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The Impact of Structural Oil Market Shocks on Stock Markets

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Abstract

Master of Science

The Impact of Structural Oil Market Shocks on Stock Markets

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In this thesis, we examine whether oil market shocks exert heterogeneous effects on the stock markets of six oil-exporting countries and four oil-importing countries. To investigate this issue, we adopt a two-stage approach. First, following Kilian (2009), we estimate a structural vector autoregression (SVAR) model and identify three structural shocks which are responsible for changes in oil prices. Second, through a set of linear regression models, we analyze the behaviour of the stock markets in relationship with the oil market shocks. Our main findings can be summarized as follows. First, we find that oil market shocks impact on the stock returns of all six oil-exporting countries whereas they only affect the stock returns of one oil-importing country. For the oil-exporting countries, positive demand-side oil shocks increase stock returns in Canada, Norway, Russia, Saudi Arabia and the U.A.E whereas positive oil supply shocks adversely affect stock returns in Mexico. For the oil-importing countries, a positive aggregate demand shock increases stock returns in India. Second, we find that positive aggregate demand shocks induce more stock market co-movement among oil-exporting countries. On the other hand, none of the three structural shocks exert an effect on the stock market co-movement among oil-importing countries.

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Chapter 1

Introduction

On April 20, 2020, for the first time in history, the U.S. oil prices plummeted below zero. That means oil producers were willing to pay buyers to take the commodity off their hands over fears that storage capacity could soon run out (BBC, 2020). Extending the time horizon, oil prices have been falling almost monotonously since the beginning of the year. These events can be primarily attributed to the impact of the 2019 novel coronavirus (COVID-19) disease. In particular, the COVID-19 pandemic has caused significant shocks in oil supply and demand leading to falling oil prices. According to the U.S. Energy Information Administration (2020) report, the plunge in oil prices has been primarily driven by the economic slowdown caused by the pandemic and, to a lower extent, by a sudden increase in oil supply following the interruption of previously agreed upon production cuts among the OPEC and partner countries.[1]

At the same time, oil companies such as Shell and Exxon, have reacted to the oversupply issues by delaying new projects (Strachan, 2020). Likewise, oil dependent countries face a particularly testing time, with a gloomy present and uncertain future. Emerging economies reliant on oil exports are especially exposed to this environment given their low level of industry diversification other than energy. Several oil and gas pre-construction projects in the Middle East and in Russia are currently facing further scrutiny as doubts grow about their viability in the present economic climate (Strachan, 2020). Developed economies are also suffering from the current status of the oil market. On April 1, 2020, Aker Solutions, an engineering company

[1] The Energy Information Administration (EIA) is an agency of the U.S. Federal Statistical System responsible for collecting, analyzing, and disclosing energy information to promote sound policymaking and public understanding of energy dynamics.

which provides services to unlock energy from sources such as oil and gas, laid off 400 employees in Norway with further 6000 cuts expected in the following months. On May 4, 2020, Norway's PM disclosed a package of measures intended to assist the oil and gas industry during the health crisis. In the same way, Canadian oil companies have shut down many facilities as low oil prices push down revenues. Needless to say, the adverse effects on real economic activity following these events should be anticipated by the stock markets.[2]

Although the current situation is unprecedented, oil shocks of different magnitudes and directions have continuously shaped the international stock markets through the years. As a matter of fact, there is a bulk of literature arguing that stock price movements can be accounted for by the impact of oil shocks.[3] Understanding the reaction of the stock markets to oil shocks is fundamental for policymakers and market participants making financial decisions. Besides, we can expect that the impact of oil shocks across markets differs contingent the country's economic structure, such as its net position in the global oil market.

With these premises we believe it is of interest investigating whether oil shocks exert heterogeneous effects on the stock markets of different countries.

More specifically, the first issue we aim to examine is whether oil shocks have a different impact on the stock returns of net oil-exporting and net oil-importing countries. We draw this distinction based on the simple hypothesis that *oil shocks which increase (decrease) oil prices should positively (negatively) affect stock returns in an oil-exporting economy whereas the reverse holds true for an oil-importing economy*.

If this hypothesis holds, we can also expect that *oil shocks affect the common behaviour of the stock markets of countries that belong to each of the two groups*. Formally, the second issue we delve into is whether oil shocks increase the stock market co-movement among oil-exporting countries, and analogously, among oil-importing countries.

To investigate these issues, we consider six oil-exporting countries (Canada, Mexico, Norway, Russia, Saudi Arabia and the U.A.E.) and four oil-importing countries

[2] Fama (1990, p. 1107) argues that a large fraction of the variation of stock returns can be explained by forecasts of real activity.

[3] Degiannakis, Filis, and Arora (2018) provide a detailed review of the literature on oil prices and stock markets.

(China, Germany, India and the U.S.).

For the empirical investigation, we adopt a two-stage approach.

First, following Kilian (2009), we estimate a structural vector autoregression (SVAR) model and identify three structural shocks which are responsible for changes in oil prices. The three shocks are defined as oil supply shocks, aggregate demand shocks and oil-specific demand shocks.

Second, through a set of linear regression models, we analyze the behaviour of stock returns and stock market co-movements in relationship with the oil shocks.

Distinguishing the underlying source of oil price changes is important in order to understand stock market reactions. As illustrated by Kilian and Park (2009), studies that ignore the source of oil shocks tend to find no statistically significant relationships between oil shocks and stock prices.

Most of the existing studies on oil prices and stock returns have focused on either oil-importing countries (see, e.g., Cunado and Perez De Gracia (2005)) or oil-exporting countries (see, e.g., Basher, Haug, and Sadorsky (2018)), whereas the few studies which have compared the two groups have reached conflicting conclusions (see, e.g., Apergis and Miller (2009); Zhu et al. (2016)). In addition, most of the literature has focused on traditional markets only. Thus, with our sample of countries, which includes both traditional and emerging markets, we can give our contribution to the literature. Also, to the best of our knowledge, the linkage between oil shocks and stock market co-movement has been analyzed only by Yang, Wang, and Wu (2013). In this regard, we provide new insights on such relationship by using a different set of countries, methodology and sample period compared to their work, as well as by discriminating between traditional and emerging markets.

The key findings of our study can be summarized as follows.

First, we find that oil market shocks impact on the stock returns of all six oil-exporting countries whereas they only affect the stock returns of one oil-importing country. For the oil-exporting countries, demand-side oil shocks affect stock returns in Canada, Norway, Russia, Saudi Arabia and and the U.A.E whereas unanticipated oil supply shocks only matter for stock returns in Mexico. The direction of the shocks is consistent with the hypothesis for which oil price increases (decreases) exert a positive (negative) effect on stock returns in economies reliant on oil exports. For the oil-importing countries, only India's stock market reacts to oil market shocks. An unanticipated aggregate demand shock, which raises oil prices, has a positive effect on Indian stock returns, meaning that economic growth in India tends to dominate the negative impact of higher oil prices. In general, the hypothesis for which higher (lower) oil prices adversely (positively) affect stock returns in oil-importing economies is not supported by our results.

Second, we find that positive aggregate demand shocks increase the stock market co-movement among oil-exporting countries. On the other hand, none of the three structural shocks exert an effect on the stock market co-movement among oil-importing countries. Hence, our results corroborate the findings of Yang, Wang, and Wu (2013). In addition, positive supply shocks, that exert downward pressures on oil prices, induce more co-movement between the Canadian and Norwegian stock markets.

The remainder of this text is organized as follows. In Chapter 2 we lay out a brief survey of the literature. In Chapter 3 we provide an overview of the oil market and the theoretical transmission channels through which changes in oil prices affect stock returns. In Chapter 4 we describe the data employed in this thesis. In Chapter 5 we outline the econometric models used in the empirical analysis. In Chapter 6 we present the outcome of the empirical analysis and show that our results are not sensitive to an alternative proxy of global oil prices. In Chapter 7 we conclude by outlining the main implications of our findings and provide suggestions for future research.

