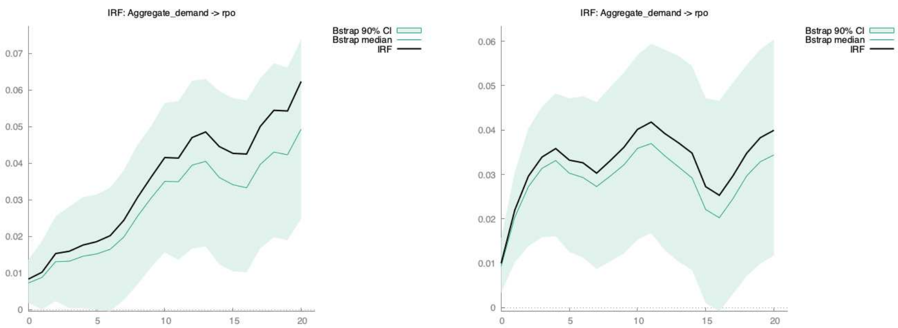


Table 3.4: The response of the real price of oil to the aggregate demand shock

Here we report the differences between the IRFs when we replicate Kilian (2009) and when we extend the sample up to 2019. On the left side, we find the IRF obtained after the SVAR estimate for the period 1974: 01-2007: 12. On the right, we find the 'IRF after model estimation for the extended sample up to 2019. The response of oil production to the three oil price shocks remains the same when we extend the sample. The oil price response to an oil supply shock and an oil demand shock also does not change. We notice slight differences in the RPO's response to an aggregate demand shock. When the sample is extended, the price of oil reacts sharply to a shock in aggregate demand in the first 2 months and thereafter the effect remains more or less constant. When replicating Kilian (2009) this response has a sharply increasing trend. In both cases, the effect is positive and significant.

When the sample stretches, the response of the Kilian index to an oil supply shock is positive after 6 months, while in the first example the median (the black line) bounces around zero.

In both cases, the response is insignificant because the confidence limits include positive and negative values[67].

The response of the Kilian index to a shock of the aggregate demand in the second case is greater at the impact, but decreases dramatically after 2 months and becomes very small from the 13th month onward. In the first case, this response remains constant across all horizons and reaches its maximum value after 1 year. In the second case, however, the maximum value is reached immediately after 1 month.

The response of the Kilian index to an oil demand shock in the second case peaks during the first five months and then starts to decline and becomes insignificant after nine months.

On the contrary, in the first case, this response increases with solemnity until it reaches its maximum value after seven months and becomes insignificant after ten months.

We note that by extending the sample the response of the Kilian index reaches higher values immediately after the shock has occurred, while in the replication and the original results the Kilian index reacts with a certain delay.

When we replicate [Kilian, 2009] most of the IRF does not change. There are slight changes in values and significance when stretching the sample. The response that changes the most is the response of the Kilian index to shocks. One explanation for this is that the construction of this index after 2009 has changed significantly. This explains why it reacts differently to oil price shocks. However, our interest variables (oil production and price) react similarly to oil price shocks.

[67]The first example answers[Kilian, 2009] and his results are in line with those of the original article.

3.7.2 SVAR with Cholesky identification across REAs

Here we report the results of the estimation of the SVAR model for the period 1974: 01 to 2019: 12 when different indices are used to measure economic activity. The response of oil production to an oil supply shock and oil demand is not affected by the change in the index [68]. The response to an oil supply shock is negative and significant across all horizons. The response to an oil demand shock is not significant and assumes different values across all horizons and indices used as a proxy for the real economic activity. [69]. This answer is also in line with the original results. The response of oil production to a shock in aggregate demand is positive and significant over 20 horizons if the GECON and OECD IP indices are used, while it is positive but insignificant when using the Kilian and WSP indices [70]. When aggregate demand increases, oil production should increase in response, so it makes sense that this IRF is positive and meaningful. We conclude that GECON and OECD IP are better proxies in this case.

The oil price response to an oiL supply shock is positive and insignificant across all horizons when using the Kilian index [71]. When using the OECD IP and GECON index the response is positive and significant for the first 7 months. After the war, it becomes negative as in the first case. When using WSP the oil price response is similar to the first case (when using the Kilian index) for the first 9 months. After that, it becomes positive and meaningful. It is more plausible from an economic point of view to think that the oil price is affected by the supply shock immediately after the shock occurs and for the first few months after the shock. So it appears that once again the OECD IP and GECON indices are still better proxies.

In the first three models, the response of causes to an oil supply shock is mostly insignificant. However, the shape of the median and its values change significantly in the different examples.

The response to a shock of the aggregate demand of the various indices used as a proxy for economic activity differs in terms of impact and horizon. However, in all cases, it is positive and significant and tends to decrease along the horizons.

When using GECON, it has the highest impact value and after 12 months it becomes negative. [72].

The response of the indices to oil demand shocks tends to be positive and significant for the first 7 months. Later it becomes negative and insignificant.

When considering the GECON, its answer is negative and most significant across all horizons.

This difference probably depends on how the indexes are constructed and the variables they include.

[68] When using the WSP as a proxy for real economic activity, the response of the oil production to an oil supply shock is less negative across all horizons.

[69] However, the median line is negative when using OECD IP and GECON and positive when using use WSP.

[70] There are few months in which this response can hardly be considered significant.

[71] Even in the original results.

[72] The IRF for KI and WSP are more similar in terms of values. When using the OECD IP, the IRF has small absolute values compared to the others.

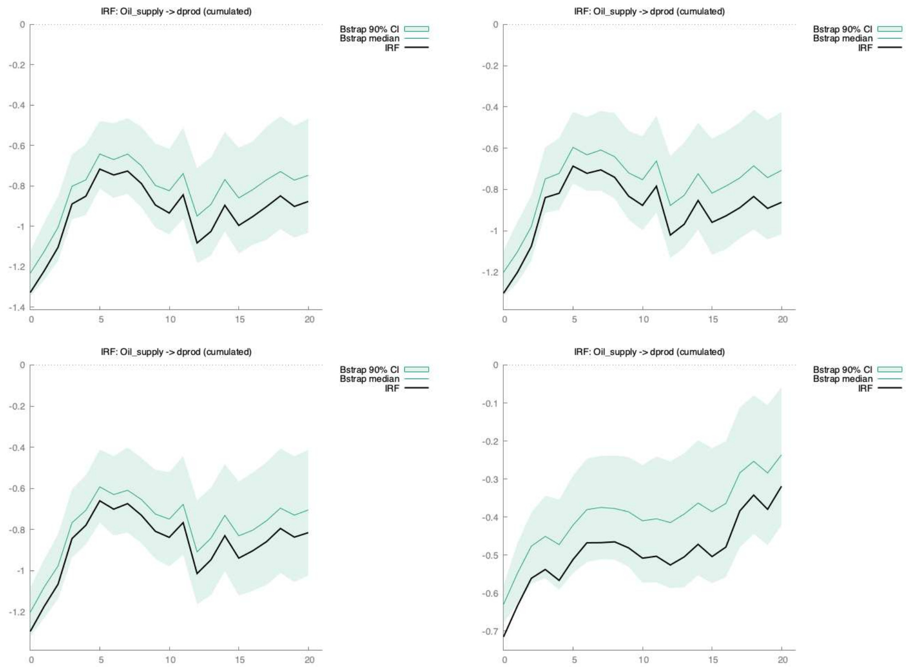


Table 3.5: The response of oil production to an oil supply shock

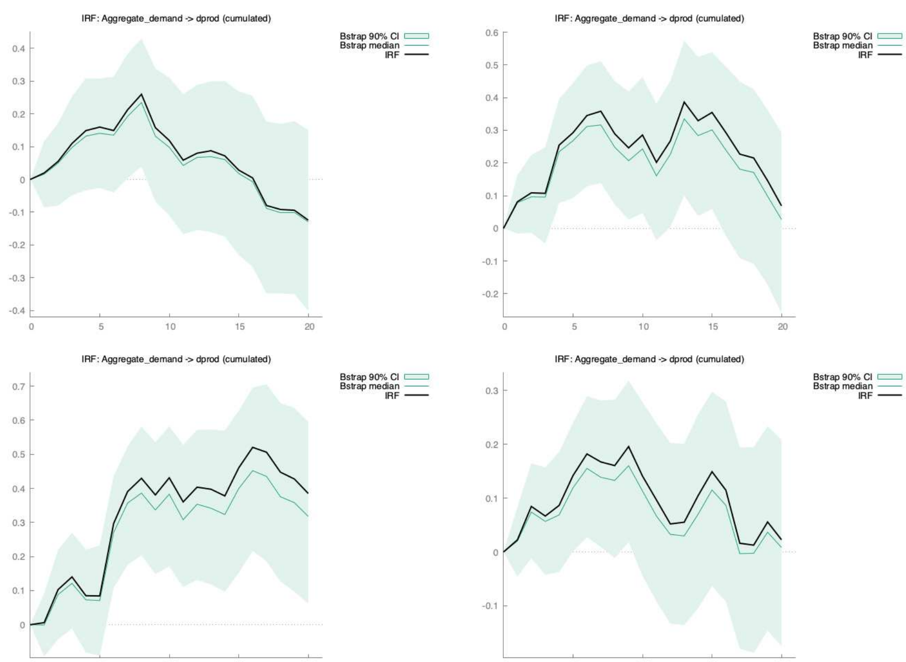


Table 3.6: The response of oil production to an aggregate demand shock

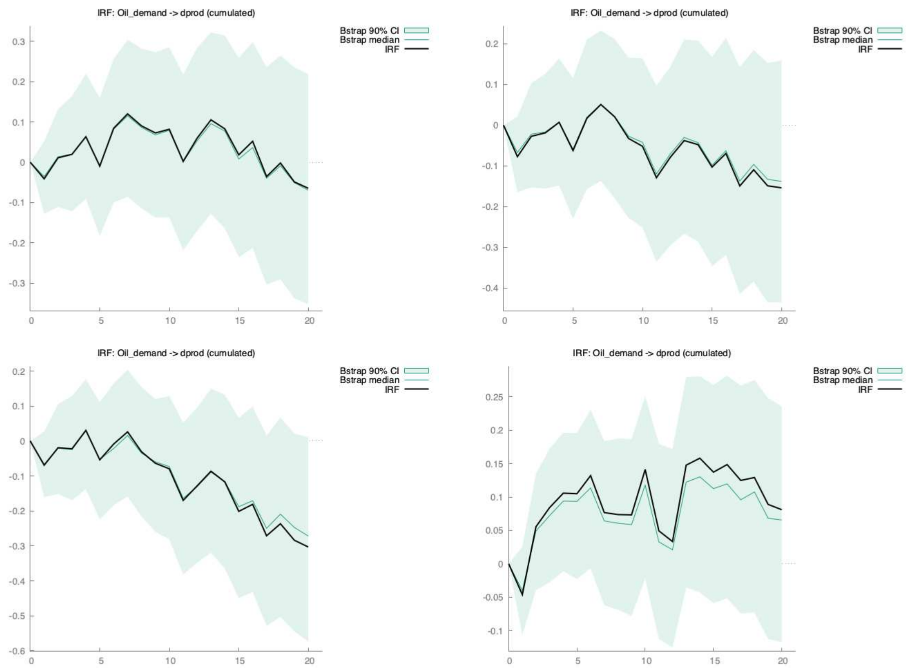


Table 3.7: The response of oil production to an oil demand shock

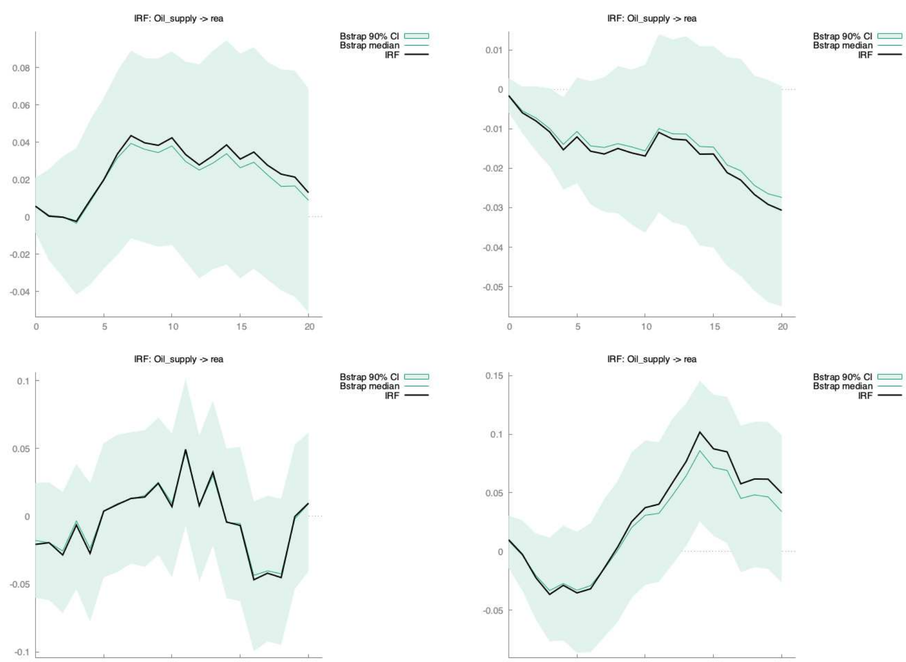


Table 3.8: The response of the real economic activity indexes to an oil supply shock

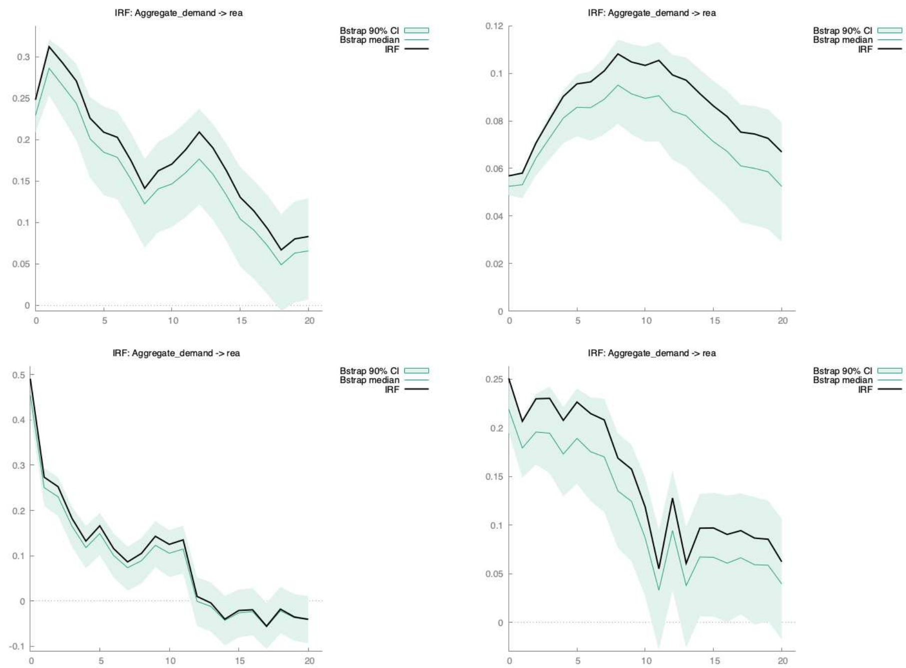


Table 3.9: The response of the real economic activity indexes to an aggregate demand shock

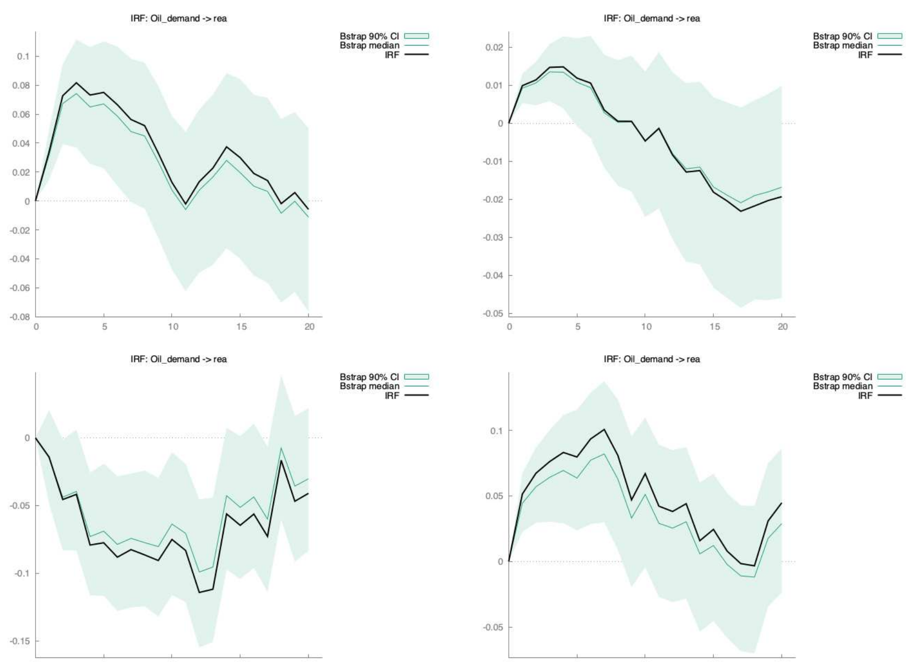


Table 3.10: The response of the real economic activity indexes to an oil demand shock

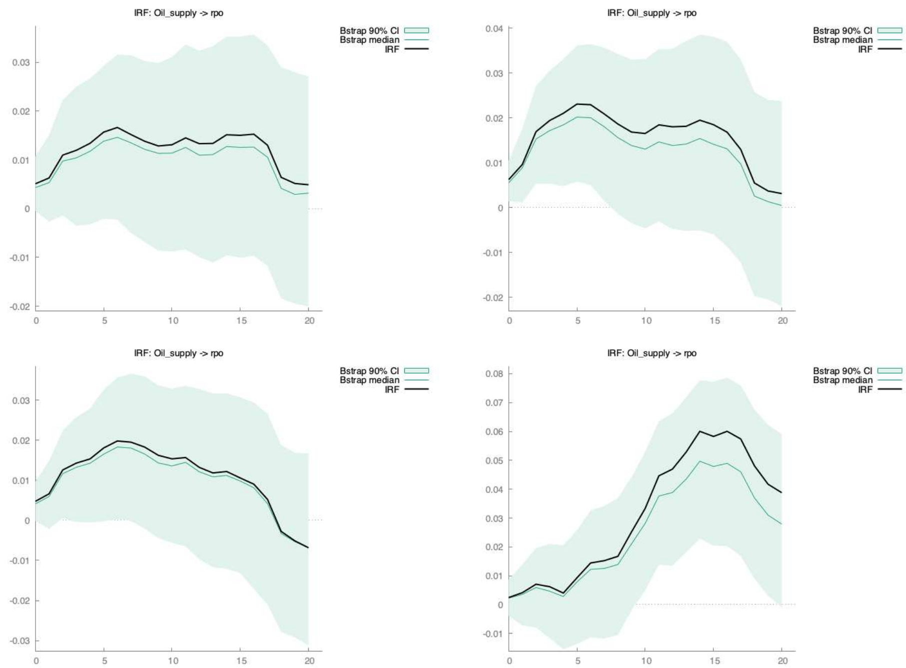


Table 3.11: The response of the real price of oil to an oil supply shock

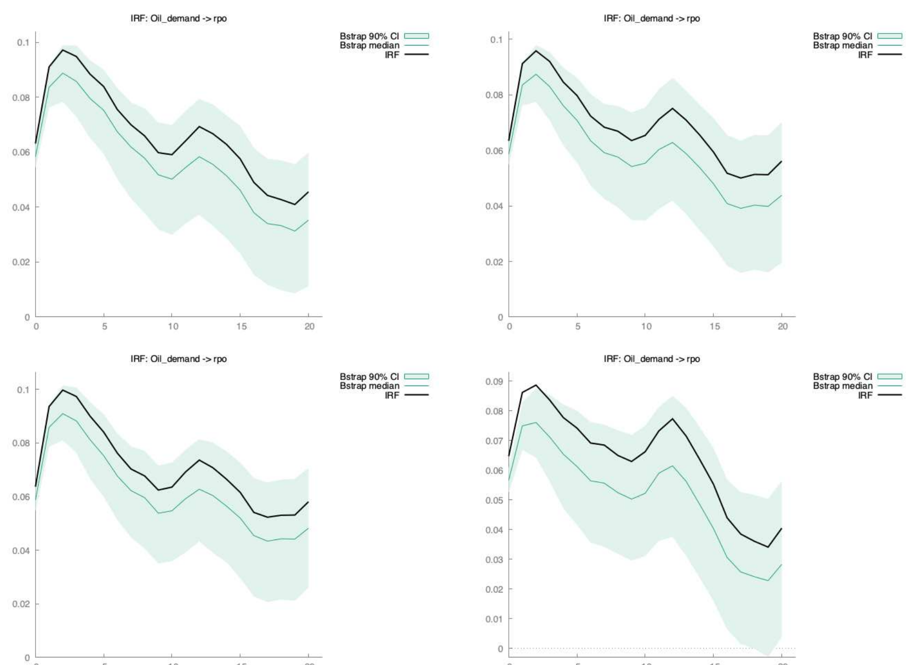


Table 3.12: The response of the real price of oil to an oil demand shock

3.7.3 SVAR with sign restriction identification

Here we report the results of the SVAR estimation using the sign and dynamic restrictions and elasticity bounds for supply and demand as in KM. The difference here is that we relax the lower bound for the elasticity of oil supply and the upper bound for the elasticity of oil demand. When extending the sample, the IRF does not change. However, when comparing to the originals there are some differences. The response of oil production to oil supply and aggregate shocks is in line with the original results. The response of oil production to an oil demand shock is positive and insignificant in our case, while it is negative and significant in the original KM results. According to the restrictions imposed, the answer should be positive, so it is strange that in the original results it is negative.

The oil price response to a supply and aggregate shock is in line with the original results. The oil price response to an oil demand shock is different from the original one. In our example, the answer is positive and insignificant, while in the original it is positive and significant in all horizons.

The response of oil inventories to a shock in oil supply and aggregate demand is negative and significant in the original results. In our case, it is negative but insignificant. The response of inventories to a demand shock is both positive and significant. The response of the Kilian index to shocks is in the line with the original results. These differences are attributed to the different identifications and different ways of showing the IRF functions.

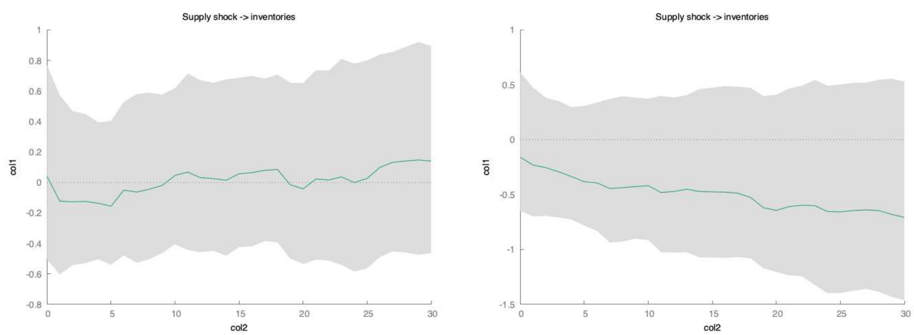


Table 3.13: The response of the inventories to an oil supply shocks

3.7.4 SVAR with sign restriction identification across REAs

The OECD response to an oil supply shock is less negative on impact than other indices. The GECON and the WSP converge to zero faster than the OECD IP and Kilian indices. The effect of an aggregate demand shock on the impact is greater when considering the GECON and smaller for the OECD IP. The answer on impact for the Kilian and WSP index is more similar. From the spaghetti plots, it can be seen that for GECON the response coming from the different models differs less than in the other cases.

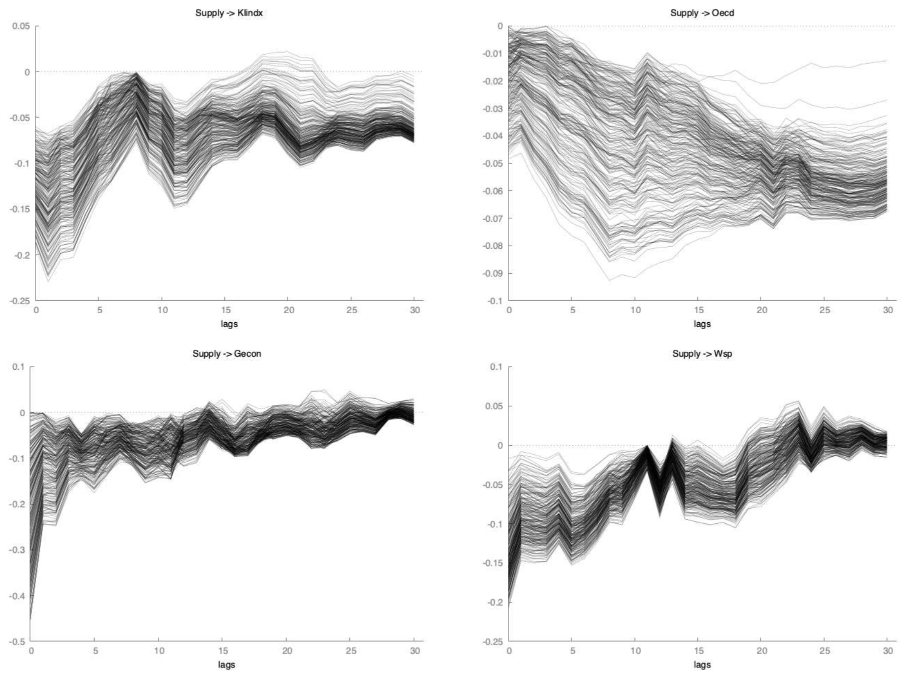


Table 3.14: The response of the real economic activity indexes to an oil supply shocks

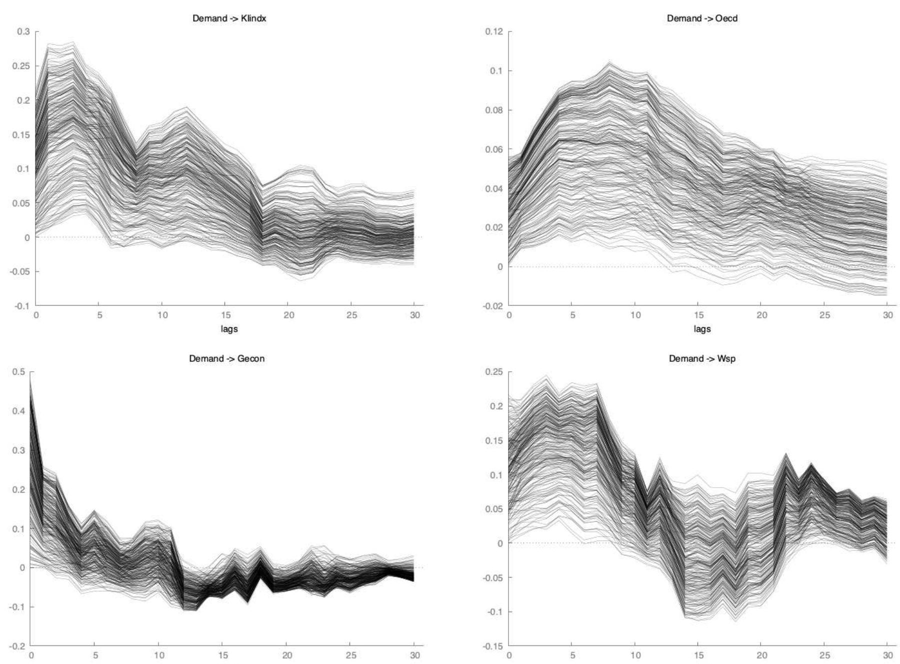


Table 3.15: The response of the real economic activity indexes to an oil aggregate demand shocks

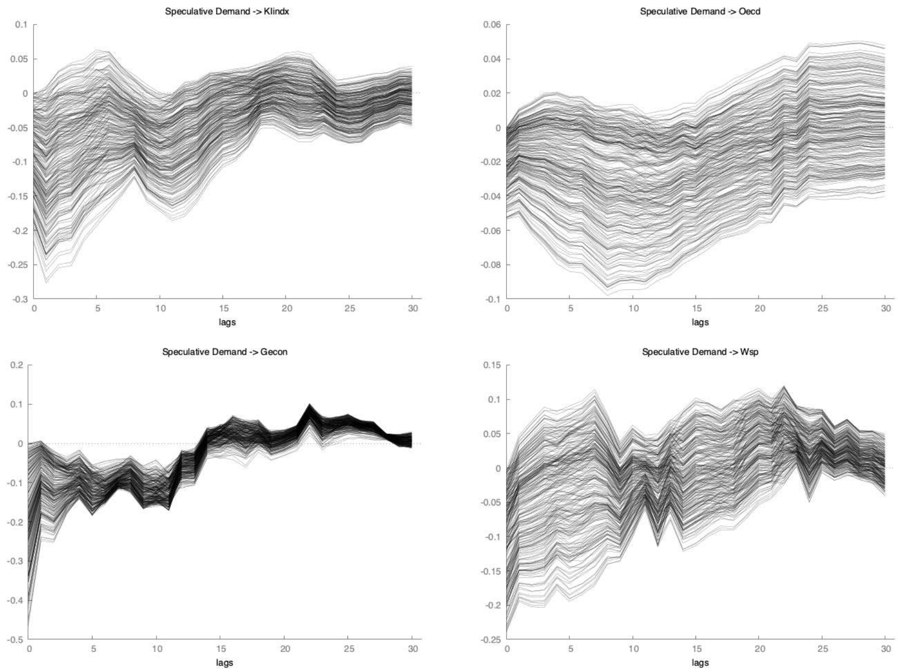


Table 3.16: The response of the real economic activity indexes to an oil demand shocks

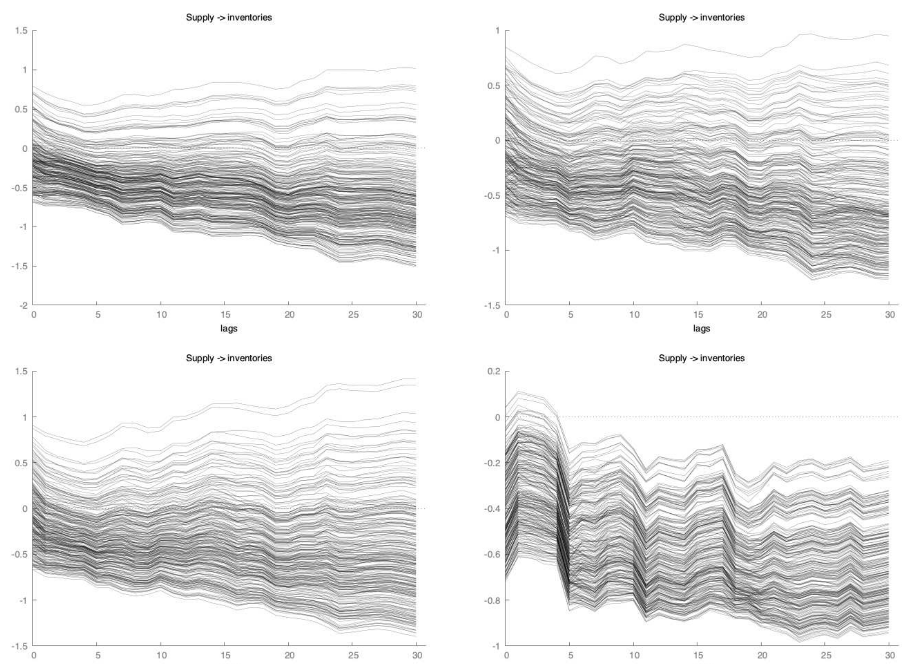


Table 3.17: The response of the inventories to an oil supply shocks

3.8 Forecasting VAR model

To understand which of the real economic indices is the best for modeling the oil market, we perform some forecast analysis. We estimate the VAR model for two different periods: the period from 1974:01 to 2018:12 and for 1990:01 to 2018:12. The number of lags that we use is 12 since has been shown that it delivers the most accurate out-of-sample forecasts for the real RAC ([Baumeister et al., 2020] and [Baumeister and Kilian, 2015]). We estimate our model for two different time samples for two reasons. First, the index for the WSP is available only from 1990:01. Second, we want to check if the forecasting performance of different models changes when we estimate the real price of oil for different sub-samples. The variables that enter the VAR model are oil production, the different measures of global economic activity, and the real price of oil. We perform an out-of-sample dynamic forecast for the period from 2019:01 to 2019:12 in the first case and the period from 2018:06 to 2019:05 in the second case. To evaluate the forecast performance among the alternative models, we compare some forecast statistics as shown in the Table 3.18. The main forecasting statistic that we consider to conclude which model does better is the RMSE (Root Mean Squared Error).