Chapter 2

Literature Review

In this chapter, we survey the major contributions to the literature on oil and stock markets. We begin by providing an overview of the most relevant oil market models employed by researchers through the years. We continue with a summary of the key findings on the relationship between oil and the macroeconomy. Lastly, we describe the main developments on the rich literature studying the effects of oil market shocks on stock returns.

2.1 Oil Market Models

Huntington et al. (2013) categorize oil market models into three groups: structural, computational and reduced form (or financial) models. The variety in approaches is, at least in part, explained by the scope of the study at hand. Different elements characterize each type of model, and none of the models fully represent the complexity of actors and relations at play in the oil market. Conversely, the scope of a model is to simplify a complex real-world phenomenon and provide useful insights to stakeholders such as policymakers, firm managers and investors. A brief description of the three categories is given as follows.

Structural models focus on fundamental microeconomic theories about the objectives, constraints and behaviours of market actors. Typically these models rely upon a limited number of variables like oil supply and demand. Despite the convoluted mathematical structure, the models give insights into the driving forces of the market.

Computational models, instead, employ a broad set of factors which might affect the oil market. By relying on heavy computing power, these models describe the market in great detail and, hence, are commonly used by oil-related organizations such as the OPEC Secretariat and the EIA.

Reduced form or financial models, unlike the first two categories, aim at investigating short-term price movements without necessarily explaining in great detail the fundamental analysis. Within this framework, researchers adopt time series methods in order to explain the, possibly time-varying and asymmetric, relationships among oil prices and other variables. The vector autoregression (VAR) is the most popular family of reduced form models. In recent years, structural vector autoregression (SVAR) models have gained increased interest from both industry and academia. Compared to its reduced-form version, a SVAR model facilitates the economic explanation of observed and predicted fluctuations in oil prices. SVAR models offer several tools which allow the econometric specification to match with the design of the oil market. For example, econometricians often impose parametric or sign restrictions on the structural equations to simulate the magnitude of the elasticities of oil supply and demand. The SVAR model shares the benefits of its reduced form version, as well as the advantages of the conventional structural models in terms of economic interpretation. Since this study builds upon a SVAR model, it is worth describing in greater detail the advantages and limitations of such methodology.

The general VAR model extends the univariate autoregressive (AR) model to capture the evolution of different time series in a multivariate framework. Introduced by Sims (1980), the SVAR model tries to recover economic shocks from observable variables by imposing a minimum set of assumptions. As pointed out by Huntington et al. (2013) the power of this model critically rests on whether the imposed restrictions are economically sound. The key advantage of a SVAR model is that it allows the researcher to tackle endogeneity problems as in the case in which one simultaneously models supply and demand of crude oil.[1]

Several authors have used SVAR models with parametric restrictions to understand the oil markets dynamics. All these studies show how crucial is to correctly

[1]In econometrics, endogeneity broadly refers to situations in which an explanatory variable is correlated with the error term (Wooldridge, 2009, p. 87).

state the economic assumptions governing the oil market in order to obtain a well-specified model. However, we shall point out that the literature has not yet reached clear-cut conclusions regarding the set of identifying assumptions to be imposed in a SVAR model of the oil market.

Two pivotal studies in the literature on oil market models are the works of Hamilton and Herrera (2004) and Kilian (2009). The work of Hamilton and Herrera (2004) emphasizes the importance of the identifying assumptions. The authors provide a critique to the results of Bernanke, Gertler, and Watson (1997) who demonstrated that the effect of oil shocks on the macroeconomy was much smaller than previously thought. Using monthly data, Bernanke, Gertler, and Watson (1997) specified a VAR model with seven lags based on the results of the Akaike Information Criterion (AIC).[2] Hamilton and Herrera (2004) challenge this choice as it ignores seasonality which is a critical feature in commodity markets. The authors claim that setting, at least, twelve lags in the model is a more appropriate choice to capture seasonal patterns. In fact, by repeating the analysis of Bernanke, Gertler, and Watson (1997), with an adequate number of lags, Hamilton and Herrera (2004) show how the largest effects of an oil shock do not appear until three or four quarters after the shock. This finding underlines the importance of lag length selection for setting up a proper oil market model and the fact that standard econometric tools may be in contrast with real-life phenomena.

The study of Kilian (2009) dramatically contributes to the literature on oil markets and sets the ground for a number of subsequent studies. The author proposes a model which is capable of identifying the different sources of oil shocks and their relative importance in determining the real price of oil. The author's model identifies three forces characterizing the fluctuations of oil prices, namely oil supply shocks, aggregate demand shocks and oil-specific demand shocks. The latter reflect the movements in precautionary demand for crude oil driven by concerns regarding future oil supply shortfalls. By showing that *"not all the oil price shocks are alike"*, Kilian (2009) challenges the strong-held belief that an increase in oil prices generates the same effect regardless of the underlying cause of that increase.

[2] In econometrics, it is common practice to use information criteria to set the optimal lag length of a univariate or multivariate time series model.

2.2 Oil and the Macroeconomy

Oil prices interact with a variety of economic variables, including output, inflation and interest rates. For this reason, a wide range of empirical studies examines the impact of oil shocks on macroeconomic factors.

The work of Hamilton (1983) provides one of the first evidence of the link between oil and the macroeconomy. The author illustrates that the majority of post-war recessions in the U.S., until 1972, was preceded by sharp increases in oil prices. However, a main concern in applied work is the presence of a third set of influences driving the relationship between two variables. Hamilton (1983) provides evidence for claiming that the link between oil prices and output was indeed nonspurious. To prove this, he studies the role of oil within the macroeconomic system of Sims (1980), which consists of three price variables, two output variables and money supply, and demonstrates that none of the six variables exhibited any unusual behaviours in the year before the oil price spikes that could have been used statistically to predict the oil episodes.

Following Hamilton (1983), a bulk of literature points toward possible asymmetries in the nexus between oil prices and the macroeconomy. The motivation behind these studies is connected to the occurrence of two events that shaped the oil market in the 1970s and 1980s. The 1979 oil crisis, in the wake of the Iranian Revolution, led to a dramatic increase in oil prices which was followed by a recession. The 1986 oil price collapse, on the other hand, was not followed by an economic expansion as one might have expected given the inferred symmetry of oil price ups and downs.

The work of Mork (1989) is one of the first studies on the asymmetric effects of oil price changes on the macroeconomy. The author extends the framework of Hamilton (1983) by distinguishing between the different impacts of oil price increases and decreases. The key findings are the presence of a strong negative correlation between oil price increases and economic growth and the lack of any significant effects of oil price decreases on output. Mork, Olsen, and Mysen (1994) further develop the analysis on asymmetric effects to include a range of OECD countries and confirm that the impacts of oil surges and dips are substantially different. Hamilton (2010) also argues for a nonlinear relationship between oil prices and output growth.

More recent studies have broadened the spectrum of macroeconomic variables under investigation. Cunado and Perez De Gracia (2005) shed light on the repercussion of an oil price increase on the consumer price index (CPI) of six Asian countries over the period 1975-2002. They report that this impact is short-lived but more significant when oil prices are defined in local currencies. Cologni and Manera (2008) combine the relationships among oil prices, inflation and interest rates under a cointegrated VAR model. The authors find evidence for significant effects of oil shocks on the inflation level for five G-7 countries. Besides, they note that inflationary shocks are transmitted to the real economy through higher interest rates.[3]

2.3 Oil and Stock Markets

In the last two decades, the relationship between oil prices and financial variables has increasingly caught the attention of empirical researchers. A large body of literature has focused on the link between oil shocks and international stock markets, nevertheless, no consensus has been reached on the matter. The papers relating oil and stock price movements are very heterogeneous in their scopes, econometric models and types of data employed. In loose terms, these studies can be classified in three ways. A first distinction can be made with respect to the type of data employed. Researchers have typically used either firm-level data or sector-level data on stock markets. A second distinction is made on the basis of whether the researchers are interested in modelling the mean, the variance or both of oil and stock market variables. A third distinction characterizes the frequency of data utilised. On the one hand, researchers prefer to use daily data mostly for studying the dynamic correlations and volatility spillovers between oil and stock prices. On the other hand, monthly data are used for structural models which incorporate the effects of oil shocks on the fundamental value of stock prices.

For brevity, we only survey the studies which have investigated the effect of oil shocks on stock returns.[4]

[3] This transmission mechanism is referred to as monetary channel and is discussed in Chapter 3.

[4] An oil (market) shock is defined as a variation in the price of oil propelled by an unanticipated change in oil market fundamentals (Degiannakis, Filis, and Arora, 2018). It follows that oil price changes and oil shocks cannot be treated as synonyms.

One of the first investigations on the nexus between oil shocks and stock markets is the paper by Jones and Kaul (1996). In their work, the authors try to understand whether the reactions of Canadian and U.S. stock markets to oil shocks could be justified by current and future changes in real cash flows and changes in expected returns. The main finding is that the feedback of stock prices to oil shocks can be completely accounted for by the impact of these shocks on real cash flows alone.

Using the oil price decomposition proposed by Kilian (2009), Kilian and Park (2009) illustrate that the source of oil shock matters for the response of the U.S. stock market. In particular, stock prices react minimally to supply-side oil shocks, whereas demand-side oil shocks explain a significant part of the variation in U.S. stock prices. A plausible explanation for the weak impact of oil supply shocks is that production restrictions can be somehow anticipated, and thus discounted, by market participants. On the other hand, oil price increases, which are driven by rising aggregate demand, face a positive response from the stock markets. Oil-specific demand shocks lead to an adverse reaction of stock prices as the uncertainty in the oil market is transmitted to the financial markets. Kilian and Park (2009) conclude that the responses of stock prices to innovations in the crude oil market reflect in part changes in expected returns and in part changes in expected dividend growth.

Turning to the studies which focus on stock markets of oil-importing and oil-exporting countries, Apergis and Miller (2009) evaluate the impact of oil shocks on the stock markets of various developed countries. The authors report results which are similar to the ones of Kilian and Park (2009), but do not find clear evidence of distinct patterns in the behaviour of oil-importing and oil-exporting countries. Basher, Haug, and Sadorsky (2011) combine oil prices, exchange rates and stock returns in a SVAR model of emerging countries. As it was the case in Kilian and Park (2009), oil supply shocks do not seem to be an important factor for explaining stock returns compared to demand-driven shocks. The authors highlight possible heterogeneous responses of countries which are net oil-producers and net-oil consumers. Fang and You (2014) examine the responses of Newly Industrialized Countries (NICs) to oil shocks. The authors report that while the Indian and Russian stock markets react to demand-side oil shocks, returns on the Chinese stock market do not manifest any significant response.

Chapter 3

Theoretical Framework

This study focuses on the dynamics of oil prices by integrating fundamental supply and demand factors. Hence, it is pertinent to lay out the basic foundation of the global crude oil market. Also, it is of interest to understand how oil market shocks may affect stock returns. Consequently, we sketch out the theoretical transmission channels linking oil price changes and stock returns.

3.1 About Oil

In this section, we introduce the reader to the basic chemical properties of oil and refined products, and distil the most fundamental reasons why oil is a unique commodity. We continue by providing knowledge about global supply and demand forces which shape the market for this commodity. It is worth mentioning that most of the information outlined in the following pages is extracted from the work of Paltseva (2019).

3.1.1 Properties

Crude oil is a mixture of liquid hydrocarbons (compounds composed mainly of hydrogen and carbon), though it may also contain some nitrogen, sulfur, oxygen, metals and other chemical elements. The composition of the mixture varies from field to field. Types of oil are primarily distinguished on the basis of different properties. Two of the main properties of oil are density and gravity. The former refers to the mass per unit of volume whereas the latter denotes the ratio of density of oil over density of water. Gravity affects the refining technology, type, quality and amount of products obtained from crude oil. For instance, lighter "crudes" yield more liquid fuels such as petrol, diesel and jet fuels and the refining is relatively easy. On the other hand, heavier "crudes" are more difficult to refine, and the yield of (most demanded) liquid fuels is lower. Another feature is viscosity which is a measure of fluid's internal resistance to flow ("thickness"). Viscosity is important for crude oil as wells production is affected by it. More viscous crude oil is harder and more costly to extract. Oil is also classified depending on the amount of sulfur contained in it. Sulfur represents the 0.1%-6.0% of the crude oil's composition. Sulfur and other metals are impurities that need to be removed, or at least minimized, during the refining process. Typically, "sweet" crude oil contains less than 1% of sulfur, whereas "sour" crude oil presents a percentage of sulfur higher than that. Roughly 75% of world oil reserves is "sour". Lastly, it is worth noting that these distinctions are very broad-based in comparison to the enormous variation in types of oil in the world.[1]

3.1.2 Demand

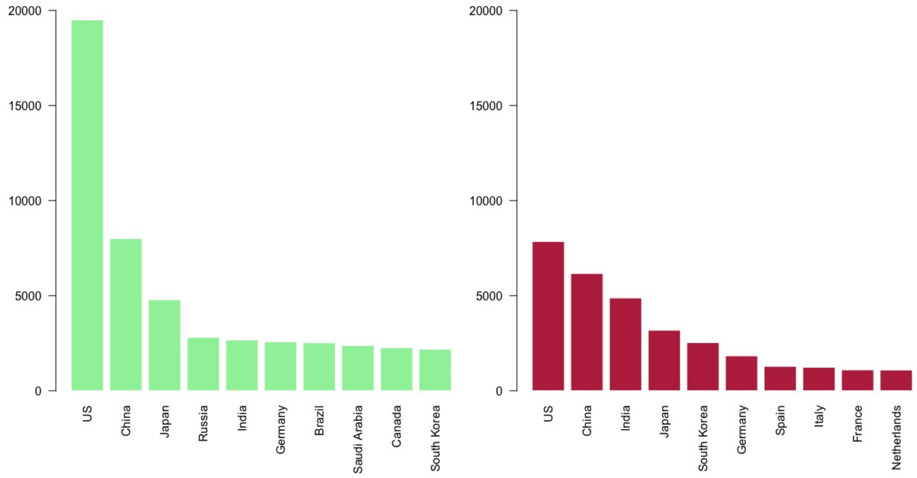
According to the EIA, in 2017 the world consumption of oil amounted to 98 million barrels per day with a very uneven distribution across the globe. The U.S. and China account for 35% of world oil consumption, and just ten countries consume 60% of global oil (see Figure 3.1a). As reported on The World Factbook website, the major oil-importing countries are in order: the U.S., China, India, Japan and South Korea (see Figure 3.1b).[2] It is also worth noting that the European Union imports roughly twice as much crude oil as the U.S. as of 2017. In the last couple of decades oil consumption growth has been mostly positive, with the exception of the 2007-2008 financial crisis. According to the forecasts of British Petroleum (2019), the share of oil will be falling in the following years but it will still be large. Most of the future consumption growth is expected to be from non-OECD countries.