In Table 3.18, we show the results of the main forecasting statistics for four different VAR models. The difference between these VAR models consists of the usage of the real economic activity variable. These VAR models are estimated for the period from 1974:01 to 2018:12. We perform the out-of-sample dynamic forecast for the period from 2019:01 to 2019:12. In the first column, we show the results of the forecasting accuracy for the VAR which uses the KI as a proxy for the real economic activity. In the second column, we show the results of the forecasting accuracy for the VAR which uses the OECD IP+IP of six emerging counties index as a proxy for the real economic activity. In the third column, we show the results of the forecasting accuracy for the VAR which uses the GECON index as a proxy for the real economic activity. From the comparison of the RMSE statistic, we find that the KI followed from the GECON one are the best in terms of forecasting accuracy for the real price of oil. The forecasting accuracy increases by 18% when using the KI instead of GECON (it means that the RMSE decreases by 18%). It increases by 20% when using the KI instead of the OECD, and by 1.6% when using the GECON instead of OECD. From this forecasting exercise, we find that the Kilian index has a better forecasting performance followed by GECON and OECD.

In Table 3.19, we show the results of the main forecasting statistics for the VAR models estimated for the period from 1990:01 to 2018:05. We perform the out-of-sample dynamic forecast for the period from 2018:06 to 2019:05. As in the previous example, the difference between these VAR models consists of the usage of the real economic activity variable. The interpretation of Table 3.19 is the same as for the previous table. The difference between the two tables is that in the second one we estimate one more VAR model which uses the WSP as a proxy for the real economic activity. In this table, we have one more column. In the fourth column, we show the results of the forecasting accuracy for the VAR which uses the WSP (World Industrial Production) index as a proxy for the real economic activity.

From the comparison of the RMSE, we find that when using the GECON index the forecasting performance improves. The following best indexes are the OECD, KI, and WSP. The forecasting performance increases by 0.6% when using the GECON index instead of the OECD one and by 11% when using it instead of the KI. WSP shows the worst forecasting performance for the real price of oil. The forecasting accuracy decreases by 53% when using the GECON index instead of the WSP one. The forecast improves by 10% when we use the OECD index instead of the KI and by 46% when we use the KI instead of the WSP.

A similar result between the two different forecasting periods is that the forecasting performance of the GECON and the OECD indexes are much close to each other than the forecasting performance between other indexes. Moreover, in both cases, the GECON performs better than the OECD.

For the first sub-sample, we estimate an AR(1) model which is usually used as a benchmark for analyzing the forecasting accuracy of models. However, in this example, our aim is not to analyze the forecasting accuracy of the models, but to compare them with each other. In the first sub-sample forecast, no model outperforms the benchmark. For the AR(1) the RMSE=0.283. In the second sub-sample the AR(1) the RMSE=0.154. In this case, only the OECD and GECON indexes outperform the benchmark.

The Diebold-Mariano (DM) test can be used for testing the forecasting accuracy between to different models [73]. It is a test for predictive accuracy and of equivalent expected loss takes that takes into account the underlying loss function as well as sampling variation in the average losses.

The null hypothesis is that the two forecasts have the same accuracy. The alternative hypothesis is that the two forecasts have different levels of accuracy. When we perform this test for the previous models, we perform it for different loss functions(U-shape loss function (symmetric), V-shape loss function (symmetric), Lin-Lin loss function (asymmetric), Linex loss function (asymmetric) [74]. After performing this test for VAR models estimated previously, we fail to reject the null hypothesis. Thus, he Diebold-Mariano test suggest that all modes have the same forecasting accuracy [75].

The Giacomini-White (GW) test is another test on equal conditional predictive ability. We perform this test to compare the forecasting accuracy of the models estimated previously [76]. We use two loss functions, namely symmetric quadratic (U-shape) loss. The output of the test shows us which forecasting model dominates. If the sign of the mean of the loss is positive the 2nd model dominates, and vice-versa. The results of the GW test are in line with the ones derived from the comparison of the RMSE. For the first forecasting sub-sample, the KI has a better forecasting performance followed by GECON and OECD.

For the second sub-sample, the GECON index has a better forecasting performance followed by OECD, KI, and WSP.

The tests we have done so far to compare forecasts are considered Equal Predictive Ability Tests (EPAs). These tests compare two (or more) competing forecasts and tell us if they are equally good. There is the possibility of using other tests such as SPA (Superior Predictive Ability) and MCS (Model Confidence Set). These tests allow us multiple competing forecasts, one of which is a "benchmark". Based on the test results we can understand if any alternative predictions beat the benchmark. However, in this analysis, we do not include the SPA and MCS tests.

REAS	KI	OECD	GECON	WSP
Mean Error	0.284	0.364	0.354	0.39185
Root Mean Squared Error	0.297	0.372	0.366	0.4006
Mean Absolute Error	0.284	0.364	0.354	0.39185
Mean Percentage Error	− 19.387	-24.779	-24.172	-26.656
Mean Absolute Percentage Error	19.387	24.779	24.172	26.656
Theil's U	4.655	5.843	5.753	6.27
Bias proportion, U^M	0.912	0.956	0.936	0.9568
Regression proportion, U^R	0.028	0.006	0.024694	0.010138
Disturbance proportion, U^D	0.059	0.03	0.038	0.033

Table 3.18: Forecast evaluation statistics

73 [Diebold and Mariano, 2002]

74 [Pesaran and Timmermann, 1992]

75 See the results of these test in Appendix A

76 [Giacomini and White, 2006]

REAS	KI	OECD	GECON	WSP
Mean Error	-0.11868	-0.084989	-0.082913	-0.27276
Root Mean Squared Error	0.16762	0.14987	0.14899	0.31853
Mean Absolute Error	0.12033	0.10253	0.095063	0.27276
Mean Percentage Error	7.6288	5.2277	5.1032	18.175
Mean Absolute Percentage Error	7.7539	6.5549	6.0084	18.175
Theil's U	1.4196	1.2645	1.2648	2.771
Bias proportion, U^M	0.50132	0.32159	0.30971	0.73329
Regression proportion, U^R	0.17248	0.13912	0.046528	0.13055
Disturbance proportion, U^D	0.32619	0.53929	0.64376	0.13616

Table 3.19: Forecast evaluation statistics

3.8.1 Forecasting Pre and Post Recession

In this section, we perform a forecasting analysis similar to the previous one. The difference here is that we analyze two different sub-samples: Pre-Great Recession and Post-Great Recession. To compare the forecasting accuracy of the real economic activity indexes Pre-Great Recession, we estimate the VAR for the period from 1990:01 to 2006:12. Then we perform the dynamic out-of-sample forecast for the period from 2007:01 to 2007:12. For the Post-Great Recession, we estimate the VAR from 2009:01 to 2018:05. Similar to the previous case, we perform the dynamic out-of-sample forecast for the period from 2018:06 to 2019:05. We are doing this distinction because we know that in 2008 the oil price reaches its highest values and after the great recession it decreased dramatically. We want to check if this episode has altered the forecasting accuracy of the real economic activity indexes. Moreover, [Baumeister and Guérin, 2021] suggests that the Great Recession is a key episode for some monthly global indicators to outperform the AR(1) benchmark.

From the estimation pre this episode, all the indexes outperform the forecasting results derived from an AR(1). In the AR(1) benchmark model the RMSE= 0.306. In this forecasting exercise, we find that the OECD index performs better, followed by the KI, GECON, WSP.

From the estimation post this episode, only the OECD outperform the forecasting results derived from an AR(1). The KI, GECON, and WSP indices fail to outperform the AR(1) MODEL. In this benchmark model the RMSE= 0.167. Similar to the previous example, we find that the OECD index performs better, followed by the KI, GECON, WSP.

After performing the Diebold-Mariano test for VAR models estimated previously, we fail to reject the null hypothesis. Thus, the Diebold-Mariano test suggests that all modes have the same forecasting accuracy [77].

We perform the Giacomini-White (GW) test to compare the forecasting accuracy of the models estimated previously. We use two loss functions, namely symmetric quadratic (U-shape) loss. The output of the test shows us which forecasting model dominates. If the sign of the mean of the loss is positive the 2nd model dominates, and vice-versa. The results of the GW test are in line with the ones derived from the comparison of the RMSE. For the first forecasting sub-sample, the OECD has a better forecasting performance followed by KI, GECON, and WSP. For the second sub-sample, the OECD index has a better forecasting performance followed by KI, GECON, and WSP. The results of these two forecasting exercises are the same.

After making some forecasting analysis for the real price of oil for different sub-sample we show that most of the time the model which performs better is the one that uses the OECD IP as a proxy for the real economic activity index. This is the reason why we choose this model

[77] See the results of these test in Appendix A

as the best one and use the three oil price shocks obtained from it for the analyses that we are going to conduct in the third chapter.

REAS	KI	OECD	GECON	WSP
Mean Error	0.28347	0.22772	0.28586	0.30049
Root Mean Squared Error	0.37461	0.35815	0.39085	0.42014
Mean Absolute Error	0.3049	0.27945	0.31481	0.33817
Mean Percentage Error	-28.247	-23.657	-28.73	-30.373
Mean Absolute Percentage Error	29.785	27.472	30.822	33.118
Theil's U	7.3293	7.1011	7.6832	8.2938
Bias proportion, U^M	0.57262	0.40425	0.53492	0.51154
Regression proportion, U^R	0.40475	0.55849	0.44804	0.47553
Disturbance proportion, U^D	0.022629	0.037257	0.017031	0.012926

Table 3.20: Forecast evaluation statistics

REAS	KI	OECD	GECON	WSP
Mean Error	-0.17423	-0.0075679	-0.21794	-0.30888
Root Mean Squared Error	0.22562	0.1282	0.26542	0.35459
Mean Absolute Error	0.17423	0.094733	0.21794	0.30888
Mean Percentage Error	11.374	-0.18442	14.4	20.657
Mean Absolute Percentage Error	11.374	6.2809	14.4	20.657
Theil's U	1.9164	1.1135	2.2679	3.0831
Bias proportion, U^M	0.59631	0.0034846	0.67425	0.75881
Regression proportion, U^R	0.023898	0.0004799	0.028896	0.13318
Disturbance proportion, U^D	0.37979	0.99604	0.26326	0.10801

Table 3.21: Forecast evaluation statistics

3.9 Conclusions

Our findings are robust to an alternative measure of global real economic activity.

Understanding the determinants of oil prices and their relationship to macroeconomic variables has been a challenge for researchers in recent years. Many studies have been done to model the oil market and many different models have been used in the literature.

In this article we are basing our research on two other very important studies on this topic: [Kilian, 2009] and[Kilian and Murphy, 2014].

We replicate and extend the [Kilian, 2009] results by extending the sample. We are conducting some additional robustness checks to verify the reliability of their results. We identify three price components of crude oil shocks: oil supply shock, aggregate demand shock, and oil market-specific demand shock.

First, we estimate a SVAR model identified through the Cholesky decomposition after [Kilian, 2009]. We conclude that the results after estimating the SVAR model are in line with the original ones in [Kilian, 2009]. After these robustness checks, we conclude that the results do not change significantly even after expanding the estimation sample.

The effect of a positive aggregate demand shock and an oil-specific demand shock on the real oil price is positive and significant over 20 horizons. Conversely, the effect of a negative oil supply shock on the real oil price is nil and not significant.

Oil production has a negative response to a negative oil supply shock, while its response to positive aggregate demand and specific oil demand shock is zero and insignificant.

These results do not change when the sample is extended or when different proxies are used for real economic activity. Policymakers when trying to model the oil price should consider that it increases after a positive aggregate demand shock and a specific oil demand shock. Furthermore, the supply side does not affect the real price of oil. The main drivers of the oil price can be found on the demand side of the economy.

Secondly, when we replicate [Kilian and Murphy, 2014], we find that the results are very sensitive because, after a very large number of rotations, the number of good extractions we get is very small. Usually, if the model is significant, we expect it to converge after a reasonably low number of rotations.

We find that the reason behind the first statement is a very "tight" restriction which is the upper bound for the elasticity of oil supply and the lower bound for the elasticity of oil demand. The elasticity of the oil supply is assumed to be between 0 and 0.025. The elasticity of oil demand is between -0.8 and 0.

For this reason, in addition to the sample extension, we use a different set of restrictions. In this case, we are not doing true replication because the identification of the models we estimate is different. After relaxing these restrictions, the number of good extractions increases significantly. We conclude that the elasticities bounds used in the original document are very restrictive and problematic.

Third, we estimate the SVAR model identified by sign and dynamics restrictions and some elasticity bounds for oil demand and supply. We emphasize that not all results are in line with [Kilian and Murphy, 2014]. This is probably attributed to the fact that we have relaxed some of the restrictions imposed in [Kilian and Murphy, 2014]. We conclude that the relaxed restrictions were an important factor in achieving the results in [Kilian and Murphy, 2014]. These results are sensitive when the identification strategy is changed.

The response of oil production to an oil demand shock is positive and insignificant in our case, while it is negative and significant in the original KM results. According to the restrictions imposed, the answer should be positive, so it is strange that the original results are negative. The oil price response to an oil demand shock is different from the original one. In our example, the answer is positive and insignificant, while in the original it is positive and meaningful significant over all horizons. The response of oil inventories to a shock in oil supply and aggregate demand is negative and significant in the original results. In our case, it is negative but insignificant. These differences are attributed to the different identifications and different ways of showing the IRF functions.

Fourth, we replicate [Kilian and Murphy, 2014] using different proxies for the real economic activity index. We estimate the SVAR model, replacing the variable for real economic activity with different indices proposed in the literature. We find that after replacing the Kilian index with other proxies, only some of the results differ from the originals. The IRFs that change the most are those that represent the response of the economic activity indices to the various oil shocks. The novelty here is that we use different proxies for real economic activity to identify the aggregate demand shock.

Fifth, we use another form of representation for the IRF compared to the original paper. When representing IRFs à la [Uhlig, 2005] instead of representing them as KM, the visual part is different and the interpretation of the responses of the variables to shocks could change significantly. For this, we decide to report the entire set of IRFs through the so-called "Spaghetti Plots". Using this type of graphical representation, we show all IRFs of all models that meet the restrictions imposed. We can visualize how much the magnitude, shape, and significance of these responses may differ between models. The use of these IRF plots is a novelty in research on oil market models. We suggest these charts are better than others because they provide comprehensive information.

Finally, after using alternative indices for real economic activity, we want to select the one that can best model the oil market. We compute some forecasting exercises for the real oil price using the VAR model and various indices for global economic activity. We estimate several subsamples and perform an out-of-sample dynamic forecast. To compare the accuracy of the forecast, we compare some forecast evaluation statistics. Furthermore, after running the Diebold-Mariano and Giacomini-White tests for the accuracy of the predictions, we conclude that the VAR model using the OECD IP as a proxy has the best predictive power for the price of oil. We choose the OECD IP index as the best real economic activity index to predict the real price of oil.

For the first forecast subsample from 1974:01 to 2018:12, the KI has better forecast performance, followed by GECON and the OECD. For the second subsample from 1990:01 to 2018:12, the GECON index has a better forecasting performance followed by OECD, KI, and WSP.

For the first forecast subsample from 1990:01 to 2006:12, the OECD has better forecast performance, followed by KI, GECON, and WSP. For the second subsample from 2009:01 to 2018:05, the OECD index has a better forecast performance, followed by KI, GECON, and WSP. The results of these two forecasting exercises are the same.

After making some forward-looking analyzes of the real oil price for several subsamples, we show that most of the time the model that works best is the one that uses the OECD IP as a proxy for the real economic activity index. That is why we choose this model as the best and use the three oil price shocks obtained from it for the analyzes we are going to conduct in the third chapter.

Policymakers should bear in mind that global economic activity is an important factor influencing the evolution of the oil price. Also, when choosing the right proxy for this variable, we suggest that they choose the OECD IP because it has a better forecasting performance.

Chapter 4

Oil price shocks and the Russian economy

4.1 Introduction

For a long time, researchers have focused on identifying the impact of oil price shocks on macroeconomic variables [1].

Strong increases in the price of oil have always been linked to critical values of macroeconomic aggregates. One of the most crucial episodes of this kind was in the 1970s when the economy of some of the most industrialized countries was characterized by low growth, high unemployment, and high inflation [2]. Therefore, oil price fluctuations were considered to be the main sources of variation in macroeconomic variables.

As a result, for many years researchers have been concentrated on analyzing the effects that the oil price fluctuations had on the economy. However, most of these articles were interested in the developed countries and especially in the oil-importing countries. Only recently few authors started to exploit the link between the oil price shocks and macro variables in the developing economies and oil exporter countries.

This paper examines the effect of oil price shocks on the Russian economy [3]. The reason behind this analysis is the fact that Russia is part of the developing countries and is also a major oil exporter. Russia is one of the leading countries for total energy production. In 2017, it was the third-largest energy producer after China and the United States with a production o 61.276 quadrillions Btu [4]. In 2016 it was the third-largest producer of petroleum and other liquids (after Saudi Arabia and the United States) [5]. Crude oil is a crucial energy source for Russia. In 2017, Russia was the world's largest producer of crude oil (including lease condensate) and the second-largest producer of dry natural gas. After 2017 the leading country in the production of crude oil turns out to be the United States. The percentage shares of world crude oil production in 2019 for Russia was 13%. [6].

The Russian main economic indicators are highly affected by the oil price volatility. This

[1] According to [Hamilton, 1983], 90 % of the US recession was preceded by a peak of the oil price and subsequent economic downturns.

[2] Source: FRED. https://fred.stlouisfed.org.

[3] This analysis is inspired by [Baumeister et al., 2010a]

[4] Source: EIA. https://www.eia.gov/international/analysis/country/RUS.

[5] Russia was the second-largest producer of dry natural gas in 2016.

[6] The percentage shares of the major world crude oil producer (US) in 2019 was 15%.

is possible because the Russian economy is heavily dependent on oil revenue [7]. As a major oil producer and exporter, Russia's economic growth is driven by energy exports [8].

The first set of graphs shows the time series for Petroleum and other liquid production for Russia (first graph) and its global level (second graph). The second set of graphs shows the time series for the export level of crude oil and lease condensate in Russia (first graph) and its global level (second graph).

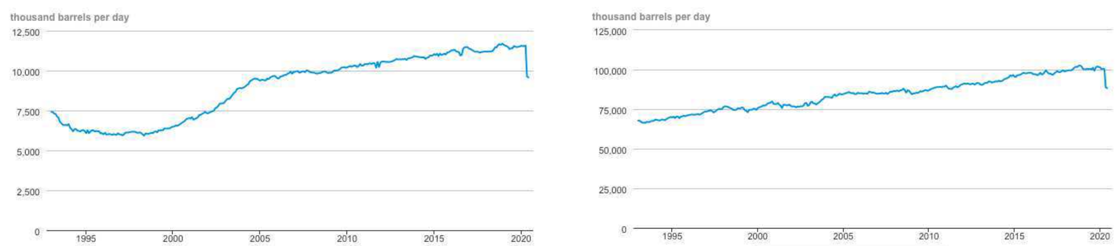


Table 4.1: Petroleum and other liquid production: Russia and World

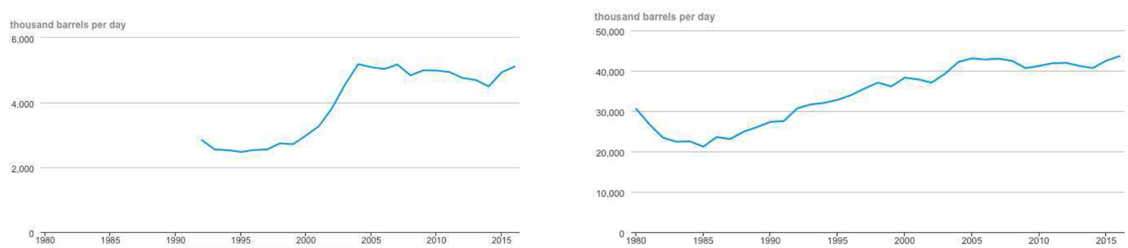


Table 4.2: Oil Exports: Russia and World [9]

To capture the effect that oil price shocks have on the Russian GDP growth and inflation we use three different models. The GDP is usually available in quarterly frequencies and the oil price shocks that we have constructed are available in monthly frequencies. To fit in a unique model variable of different frequencies, we use the MIDAS models. Besides MIDAS, we estimate a monthly and a quarterly ARDL model making use of techniques such as aggregation and temporal disaggregation.

Literature review Many studies attempt to detect the effect of oil price shocks on macroeconomic aggregates. [Baumeister et al., 2010a] provides very important conclusions about the different responses of many countries to oil price shocks. In this article, we find an examination of the economic consequences of oil shocks over time in several industrialized economies. They analyze industrialized economies that are structurally diverse in terms of size, labor market characteristics, monetary policy regimes, and the role of oil and other forms of energy (Australia, Canada, the euro area, Japan, Norway, Switzerland, the United Kingdom, and the United States).

[7] Russian revenues deriving from its hydrocarbons, oil, and natural gas account for more than one-third of the federal budget revenues.

[8] Oil and natural gas revenues accounted for 36% of Russia's federal budget revenues in 2016.

[9] Source: EIA

Although much empirical research has investigated the relationship between changes in oil prices and economic activity, it is surprising that little research has been conducted into the relationship between oil price shocks and the large Newly Industrialized Economies (NIEs).For the oil-exporting countries, different conclusions are expected, but this can only be ascertained empirically.

Furthermore, the relationship between oil price shocks and the Russian economy has not been studied as much as the relationship itself, but for other countries (United States or industrialized European countries) [10].

[Semko, 2013] investigate the oil price shocks in Russia and the optimal economic policy. Through an augmented New Keynesian DSGE small open economy model is shown that Central Bank's mild response to the oil price changes may be desired in terms of minimizing fluctuations of inflation and output only in the case when stabilization fund would be absent, while this response is redundant when "excess" oil revenues can be saved in the fund.

[Benedictow et al., 2013] investigate the oil dependency of the Russian economy using a standard macroeconomic IS-LM framework. The simulations indicated that the oil price is important for the Russian economy. High oil prices cause economic growth, increased savings in the sovereign wealth fund and, also high inflation. However, under this scenario, the traditional export-oriented industries face difficulties because of the appreciation of the ruble and the increasing interest rate. But the results show that the Russian economy grows even in absence of increases in the oil price.

[Merlevede et al., 2009] estimates a small macroeconomic model of the Russian economy and finds out that the Russian economy is vulnerable to downward oil price shocks.

[Nasir et al., 2018] analyses the effect of oil prices shocks for the BRICS economies using a time-varying structural vector autoregressive (TV-SVA) framework. They show that the Russian economy is highly influenced by oil price shocks.

[Bayramov and Abbas, 2017] authors conclude that the oil price shocks of 2014 resulted in a substantial economic slowdown in Russia.

[Ito et al., 2008] using a VEC model the authors find that the effect of 1% increase in oil price increase the real GDP growth by 0.25% and the inflation by 0.36%.

[Ghalayini, 2011] use the Granger Causality tests to find if there is a relationship between changes in the oil price and the economic growth in different countries. The overall results proved to show that there is not a clear relationship between oil price and world economic growth. For exporter countries, they found that the increase in oil price did not cause an increase in economic growth.

[Balashova and Serletis, 2020] through a bivariate VAR model investigate the effect of the oil price shocks on different economic indicators for Russia. They find that oil prices are procyclical and lead the business cycles. The results show that a positive oil price shock has a positive and statistically significant impact on almost all types of Russian economic activity.

[Idrisov et al., 2015] using classical models analyze the impact of global oil prices on Russia's economic growth and its growth rate in terms of output. They find a positive correlation between the real GDP and global oil prices, i.e., higher oil prices will correspond to a higher level of production of goods and services by the domestic economy, as well as greater wealth for Russian economic agents. However, a constant increase in oil prices can not influence the long-term economic growth rate but only the short-term transitional trends from one long-term equilibrium to another.

[10] Recently, a few studies have attempted to examine this relationship and these include studies by such as [Farzanegan and Markwardt, 2009]for Iran, [Mehrara, 2008] for 13 countries, [Lorde et al., 2009], [Ito et al., 2008], [Balashova and Serletis, 2020], [Semko, 2013]and [Olomola and Adejumo, 2006] for Nigeria.

The impact of oil *shocks* on Russia First, we define the type of oil price shocks used as explanatory variables in our model specification. We obtain the time series for oil supply shock, aggregate demand shock, and oil specific demand shock through of the estimation af a SVAR model.

Second, we use an ARDL model to detect the effect that the three different oil shocks have on Russian GDP growth and inflation. Considering that Russian GDP is available quarterly, we first estimate a quarterly ARDL model. Analyzing the IRFs we find that the aggregate demand shock overall has a positive effect on Russian GDP growth. On the other hand, the oil supply shock and the specific oil demand shock have not a significant effect on Russian GDP growth. The effect of a positive aggregate demand shock and negative oil supply shock is non-significant. The effect of a positive oil-specific demand shocks on inflation is negative.

Third, we estimate an ARDL model by reporting all data on a monthly basis.

The results based on the IRF are similar to the first ADL model, which means that the two oil demand shocks have a positive effect on Russian GDP growth. Conversely, the oil supply shock has a positive effect on GDP growth while in the first model the effect was positive but not significant. The effect of a positive oil-specific demand shock and negative oil supply shock on inflation is negative, while the effect of a positive aggregate demand shock is non-significant.

Fourth, we use three different MIDAS models (restricted and unrestricted) to detect the effect of oil price shocks on the leading Russian economic indicator. The MIDAS model is used because the data frequency of our variable of interest is not the same as for the explanatory variables. To avoid aggregation or temporal disaggregation of data we can use a MIDAS model instead of an ARDL model. This way we can use more information by leaving the data at their original frequency. The results between different typologies of MIDAS are similar.

Finally, to choose the best model in terms of forecasting, we compare the forecasting evaluation indicators for all models. After comparing all the models we choose the model with the lowest values of the statistical indicators we analyze. Based on the results, the non-normalized Almon Polynomial is the best model among all the models that we have used.

The remainder of the paper is organized as follows. Section 4.2 focuses on the identification of the structural shocks that drive the real price of oil. We identify these shocks and obtain their time series. Moreover, it describes the methodology used to quantify the effects of oil price shocks on leading Russian economic indicators. This section explains the main features of the ARDL and MIDAS models. In Section 4.3, you find the description of the data and their source.

In section 4.4, we examine the impact of oil price shocks identified in Section 4.2 on the Russian macroeconomic aggregates. In Section 4.5, we analyze the forecasting accuracy of the models used in this paper. The concluding remarks are in section 4.6.

4.2 Econometric Methods

4.2.1 Recovering the oil price shocks

This paper uses two different models to detect the relationship between the oil market and the Russian economy: the ARDL and MIDAS model. Furthermore, we use a SVAR model to derive the three oil price shocks: oil supply shock, aggregate demand shock, oil specific-demand shocks. These shocks are subsequently used as explanatory variables in previous models. In this section, we briefly introduce the SVAR model and the identification procedure through which to derive oil shocks. A Structural Vector Autoregressive regression (SVAR) model is used to obtain the oil price shocks [11]. SVAR is a structural dynamic simultaneous-equation model [12].

[11] [Kilian, 2009].
[12] [Kilian and Lütkepohl, 2017]

The SVAR representation is shown below:

$$A_0 z_t = \alpha + \sum_{i=1}^{24} A_i z_{t-i} + \epsilon_t \tag{4.1}$$

where:

$$z_t = \Delta prod_t, rea_t, rpo_t \tag{4.2}$$

The variables used in this model are: world oil production ($prod_t$), the real economic. The vector ϵ_t denotes the serially and mutually uncorrelated structural innovations. The matrix A_0^{-1} has a recursive structure such that the reduced-form errors e_t can be decomposed according to $e_t = A_0^{-1}\epsilon_t$.

Estimating the SVAR model following [Kilian, 2009] we can compute the structural decomposition of the real price of oil into three different types of shocks: oil supply shocks, aggregate demand shocks, oil specific-demand shocks. In the SVAR framework, we need to use an identification scheme for the shocks. To do this, we need to impose some restrictions [13]. In our model we use the Cholesky decomposition to identify the shocks:

$$e_t = \begin{bmatrix} e_t^{\Delta prod} \\ e_t^{rea} \\ e_t^{rpo} \end{bmatrix} = \begin{bmatrix} a_{11} & 0 & 0 \\ a_{21} & a_{22} & 0 \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} \epsilon_t^{oilsupplyshock} \\ \epsilon_t^{aggregatedemandshock} \\ \epsilon_t^{oilspecific-demandshock} \end{bmatrix} \tag{4.3}$$

After estimating the SVAR model based on monthly data for the period 1974:01 - 2019:12, we obtain three unique time series for the shocks. These time series will be used as explanatory variables within the ARDL and MIDAS model in the following sections.

4.2.2 Computing the multipliers

To detect the effect that oil price shocks have on the Russian macroeconomy, we use a traditional time-series regression. However, a complication arises since we compute the shocks on a monthly frequency whereas GDP is available quarterly. This problem can be circumvented by three approaches:

1. Aggregate the monthly shocks to quarterly and use an ordinary ARDL model on quarterly data.
2. Disaggregate the GDP series to a monthly frequency using additional information and use an ordinary ARDL model on monthly data.
3. Use a mixed-frequency (MIDAS) model.

ARDL Model: The general level ARDL(p,q) model can be written as:

$$y_t = a_t + \sum_{j=1}^{p} \phi_j y_{t-j} + \sum_{j=0}^{q} c_j x_{t-j} + u_t \tag{4.4}$$

where ϕ_j, c_j, are unknown parameters, and where u_t is an error terms. The term a_t include the constant and the time trend. The values of p and q denote the respective lag length. We include also the contemporaneous values of x_t [14]. All model parameters are estimated using the OLS estimator.

[13] So far, in the literature different identification methods have been used applying: short term restrictions, long-term restrictions, dynamic restrictions and sign restrictions. [Sims, 1980] originally proposed a recursive identification scheme based on exclusion restrictions, the so-called Cholesky decomposition.

[14] In this case the ARDL model is considered a conditional ARDL.

MIDAS Model Mixed Data Sampling (henceforth MIDAS) regression models involve time series data sampled at different frequencies. Typically, time-series data within a regression model is sampled with the same frequency. [Ghysels et al., 2004] introduce MIDAS regression models. In the past, before the introduction of this model, there is no evidence of such a concept. The only exception is a chapter in John Geweke's Ph.D. thesis([Geweke, 1975] Chap.8), where he studied mixed temporal aggregation with heterogeneous observational frequencies.

MIDAS regressions have been used extensively in macroeconomics and finance. The main reason is that in these two fields it is very common to encounter a situation such as the variable of interest is available at a lower frequency and the explanatory variables at higher frequencies. [15]. When the variable of interest is available quarterly, instead of aggregating the explanatory variables to equalize the frequency of the data,[Ghysels et al., 2004] used MIDAS models for the first time. By using MIDAS models we can avoid changing the frequency of the data and we can use all available information to explain the variable of interest [16]. Instead of aggregating inflation time series at a quarterly sampling frequency to match GDP data, one can run a MIDAS regression by combining monthly and quarterly data.

MIDAS models have some common features with distributed lag models [17]. However, the main difference between the two is that in MIDAS models the data is not at the same frequency while in autoregressive models data is sampled at the same frequency.

A simple linear Midas model is defined as follows [18]:

$$Y_t = \beta_0 + \beta_1 B(L^{1/m}) X_{t-1}^{(m)} + \epsilon_t^{(m)} \tag{4.5}$$

where:

$B(L^{1/m}) = \sum_{j=0}^{j=max} B(j)(L^{j/m})$ is a polynomial of length j^{max} in the $L^{1/m}$ operator, and $L^{j/m} x_t^{(m)} = x_{t-j/m}$. The $L^{j/m}$ operator produces the value of x_t lagged by j/m periods. To identify the parameter β_1 it is assumed that the weights of the polynomial $B(L^{1/m})$ sum to one. In this simple model, the order of the polynomial $B(L^{1/m})$ is assumed to be finite. The annual/quarterly example would imply that the above equation is a projection of yearly Y_t onto quarterly data $X_t^{(m)}$ using up to jmax quarterly lags. We suppose that Y_t is sampled in some lower frequency with respect to $X_t^{(m)}$ (say:annual, quarterly monthly or daily). Let $X^{(m)}$ be sampled m times faster. For instance, if Y_t sampling frequency is annual and $m = 4$, then $X^{(4)}$.