Another important aspect of the demand is the oil consumption by sector. Currently, global oil demand is driven by the transportation sector. According to the report of the Organization of the Petroleum Exporting Countries (2019), this trend

[1] Kenny (2007) lists 187 different types of crude oil.

[2] The World Factbook is a database of the U.S. Central Intelligence Agency (CIA). Data are available at https://www.nationsencyclopedia.com/WorldStats/CIA-World-Factbook-Oil-consumption.html.

FIGURE (3.1) Crude Oil Demand



(A) Crude Oil Consumption (B) Crude Oil Imports

Notes: Crude oil consumption and imports in thousand barrels per day. Data from The World Factbook based on 2015-2018 estimates.

is expected to continue in the next future. Again, this tendency will be mostly due to the rising demand for cars coming from developing countries. British Petroleum (2019) forecasts that Asian dependence on oil is going to increase. Conversely, the demand of OECD countries' transport sector will likely decline due to alternative technological solutions which may also improve the efficiency of oil use.

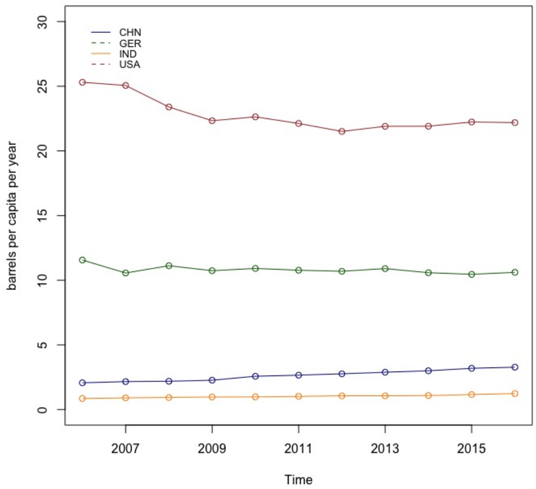
Turning to the oil-importing countries included in our sample, Figure 3.2 shows the annual oil consumption per capita in China, Germany, India and the U.S. for the period 2006-2016.[3] What stands out in Figure 3.2 is the massive difference in consumption per capita between the developed and emerging countries.

In 2020, following the COVID-19 outbreak, global oil demand is expected to decline for the first time after 2009 (International Energy Agency, 2020).[4] The drop in demand is mainly driven by the deep contraction in oil consumption in Asia and by the major disruptions to global trade.

[3]Unfortunately, data on oil imports over time is not available. Also, note that oil consumption and imports for these countries may be substantially different. For instance, a large share of oil consumption in the U.S. comes from own production.

[4]The International Energy Agency (IEA) is an intergovernmental organization which acts as an energy policy adviser to its member countries.

FIGURE (3.2) Annual Oil Consumption per Capita



Notes: Own calculations based on data from British Petroleum (2019) and the World Bank for the period 2006-2016.

3.1.3 Supply

Having surveyed the magnitude of oil consumption, it is normal to ask ourselves how to satisfy all this demand. Discoveries of conventional oil have gone from roughly 55 billion barrels per year during the 1960s to less than 15 billion barrels per year during the 2000s, with an approximately monotonic decrease over the period (International Energy Agency, 2014). Hence, it is legit to ask whether the world is, or soon will be, running out of oil. The hypothesis that oil and gas reserves would be exhausted soon has been around since the 1970s. In this respect, Smil (2000, p. 28) writes:

> *"In 1977 the Workshop on Alternative Energy Strategies predicted that oil supply would peak between 1994–1997 and fail to meet rising demand afterwards. A year later the U.S. Central Intelligence Agency concluded that the global output "must fall within a decade ahead," and that the world "does not have years in which to make a smooth transition to alternative energy sources." Latest exhaustion forecasts see the decline of conventional oil output setting in before 2010."*

At the same time, by looking at the reserves-to-production ratio (RPR), we note that the ratio has been stable for the last 30 years.[5] This surprising finding is motivated by the fact that the ratio is based on proved reserves. The latter include *"quantities that geological and engineering information indicate, with reasonable certainty, can be recovered in the future from known reservoirs under existing economic and operating conditions"* (Johansson et al., 2012, p. 434). Put differently, proved reserves ought to be economically recoverable. As a result of technology and market conditions changes, and new (unconventional) types of energy availability, the stock of proven reserves have been increasing in spite of the low discovery rate. Proved reserves more than doubled over the last 35 years. According to the estimates of British Petroleum (2019), Venezuela had the highest amount of proved oil reserves by the end of 2018, followed by Saudi Arabia and Canada. Clearly, this does not imply that oil and other non-renewable sources are everlasting. Simply, it means that new technologies may delay the depletion of these resources for human use. However, economic and political factors may matter as much as technological and geological ones. Oil and natural resources in general are highly concentrated in few areas of the world, which implies a big role for the geopolitics.

In 2019, the U.S. was the largest oil-producing country with a global market share of roughly 20%. The second and third largest oil producers were Russia and Saudi Arabia, respectively (see Figure 3.3a). As it was the case for consumption, also production is very unevenly allocated around the globe. Indeed the top 10 oil-producing countries account for a market share of 71%.

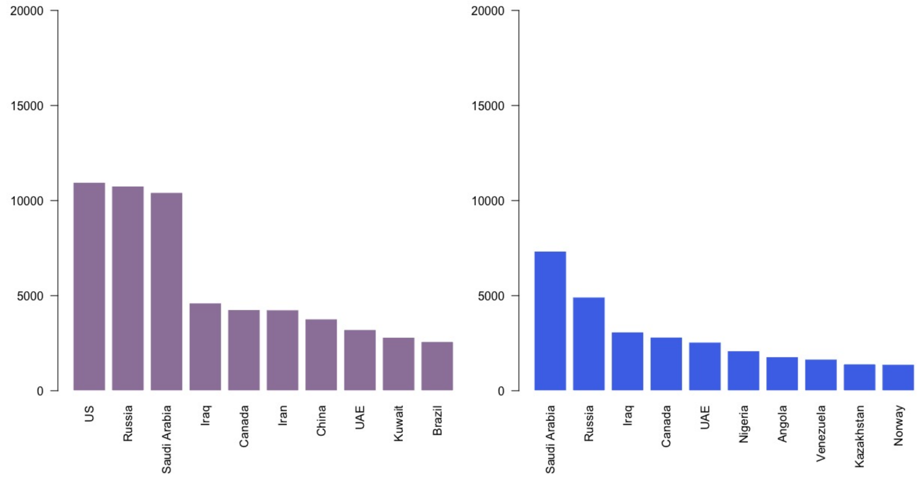
Since the U.S. is in the first place for both oil production and consumption, we would expect a different picture when looking at oil exports. In fact, the U.S. only ranks in the 23^{th} position in oil exports by country. The three major oil exporters are, instead, Saudi Arabia, Russia and Iraq (see Figure 3.3b). In the next 20 years oil supply is expected to increase with a larger share coming from non-OPEC countries. In particular, experts predict a booming production of unconventional oil such the U.S. shale, Brazilian deepwater and Canadian oil sands.

Focusing on the oil-exporting countries in our sample, Figure 3.4 displays the oil

[5] The RPR ratio indicates the remaining lifespan (in years) of a natural resource, given a production rate, and is calculated as

$$\text{RPR} = \frac{\text{Amount of known resource}}{\text{Amount produced per year}}$$

FIGURE (3.3) Crude Oil Supply



(A) Crude Oil Production (B) Crude Oil Exports

Notes: Crude oil production and exports in thousand barrels per day. Data from The World Factbook based on 2014-2018 estimates.