However, in this Unrestricted Midas(U-Midas) the number of parameters can be very large. In order to reduce the number of parameters to estimate, we can proceed by imposing some prior restrictions on the parameters of $B(L^{1/m})$ polynomial to reduce the parameter space. Afterwards, it is possible to estimate the model as a simple regression model. In the latter case, the Midas model is considered to be a Restricted Midas.

Advantages and disadvantages of MIDAS Model The mixed data sampling regression uses more information and is more flexible. However, the disadvantage and the trade-off is that the number of parameters to estimate is very large (known as parameter proliferation). Nevertheless, when it comes to the macroeconomic data the number of parameters is not very

[15] For example, GDP growth is usually available at quarterly frequency and there are many other variables used as explanatory variables (e.g. inflation), that are available at higher frequencies.

[16] For different MIDAS application see [Ghysels et al., 2004].

[17] A stylized distributed lag model is a regression of the following type:
$Y_t = \beta_0 + B(L) X_t + \epsilon_t$, where B(L) is some finite or infinite lag polynomial operator, usually parameterized by a small set of hyperparameters. See [Ghysels et al., 2007]

[18] It is possible to define a MIDAS model in the multivariate context and also including non-linear relations.

large because usually the data used are sampled at monthly or quarterly frequency. This problem is more relevant when we model the financial market where the variables can be sampled at higher frequency (daily or weekly).

4.3 Empirical evidence

4.3.1 The data

The data used in the following models are Russian GDP (available quarterly), and Russian inflation(available monthly). The GDP measure used in our models is The Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product for the Russian Federation (Chained 2000 National Currency Units, Quarterly, Seasonally Adjusted)[19].

To calculate Russian inflation we use the Consumer Price index: all items for Russian Federation(Index 2015=100, Not Seasonally Adjusted) [20]. Data for CPI are available in monthly frequency and as a consequence, we can obtain the monthly data for inflation.

Furthermore, we use three time series corresponding to three different oil price shocks: oil supply shock, aggregate demand shock, oil specific demand shock. These time series are obtained after the estimation of a SVAR model used to model the global oil market.

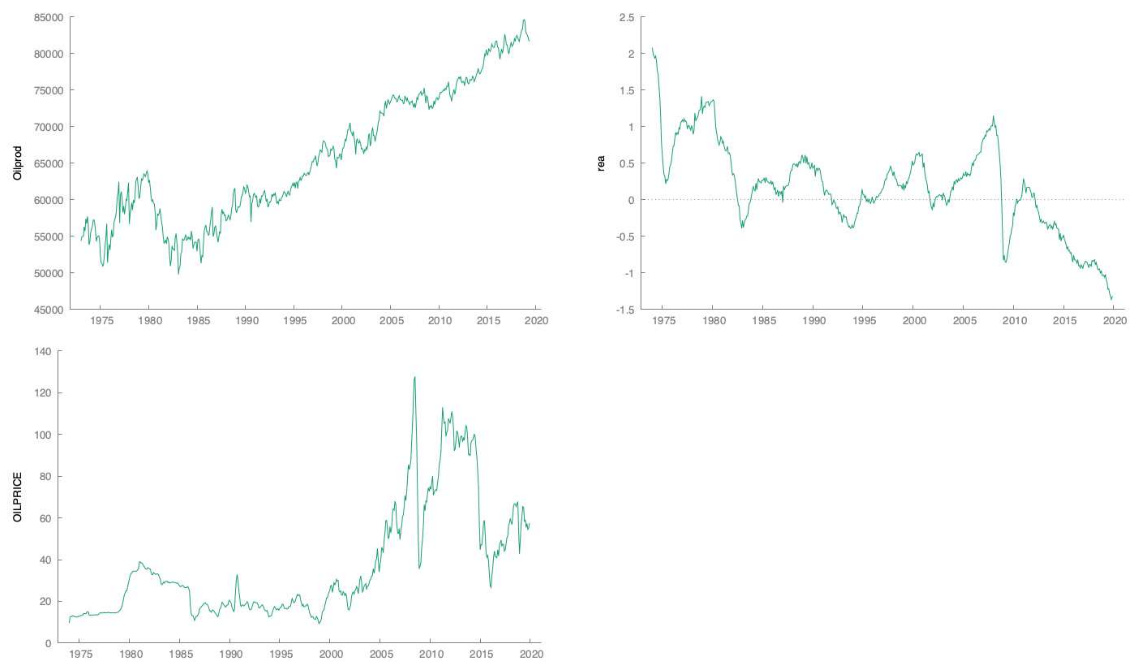


Table 4.3: SVAR model: Variables

[19] Organization for Economic Co-operation and Development, Production of Total Industry in Russian Federation [RUSPROINDMISMEI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RUSPROINDMISMEI

[20] Organization for Economic Co-operation and Development, Consumer Price Index: All Items for Russian Federation [RUSCPIALLMINMEI], retrieved from FRED, Federal Reserve Bank of St. Louis; https://fred.stlouisfed.org/series/RUSCPIALLMINMEI

The variables used in this SVAR model are the oil production (the percent change in global crude oil production), the index of real economic activity (OECD IP Index used as a proxy for real world economic activity), and the real price of oil (the refiner acquisition cost of imported crude oil deflated by the US CPI and expressed in log) [21]. The data entering the SVAR model is available in monthly frequency. We estimate the model for the period: 2003:02 to 2019:12. The start date is due to the availability of time series for Russian GDP (available from 2003:01).

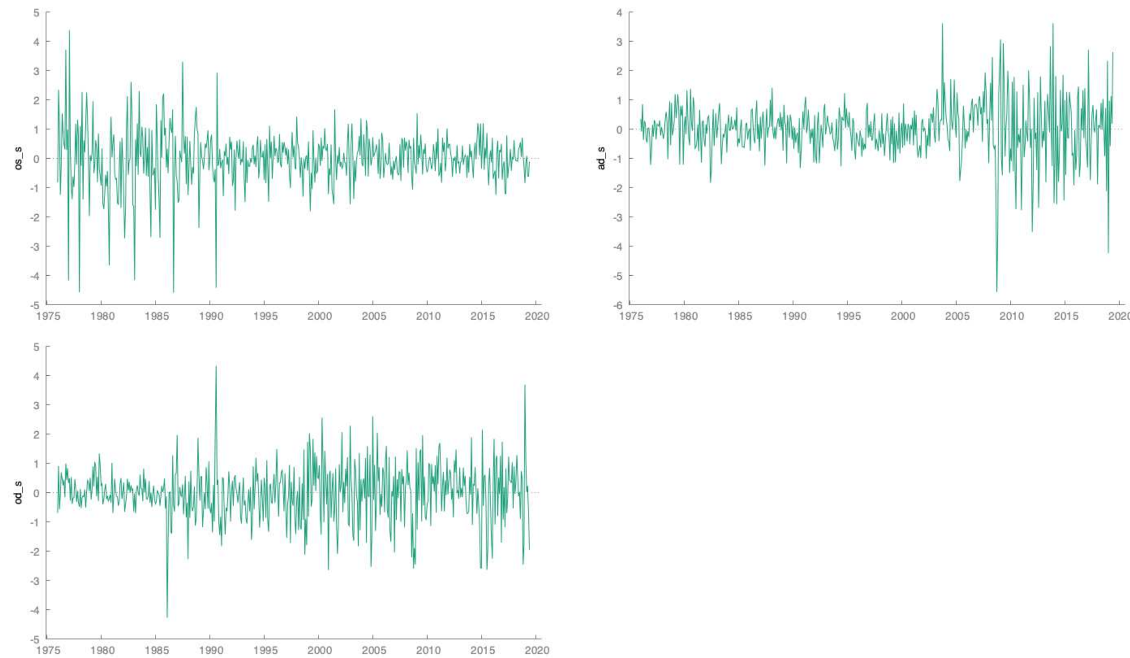


Table 4.4: Oil price shocks

ARDL - Quarterly Data The three oil shocks obtained from the SVAR model explained above are used as explanatory variables in an ARDL model. Through the ARDL model, we want to determine the effect these three oil price shocks have on Russian GDP growth and inflation. GDP is available in quarterly frequency and the data on the oil price shocks are available in monthly frequency. Since the variables entering the ARDL model should be at the same frequency, we aggregate the time series of the three shocks to bring the data to quarterly frequency.

Firstly, we estimate the Quarterly ARDL model. The dependent variable is Russian real GDP growth(or inflation) and the explanatory variables are oil supply shock, aggregate demand shock, specific oil demand shock[22]. Beside the oil price shocks, we include a constant and a time trend in the model. Data on oil shocks are available for the period 1976:01 to 2019:12 (after the aggregation the sample period is 1976:01 to 2019:04). Russian GDP data is available from 2003:01 to 2019:04 in quarterly frequency.[23] After obtaining GDP data at constant prices, it is easy to calculate GDP growth as the logarithmic difference of the time series of real GDP. All

[21] EIA: the source for the data regarding the world oil production and the oil price: https://www.eia.gov. The data for the OECD IP Index are available on the Christiane Baumeister website.

[22] Based on the lag selection criteria (Akaike) the number of lags used is ARDL(2,2) in both cases.

[23] The estimation period is 2003:02 2019:04 because we lose an observation after computing the growth rate of the GDP.

the variables are expressed in difference so we exclude the co-integration relationship between them.

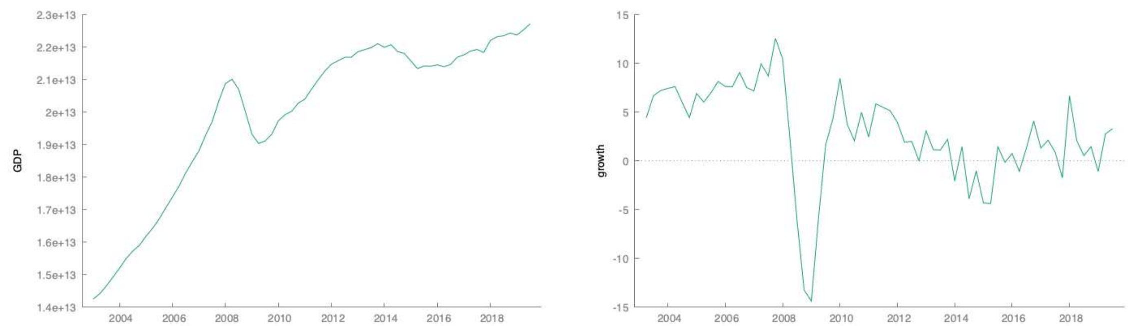


Table 4.5: Russian GDP and GDP growth

ARDL - Monthly Data This is the main reason why we want to estimate a monthly ADL, where instead of aggregating the oil price shocks we disaggregate the quarterly time series of GDP using the monthly time series of industrial production as a reference. In the second ARDL model, the dependent variable is Russian real GDP growth(or inflation) and the explanatory variables are: oil supply shock, aggregate demand shock, oil-specific demand shock. Oil shocks data is available for the period 1976:01 to 2019:12. Russian GDP data is available from 2003:01 to 2019:12 in quarterly frequency. The variables entering the ARDL model should be at the same frequency. To bring GDP to the same (monthly) frequency as oil shocks, we compute the temporal disaggregation. To compute the temporal disaggregation of GDP from the quarterly frequency to the monthly frequency we must use the monthly data of another variable that has a similar trend to GDP. In this case, we use Russian Industrial Production to compute the disaggregation. The method used for the temporal disaggregation is the Traditional Chow-Lin. After taking all the variables monthly we can estimate the ARDL. [24] Based on the lag selection criteria, we use an 8 lag when we estimate ARDL with GDP growth as the dependent variable. On the other hand, we use 1 lag when we estimate ARDL with inflation as a dependent variable.

Temporal Disaggregation: Temporal disaggregation is a technique for deriving high-frequency data from low-frequency data. Often economists would like to have data in higher frequency despite the "natural" frequency of some variables (eg GDP). This is especially useful for forecasting purposes.

We can take data from a time series observed at a certain frequency (say quarterly) and produce a series of counterparts at a higher-frequency (say, monthly). The new time series should be consistent with the low-frequency data. The implementation of this technique is similar to the aggregation technique and is related to interpolation [25].

A central idea in temporal disaggregation is that the high frequency series must respect both the given low frequency data and the aggregation method. Thus, the disaggregation should respect the "sum" rule, which means that the sum of the monthly values of the new monthly

[24] The IP and GDP are available from 2003:01 to 2019:12. The estimation period (final sample period) is 2003:02 2019:12.

[25] There are several types of aggregation: sum, average (avg), last or first.

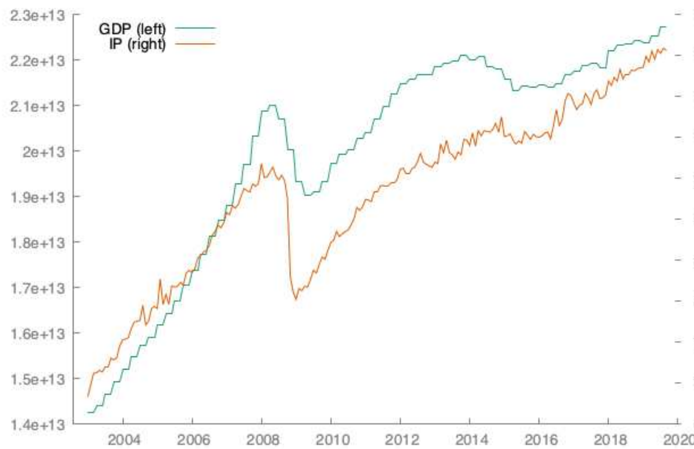


Figure 4.1: Russian GDP and Industrial Production-Monthly

time series should be equal to the corresponding quarterly value [26]. This is the case when we disaggregate the GDP. When you want to disaggregate the index variables or the ratio, the average option is more appropriate. In this case. the average value of the high-frequency data should be the same as the average value of the low-frequeny data. For stock variables, usually, the first or last value for the high-frequency data should be the first or last value of the low-frequency data.

After choosing the type of aggregation, we need to choose the type of disaggregation. If we want to disaggregate a time series and do not have a higher frequency indicator available, some smoothing methods are required: Cubic spines and Boot, Feibes, and Lisman (BFL) smoothing method. When a higher frequency indicator is available, we can use some statistical methods. Here we can choose between "Regression based method" or "Denton method".

The regression-based method is basically the Chow-Lin method which has three variants: Fernández random walk model, Litterman random walk Markov model, and AR(1) model. The Fernández method is generally used when the time series that we want to disaggregate has a unit root. The Denton method is considered as the "benchmarking" [27]. Temporal disaggregation is sometimes called "benchmarking" because low-frequency data is used as a benchmark for creating new high-frequency data. The high-frequency series used to disaggregate the low-frequency series should be related to it and we might expect the two series to share short-term dynamics.

The two main ingredients in temporal disaggregation are the two matrices: X and Y. The matrix Y holds the series that we want to disaggregate and the matrix X can be another underlying time series that we use for the disaggregation (Denton method). In some cases when we do not have a time series to compute the disaggregation the matrix X can be a combination of a deterministic term (e.g. constant, trend) and a stochastic series(Chow–Lin methods). It is possible to compute the disaggregation when X contains only a constant.

AR-MIDAS MIDAS models find application above all in macroeconomic and financial issues, where the variables of interest are often expressed in different frequencies. The modeling

[26] It means that the sum of the quarterly data should be the same as the sum of the new monthly data, so the yearly total should be the same.

[27] Three variants of the method of [Chow and Lin, 1971]); the method of [Fernandez, 1981]; and two variants of the method of [Denton, 1971] .

of macroeconomic variables usually requires the inclusion of the autoregressive part through the inclusion of lags. However, the consideration of autoregressive dynamics in the MIDAS model is somewhat complicated. [Ghysels et al., 2007] and[Andreou et al., 2011] explains that the impulse response function of the regressor $X_t^{(m)}$ on the variable of interest Y_t is discontinuous. To overcome this issue, [Clements and Galvão, 2008] suggested interpreting the dynamics on Y_t as a common factor. However, this requires that Y_t and $X_t^{(m)}$ share the same autoregressive dynamics. Still,the commune factor is not always possible to be found- [Hendry and Mizon, 1978]. [Duarte et al., 2014] introduce an alternative technique to insert the autoregressive part without using the commune factor. Based on some forecasting exercises, they conclude that AR-MIDAS proved to be good alternatives and in some cases are the best performing MIDAS regression. In our example, we estimate the MIDAS with and without the autoregressive part. After some forecasting exercises, we conclude that adding the autoregressive part does not augment the forecasting accuracy. For this reason, we report in the following sections the results of the estimation of MIDAS without the autoregressive dynamics.

MIDAS for Russian economy As in the ARDL models described above, in the MIDAS model, the variable of interest is the growth of Russian real GDP. GDP is available quarterly. As an explanatory variable, we use the same data for oil price shocks as in the ARDL models.

U-MIDAS or "unrestricted" MIDAS are models in which each lag has its own coefficient. However, it is possible to have a different type of parameterization for the set of high-frequency terms [28]. Other supported parameterization types are:

- Normalized exponential Almon with two parameters (normally requires one or two parameters). We have chosen two because is communally used.
- Normalized beta with a zero last lag with two parameters (which is the exact number of parameters it requires).
- Normalized beta with non-zero last lag with three parameters (the exact number of parameters it requires).
- Almon polynomial with one parameter (the minimum number of parameters it requires).

Beside the U-MIDAS model, we estimate the Normalized exponential Almon and the Almon polynomial using six lags. The estimation period is the same in all different types of MIDAS and runs from 2003:02 to 2019:12. [29].

$$Y_t = \beta_0 + B(L^{1/m})X_t^{(m)} + \epsilon_t^{(m)} \tag{4.6}$$

Y_t includes data on the real GDP Growth and X_t includes the three oil price shocks time series (including delays).

[28] [Ghysels et al., 2007]

[29] This is the availability of data for GDP growth. We have more data on oil price shocks for the period before 2003, which can not be used because we do not have Russian GDP data at that time.

4.4 Results

4.4.1 The effect of oil price shocks on Russian GDP growth

In this section, we show the results obtained from the estimation of the monthly and quarterly ARDL model and the MIDAS model (Unrestricted MIDAS, Normalized exponential Almon, Almon polynomial).

This first set of graphs (Table 4.6), is shown the response of Russian GDP growth to a negative oil supply shock. In the first graph, the IRF derives from an ARDL (8.8) model that uses monthly data for the period 2003:02 to 2019:12. The effect of a negative oil supply shock on GDP growth on the impact and for 9 months seems to be positive and significant. However, in the fourth month, it shows a non-significant behavior. After one year, the effect is positive but non-significant.

If a negative oil supply shock occurs, it means that the global oil supply will decrease. If the global supply of oil decreases the oil price increase. Since Russia is an oil-exporting country, its revenues will increase, and consequently, the effect on the GDP growth could be positive. Furthermore, if the supply of oil in the rest of the world decreases, Russia can decide to augment its oil supply, increasing in this way the revenues. Consequently, the effect on GDP growth will be positive. The IRF is in line with economic theory.

In the second graph, the IRF derives from an ARDL(2.2) model that uses quarterly data for the period 2003:02 2019:04. The effect of a negative supply shock on GDP growth on the impact is negative. Afterward, for the rest of 30 quarters, it is positive but non-significant.

In the third graph, the IRF derives from a U-MIDAS model that uses monthly data for the explanatory variables (the three oil shocks) and quarterly data for the dependent variable (GDP growth). In the fourth graph, the IRF derives from a restricted version of MIDAS called "normalized exponential Almon". In the fifth graph, the IRF derives from a restricted version of MIDAS called "(non-normalized) Almon polynomial". In the last three graphs, the IRFs show that the effect of a negative oil supply shock on Russian GDP growth is positive but non-significant over time. These IRFs turn to be positive and significant after the fifth quarter. The results of the three versions of the MIDAS model are not the same as for the monthly and quarterly ARDL models.

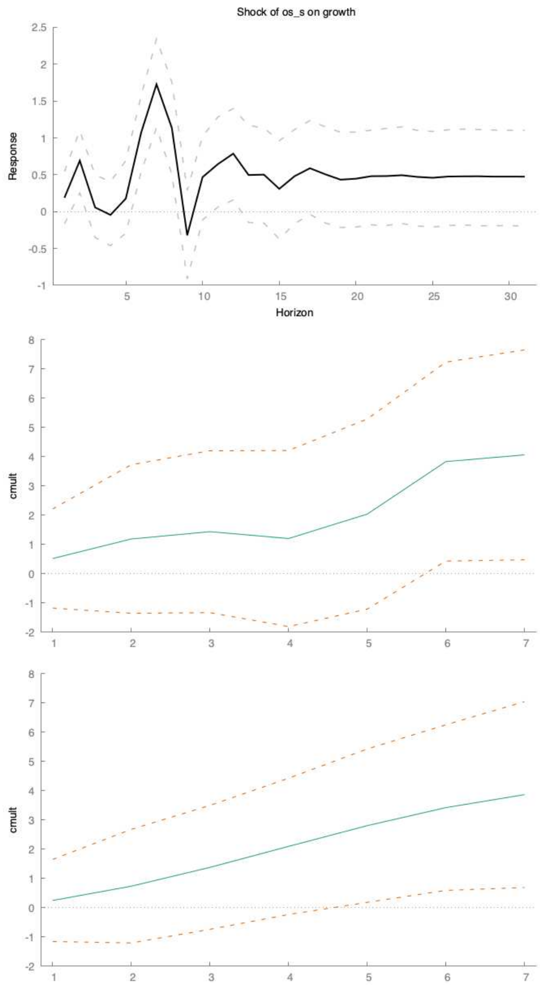


Table 4.6: The effect of the oil supply shock on GDP growth

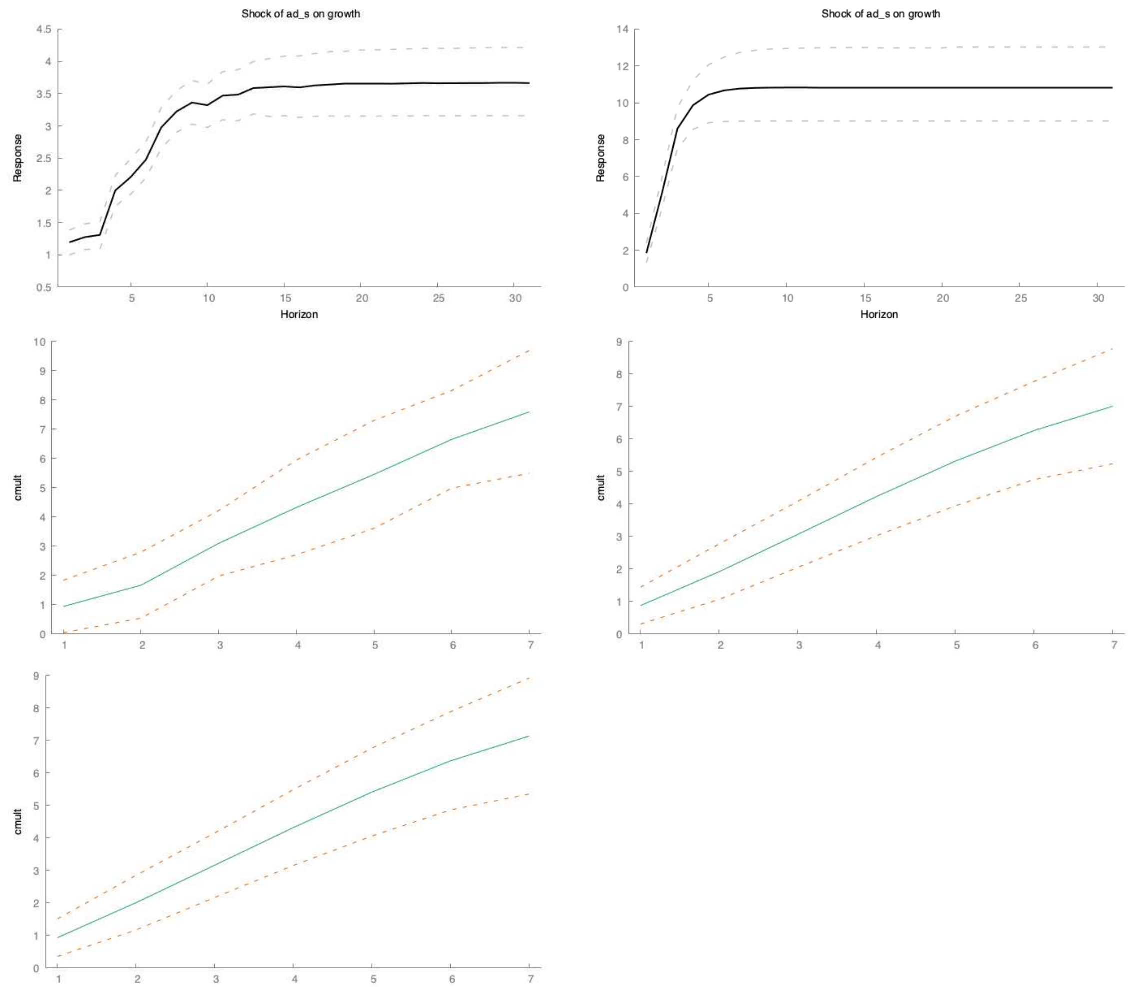


Table 4.7: The effect of the aggregate demand shock on GDP growth

This second set of graphs (Table 4.7) shows the response of Russian GDP growth to a positive aggregate demand shock. The ordering of the IRFs that derive from different models is the same as explained previously. In the first graph, the IRF, suggests that the effect of a positive aggregate demand shock on GDP growth on the impact is close to zero and increases up to 10 months later. From 10 months to 30 months the increase remains constant. The response is positive and significant across all horizons.

Russia is an oil-exporting country, so if global oil demand increases, the oil demand will increase, and Russian revenues also. This will have a positive effect on Russian GDP growth. The IRF is in line with economic theory.

In the second graph, the IRF shows that the effect of a positive aggregate demand shock on GDP growth on the impact is close to zero. Subsequently, the effect becomes more positive increasing. After the first 6 quarters, this IRF remains constant. Along all the horizons this response is positive and significant.

In the last three graphs, the IRFs show that the effect of a positive aggregate demand shock on Russian GDP growth is positive and significant over time. The results of the three versions of the MIDAS model are in line with the monthly and quarterly ARDL model.

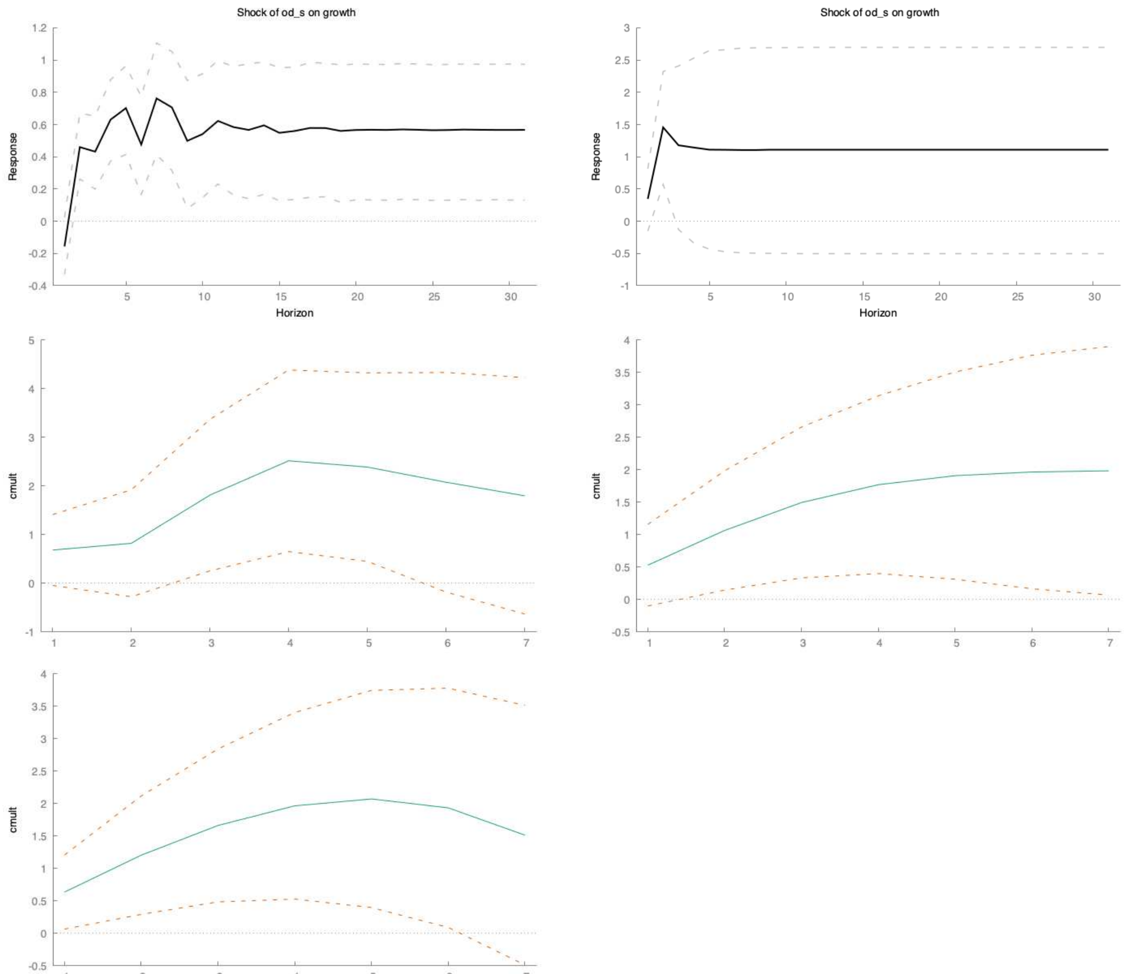


Table 4.8: The effect of the oil specific demand shock on GDP growth

This third set of graphs (Table 4.8) shows the response of the Russian GDP growth to a positive oil-specific demand shock. In the first graph, the IRF shows that the effect of a positive oil-specific demand shock on GDP growth on the impact is negative and non-significant. Thereafter the response is positive and significant for at least 30 months.

In the second graph, the IRF suggests that the effect of a positive oil-specific demand shock on GDP growth on impact is positive and significant for nearly 2 quarters. Thereafter, the effect becomes non-significant.

In the last three graphs, the IRFs, show that the response of the GDP growth to a specific oil demand shock is positive and significant across all horizons. It becomes insignificant after 6 quarters. If the demand for oil or inventories increases, oil exports from Russia will most likely increase and consequently Russian GDP growth will be positively affected.

In the last set of graphs, we notice that the IRF coming from the quarterly ARDL gives us a very different response in comparison to the other IRs. This is the reason why it is better to use a MIDAS model which allows us to leave the data at their original frequency. Disaggregation could be another good option that is better than aggregation. Aggregating the data, we lose information and this can lead to wrong results.

We conclude that the two demand shocks have a positive and significant effect on Russian GDP growth, while the effect of the oil supply shock is more muted and almost non-existent.

4.4.2 The effect of oil price shocks on Russian inflation

In the current section, we report the results regarding the Russian inflation response to various oil price shocks.

In Table 4.9, we show the effect of a negative oil supply shock on Russian inflation. The ordering of the graphs is the same as in the previous section. The Quarterly ARDL model suggests a non-significant response of inflation to a negative oil supply shock. Furthermore, in the Quarterly ARDL, the response is negative but very close to zero, so it is almost nil. The same negative response is suggested from the 3 variants of MIDAS. However, in the MIDAS models, the response is negative and non-significant only for the first 3-4 quarters. After that, the response becomes more negative and significant.

On the other hand, the results obtained after the monthly ARDL estimation are in contrast with the previous ones. This IRF suggests a negative inflation response to a negative oil supply shock. Normally, when the oil supply decreases, the price of oil increases and inflation should increase. This happens usually in the oil-importing countries that depends on the crude oil. Russia is an oil-exporting country, so apparently, the increase in the oil price does not increase its inflation. on contrary, Russian inflation decreases, after the increase in the oil price. It may be caused by the increase in the Russian revenues which on the other hand increase the internal production, so the overall level of prices may decrease. It seems that the two effects, which goes on different direction do not offset each other. On contrary, the decrease in the price level is more relevant than the increase caused by the increment of the oil price.

Furthermore, the results suggest that Russian inflation is not affected by the aggregate demand shock. From the graphs, we can see that this response is not significant.On the contrary, the specific oil demand shock appears to have a negative, and significant effect on Russian inflation. When the demand for oil increases, the price of oil rises, and inflation tends to rise accordingly.

Here the opposite happens. To explain this we must consider that Russia is an oil exporter and that the latest shock is related to oil stocks. The oil-specific demand shock is the demand for oil inventories, and it is just a precautionary demand. In this context, since the cost that companies affront for demanding more oil stocks is not required by the production process, it apparently does not increase the general price level.

On the other hand, Russia is an oil-exporting country. Thus, when the demand for oil increases, its revenues will increase. However, the general price level does not increase, so the cost of products for Russia remains the same in the face of an increase in revenues. Arguably, this can be an incentive for some companies to lower product prices. This is a possible explanation for the fact that precautionary oil demand has a negative effect on Russian inflation.

We conclude that the aggregate demand shock and the oil supply shock have a non-significant effect on Russian inflation, while the oil-specific demand shock has a negative effect on Russian inflation.

Both, a positive demand shock and a negative supply shock cause an oil price increase. From the previous results, we conclude that not all oil price increases have the same effect on the Russian economy. The effect that an increase in the oil price will have on the Russian economy depends on the underlying shock that causes it.

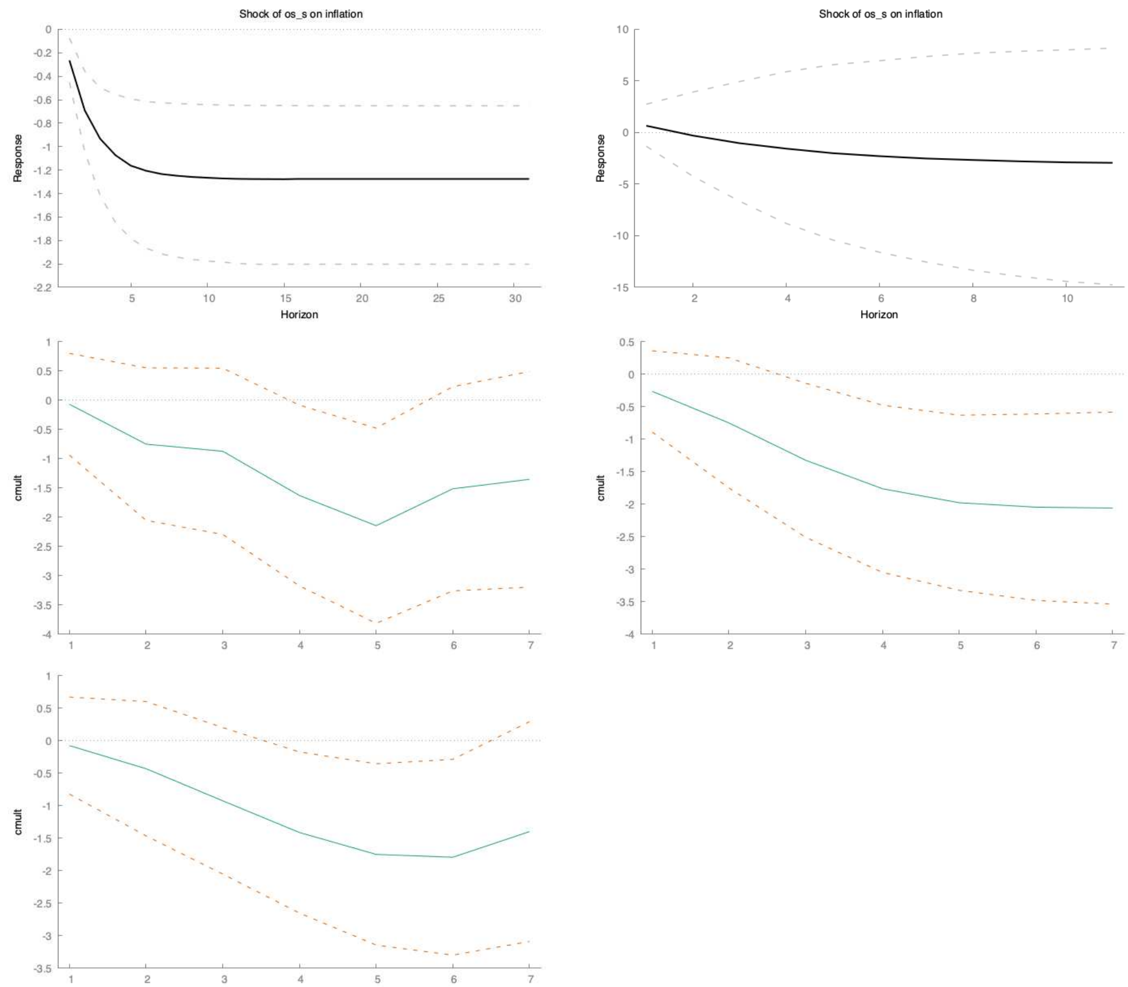


Table 4.9: The effect of the oil supply shock on inflation

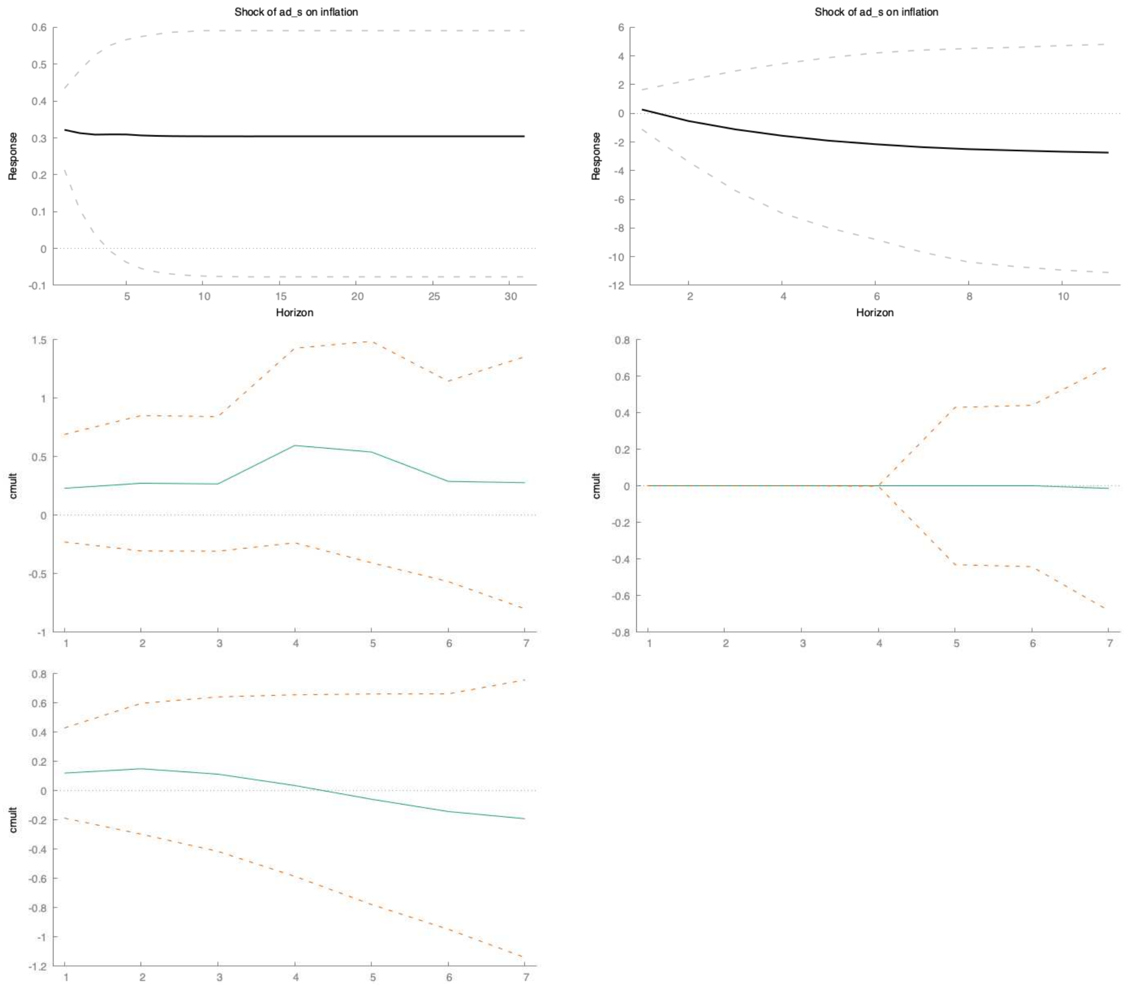


Table 4.10: The effect of the aggregate demand shock on inflation

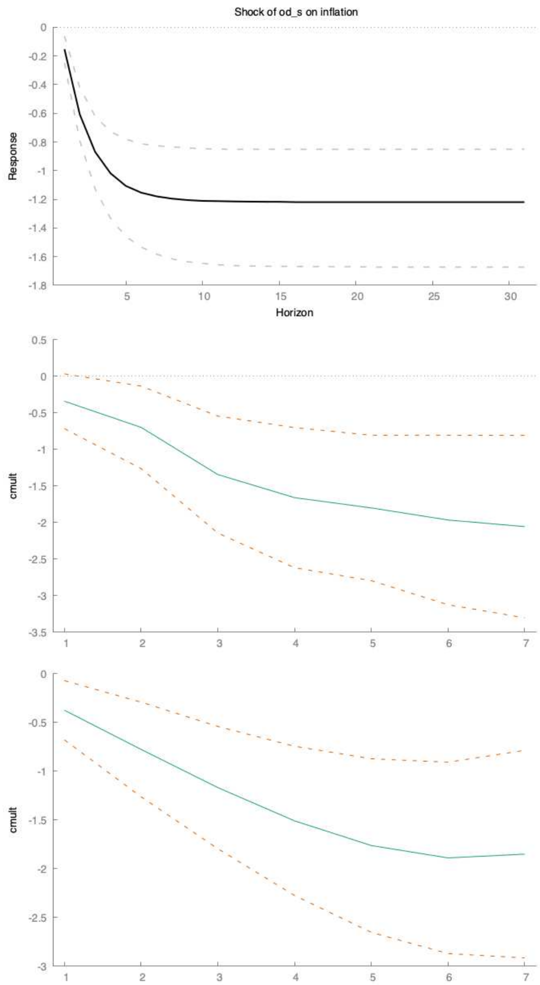


Table 4.11: The effect of the oil specific demand shock on inflation

4.4.3 Temporary Shocks - GDP Growth

In this section, we show the effect of the temporary oil price shocks on the Russian GDP growth. These shocks are not accumulated, so they are supposed to converge to zero after some months. Table 4.12 shows the effect of a negative oil supply shock on GDP growth. In the first graph, the IRF derives from the estimation of a monthly ARDL model, while in the second one from the estimation of a quarterly ARDL model. The first response oscillates around zero taking positive and negative values. For some segments, the response is significant, while for others it is not. However, after oscillating around zero, the effect converges after 15 months. When we considered the effect of the accumulated shock in the previous sections, the effect was more clear and persistent.

The quarterly ARDl suggests a clearer response. This response is positive from the 2 to 4 quarter. Afterward, the effect of the shock is absorbed.

The effect of a temporary aggregate demand shock on the GDP growth is positive and significant for the first 8 months in the first model and the first 6 quarters in the second model. Afterward, the IRFs converges to zero. If we compare the response of the GDP Growth to this temporary demand shock with the response to the accumulated demand shock the only difference is that here the IRFs converge to zero, while in the other example due to the accumulation they do not converge [30].

In comparison to the effect of an aggregate demand shock, the impact of a positive oil-specific demand shock on GDP growth lasts less. This effect lasts for 4 months in the first case and 2 quarters in the second (Table 4.14).

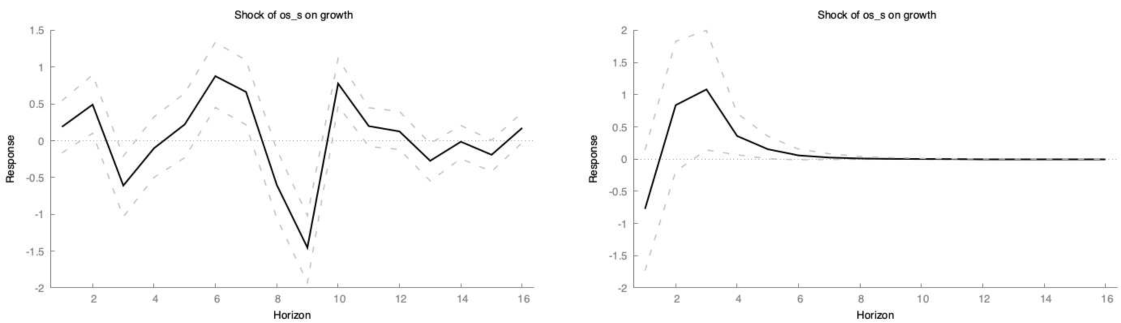


Table 4.12: The effect of the oil supply temporary shock on growth

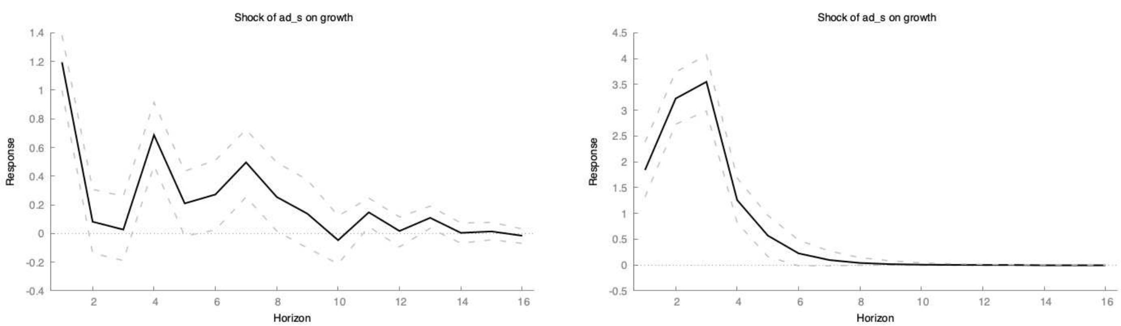


Table 4.13: The effect of the temporary aggregateoil demand shock on growth

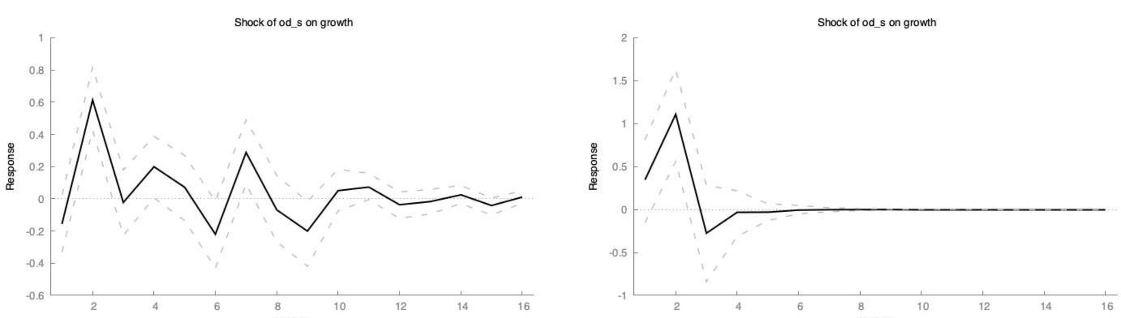


Table 4.14: The effect of the temporary oil specific demand shock on growth

[30] This fact is normal since the accumulated shocks by construction do not converge to zero, while the temporary shocks are absorbed in the short term.

4.4.4 Temporary Shocks - Inflation

In this section, we show the effect of the temporary oil price shocks on the Russian inflation.

According to the results from the monthly ARDL model, a negative oil supply shock has a negative and significant effect on inflation for the first 6 months. After, it converges to zero. The quarterly ARDL suggests a non-significant effect.

The effect of a positive aggregate demand shock seems to be positive and significant in the first month (first plot in Table 4.16). Afterward, the effect converges to zero. The quarterly ARDL suggests a non-significant effect along all horizons.

The effect of a positive oil-specific demand is negative and significant according to the results of both models. It converges to zero after 10 months in the first model, and after 8 quarters in the second one.

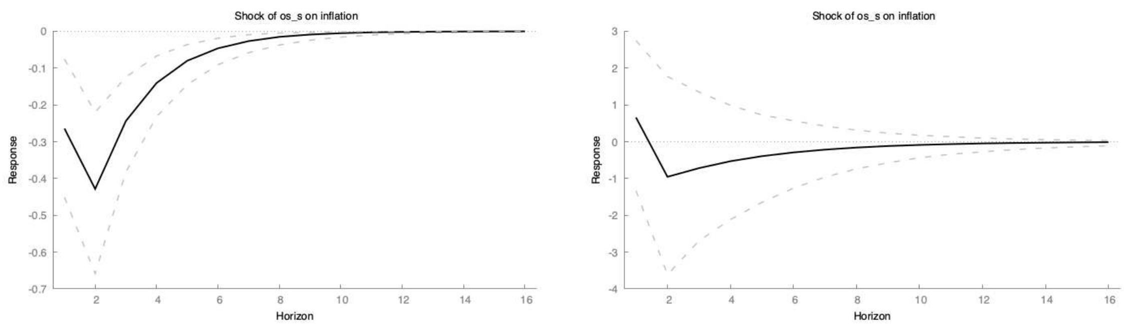


Table 4.15: The effect of the temporary oil supply shock on inflation

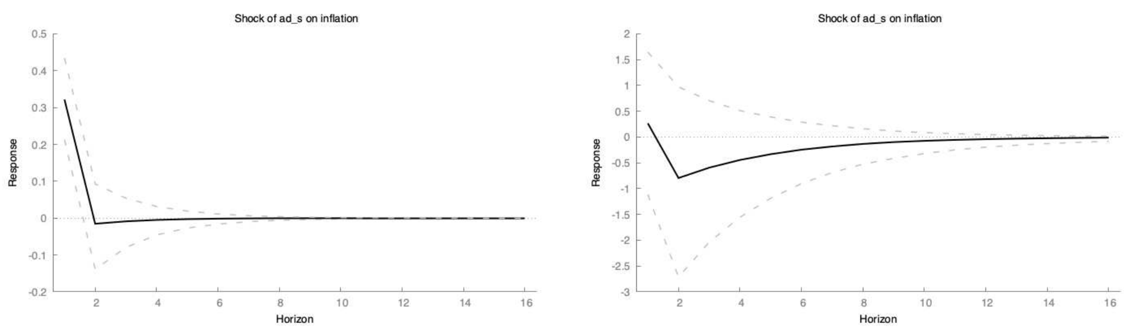


Table 4.16: The effect of the oil aggregate demand shock on inflation

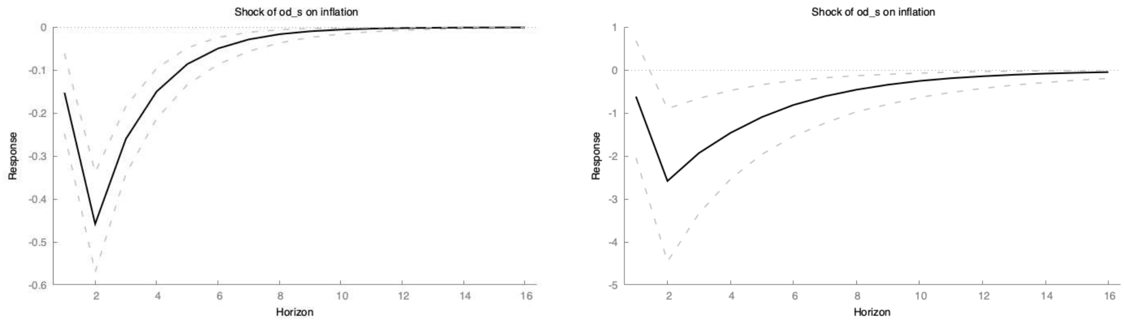


Table 4.17: The effect of the oil demand shock on inflation

4.5 MIDAS Model forecasting

To understand which of the alternative versions of the MIDAS model is best for predicting GDP growth, we perform some forecasting analysis. We estimate the alternative MIDAS model for the period 2003:02 2018:04. The variables that enter the MIDAS model are the three oil price shocks. The number of lags we use to estimate these models is 6. Moreover, we estimate a monthly and a quarterly ARDL model. For the monthly ARDL model, we use 8 lag, while for the quarterly we use 2 lags [31]. We run an out-of-sample dynamic forecast for the period 2019:01 to 2019:04. To evaluate the forecast performance among the alternative models, we compare some forecast statistics as shown in Table 3.18. The main forecasting statistic that we consider to conclude which model does better is the RMSE (Root Mean Squared Error).

In the first column, we show the results of the forecasting accuracy for the U-MIDAS model, while in the second column, we show the results for the "normalized exponential Almon" MIDAS model. In the third column, we show the results for the (non-normalized) Almon polynomial Midas model, while in the fourth and the fifth column we show the results respectively for the monthly and quarterly ARDL model.

By comparing the RMSE, we show that (non-normalized) Almon polynomial Midas has the best forecasting performance across the MIDAS variants. This model is followed by the "normalized exponential Almon", and U-Midas. The forecasting accuracy increases by 5.4% when using the (non-normalized) Almon polynomial model instead of the "normalized exponential Almon", and by 7.6% when using it instead of the U-Midas. However, the monthly ARDL shows the best forecasting performance through all the models, since it minimizes the RMSE. On contrary, the worst forecasting performance is showed by quarterly ARDL

Also, for the same comparative reasons, the Diebold-Mariano (DM) test is performed. The test shows that all forecast series have the same predictive accuracy. The null hypothesis is that the two forecasts have the same accuracy. The alternative hypothesis is that the two forecasts have different levels of accuracy. When we perform this test for the previous models, we perform it for different loss functions(U-shape loss function (symmetric), V-shape loss function (symmetric), Lin-Lin loss function (asymmetric), Linex loss function (asymmetric). After performing this test for the estimated models, we fail to reject the null hypothesis. Thus, the Diebold-Mariano test suggests that all modes have the same forecasting accuracy.

The Giacomini-White (GW) test is another test on equal conditional predictive ability. We perform this test to compare the forecasting accuracy of the models estimated previously. We use two loss functions, namely symmetric quadratic (U-shape) loss. The output of the test shows us which forecasting model dominates. If the sign of the mean of the loss is positive the 2nd

[31] The number of lags that we used is based on the information criteria.

model dominates, and vice-versa. The results of the GW test are in line with the ones derived from the comparison of the RMSE. The (non-normalized) Almon polynomial Midas has a better forecasting performance followed by "normalized exponential Almon", U-Midas and quarterly ARDL. We can not perform this test for the comparison of the MIDAS and quarterly ARDL to the monthly ARDL since the frequency of the data does not match. This test suggests that the prediction performance of "normalized exponential Almon" dominates that of U-MIDAS. Based on subsequent tests, we conclude that the (non-normalized) Almon polynomial Midas version provides the best forecasts for Russian GDP growth. However, as the GW test cannot be performed for the monthly ARDL, we will base our conclusions on comparing the values of the RMSE statistic as it can be calculated for all models. We conclude that the monthly ARDL provides the bests forecasts for Russian GDP growth.

We conduct the same forecasting analysis for inflation. We estimate the three versions of MIDAS for the period 2003:02 2018:04. The variables that enter the MIDAS model are the three oil price shocks. The number of lags we use to estimate these models is 6. Moreover, we estimate a monthly and a quarterly ARDL model. For the monthly ARDL model, we use 1 lag, while for the quarterly we use 2 lags. We run an out-of-sample dynamic forecast for the period 2019:01 to 2019:04. The construction of the table is the same as in the previous example.

In Table 3.19 we show the main forecasting evaluation statistics. Comparing RMSE, we conclude that the best model for forecasting Russian among the MIDAS variants is "normalized exponential Almon". The forecasting accuracy increases by 23% when using this model instead of the (non-normalized) Almon polynomial, and by 29% when using it instead of the U-MIDAS. However, when comparing these RMSEs with the ones of the two ARDL models, we conclude that the quarterly ARDL model performs better for forecasting Russian inflation.

Also, for the same reason, the Diebold-Mariano (DM) test is performed. The test shows that all forecast series have the same predictive accuracy. After performing this test for the estimated models, we fail to reject the null hypothesis. Thus, the Diebold-Mariano test suggests that all modes have the same forecasting accuracy [32].

The results of the Giacomini-White (GW) test are in line with the ones derived from the comparison of the RMSE. The Giacomini-White test suggests that the prediction performance of "normalized exponential Almon" and (non-normalized) Almon polynomial dominates that of U-MIDAS. However, the prediction performance of "normalized exponential Almon" dominates that of (non-normalized) Almon polynomial, while the prediction performance of the quarterly ARDL dominates all models. Based on subsequent tests and forecast evaluation statistics, we conclude that the quarterly ARDL followed by MIDAS's "normalized exponential Almon" version provides the best forecasts for Russian inflation.

We conclude that for forecasting the Russian GDP growth the best model we can use is the monthly ARDL. On the other hand, for forecasting the Russian inflation the best model we can use is the quarterly ARDL.

[32]See the results of these tests in Appendix D

Models	U-MIDAS	neAlmon	Almonp	Monthly ARDL	Quarterly ARDL
Mean Error	0.394	-0.112	0.101	-0.134	-0.501
Root Mean Squared Error	5.43	5.308	5.019	4.381	6.081
Mean Absolute Error	4.316	4.574	4.223	3.89	5.468
Mean Percentage Error	113.479	119.461	106.874	-270.61	144.59
Mean Absolute Percentage Error	113.479	119.461	106.874	566.33	144.59
Theil's U	0.745	0.798	0.766	1.764	0.890
Bias proportion, U^M	0.005	0.0004	0.0004	0.0009	0.0068
Regression proportion, U^R	0.064	0.020	0.008	0.482	0.436
Disturbance proportion, U^D	0.930	0.979	0.991	0.516	0.556

Table 4.18: Forecast evaluation statistics-growth

Models	U-MIDAS	neAlmon	Almonp	Monthly ARDL	Quarterly ARDL
Mean Error	-0.857	-0.283	-0.265	-0.960	-0.686
Root Mean Squared Error	1.846	1.299	1.799	1.595	1.201
Mean Absolute Error	1.555	1.186	1.365	1.309	1.163
Mean Percentage Error	343.532	193.210	335.372	-68.714	74.542
Mean Absolute Percentage Error	343.532	193.210	335.372	208.9	161.28
Theil's U	0.478	0.375	0.534	2.461	0.810
Bias proportion, U^M	0.215	0.047	0.021	0.362	0.326
Regression proportion, U^R	0.556	0.659	0.712	0.089	0.457
Disturbance proportion, U^D	0.228	0.293	0.265	0.547	0.216

Table 4.19: Forecast evaluation statistics-inflation

4.6 Conclusion

In this chapter we have compared the dynamic effects of different types of oil shocks on Russia's economic indicators. Although much empirical research has investigated the relationship between oil price changes and economic activity, there is little research into the relationship between oil price shocks and large Newly Industrialized Economies (NIEs). Furthermore, the relationship between oil price shock and the Russian economy has not been studied as much as the relationship itself, but for other countries (e.g. the United States). We expect the effects of these shocks to be different in oil-exporting countries. The novelty of this study is that we try to identify the effect of three oil price shocks on Russian GDP and inflation. In the current literature, researchers have tried to understand the effect of oil price changes on Russian macroeconomic aggregates, but none have detected the effect of oil price shocks (on the supply and demand side) on the Russian economy. Furthermore, for the first time we are using a MIDAS model to model Russian GDP and inflation.

We involve five different models (monthly and quarterly ARDL, three variants of the MIDAS model) to conduct the empirical analysis of the effect of oil price shocks on Russian macroeconomic aggregates. Several important points(or insights) emerge from this analysis.

First, the source behind the change in the oil price is crucial in determining the economic consequences for the Russian economy, which is in line with [Peersman and Van Robays, 2009] and [Kilian, 2009] results for the United States and Euro area. The oil price increases driven by different shocks have different effects on the Russian economy. More specifically, based on the results of all models, a positive aggregate demand shock has a positive and significant effect on Russian GDP growth. [33]. The effect of oil-specific demand shocks is also positive and significant for the monthly ARDL and MIDAS, while for the quarterly ARDL it is not significant. Hence, the demand-driven rise in oil price has a positive effect on Russian GDP. Growing world demand for oil drives Russia's oil earnings, as well as its economic growth.

The effect of a negative oil supply shock is mostly positive not significant for Russian economic growth. When other oil-producing countries decrease production (so the overall oil supply decrease), Russia has more market power. In this case, Russia can increase its oil production to respond to the reduction in the oil production by other oil exporters. These results could have positive effects on the Russian economy because they increase the earnings of the oil industry. Hence, the decrease in oil production also has a positive effect on Russian GDP but not significant. It means that the supply side dynamics of the oil market are not important to the Russian GDP.

The effect of oil price shocks on inflation differs across the shocks. A positive oil specific demand shock mostly has a negative effect on Russian inflation. On the other hand, the effect of an aggregate demand shock and a negative oil supply shock is insignificant.

We conclude that oil price increases driven by a specific oil demand shock are the only ones that matter to Russian inflation.

Both a positive demand shock and a negative supply shock cause the price of oil to rise. From previous results, we conclude that not all oil price increases have the same effect on the Russian economy. The effect that a rise in oil prices will have on the Russian economy depends on the underlying shock that causes it. The different oil shocks have a different effect on Russia's economic growth and inflation as an oil exporter. Consequently, not disentangling oil price shocks based on their underlying source could cause difficulties in estimating the response of Russian macroeconomic aggregates to changes in oil prices.

We suggest to policymakers the importance of understanding the underlying source of oil price fluctuations in order to then understand the effect its fluctuations will have on the Russian

[33]This result is also similar for oil-importing countries. See [Baumeister et al., 2010a]

economy.

Second, we try different models to model Russia's major economic aggregates using oil price shocks. The effect of different shocks on Russian GDP growth and inflation does not differ much when different model specifications are used. However, some of the responses are different across models. By analyzing the effect of a negative oil supply shock on inflation using a monthly ADL, the response is negative and significant. In the other four cases, the effect is not significant. Another difference between the model results emerges when considering the response of GDP growth to a specific oil demand shock. According to the results obtained from the quarterly ARDL model, this response is not significant after 4 quarters, while the other models suggest a positive and significant response across all horizons.

Third, to select the best model for modeling Russian GDP and inflation, let's calculate some forecasts. Based on predictive power, the best model for predicting Russian GDP growth is the monthly ARDL model. On the other hand, the best model for predicting Russian inflation is the quarterly ARDL model.

Finally, policymakers should take into account that the change in the price of oil caused by a positive aggregate demand shock or an oil-specific demand, have a positive effect on Russian GDP growth and a negative effect or not significant on its inflation. Conversely, when the change is caused by a negative supply shock, the effect on Russian GDP growth and inflation would be insignificant for the first variable and negative for the second.

Chapter 5

Conclusions

Understanding the determinants of oil prices and their relationship to macroeconomic variables has been a challenge for researchers in recent years. Many studies have been done to model the oil market and many different models have been used in the literature.

We replicate [Kilian, 2009] and estimate the same model by extending the sampling period. The results of our analysis do not differ from the original ones. Furthermore, we estimate the same [Kilian and Murphy, 2014] model but using a different identification strategy. We find that the original results are sensitive to the changes we have made. In addition, we suggest other elasticity limits for oil demand and supply. In this study, we estimate a SVAR model to identify three different oil price shocks: oil supply shock, aggregate demand shock, and oil-specific demand shock. One of the variables that enter the SVAR model is the index for the global economic activity. The novelty of this study is that we use different proxies for this variable. Based on the results we get after predicting the oil price through a VAR model, we conclude that the OECD IP is the best index to model the oil market. In modeling the oil market, researchers should consider that the restrictions used greatly affect the results obtained. Policy makers should include the global economic activity index in modeling the real oil price. Furthermore, we suggest that the best proxy that can be used for real economic activity is the OECD IP index.

Afterward, we have compared the dynamic effects of several types of oil shocks on Russia's economic indicators. Although much empirical research has studied the relationship between changes in oil prices and economic activity, there is little research on the relationship between oil price shocks and the large Newly Industrialized Economies (NIEs). Furthermore, the relationship between oil price shocks and the Russian economy has not been studied as much as the relationship itself, but for other countries (for example United States). We expect the effects of these shocks to be different in oil-exporting countries.

We involve four different models to conduct the empirical analysis of the effect of oil price shocks on Russian macroeconomic aggregates. Several important insights emerge from this analysis.

We conclude that different oil shocks have a different effect on Russia's economic growth and inflation as an oil exporter. As a result, not disentangling oil price shocks based on their underlying source could cause difficulties in estimating the real effect of oil price changes.