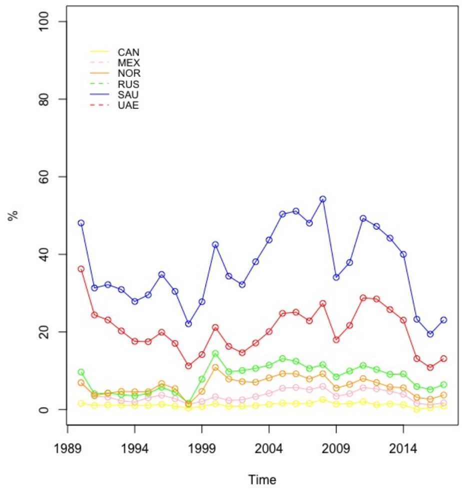
rents, as a percentage of GDP, for Canada, Mexico, Norway, Russia, Saudi Arabia and the U.A.E. for the period 1990-2017.[6] It is interesting to note how the series fluctuate in concert with the major oil events. For instance, all the series spike during the oil price surge of the early 2000s and plummet during the oil price collapse amid the 2007-2008 financial crisis. Also, Figure 3.4 highlights the evident oil dependence of the GCC countries.[7]

As it was for the demand, also the supply of oil has experienced an unprecedented situation in the recent months. In March 2020, Russia refused the proposal of Saudi Arabia to jointly cut oil production to balance the effects of the COVID-19 pandemic on demand. This triggered a dispute which lasted for weeks until the historical deal of cutting global oil production by nearly 10% was reached on April, 12. Notwithstanding, the extent of the unbalancing of oil markets appears well beyond the reach of this agreement (Tagliapietra, 2020).

[6]Oil rents are the difference between the value of crude oil production and total costs of production. For more details about oil rents by country, please consult https://data.worldbank.org/indicator/NY.GDP.PETR.RT.ZS.

[7]The Gulf Cooperation Council (GCC) is a regional intergovernmental union whose member countries are Bahrain, Kuwait, Oman, Qatar, Saudi Arabia, and the United Arab Emirates.

FIGURE (3.4) Oil Rents (% of GDP)



Notes: Data from the World Bank for the period 1990-2017.

3.1.4 Market

Despite the utterly complex structure of the industry, global oil value chain can be summarized in three phases: upstream, transportation and downstream (Paltseva, 2019).

The first phase begins with the negotiations between firms and sovereign states to access exploration and development of any natural resource discovered. Negotiations often take years or even decades. For example, the Chad–Cameroon Petroleum Development and Pipeline Project was completed in June 2003, whereas attempt to develop oil resources in the region date back to the 1960s. Next, the transportation phase requires sophisticated technology and planning to transfer the commodity. The main ways to transfer oil from one place to another is through pipelines and ships (tankers). The last phase is dedicated to activities such as refining and marketing of oil. Crude oil can be refined into a variety of end products such as motor fuels, jet fuel, heating oil, asphalt and others. Refining decisions are based on the market demand as well as the type of oil available. Oil and gas value chains may overlap downstream with the production of petrochemicals.

The oil industry is composed by a mix of state-owned companies (NOCs) and private companies (IOCs) and includes both large international and small companies (in downstream). Among the largest players in the market we find names like British

Petroleum, ExxonMobil, Saudi Aramco and Shell.

In general, oil prices are determined by supply and demand at the global level. On the one hand, supply is driven by the availability of resources, technology, force majeure, geopolitics and industry regulation. On the other hand, the major factors driving the demand are GDP growth, consumers' preferences, energy efficiency and the presence of oil substitutes. The balance between demand and supply is also governed by the local and global environmental policies in place. Despite being a global commodity, most crude oil in the world is not sold in the market. Instead, it is often sold from producer to consumer directly or in smaller market segments. Typically, contracts are not publicly observable, therefore it is problematic to infer the fair price of the commodity. However, the price in these contracts is usually set relative to one of the benchmarks. The main crude oil benchmarks are the West Texas Intermediate (WTI), Brent Crude and Dubai Crude. Oil prices are evaluated by the Price Reporting Agencies (PRAs) such as Platts and Argus Media. Furthermore, there exists a physical spot market and a market of various financial instruments (forwards, futures, swaps, options, etc.). Relative benchmark pricing may depend on market conditions, subject to arbitrage. For instance, in the beginning of 2011 the spread between Brent and WTI grew as a consequence of excess U.S. supply of crude oil, relative to refining capacity. The spread eventually closed in mid-2014 when the U.S. cut production in response to falling oil prices (Paltseva, 2019).

Given the recent developments, it is worth mentioning the role of unconventional oil, which is produced through non traditional ways of extraction. Unconventional oil production has raised many environmental concerns within the public due to higher CO_2 emissions, heavy use of water, energy intensity and possible land disturbance. Among the different techniques used to extract unconventional oil, the most famous is by far the hydraulic fracturing, commonly known as "fracking". Hydraulic fracturing is not a novel technique as it was invented in the very end of the 19^{th} century and used since the 1940s both in the U.S. and in the Soviet Union. However, for a long time it was only used to stimulate vertical wells in conventional oil reservoirs. Technological improvements made this technique financially profitable to use for wider production. Even though shale oil is widely present around the world, hydraulic fracturing has had a crucial contribution to the boom of U.S. oil production. Shale and tight oil production skyrocketed since the early 2000s going from a daily production of less than 0.5 million barrels to more than 4.5 million barrels in 2014. The shale revolution in the U.S. triggered a decrease in imports and an increase in oil supply outside the country. This behaviour put pressure on prices and OPEC behaviour, eventually leading to changes in the geopolitical climate.

3.2 Oil and Stock Prices

Even though oil price changes are often considered an important determinant for understanding fluctuations in stock prices, there is no clear consensus about the linkage between oil and stock markets among economists. Therefore, it is relevant to try to discern what are the theoretical transmission mechanisms by which oil price changes can affect stock markets. In a recent paper, Degiannakis, Filis, and Arora (2018) identify five distinct transmission channels.

3.2.1 Stock Valuation Channel

The stock valuation channel is the direct transmission mechanism by which oil prices influence stock prices and, thus, stock returns. First, it is useful to define stock returns, $R_{i,t}$, as

$$R_{i,t} = \ln\left(\frac{P_{i,t}}{P_{i,t-1}}\right) \tag{3.1}$$

where ln is the natural logarithm and $P_{i,t}$ is the stock price of firm i at time t.[8] The linkage between oil and stock markets starts from the consideration that the current price of a stock should be determined by its discounted future cash flows. Formally,

$$P_{i,t} = \sum_{n=t+1}^{N} \mathbb{E}\left(\frac{CF_n}{(1+r)^n}\right) \tag{3.2}$$

where CF is the cash flow at time n, r is the discount rate and $\mathbb{E}(\cdot)$ is the expectation operator. Therefore, any factor which could affect the discounted future cash flows should have a significant effect on the asset price (Huang, Masulis, and Stoll, 1996). Most importantly, oil prices can affect expected cash flows by influencing either the numerator or the denominator of equation (3.2) or both.

[8]Throughout the thesis we refer to the terms returns and log returns interchangeably.

Since oil is a real resource and a key input for production, any increase of its price causes a rise in costs faced by oil-user firms (cost production effect). This repercussion triggers a reduction of profits and eventually a decrease in shareholders' value. On the other hand, for an oil-producer firm the oil price increase results in higher profit margins and thus increased expected cash flows, holding everything else equal.[9] As a consequence, the effect on a specific stock depends on whether the underlying firm is a net producer or a net consumer of oil. Intuitively, we would expect oil-producing firms to exhibit a bullish behaviour in times of upward oil price pressures, whereas the reverse holds true for oil-consuming firms. An important issue for this study is whether we can extend the firmwide argument to a nationwide context. In other words, if the mechanism described above applies to net oil-exporting countries and net oil-importing countries.

3.2.2 Monetary Channel

Oil prices can also affect stock prices via the expected discount rate, also referred to as required return. Intuitively, the required return reflects the time value of money and the risk premium demanded by investors. According to Mohanty and Nandha (2011), the discount rate incorporates, at least in part, expected inflation and expected real interest rates.

Theoretically, companies adversely affected by rising oil prices should transmit the increased production costs to consumers by applying higher prices. At national level, higher oil prices adversely affect the balance of payments of a net oil-importing country, putting downward pressure on the country's foreign exchange rates and putting upward pressure on the expected domestic inflation rate. Assuming the pass-through from companies to consumers takes place, we would expect a response from the monetary authority in order to control higher inflationary pressures.[10]

A typical action taken by a central bank is to increase short-term interest rates (Basher and Sadorsky, 2004).[11] Higher short-term interest rates exert two effects

[9] Hence, the stock valuation channel exerts an effect on the numerator of equation (3.2) only.

[10] According to a study of Cologni and Manera (2008) for the G-7 countries, unexpected oil shocks trigger monetary policy responses directed to fight inflation. As a result, policymakers face a trade-off between controlling inflation and reducing output through higher interest rates.

[11] Here, we have to assume that the monetary authority follows some type of rules like the well-known Taylor rule (Taylor, 1993).

on stock prices. First, they lead to higher commercial borrowing rates for any future firm investments.[12] Second, due to increased borrowing costs, firms have fewer positive net present value (NPV) projects causing a reduction in cash flows. Hence, the response of the monetary authority, following positive changes in oil prices, increases (reduces) the denominator (numerator) of equation (3.2), depressing stock prices overall.

It should be noted that the magnitude of such effects heavily hinges on the central bank's credibility to stabilize inflation. A highly credible monetary authority maintains inflation expectations close to the inflation target regardless of the oil price increase. This argument clearly does not hold for a central bank with low credibility.

3.2.3 Output Channel

The output channel refers to the mechanism through which oil price fluctuations affect aggregate output. There exists a rich literature examining this transmission mechanism (see, e.g., Hamilton (1983); Kilian (2008a); Kilian (2008b)). Via this channel, positive oil price changes impact on aggregate output through both a production cost effect and an income effect.

As we have already described the former, we now focus on the latter. The income effect can be seen as a reduction in the discretionary income of households caused by an increase of retail prices as well as gasoline and heating oil prices (Bernanke, 2006). A decrease in income leads to lower consumption and thus aggregate output which further diminishes labor demand.[13] Svensson (2005) shows how an increase in the relative price of an imported commodity, like oil, deteriorates the terms-of-trade for an oil-importing country, eventually causing lower income and a negative wealth effect on consumption. Intuitively, the stock market of a country which heavily relies on oil imports reacts negatively to such events.

It is important to stress that the validity of these arguments hold for an oil-importing economy. Conversely, an oil-exporting country experiences, *ceteris paribus*,

[12] This effect is manifested via the bank lending channel of monetary policy. A central bank's policy change affects the amount of credit that banks issue to firms and consumers which in turn affects the real economy.

[13] Edelstein and Kilian (2009) try to quantify the direct effect on real consumption caused by energy price shocks and find that these shocks are an important factor in explaining U.S. real consumption growth.

a positive income shock due to increased oil revenues. If this positive dynamic more than offsets the negative effect of increased production costs, then an upward change in stock prices is expected.

More difficult is to assess how such developments affect different sectors of the economy of an oil-exporting country. It can be foreseen that certain sectors benefit more than others from an oil price increase. Nevertheless, there could be positive spillovers across industries following an oil price increase and, hence, the basic idea of the output channel ought to hold, in general.

3.2.4 Fiscal Channel

The fiscal channel is chiefly concerned with oil-exporting countries which are financing physical and social infrastructure using their oil revenues (Degiannakis, Filis, and Arora, 2018). Following a surge in oil prices, oil royalties for governments in oil-producing countries may increase and potentially lead to higher public expenditure. Many studies investigate the effects of oil price increases on government spending behaviour in developing oil-exporting countries.[14]

Theoretically, private consumption and government spending can be considered either as complements or substitutes. In the former case, an expansionary fiscal policy boosts household consumption and thus firms' expected cash flows. In the latter case, instead, the opposite effect realizes due to the crowding out effect. This concept refers to the phenomenon for which an expansionary fiscal policy drives down, or even wipes out, private sector spending.

In light of these considerations, the fiscal channel could be either beneficial or detrimental for stock returns in an oil-exporting economy.

3.2.5 Uncertainty Channel

The last transmission mechanism linking oil price fluctuations and stock returns is the uncertainty channel of Brown and Yucel (2002). These authors claim that upward oil price fluctuations cause higher uncertainty in the real economy resulting from shifts in inflation, aggregate demand and output. Degiannakis, Filis, and Arora

[14] See, for example, Dizaji (2012) for the case of Iran.

(2018) add that increased economic uncertainty may reduce firms' demand for irreversible investments as companies cannot foresee whether the increase in energy prices will be long-lasting or transitory.

Furthermore, higher oil prices may also affect the risk premium component of stock prices. The risk premium reflects the extra return investors demand as a compensation for the risk that the cash flows might not materialize after all, given the outlook for corporate earnings. In this sense, the effect of uncertainty driven by higher oil prices is twofold: a decrease in companies' expected cash flows as well as an increase of equity risk premia.

Finally, the studies of Bernanke (1983) and Edelstein and Kilian (2009) support the validity of the uncertainty channel. Bernanke (1983) argues that uncertainty is propagated to households which respond by reducing consumption of durable goods . Edelstein and Kilian (2009) claim that increased incentives for households to save and for companies to delay investments dampen economic growth prospects and stock returns.

3.2.6 Summary of the Channels

We have described five transmission channels which are in line with the literature on oil prices and stock markets. Before proceeding further, it is useful to raise three considerations about these theoretical transmission mechanisms.

First, the combination of effects within a specific channel or across different channels may generate ambiguous responses of the stock markets. For instance, through the output channel, increases in oil prices generate both a negative production cost effect and a positive income effect in an oil-exporting country. Basher, Haug, and Sadorsky (2018) illustrate that the weight of these effects depends on the elasticity of demand for oil and the time horizon considered (i.e. short-run versus long-run elasticities). Even though we would expect the income effect to dominate in an oil-exporting economy, the empirical evidence might be fuzzy.

Second, the pass-trough from oil prices to stock returns does not exclude possible delayed effects which are not directly imputable to oil price fluctuations. For instance, an oil-exporting country may benefit from higher oil prices due to increased revenues. Nevertheless, an appreciation of the local currency, following the oil price increase, may deteriorate the balance of trade of this country and this would eventually lead to a new equilibrium.[15]

Third, we do not try to explicitly disentangle the specific transmission channels since this would require a larger array of variables and, possibly, more sophisticated models, such as dynamic stochastic general equilibrium (DSGE) models.[16] Instead, the scope of this study is to pin down the reactions of oil-exporting and oil-importing countries to different oil market shocks based on the simple hypotheses outlined in Chapter 1, while keeping in mind the broad implications of the five channels.

[15]Basher, Haug, and Sadorsky (2016) identify substantial exchange rate appreciation pressures in oil-exporting countries following oil price increases driven by aggregate demand shocks.

[16]One of the hardest challenges for economists is to examine how a specific variable impacts on another, *ceteris paribus*. Clearly, the problem of isolating this effect is particularly relevant within a macroeconomic framework, like the one of the present study, in which several factors are at play.

Chapter 4

Data

In this chapter we shortly outline the data employed in the empirical analysis. We rely on two different types of data. In the first stage, oil market data is used for estimating the SVAR model, whereas in the second stage, stock market data is used for estimating the linear regression models.