Based on predictive power, the best model to forecast the Russian GDP growth and inflation is the ARDL model.

Finally, policymakers should take into account that the variation in the price of oil caused by a positive aggregate demand shock or an oil-specific demand shock has a positive effect on Russian GDP growth. On the other hand, these shocks have a negative(oil-specific demand shock) or insignificant(aggregate demand shock) effect on Russian inflation. Conversely, when the change in the oil price is caused by a negative supply shock, the effect on Russian GDP growth and inflation is mostly non-significant.

Appendix A

DM and GW TEST-Chapter 3

A.1 1974-2019

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:01-2019:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                 -6.4291     0.0000
   V-shape                                 -5.2546     0.0000

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*         -5.2546     0.0000
   Linex (shape parameter  0.80)**         -6.3234     0.0000

 * The highest p-value=0.0000 is for order parameter 0.95.
   The lowest p-value=0.0000 is for order parameter 0.31.

** The highest p-value=0.0000 is for shape parameter 2.
   The lowest p-value=0.0000 is for shape parameter -1.71.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure A.1: DM TEST KI-OECD

```
--------------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:01-2019:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                  -6.5190     0.0000
   V-shape                                 -15.8013     0.0000

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*         -15.8013     0.0000
   Linex (shape parameter  0.80)**          -7.2131     0.0000

 * The highest p-value=0.0000 is for order parameter 0.86.
   The lowest p-value=0.0000 is for order parameter 0.68.

** The highest p-value=0.0000 is for shape parameter -2.
   The lowest p-value=0.0000 is for shape parameter 2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------------
```

Figure A.2: DM TEST KI-GECON

```
--------------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:01-2019:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                   0.4242     0.6714
   V-shape                                   0.6420     0.5209

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*           0.6420     0.5209
   Linex (shape parameter  0.80)**           0.4588     0.6464

 * The highest p-value=0.5209 is for order parameter 0.23.
   The lowest p-value=0.5209 is for order parameter 0.83.

** The highest p-value=0.7521 is for shape parameter -2.
   The lowest p-value=0.6155 is for shape parameter 2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------------
```

Figure A.3: DM TEST OECD-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 10.1754, p-value 0.00142327 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.4: GW TEST KI-OECD

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 10.4458, p-value 0.00122929 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.5: GW TEST KI-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.390036, p-value 0.53228 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.6: GW TEST OECD-GECON

A.2 Sub-Sample: 1990-2019

```
--------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                  1.9171     0.0552
   V-shape                                  1.9681     0.0491

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*          1.9681     0.0491
   Linex (shape parameter  0.80)**          1.8636     0.0624
   Direction-of-change                     -0.6959     0.4865

 * The highest p-value=0.9757 is for order parameter 0.24.
   The lowest p-value=0.0011 is for order parameter 1.

** The highest p-value=0.0747 is for shape parameter 2.
   The lowest p-value=0.0413 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------
```

Figure A.7: DM TEST KI-OECD

```
--------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                  2.4125     0.0158
   V-shape                                  4.1118     0.0000

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*          4.1118     0.0000
   Linex (shape parameter  0.80)**          2.3241     0.0201

 * The highest p-value=0.9596 is for order parameter 0.15.
   The lowest p-value=0.0000 is for order parameter 1.

** The highest p-value=0.0285 is for shape parameter 2.
   The lowest p-value=0.0087 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------
```

Figure A.8: DM TEST KI-GECON

```
----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                  -2.4785     0.0132
   V-shape                                  -6.0456     0.0000

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*          -6.0456     0.0000
   Linex (shape parameter  0.80)**          -2.3284     0.0199
   Direction-of-change                      -1.1692     0.2423

 * The highest p-value=0.2610 is for order parameter 0.01.
   The lowest p-value=0.0000 is for order parameter 0.11.

** The highest p-value=0.0342 is for shape parameter 2.
   The lowest p-value=0.0041 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
----------------------------------------------------------------
```

Figure A.9: DM TEST KI-WSP

```
----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                   0.1660     0.8681
   V-shape                                   0.7583     0.4483

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*           0.7583     0.4483
   Linex (shape parameter  0.80)**           0.0893     0.9288
   Direction-of-change                       0.7994     0.4241

 * The highest p-value=0.7147 is for order parameter 1.
   The lowest p-value=0.2959 is for order parameter 0.31.

** The highest p-value=0.9999 is for shape parameter 1.68.
   The lowest p-value=0.7334 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
----------------------------------------------------------------
```

Figure A.10: DM TEST OECD-GECON

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                -2.4386     0.0147
   V-shape                                -7.3219     0.0000

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*        -7.3219     0.0000
   Linex (shape parameter  0.80)**        -2.2963     0.0217

 * The highest p-value=0.9178 is for order parameter 0.05.
   The lowest p-value=0.0000 is for order parameter 0.6.

** The highest p-value=0.0361 is for shape parameter 2.
   The lowest p-value=0.0049 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure A.11: DM TEST GECON-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 3.69675, p-value 0.0545185 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.12: GW TEST KI-OECD

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 5.6562, p-value 0.0173938 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.13: GW TEST KI-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 5.76371, p-value 0.0163605 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.14: GW TEST KI-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.0324616, p-value 0.857018 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.15: GW TEST OECD-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 5.61755, p-value 0.0177815 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.16: GW TEST OECD-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 5.81944, p-value 0.01585 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.17: GW TEST GECON-WSP

A.3 Sub-Sample: 1990-2007

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                   1.0693     0.2849
   V-shape                                   1.0030     0.3159

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*           1.0030     0.3159
   Linex (shape parameter  0.80)**           1.1061     0.2687

 * The highest p-value=0.9930 is for order parameter 0.73.
   The lowest p-value=0.0397 is for order parameter 0.

** The highest p-value=0.3783 is for shape parameter -2.
   The lowest p-value=0.2604 is for shape parameter 1.99.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure A.18: DM TEST KI-OECD

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                    DM test    p-value
   U-shape                                  -1.4029     0.1607
   V-shape                                  -1.1963     0.2316

Asymmetric loss functions                   DM test    p-value
   Lin-Lin (order parameter 0.50)*          -1.1963     0.2316
   Linex (shape parameter  0.80)**          -1.4054     0.1599
   Direction-of-change                      -1.0552     0.2913

 * The highest p-value=0.4808 is for order parameter 0.
   The lowest p-value=0.0889 is for order parameter 0.8.

** The highest p-value=0.1630 is for shape parameter -2.
   The lowest p-value=0.1584 is for shape parameter 2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure A.19: DM TEST KI-GECON

```
--------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                 DM test    p-value
   U-shape                               -1.5005     0.1335
   V-shape                               -1.8612     0.0627

Asymmetric loss functions                DM test    p-value
   Lin-Lin (order parameter 0.50)*       -1.8612     0.0627
   Linex (shape parameter  0.80)**       -1.5222     0.1280
   Direction-of-change                   -1.0552     0.2913

 * The highest p-value=0.1983 is for order parameter 0.
   The lowest p-value=0.0147 is for order parameter 0.77.

** The highest p-value=0.1458 is for shape parameter -2.
   The lowest p-value=0.1190 is for shape parameter 2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------
```

Figure A.20: DM TEST KI-WSP

```
--------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                 DM test    p-value
   U-shape                               -2.5258     0.0115
   V-shape                               -1.6518     0.0986

Asymmetric loss functions                DM test    p-value
   Lin-Lin (order parameter 0.50)*       -1.6518     0.0986
   Linex (shape parameter  0.80)**       -2.4520     0.0142
   Direction-of-change                   -1.1692     0.2423

 * The highest p-value=0.9784 is for order parameter 0.8.
   The lowest p-value=0.0021 is for order parameter 0.

** The highest p-value=0.0201 is for shape parameter 2.
   The lowest p-value=0.0087 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
--------------------------------------------------------------
```

Figure A.21: DM TEST OECD-GECON

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                     DM test    p-value
   U-shape                                   -2.3824     0.0172
   V-shape                                   -2.8533     0.0043

Asymmetric loss functions                    DM test    p-value
   Lin-Lin (order parameter 0.50)*           -2.8533     0.0043
   Linex (shape parameter  0.80)**           -2.4878     0.0129
   Direction-of-change                       -1.1692     0.2423

 * The highest p-value=0.9672 is for order parameter 0.9.
   The lowest p-value=0.0000 is for order parameter 0.

** The highest p-value=0.0369 is for shape parameter -2.
   The lowest p-value=0.0090 is for shape parameter 2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure A.22: DM TEST OECD-WSP

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2007:01-2007:12 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                     DM test    p-value
   U-shape                                   -1.5504     0.1210
   V-shape                                   -2.3072     0.0210

Asymmetric loss functions                    DM test    p-value
   Lin-Lin (order parameter 0.50)*           -2.3072     0.0210
   Linex (shape parameter  0.80)**           -1.5834     0.1133

 * The highest p-value=0.1632 is for order parameter 1.
   The lowest p-value=0.0030 is for order parameter 0.77.

** The highest p-value=0.1383 is for shape parameter -2.
   The lowest p-value=0.1012 is for shape parameter 2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure A.23: DM TEST GECON-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 1.96196, p-value 0.161304 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.24: GW TEST KI-OECD

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 3.00763, p-value 0.0828732 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.25: GW TEST KI-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 3.44532, p-value 0.0634311 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.26: GW TEST KI-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 6.67559, p-value 0.00977422 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.27: GW TEST OECD-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 6.34069, p-value 0.0117999 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.28: GW TEST OECD-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 3.64698, p-value 0.056171 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.29: GW TEST GECON-WSP

A.4 Sub-Sample: 2009-2019

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                      DM test    p-value
   U-shape                                     1.8329     0.0668
   V-shape                                     2.1149     0.0344

Asymmetric loss functions                     DM test    p-value
   Lin-Lin (order parameter 0.50)*             2.1149     0.0344
   Linex (shape parameter  0.80)**             1.8190     0.0689
   Direction-of-change                         0.5296     0.5964

 * The highest p-value=0.9875 is for order parameter 0.26.
   The lowest p-value=0.0000 is for order parameter 1.

** The highest p-value=0.0742 is for shape parameter 2.
   The lowest p-value=0.0659 is for shape parameter -0.98.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure A.30: DM TEST KI-OECD

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                     DM test    p-value
   U-shape                                   -2.9291     0.0034
   V-shape                                  -12.1322     0.0000

Asymmetric loss functions                    DM test    p-value
   Lin-Lin (order parameter 0.50)*          -12.1322     0.0000
   Linex (shape parameter  0.80)**           -2.7509     0.0059

 * The highest p-value=0.0000 is for order parameter 0.73.
   The lowest p-value=0.0000 is for order parameter 0.81.

** The highest p-value=0.0125 is for shape parameter 2.
   The lowest p-value=0.0007 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure A.31: DM TEST KI-GECON

```
------------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                -2.8783     0.0040
   V-shape                                -6.3600     0.0000

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*        -6.3600     0.0000
   Linex (shape parameter  0.80)**        -2.6754     0.0075

 * The highest p-value=0.0000 is for order parameter 0.96.
   The lowest p-value=0.0000 is for order parameter 0.52.

** The highest p-value=0.0168 is for shape parameter 2.
   The lowest p-value=0.0007 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
------------------------------------------------------------------
```

Figure A.32: DM TEST KI-WSP

```
------------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                -2.1255     0.0335
   V-shape                                -3.0223     0.0025

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*        -3.0223     0.0025
   Linex (shape parameter  0.80)**        -2.0790     0.0376
   Direction-of-change                    -0.5296     0.5964

 * The highest p-value=0.9709 is for order parameter 0.21.
   The lowest p-value=0.0000 is for order parameter 1.

** The highest p-value=0.0457 is for shape parameter 2.
   The lowest p-value=0.0273 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
------------------------------------------------------------------
```

Figure A.33: DM TEST OECD-GECON

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                 -2.4723     0.0134
   V-shape                                 -4.5376     0.0000

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*         -4.5376     0.0000
   Linex (shape parameter  0.80)**         -2.3611     0.0182
   Direction-of-change                     -0.5296     0.5964

 * The highest p-value=0.9316 is for order parameter 0.14.
   The lowest p-value=0.0000 is for order parameter 1.

** The highest p-value=0.0285 is for shape parameter 2.
   The lowest p-value=0.0065 is for shape parameter -2.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure A.34: DM TEST OECD-WSP

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2018:06-2019:05 (T = 12)
   Bartlett window size: 2 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                 -2.7649     0.0057
   V-shape                                 -4.3788     0.0000

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*         -4.3788     0.0000
   Linex (shape parameter  0.80)**         -2.5817     0.0098

 * The highest p-value=0.0000 is for order parameter 0.95.
   The lowest p-value=0.0000 is for order parameter 0.93.

** The highest p-value=0.0205 is for shape parameter 2.
   The lowest p-value=0.0013 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure A.35: DM TEST GECON-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 4.09213, p-value 0.0430834 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure A.36: GW TEST KI-OECD

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 6.84721, p-value 0.00887796 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.37: GW TEST KI-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 6.81264, p-value 0.00905147 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.38: GW TEST KI-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 4.93412, p-value 0.0263315 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.39: GW TEST OECD-GECON

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 5.8751, p-value 0.0153565 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.40: GW TEST OECD-WSP

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 6.57939, p-value 0.0103166 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure A.41: GW TEST GECON-WSP

Appendix B

Kilian 2009

B.1 Replication and extended sample

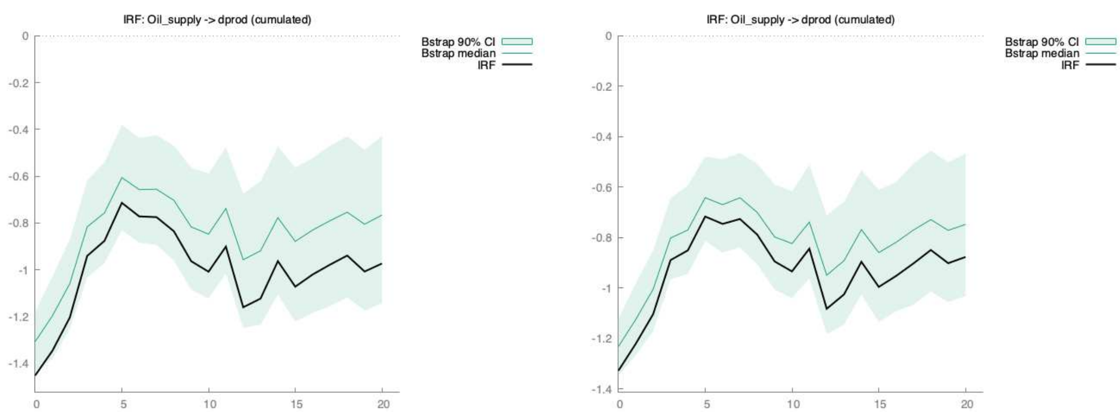


Table B.1: The response of oil production to a supply shock

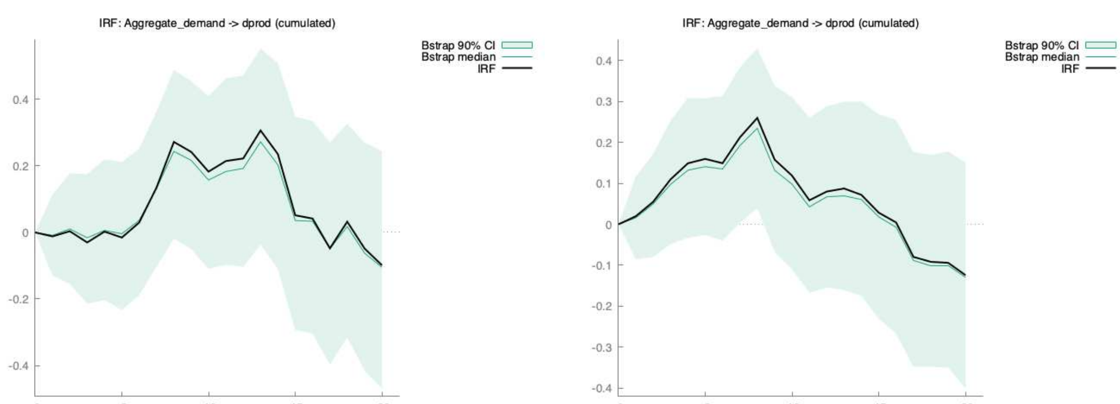


Table B.2: The response of oil production to an aggregate demand shock

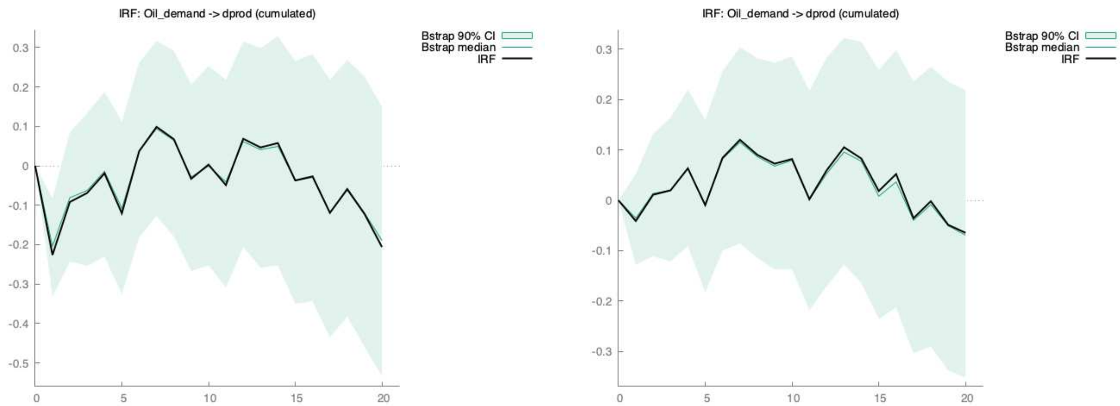


Table B.3: The response of oil production to a speculative demand shock

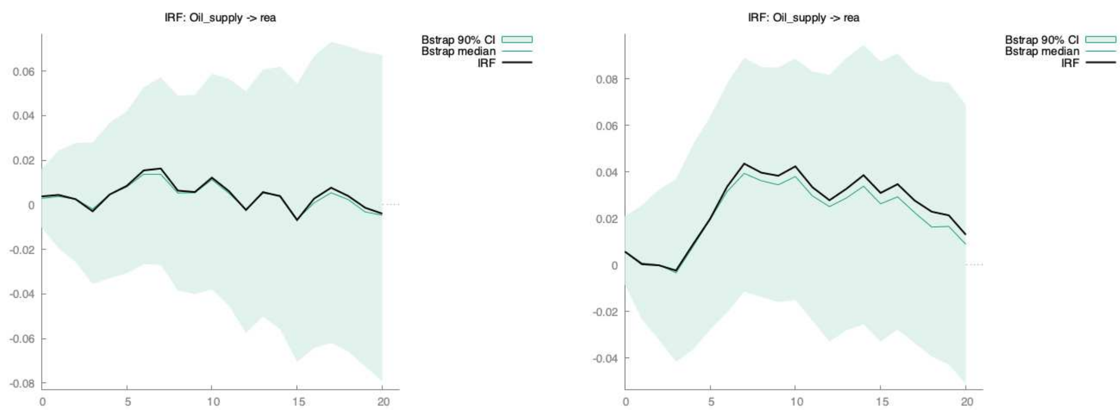


Table B.4: The response of rea to a supply shock

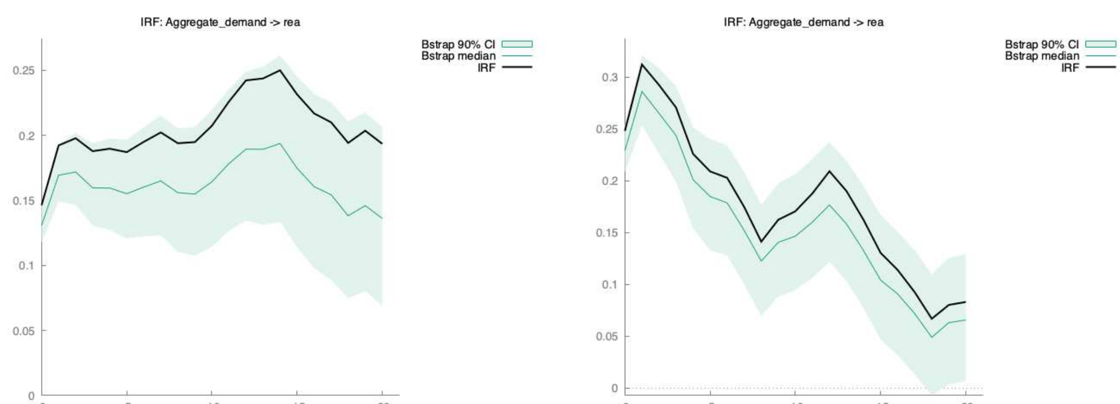


Table B.5: The response of rea to an aggregate demand shock

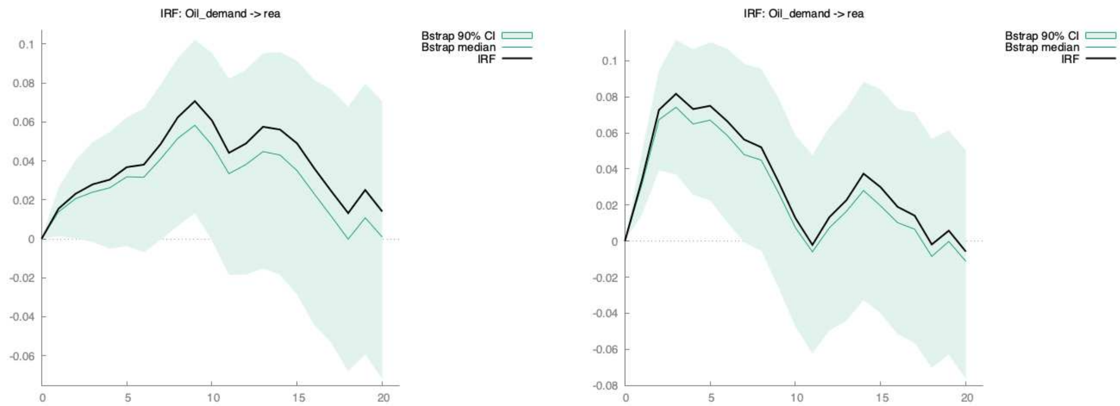


Table B.6: The response of rea to a speculative demand shock

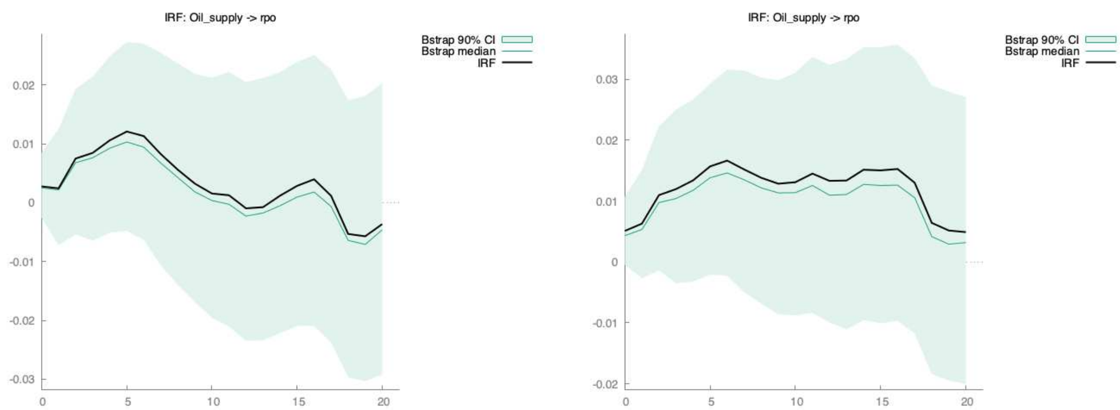


Table B.7: The response of rpo to a supply shock

Table B.8: The response of rpo to an aggregate demand shock

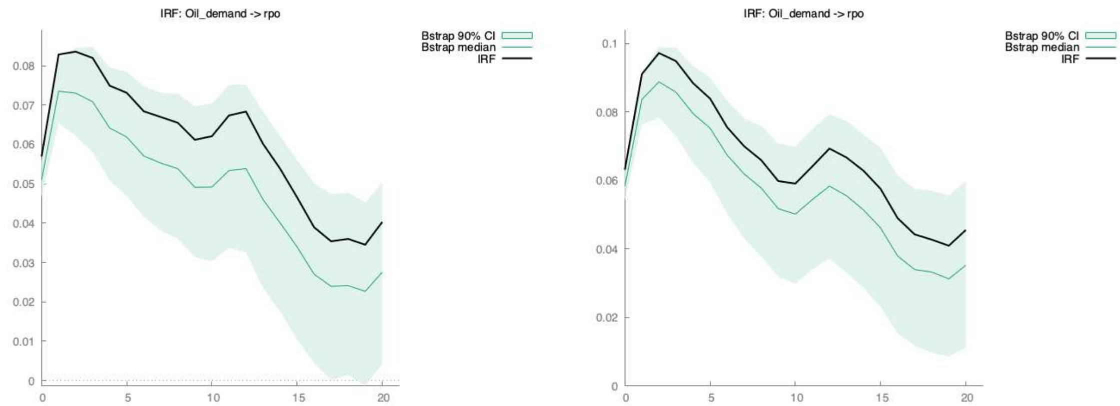


Table B.9: The response of rpo to a speculative demand shock

B.2 SVAR across reas-Kilian(2009)