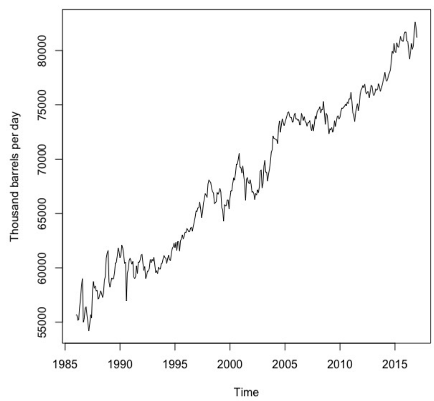
4.1 Oil Market Variables

In order to construct the oil market structural shocks, we employ three variables: the percentage change in global crude oil production, an index of real economic activity and the log returns of the real price of oil. Data are collected at a monthly frequency for the period 1986:1-2017:1.

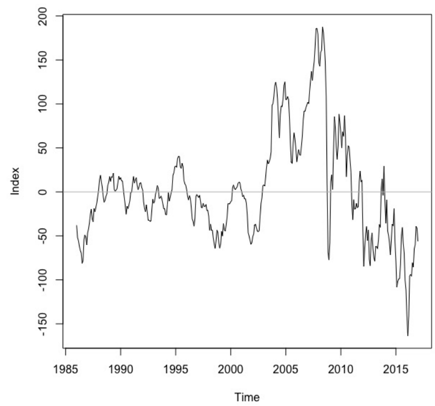
First, we use a measure of world oil supply, sourced from the EIA, which is measured in thousand barrels per day. Figure 4.1a shows the historical evolution of the series. To obtain the percentage change in global oil production, we calculate the log difference of the series and transform it into percentages.

Second, we use the index of real economic activity constructed by Kilian (2009) as a proxy for aggregate demand. The series is obtained from the dataset of Zhou (2019) which is publicly available on the Journal of Applied Econometrics Data Archive. The index is based on dry cargo single voyage ocean freight rates and is designed to capture fluctuations in the demand for industrial commodities at a global level (Kilian, 2009, p. 1055). Since global economic activity is the most relevant determinant of the demand for transport services, increases in freight rates, given a largely inelastic supply of suitable ships, are indicative of a higher demand for industrial

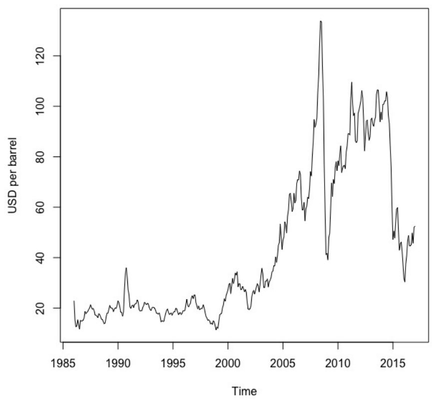
FIGURE (4.1) Oil Market Variables



(A) World Oil Production



(B) Real Economic Activity Index



(C) WTI

commodities, including oil. Kilian (2009) constructs this measure from the equal-weighted average of the percent growth of shipping rates which is then deflated by the U.S. CPI.[1] This proxy has been used by several authors studying the oil market (see, e.g., Kilian and Park (2009); Fang and You (2014); Zhu et al. (2016); Basher, Haug, and Sadorsky (2018); Zhou (2019)). Figure 4.1b displays the fluctuations in real economic activity over time.

Third, as a proxy for global oil prices we employ the WTI spot price measured in U.S. Dollars per barrel.[2] The series is sourced from the St. Louis Federal Reserve Economic Database (FRED). Figure 4.1c illustrates that oil prices have experienced some important peaks and troughs during the years. The main events that took

[1]For a detailed description of the construction of this index, the reader is referred to Kilian (2009, pp. 1055-1058).

[2]Since it is primarily sourced from the U.S., WTI is the main crude oil benchmark for North America.

place in the period under investigation are discussed in Chapter 6. To obtain the real price of oil, we deflate the WTI nominal price by the U.S. CPI, sourced from the FRED. Then, we compute the log returns of the real price of oil using formula (3.1) and convert them into percentages.

4.2 Stock Market Variables

Our dataset comprises stock market data of six oil-exporting countries (Canada, Mexico, Norway, Russia, Saudi Arabia and the U.A.E.) and four oil-importing countries (China, Germany, India and the U.S.). In addition, we include a proxy for global stock markets which serves as a control variable in the second stage of our methodology. Table A.1 in Appendix A provides information about the stock market indices employed in this study. Differences in sample periods among countries are solely due to data availability. Figures 4.2a-4.3d illustrate the historical evolution of the stock market indices.

To obtain the real stock returns we follow the same procedure adopted for computing the real log returns of oil prices. The only difference is that we use the country-specific CPIs to deflate the nominal stock indices.[3] Again, the CPIs are sourced from the FRED.

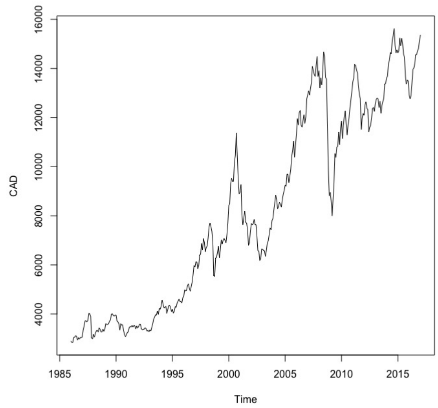
To define the sample, we fulfill the following five criteria. First, all the countries have a well established stock market.[4] Second, the selected countries are in the top 15 oil-importers and oil-exporters.[5] Third, the countries are a mixture of traditional stock markets and emerging stock markets. This source of heterogeneity could potentially provide interesting insights in the empirical analysis. Fourth, the countries represent different geographical markets. For this reason we include Germany even though it ranks after Japan and South Korea in terms of oil imports (see Figure 3.1b), since the Asian market is already represented by China and India. Fifth, the net oil position of a country has not changed over the sample period. This means that

[3]Note that we use the U.S. CPI to deflate the stock indices of the GCC countries as those are denominated in U.S. Dollars. In this sense, stock returns in Saudi Arabia and the U.A.E. can be seen from the perspective of an U.S. investor.

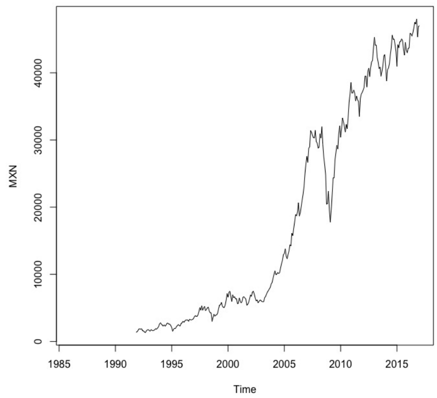
[4]In this respect, some concerns may arise about the inclusion of Saudi Arabia and the U.A.E. in our sample. We follow Basher, Haug, and Sadorsky (2016) who have assessed the validity of including the GCC countries using a measure based on market capitalization.

[5]We base our choice upon the latest available ranking of the The World Factbook.