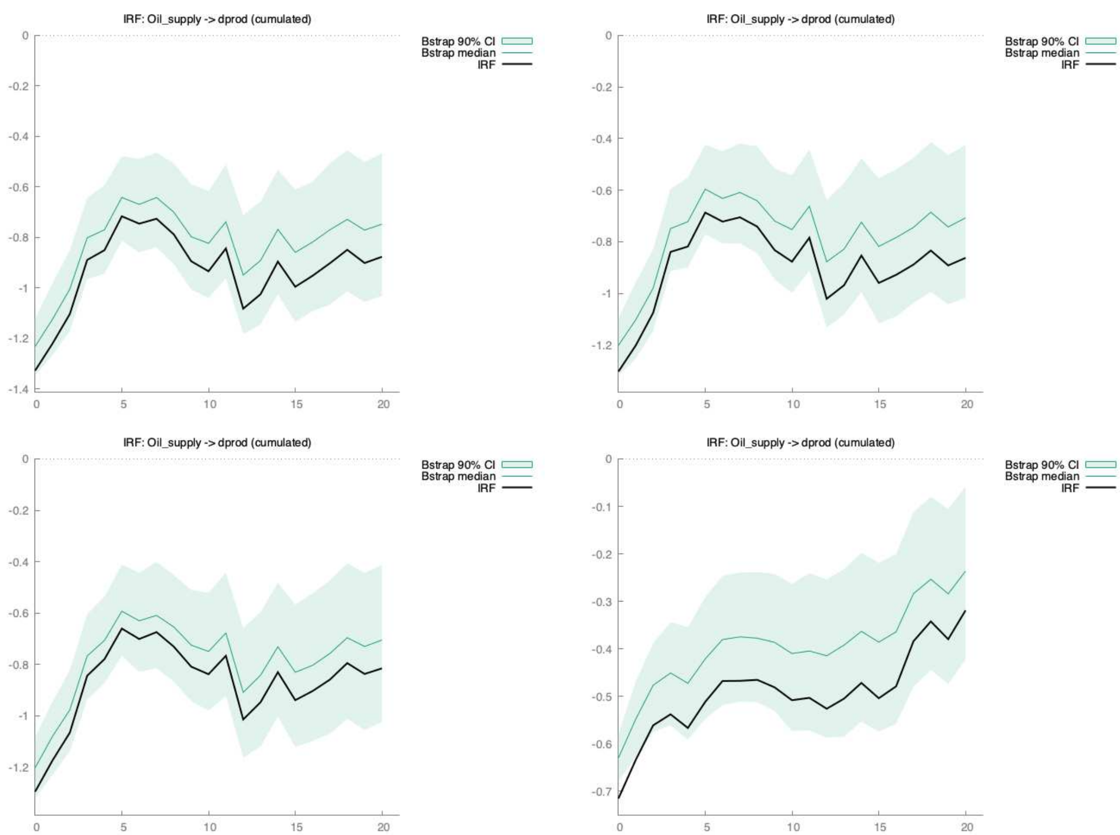


Table B.10: The response of oil production to a supply shock

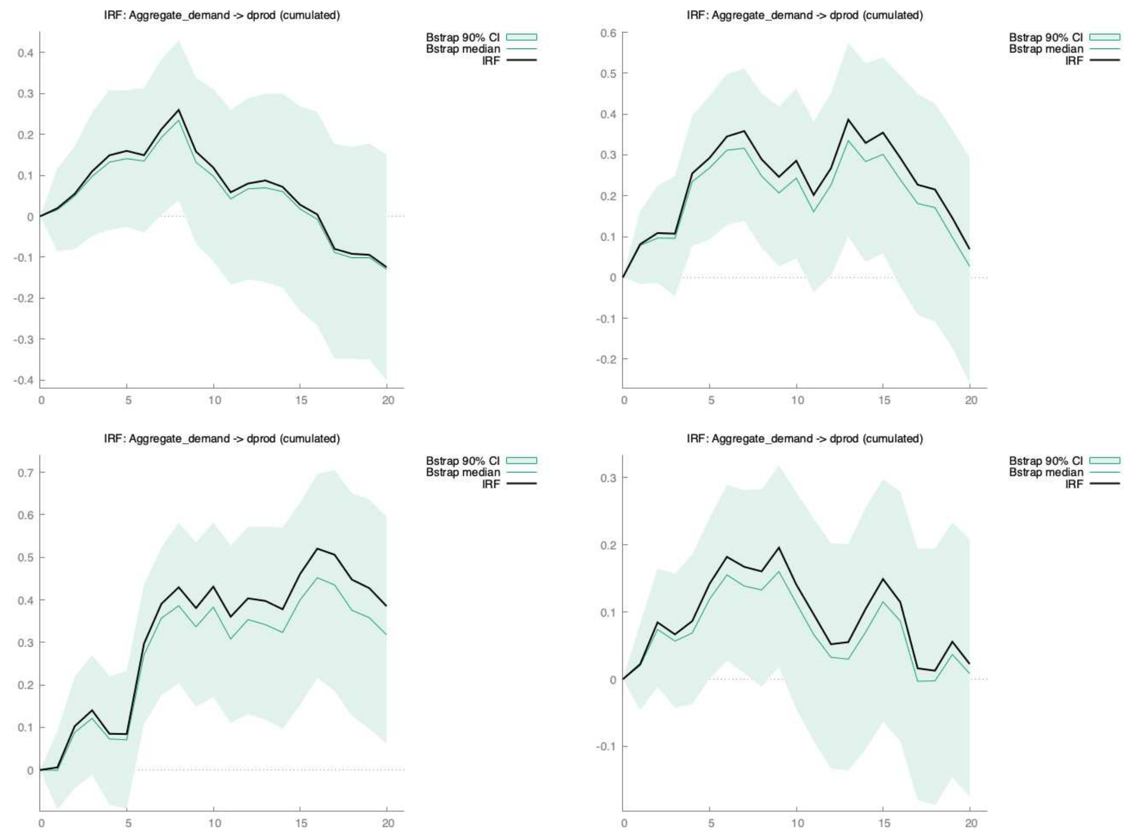


Table B.11: The response of oil production to an aggregate demand shock

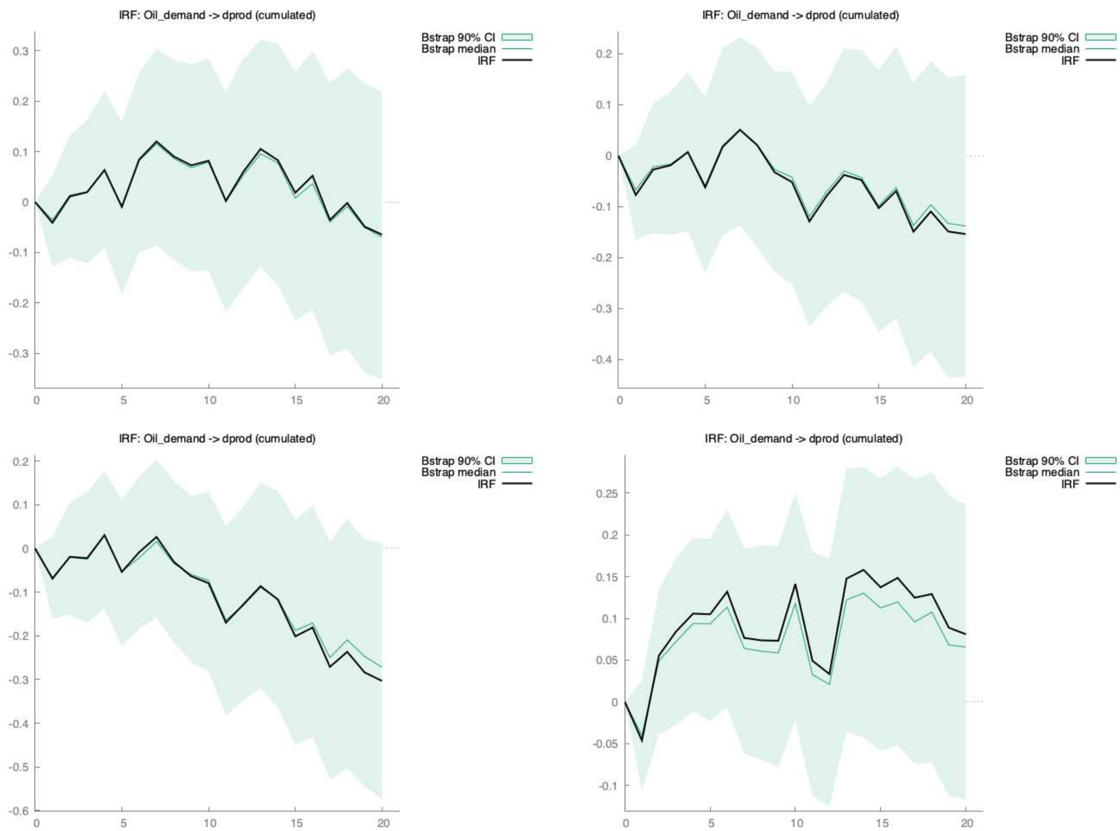


Table B.12: The response of oil production to a speculative demand shock

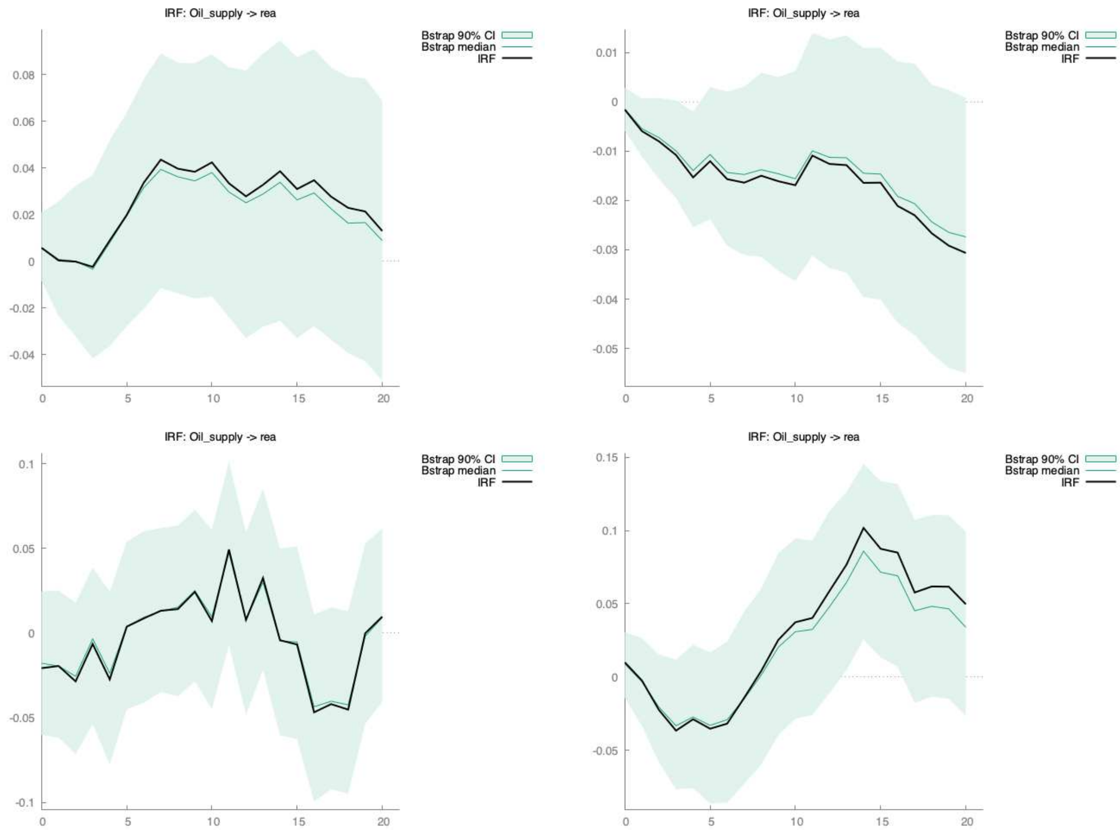


Table B.13: The response of rea to a supply shock

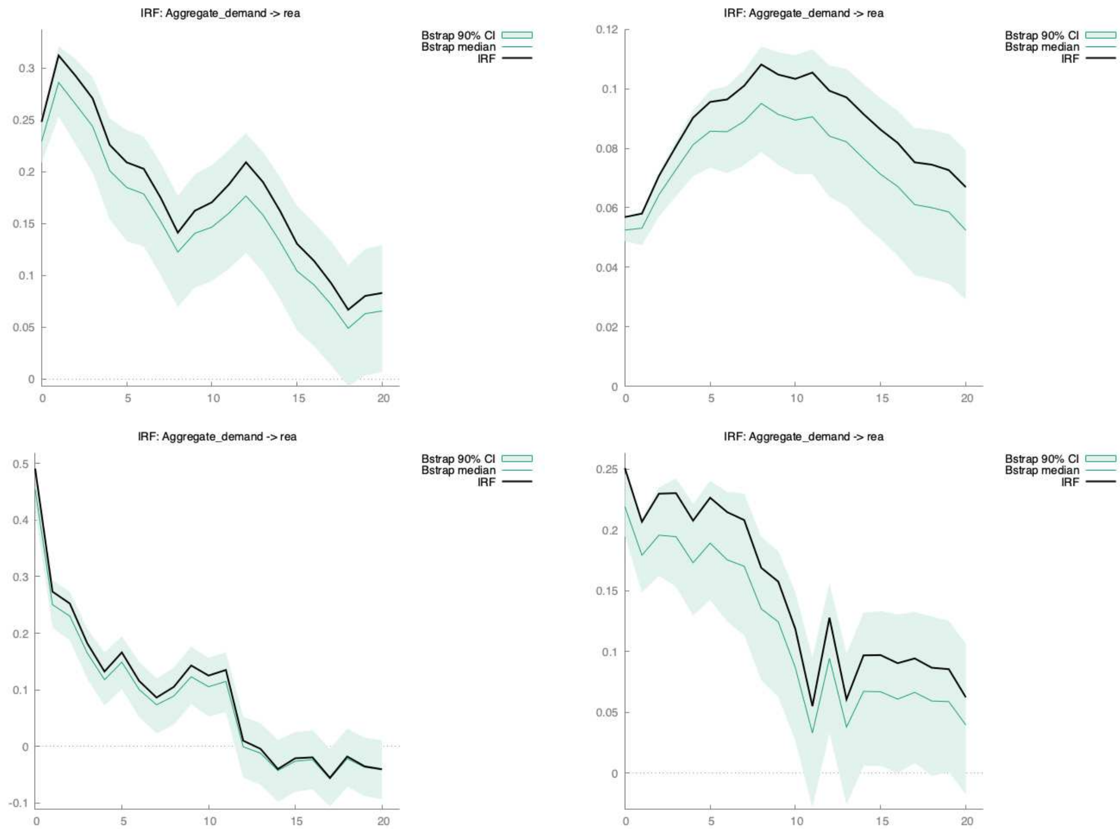


Table B.14: The response of rea to an aggregate demand shock

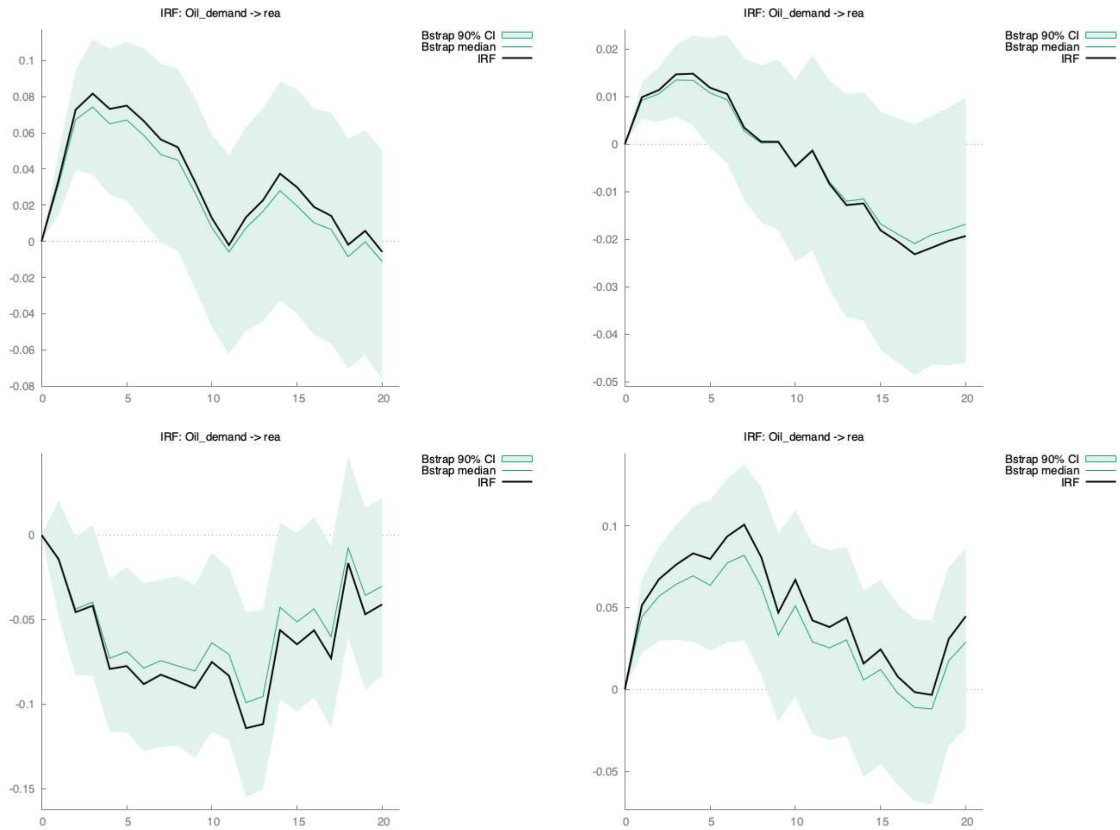


Table B.15: The response of rea to a speculative demand shock

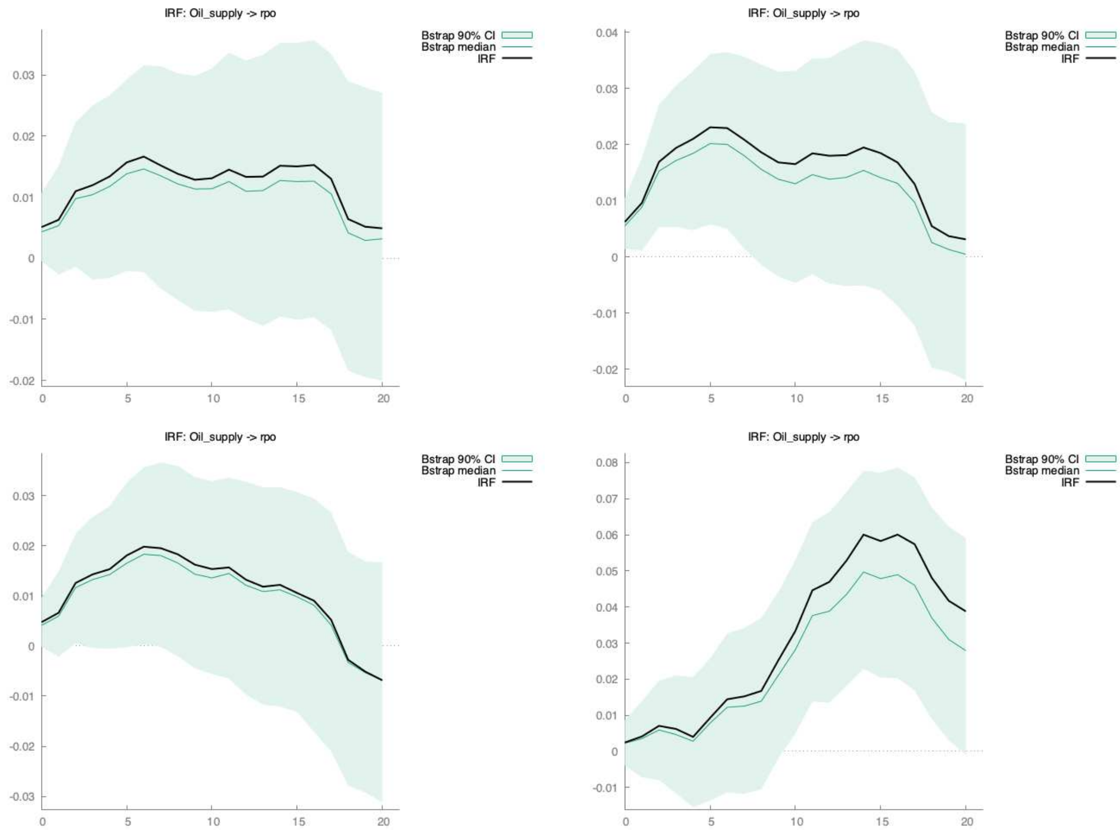


Table B.16: The response of rpo to a supply shock

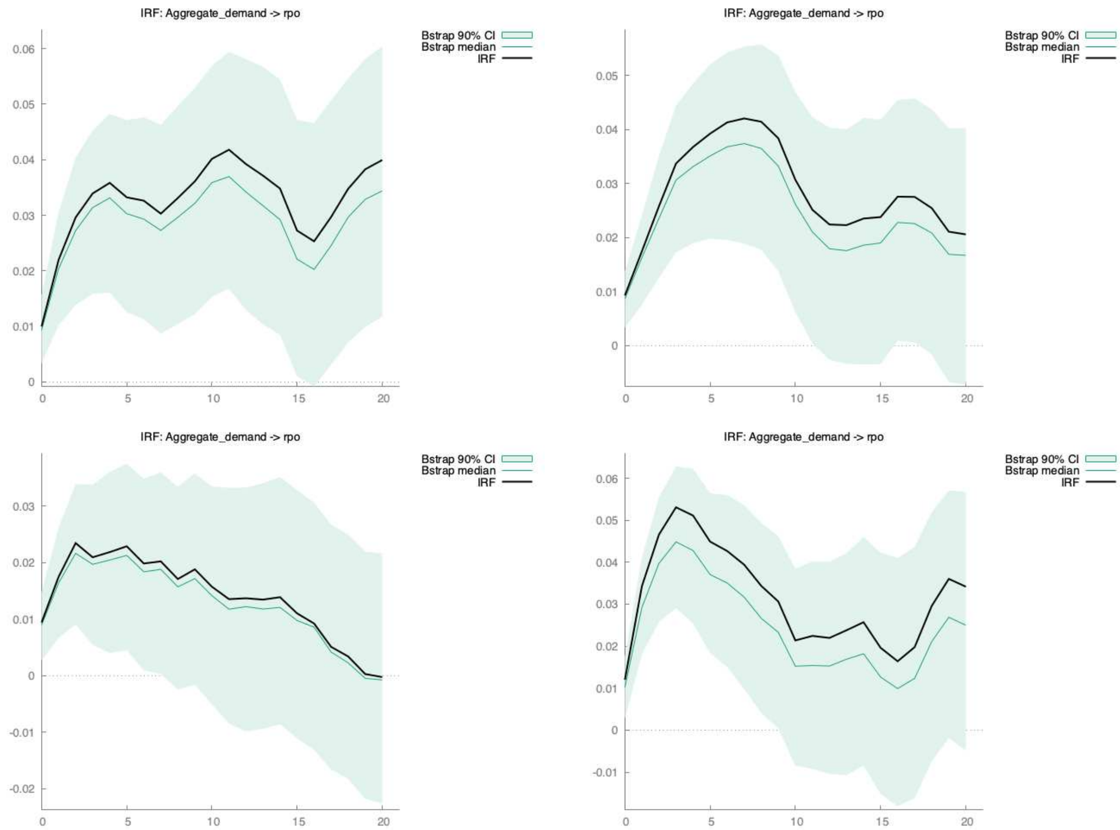


Table B.17: The response of rpo to an aggregate demand shock

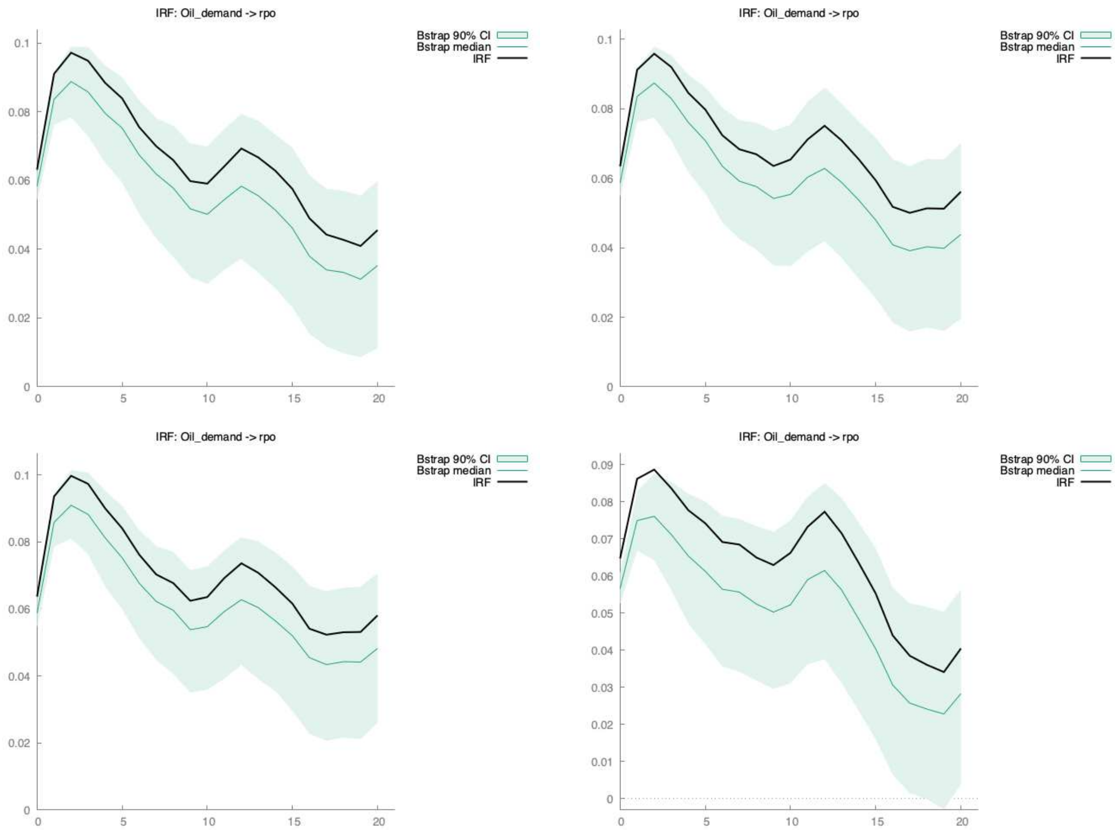


Table B.18: The response of rpo to a speculative demand shock

Appendix C

SVAR model with sign restrictions

C.0.1 SVAR model following KM (without restrictions) and extension of the sample

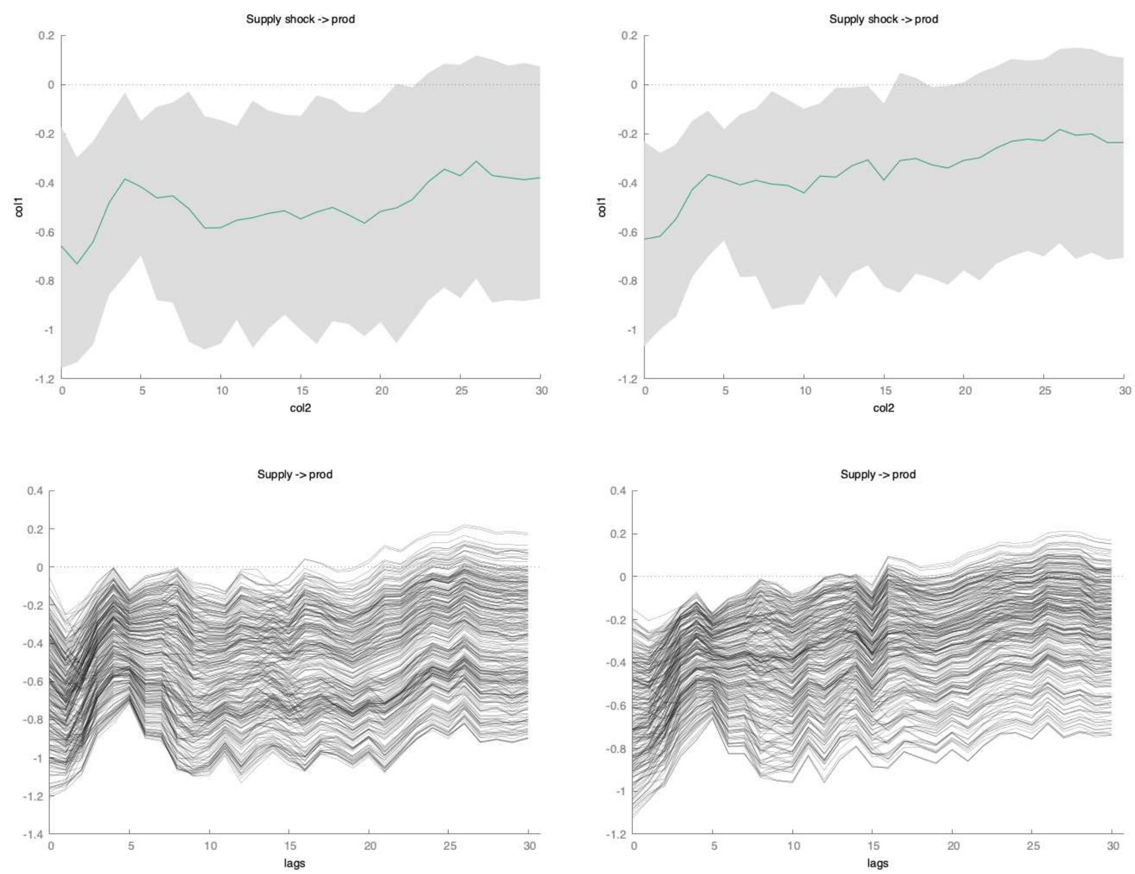


Table C.1: The response of oil production to a supply shock

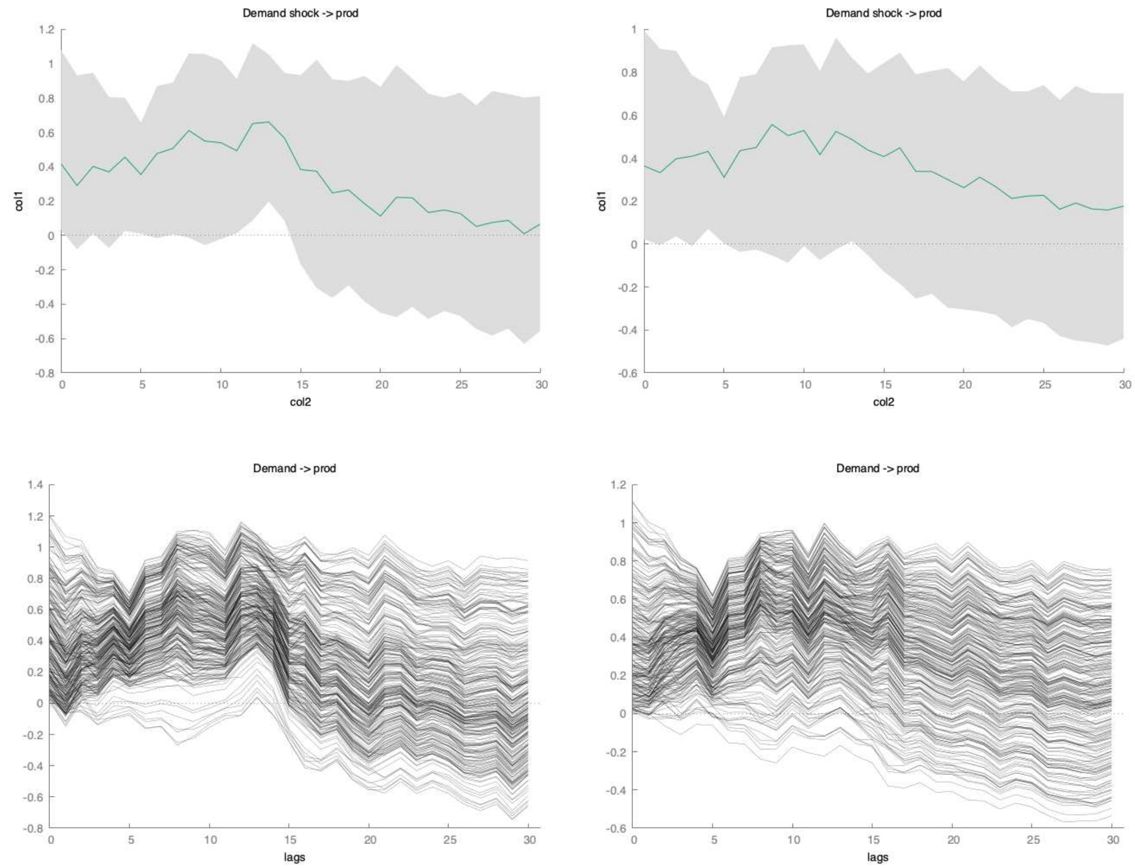
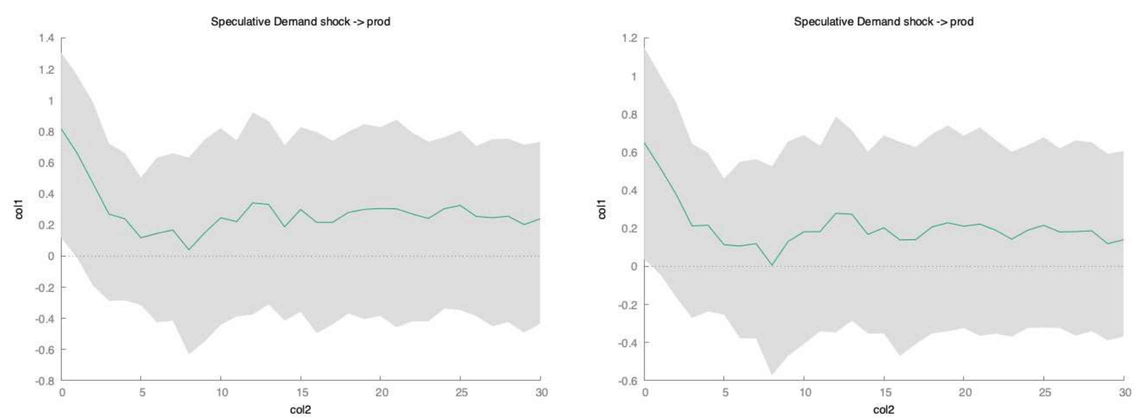


Table C.2: The response of oil production to a aggregate demand shock



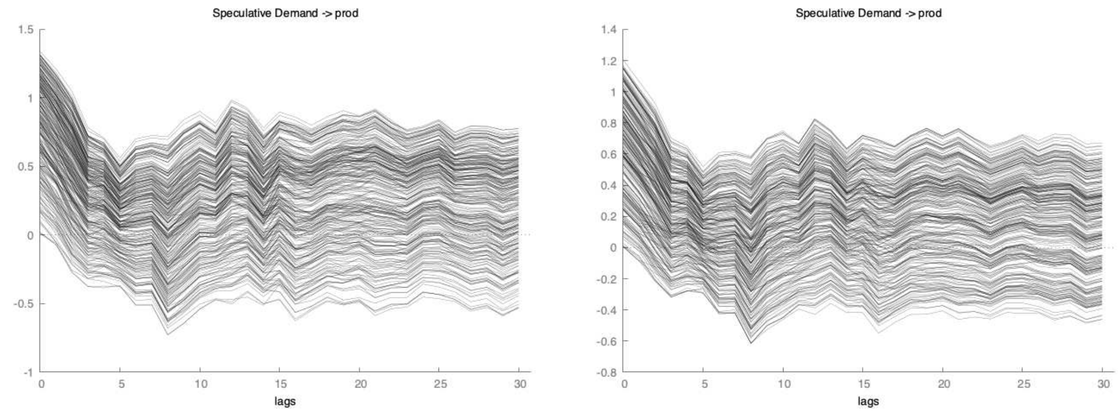


Table C.3: The response of oil production to an speculative demand shock

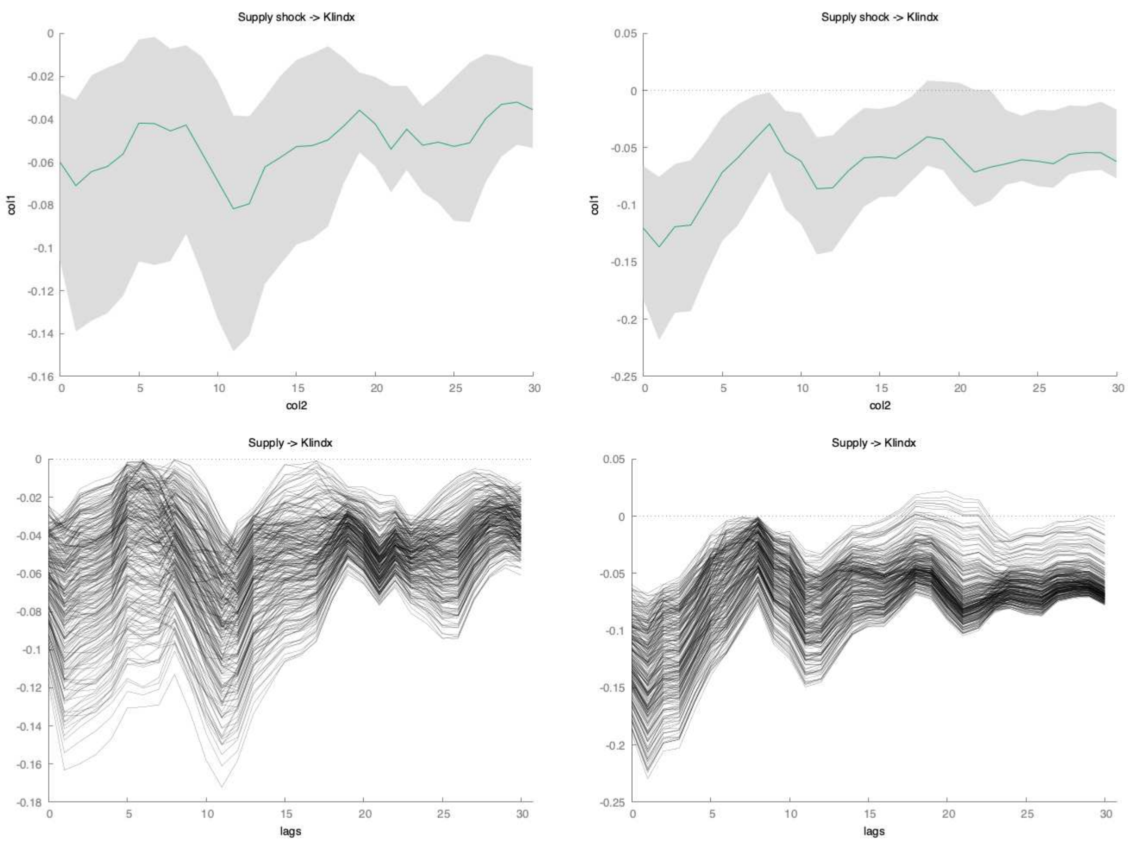


Table C.4: The response of rea to a supply shock

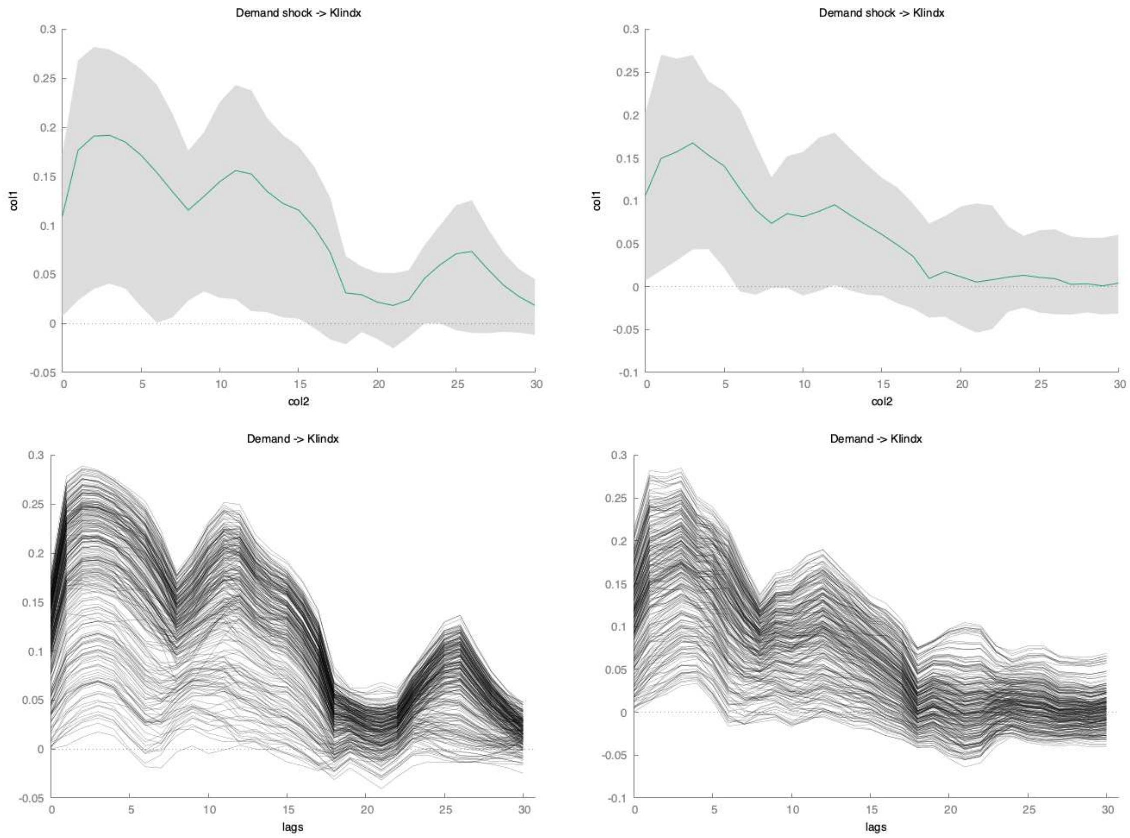
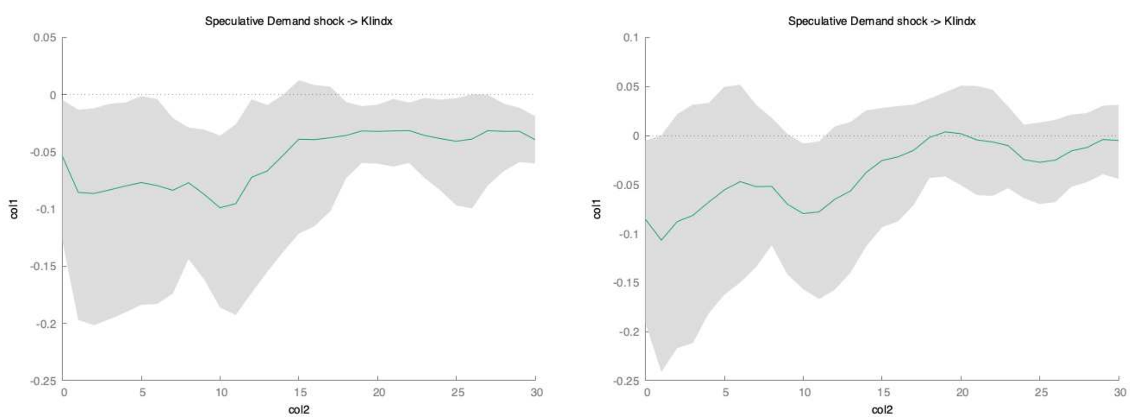


Table C.5: The response of rea to a aggregate demand shock



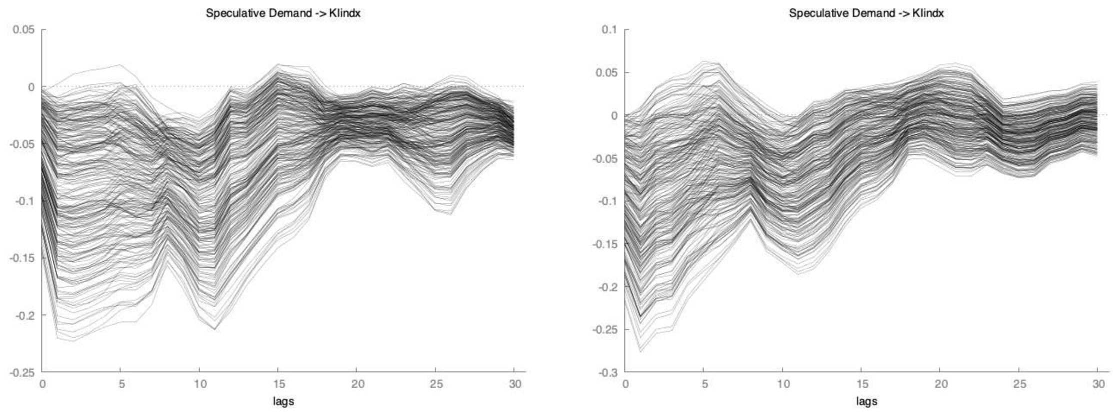


Table C.6: The response of rpo to a speculative demand shock

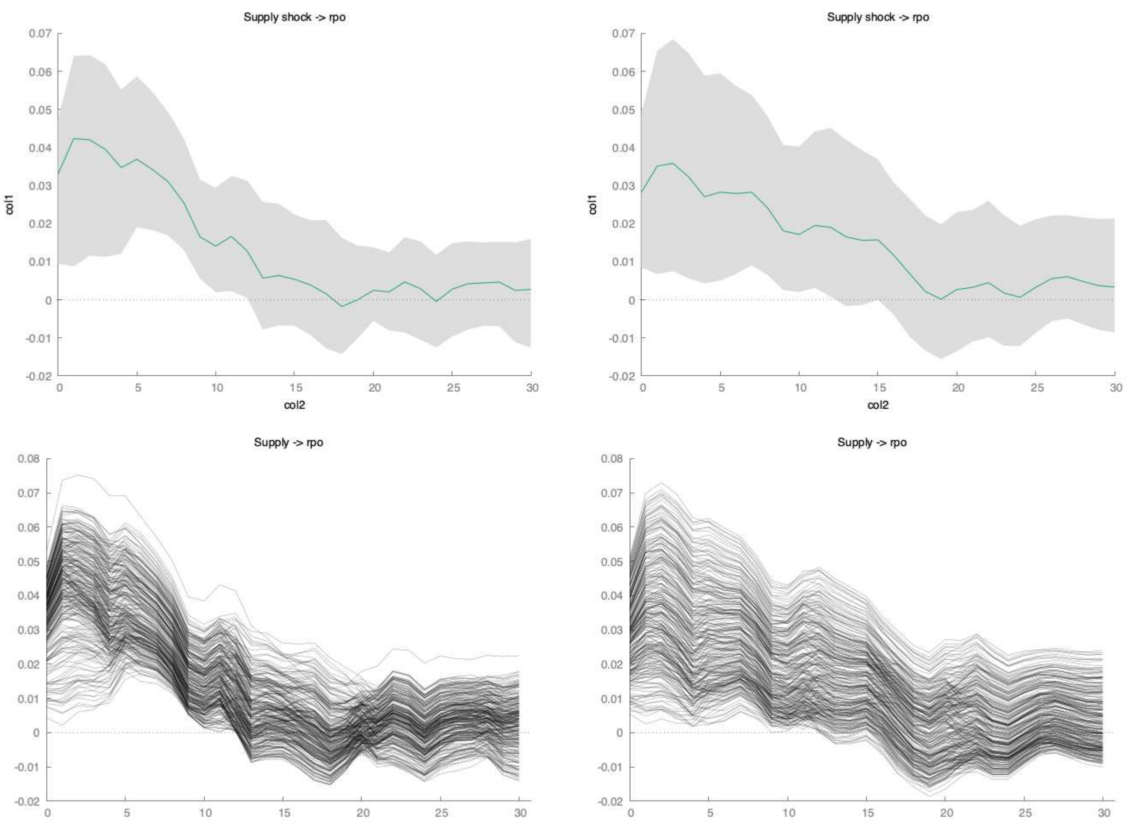


Table C.7: The response of rpo to a supply shock

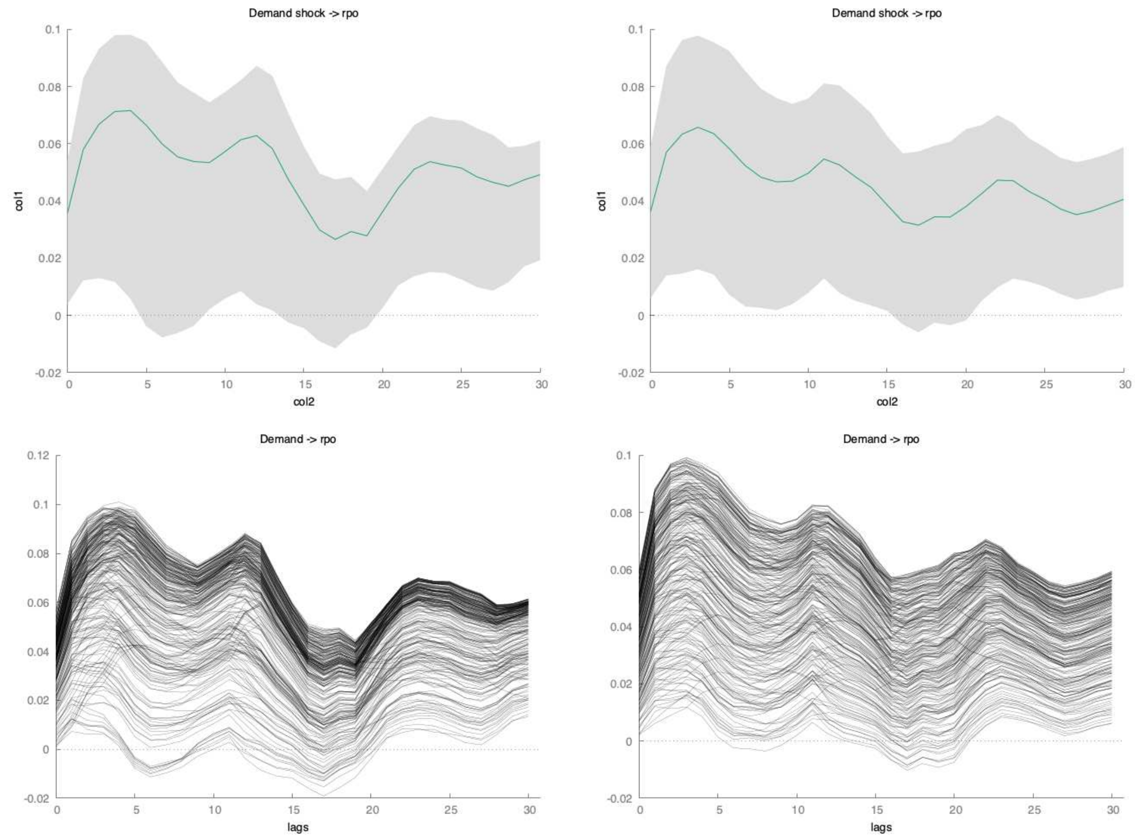
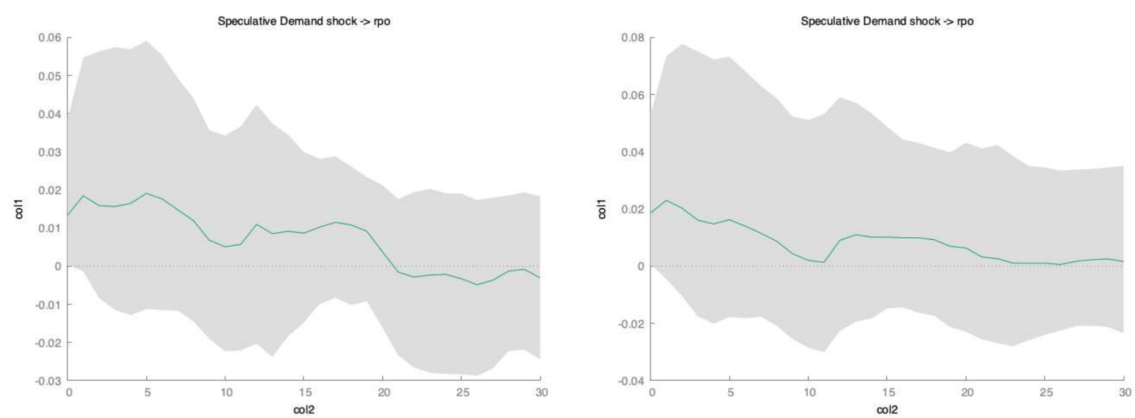


Table C.8: The response of rpo to a aggregate demand shock



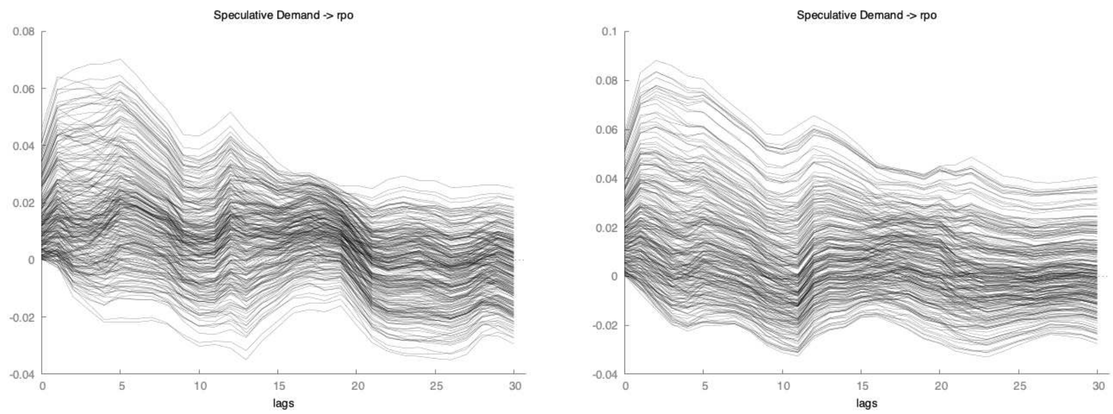


Table C.9: The response of rpo to an speculative demand shock

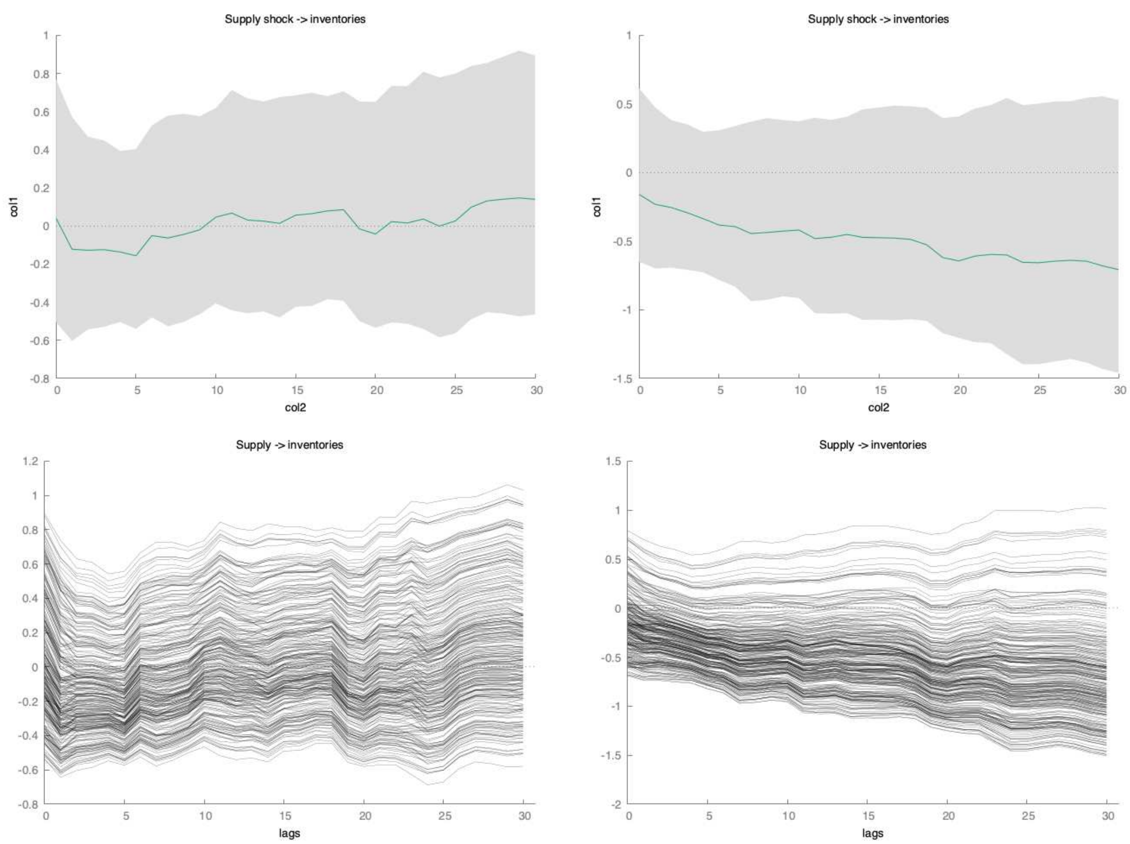


Table C.10: The response of inventories to a supply shock

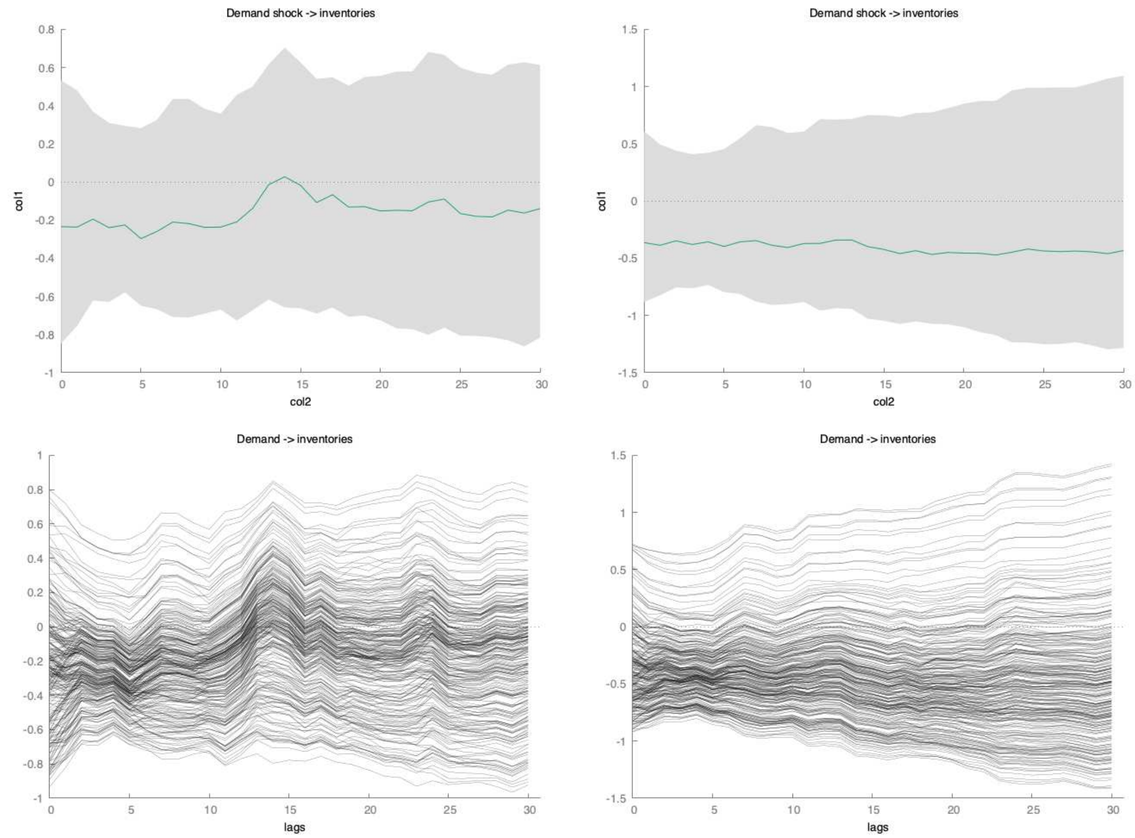
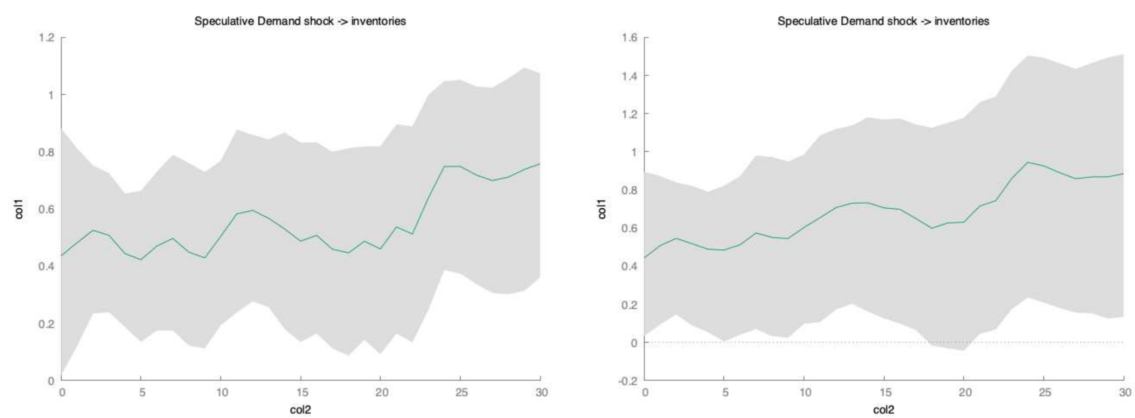


Table C.11: The response of oil inventories to a aggregate demand shock



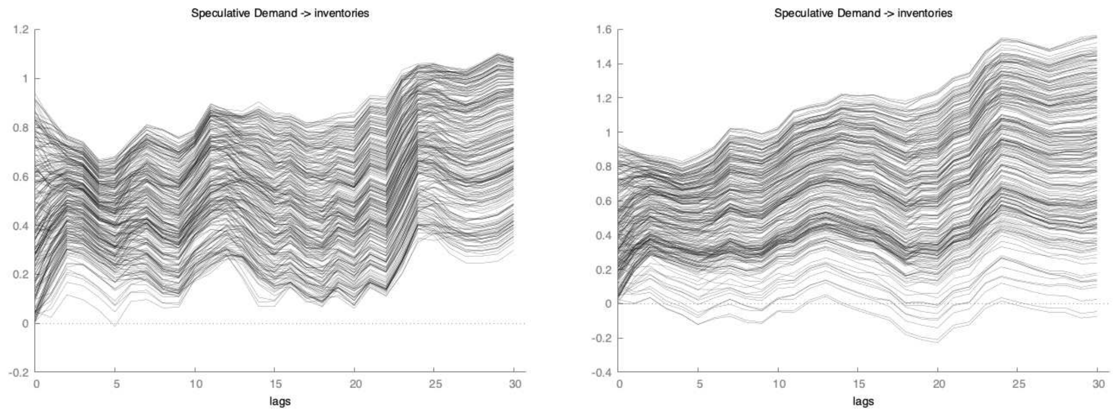


Table C.12: The response of inventories to an speculative demand shock

C.0.2 SVAR with sign restrictions across REAs

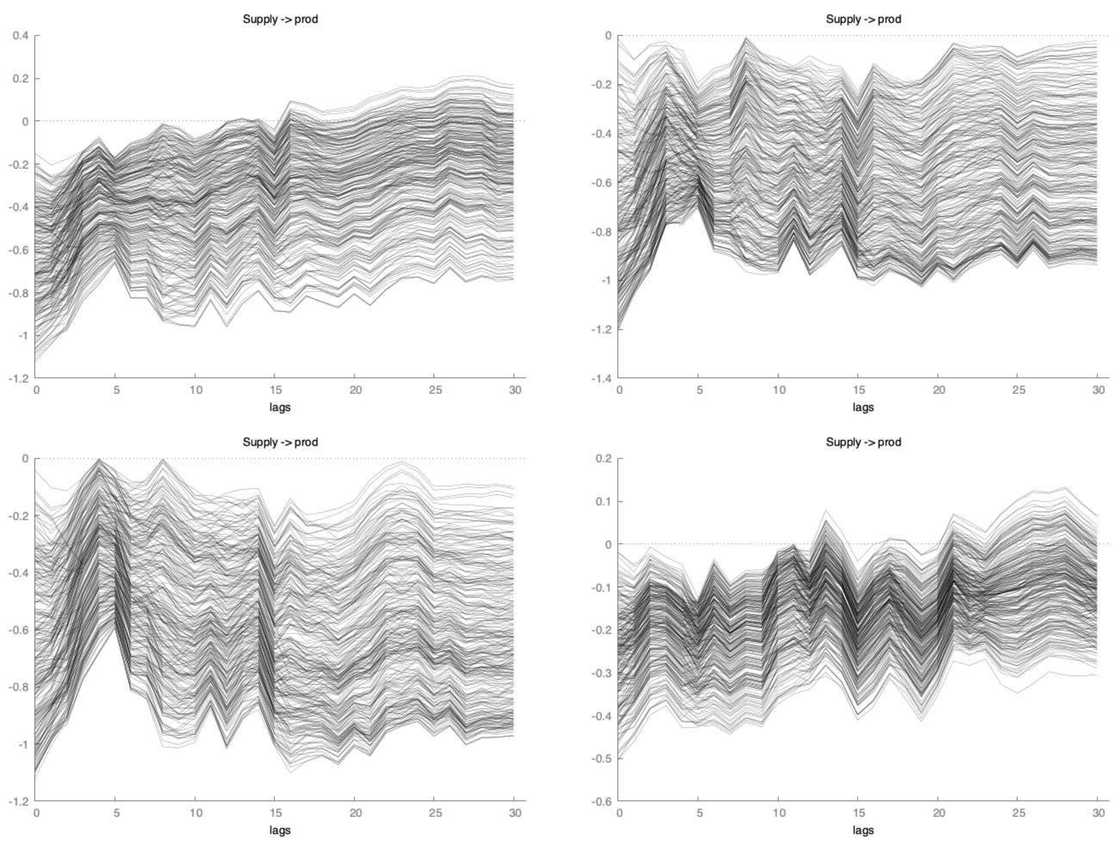


Table C.13: The response of oil production to a supply shock

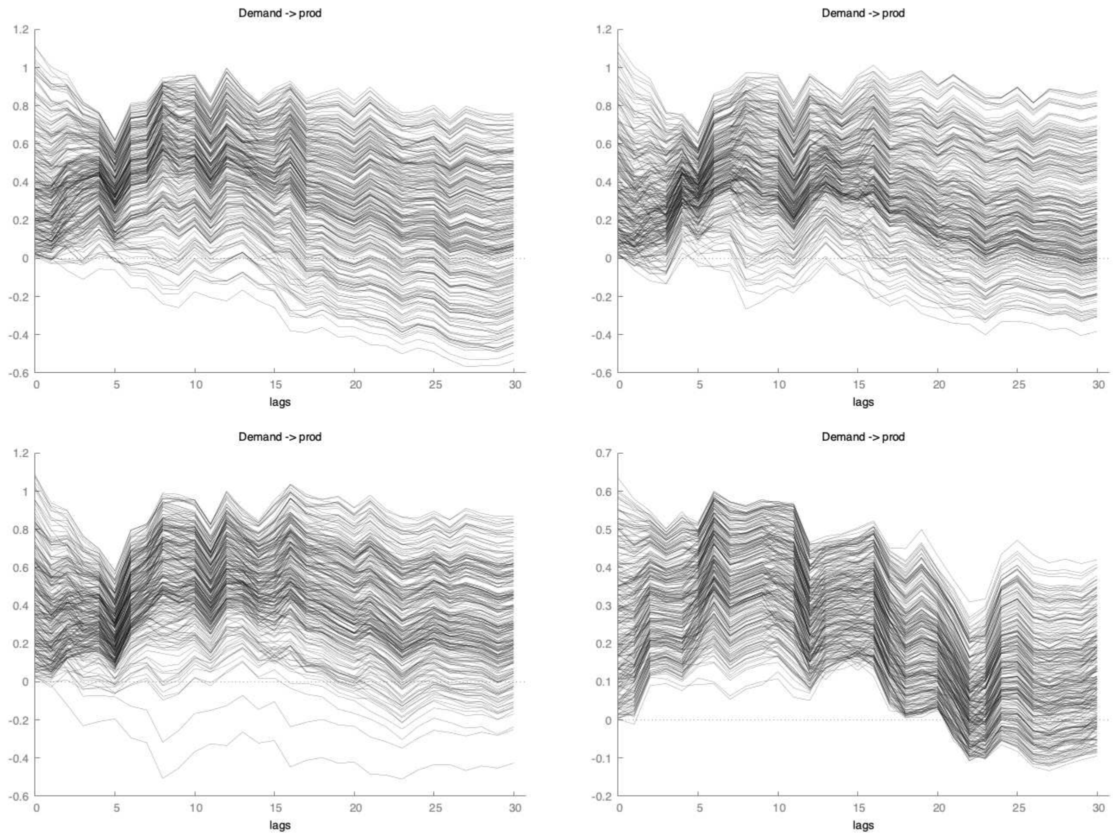


Table C.14: The response of oil production to a aggregate demand shock

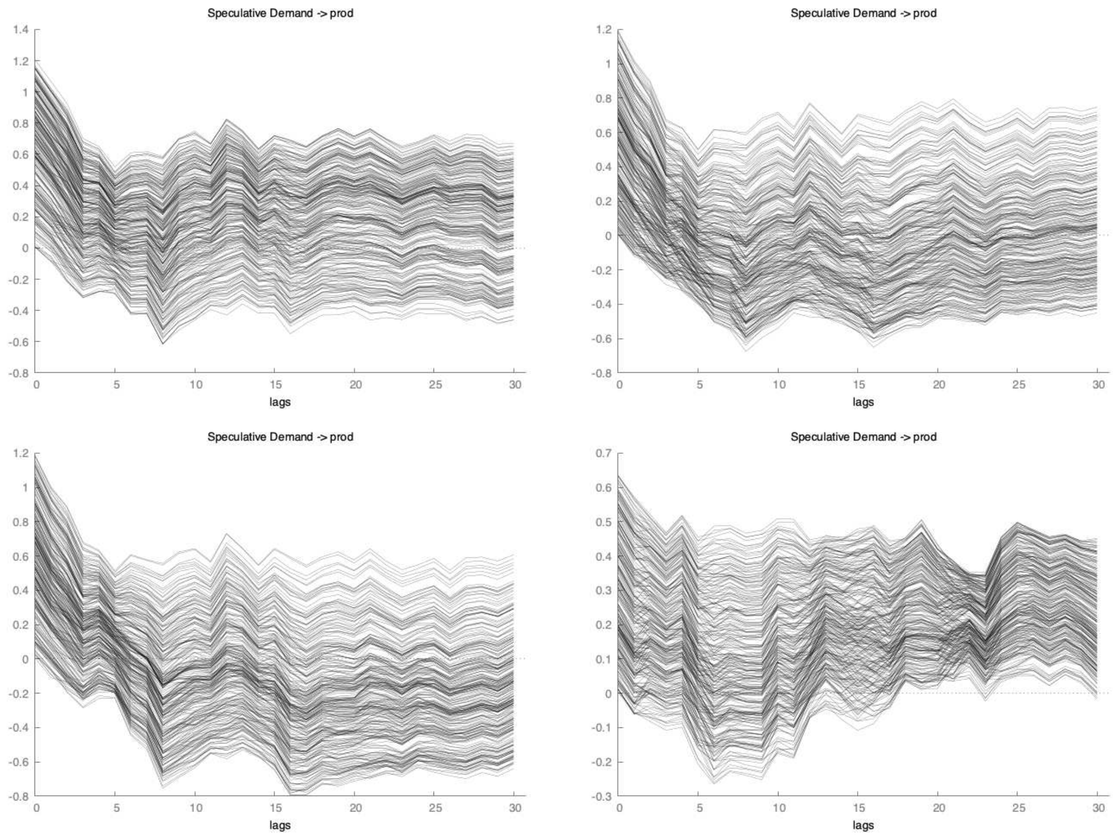


Table C.15: The response of oil production to an speculative demand shock

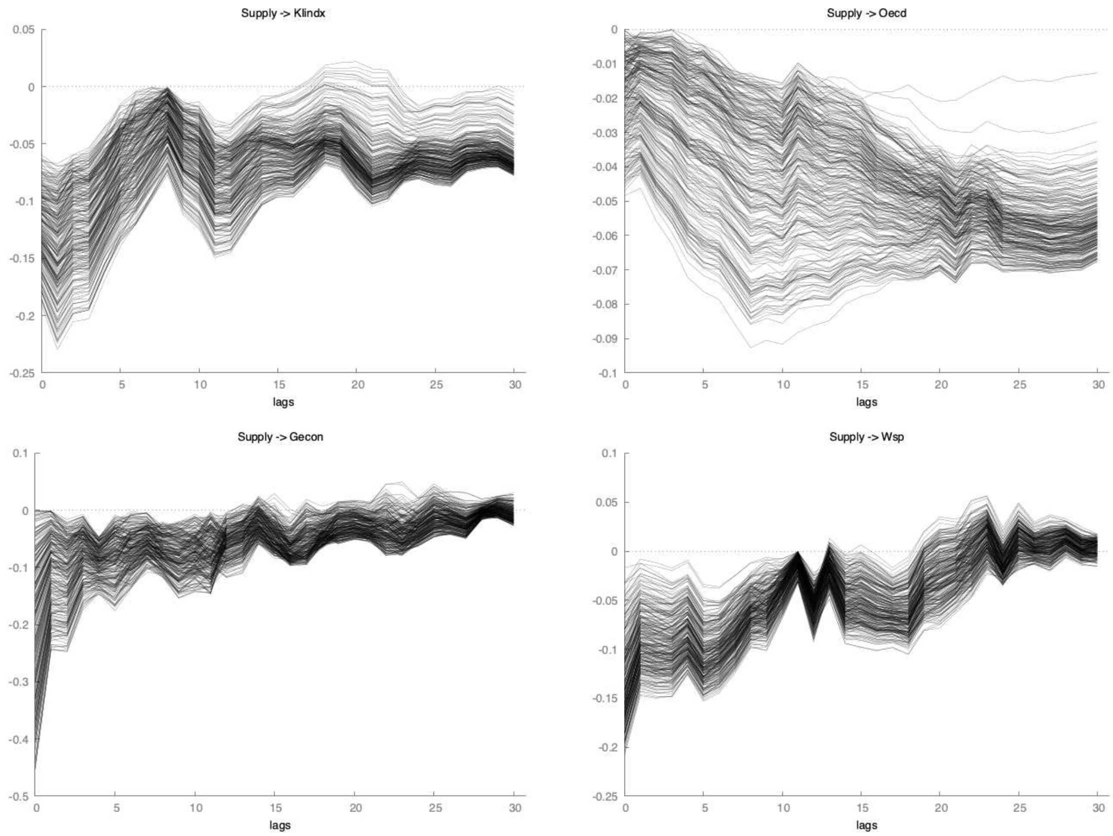


Table C.16: The response of rea to a supply shock

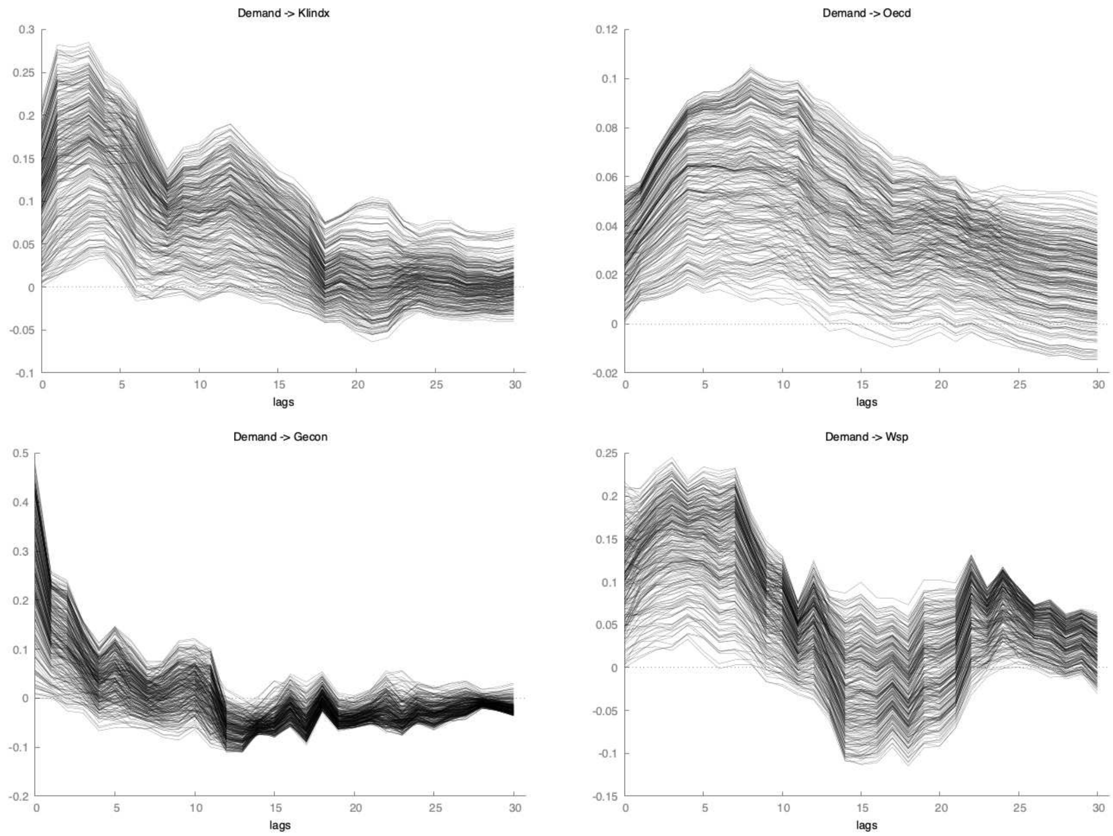


Table C.17: The response of rea to a aggregate demand shock

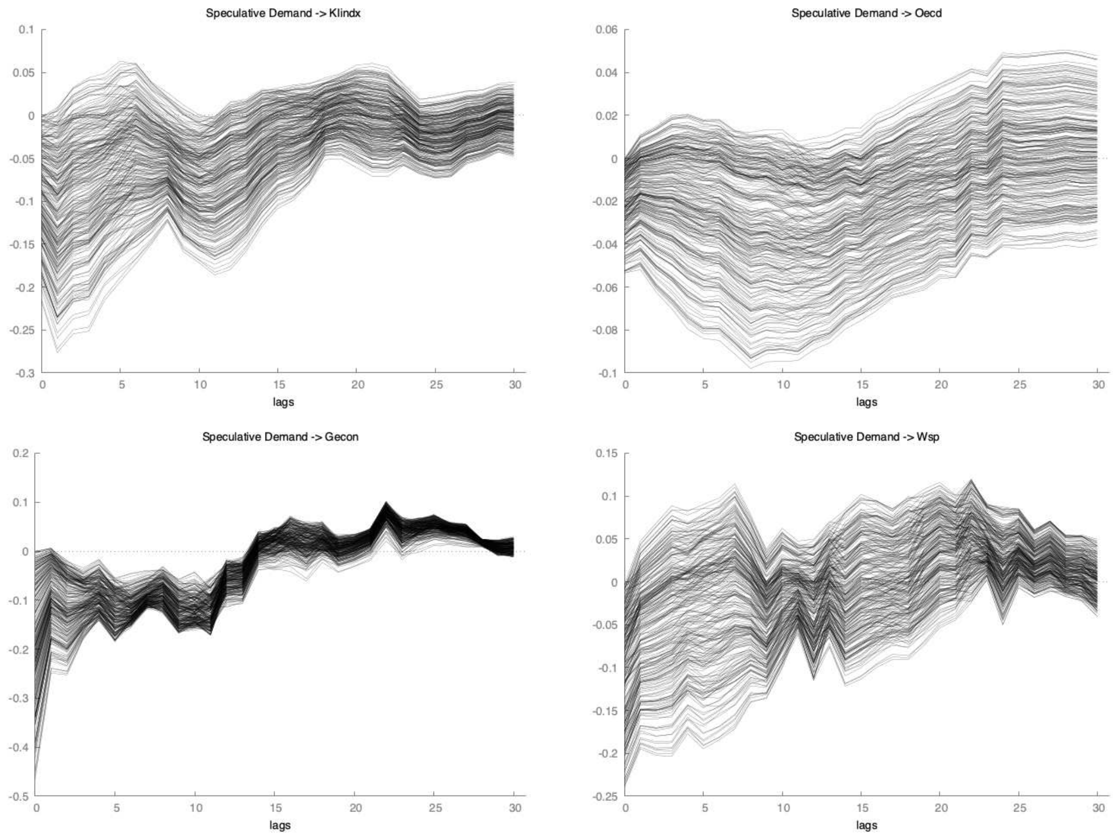


Table C.18: The response of rea to a speculative demand shock

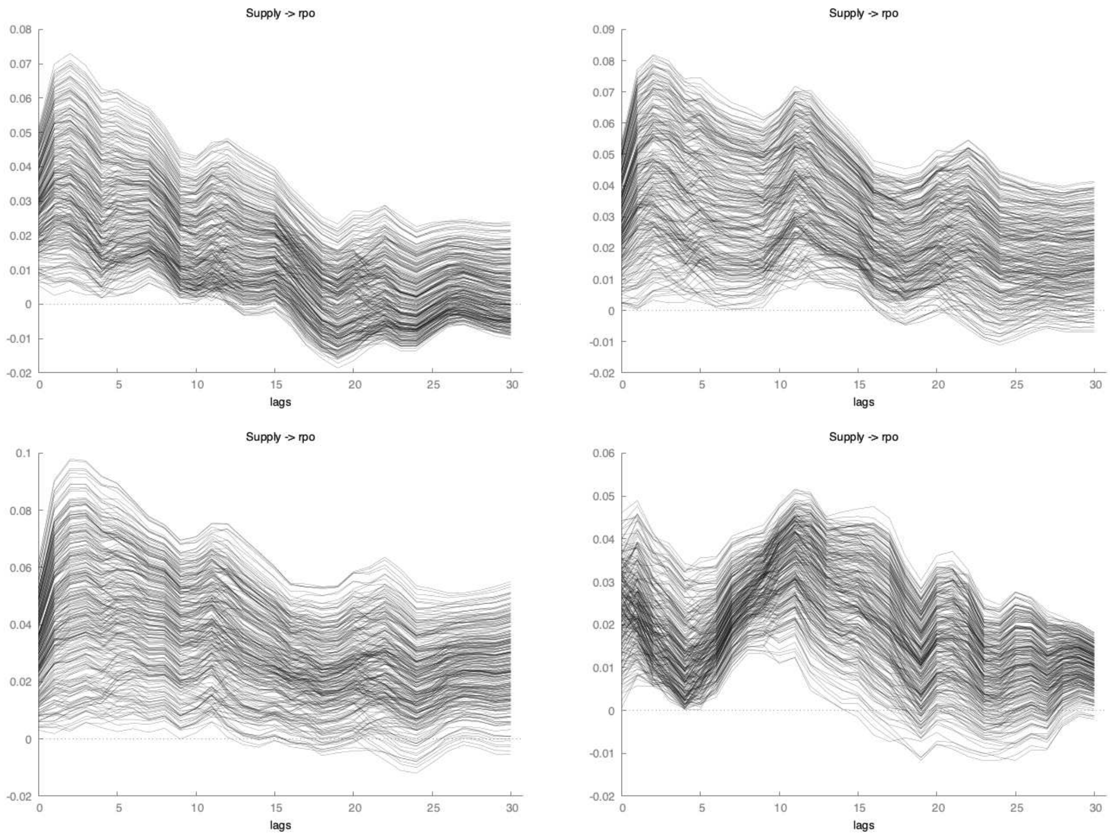


Table C.19: The response of rpo to a supply shock

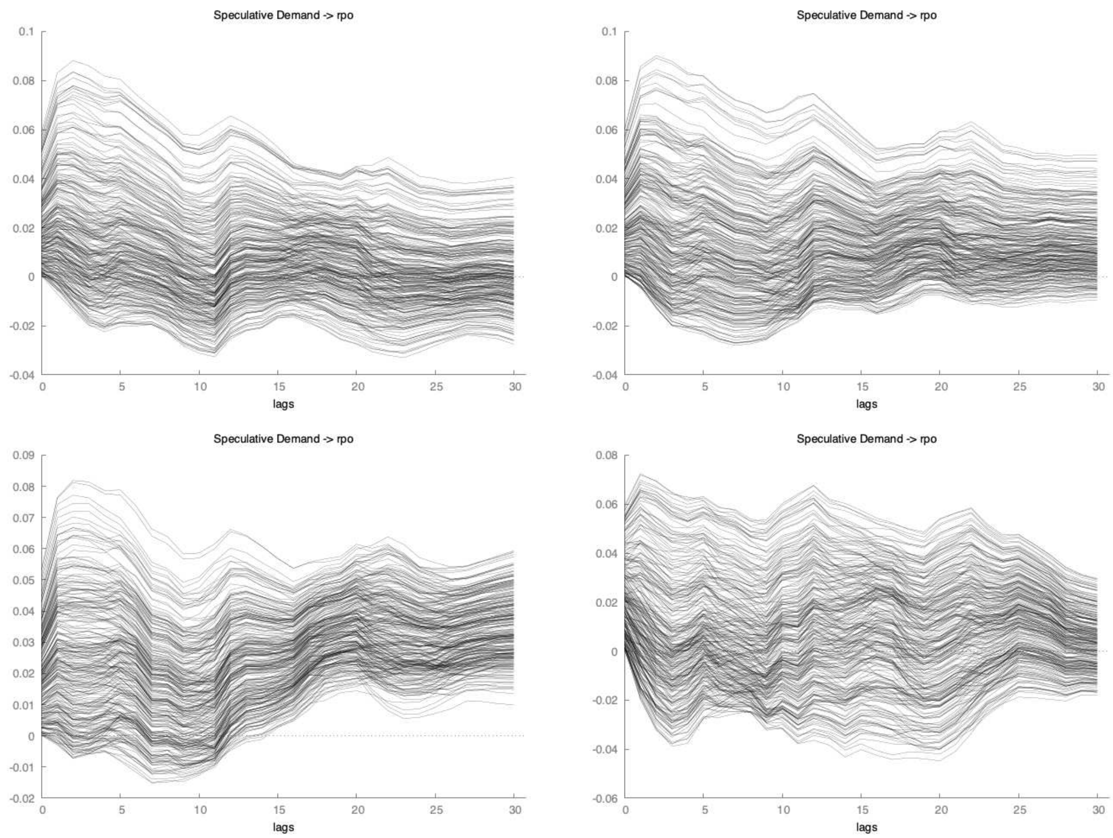


Table C.20: The response of rpo to a aggregate demand shock

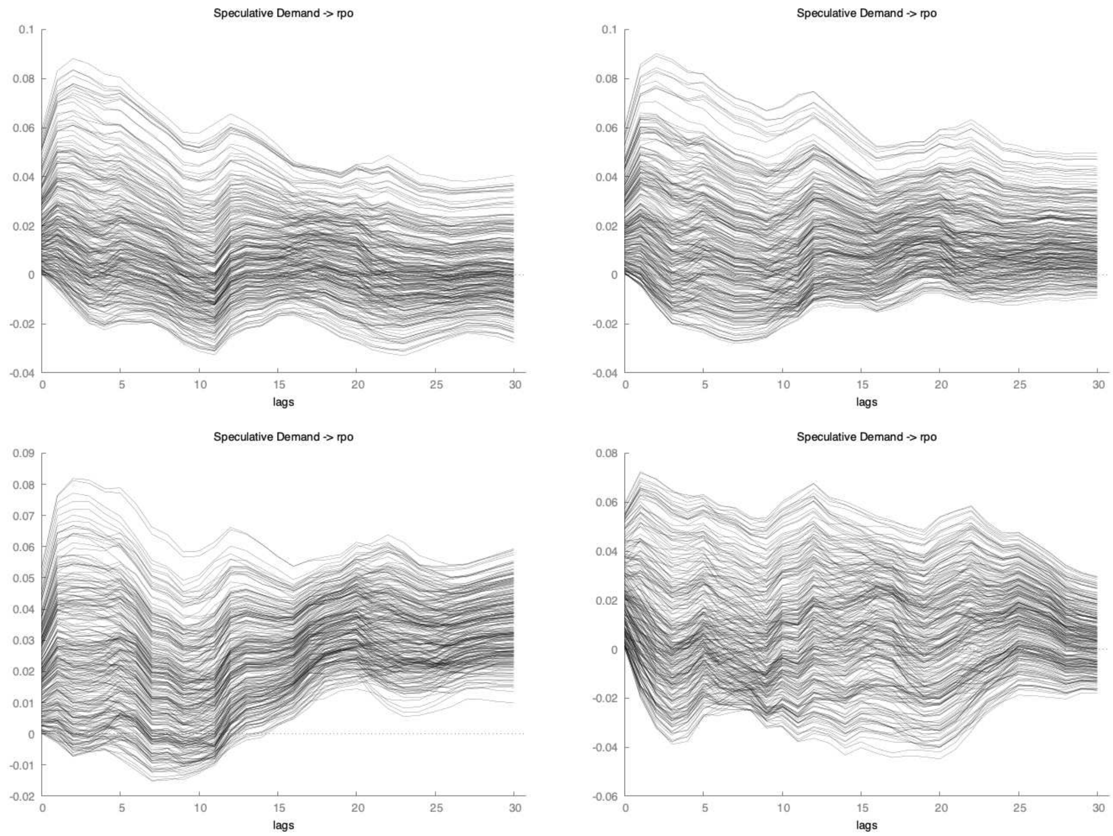


Table C.21: The response of rpo to an speculative demand shock

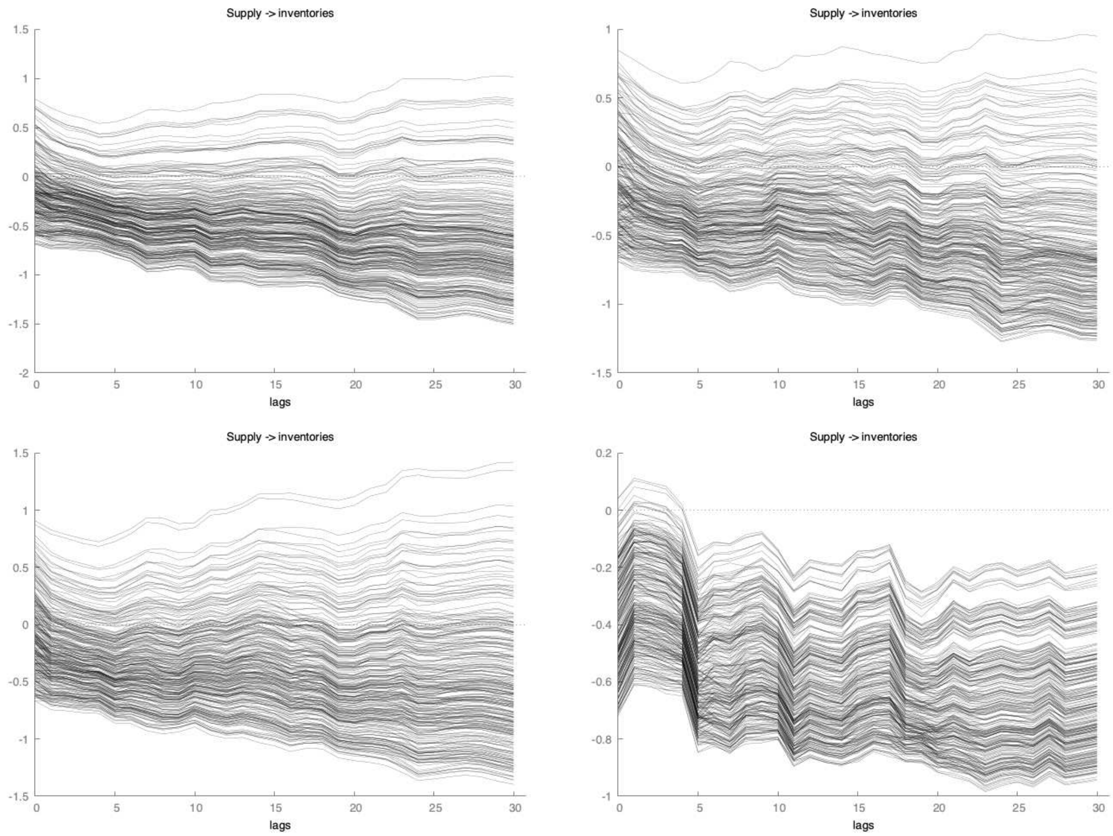


Table C.22: The response of inventories to a supply shock

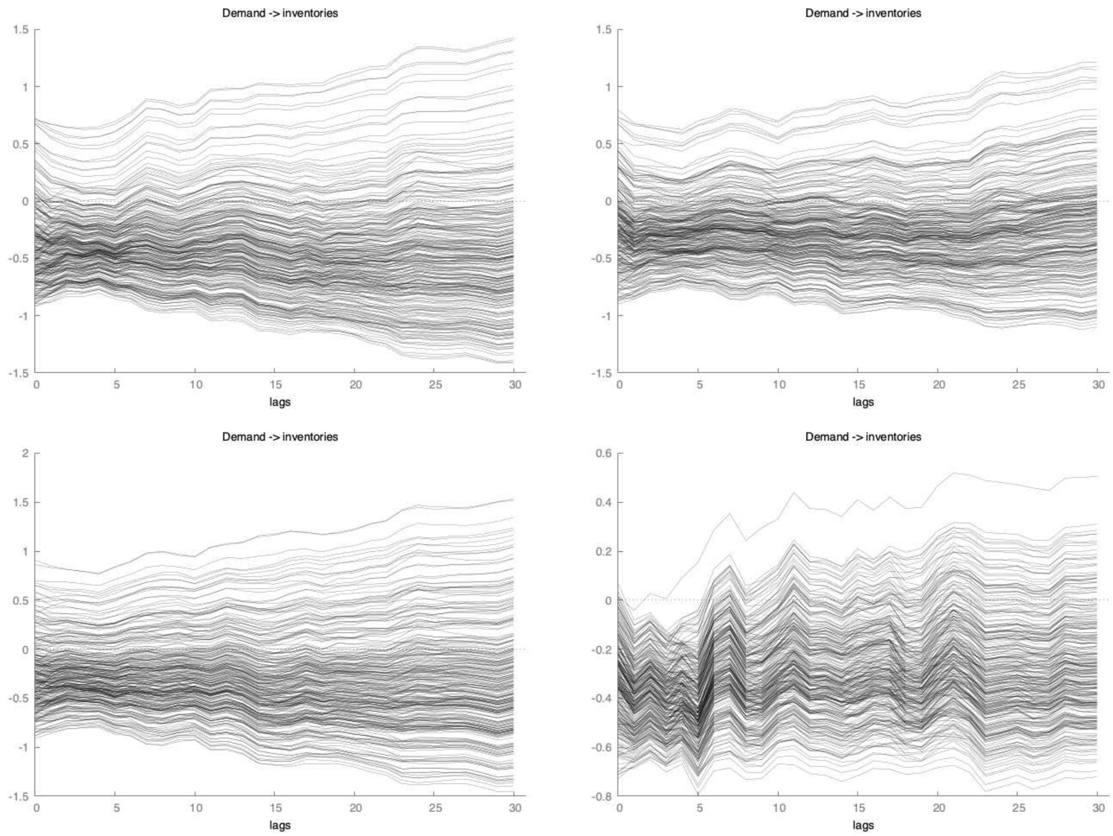


Table C.23: The response of oil inventories to a aggregate demand shock

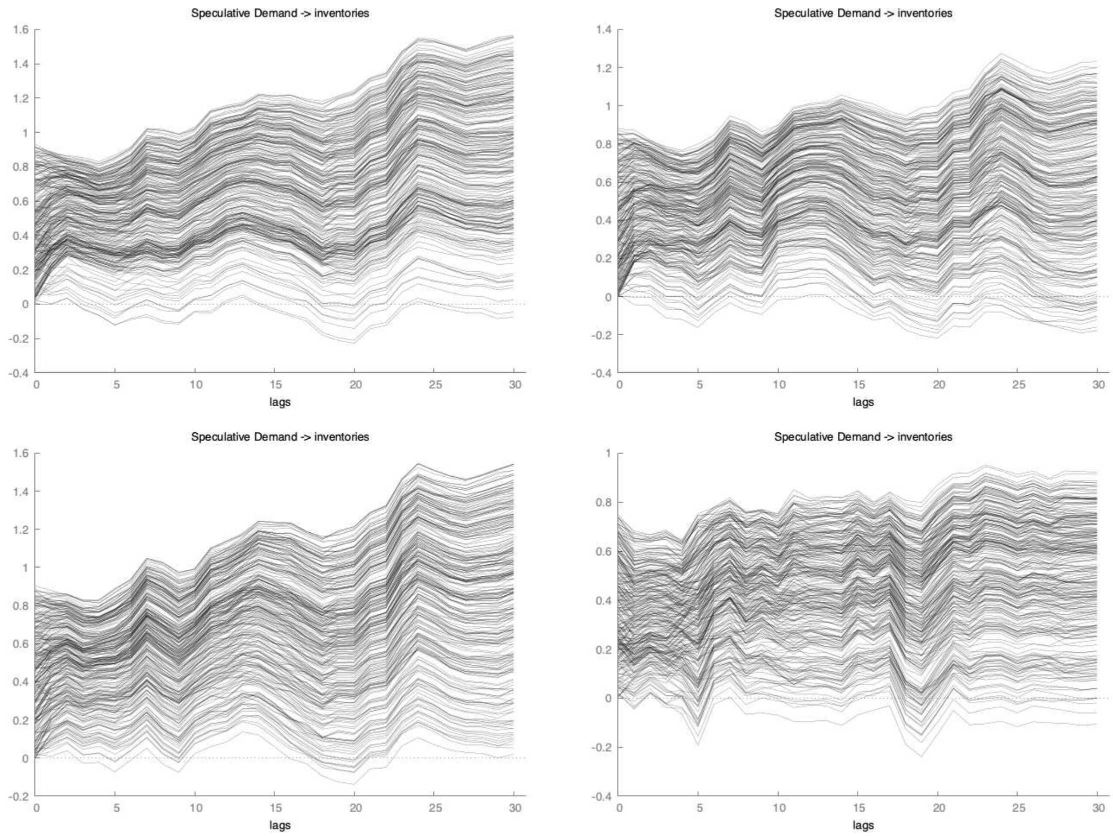


Table C.24: The response of inventories to an speculative demand shock

Appendix D

DM and GW TEST-Chapter 4

D.1 DM and GW TEST-Growth

```
---------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                 0.3965     0.6918
   V-shape                                -0.5245     0.6000

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*        -0.5245     0.6000
   Linex (shape parameter  0.80)**         0.4827     0.6293
   Forecast-direction                      1.5119     0.1306

 * The highest p-value=0.9864 is for order parameter 0.24.
   The lowest p-value=0.1306 is for order parameter 0.

** The highest p-value=0.9191 is for shape parameter 0.25.
   The lowest p-value=0.1306 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
---------------------------------------------------------------
```

Figure D.1: DM TEST-FIRST and SECOND MODEL-GROWTH

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                 1.0022     0.3162
   V-shape                                 0.1738     0.8620

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*         0.1738     0.8620
   Linex (shape parameter  0.80)**         0.8200     0.4122
   Forecast-direction                      1.5119     0.1306

 * The highest p-value=0.9993 is for order parameter 0.66.
   The lowest p-value=0.1306 is for order parameter 0.

** The highest p-value=0.5215 is for shape parameter 0.33.
   The lowest p-value=0.1306 is for shape parameter -2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure D.2: DM TEST-FIRST and THIRD MODEL-GROWTH

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                 3.3067     0.0009
   V-shape                                 7.2339     0.0000

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*         7.2339     0.0000
   Linex (shape parameter  0.80)**         2.1558     0.0311

 * The highest p-value=0.1306 is for order parameter 0.
   The lowest p-value=0.0000 is for order parameter 0.45.

** The highest p-value=0.1306 is for shape parameter -2.
   The lowest p-value=0.0005 is for shape parameter 0.09.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure D.3: DM TEST-SECOND and THIRD MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.148046, p-value 0.70041 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.4: GW TEST-FIRST and SECOND MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.838213, p-value 0.359908 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.5: GW TEST-FIRST and THIRD MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 1.18495, p-value 0.27635 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure D.6: GW TEST-FIRST and FIFTH MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 3.09412, p-value 0.0785756 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.7: GW TEST-SECOND and THIRD MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 1.48909, p-value 0.222358 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure D.8: GW TEST-SECOND and FIFTH MODEL-GROWTH

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 2.07655, p-value 0.149578 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure D.9: GW TEST-THIRD and FIFTH MODEL-GROWTH

D.2 DM and GW TEST-INFLATION

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                 1.4230     0.1547
   V-shape                                 1.3359     0.1816

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*         1.3359     0.1816
   Linex (shape parameter  0.80)**         1.4973     0.1343

 * The highest p-value=0.9903 is for order parameter 0.18.
   The lowest p-value=0.0188 is for order parameter 0.

** The highest p-value=0.9984 is for shape parameter -1.77.
   The lowest p-value=0.1304 is for shape parameter 2.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure D.10: DM TEST- FIRST and SECOND MODEL-INFLATION

```
-----------------------------------------------------------------
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                  DM test    p-value
   U-shape                                 0.2960     0.7672
   V-shape                                 0.5986     0.5495

Asymmetric loss functions                 DM test    p-value
   Lin-Lin (order parameter 0.50)*         0.5986     0.5495
   Linex (shape parameter  0.80)**         3.0176     0.0025

 * The highest p-value=0.9985 is for order parameter 0.34.
   The lowest p-value=0.1306 is for order parameter 0.

** The highest p-value=0.9954 is for shape parameter -0.12.
   The lowest p-value=0.0008 is for shape parameter 1.01.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
-----------------------------------------------------------------
```

Figure D.11: DM TEST- FIRST and THIRD MODEL-INFLATION

```
Diebold-Mariano (DM) test for forecasting accuracy,
using observations 2019:1-2019:4 (T = 4)
   Bartlett window size: 1 (default)

Symmetric loss functions                   DM test    p-value
   U-shape                                 -1.0615     0.2885
   V-shape                                 -0.3352     0.7375

Asymmetric loss functions                  DM test    p-value
   Lin-Lin (order parameter 0.50)*         -0.3352     0.7375
   Linex (shape parameter  0.80)**         -1.0295     0.3032

 * The highest p-value=0.8862 is for order parameter 1.
   The lowest p-value=0.4806 is for order parameter 0.13.

** The highest p-value=0.3226 is for shape parameter 0.42.
   The lowest p-value=0.1082 is for shape parameter -1.17.

The test with Direction-of-sign loss function is not performed:
  both forecast series have exactly the same predictive accuracy.

The test with Forecast-direction loss function is not performed:
  both forecast series have exactly the same predictive accuracy.
```

Figure D.12: DM TEST- SECOND and THIRD MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.893412, p-value 0.344554 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.13: GW TEST- FIRST and SECOND MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.029588, p-value 0.863428 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.14: GW TEST- FIRST and THIRD MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.897244, p-value 0.343522 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.15: GW TEST- FIRST and FIFTH MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.769849, p-value 0.380264 (chi^2-dist based)
Sign of the mean of the loss is (-) -- 1st model dominates
```

Figure D.16: GW TEST- SECOND and THIRD MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.244398, p-value 0.621048 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.17: GW TEST- SECOND and FIFTH MODEL-INFLATION

```
Test choice: GW
Your choice: Giacomini-White (GW) test
(Loss function shape: U)
Test stat 0.704095, p-value 0.401411 (chi^2-dist based)
Sign of the mean of the loss is (+) -- 2nd model dominates
```

Figure D.18: GW TEST- THIRD and FIFTH MODEL-INFLATION

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