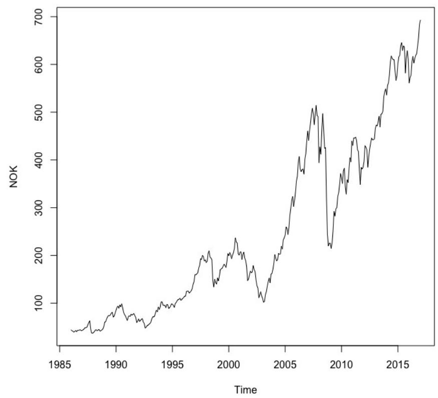
FIGURE (4.2) Stock Indices of Oil-exporting Countries



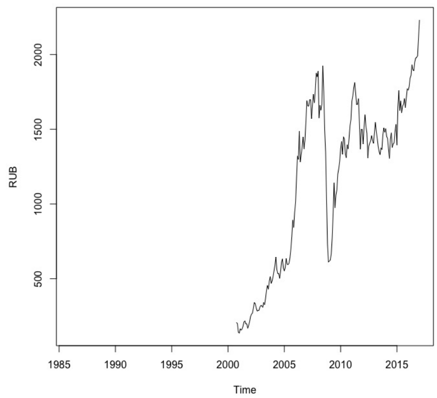
(A) Canada



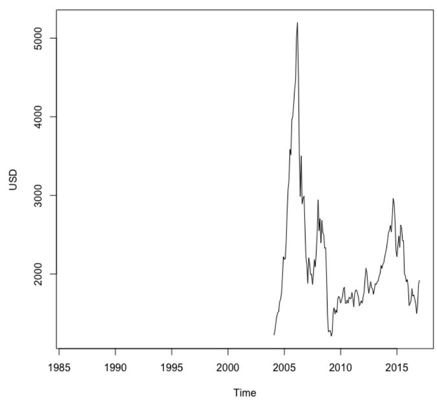
(B) Mexico



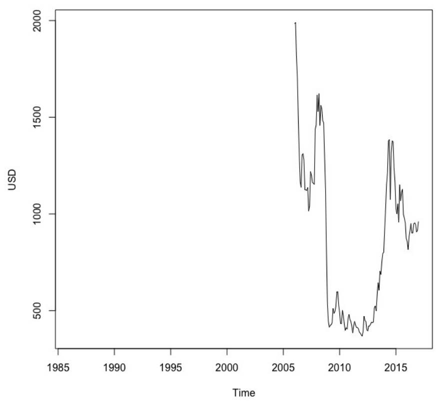
(C) Norway



(D) Russia

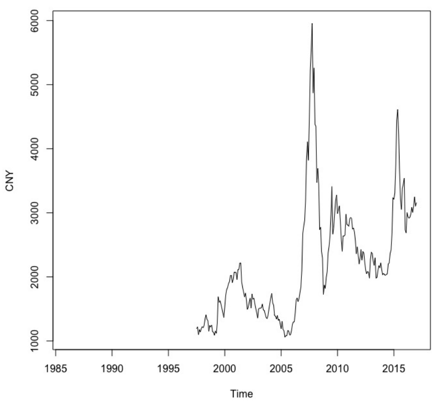


(E) Saudi Arabia

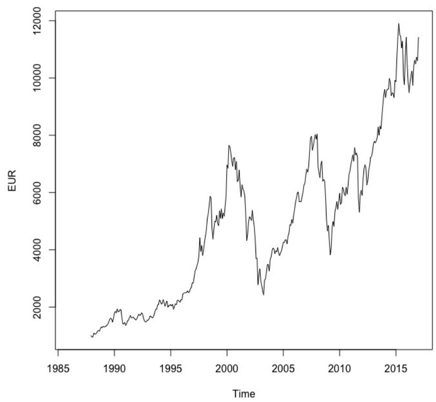


(F) United Arab Emirates

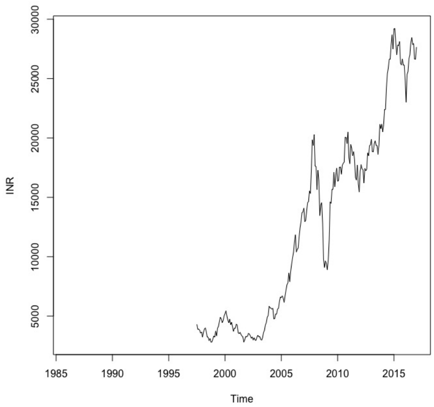
FIGURE (4.3) Stock Indices of Oil-importing Countries



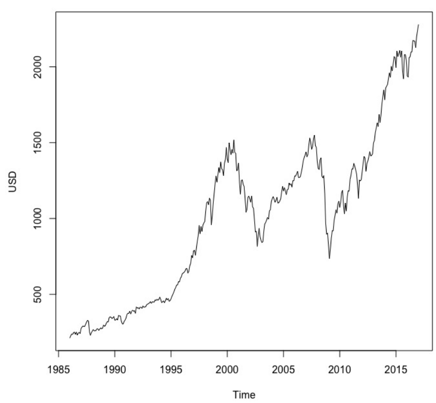
(A) China



(B) Germany



(C) India



(D) United States

an oil-importer or an oil-exporter has belonged to the same category for the whole period.

Table 4.1 displays the summary statistics of the stock return series. It is worth noting that the U.A.E. is the only country which exhibits a negative mean return and is also the country with the highest volatility of returns. This can be explained by the fact that the sample period for this country is quite short and includes the 2007-2008 financial crisis. In general, the stock returns of the emerging markets exhibit higher volatilities compared to the ones of established markets.

TABLE (4.1) Descriptive Statistics of the Stock Return Series

Country	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
CAN	372	0.261	4.301	−25.919	−1.783	2.920	12.642
MEX	302	0.464	6.990	−35.938	−2.897	4.698	17.814
RUS	195	0.380	8.330	−35.345	−4.135	5.058	19.439
NOR	372	0.519	6.515	−32.243	−2.793	4.723	15.366
SAU	155	0.121	7.899	−27.719	−3.734	4.339	17.585
UAE	132	−0.702	9.428	−39.317	−5.607	4.430	21.493
CHN	234	0.253	8.056	−27.978	−4.691	4.954	29.116
GER	349	0.543	6.054	−28.694	−2.443	4.404	19.387
IND	234	0.256	7.199	−28.660	−3.585	4.919	24.221
USA	372	0.425	4.424	−24.803	−1.997	3.166	11.747
World	372	0.305	4.461	−20.113	−2.107	2.954	10.316

Notes: N is the number of observations, St. Dev. is the standard deviation, Pctl(25) and Pctl(75) are the 25^{th} and 75^{th} percentiles, respectively.

Chapter 5

Methodology

In this chapter we direct our attention to the methodology used to investigate the effect of oil market shocks on international stock markets. We start by describing the preliminary tests used to get a first idea of the properties of our data. Testing for stationarity and cointegration of the oil market variables is crucial in order to correctly set up the oil market model. We proceed by outlining the two-stage approach. The first step consists of decomposing oil prices into three structural shocks through a SVAR model *à la Kilian*.[1] In the second step, we define the linear regression models which link stock markets to these structural shocks. Lastly, we discuss the issue of structural breaks in time series analysis.[2]

5.1 Stationarity

5.1.1 Definition

Stationarity is a key concept in time series analysis. In a very intuitive way, stationarity means that the statistical properties of a process generating a time series do not change over time. Stationarity is crucial because many useful analytical tools, statistical tests and models rely on it. Hence, a stationary time series is much easier to model, investigate and predict (Palachy, 2019). Also, testing for stationarity is a precondition for cointegration analysis which is discussed in the following pages.

[1]The expression *à la Kilian* has been extensively used in the oil market literature ever since the introduction of the oil price decomposition technique of Kilian (2009).

[2]Notice that the notation may slightly change from one section to the other. However, the notation is consistent within each section.

Using the definition of Enders (2015, p. 52), a stochastic process, y_t, having a finite mean and variance, is covariance (or weak) stationary if for all t and $t-s$,

$$\begin{aligned} \mathbb{E}(y_t) = \mathbb{E}(y_{t-s}) &= \mu \\ \mathbb{E}[(y_t-\mu)^2] = \mathbb{E}[(y_{t-s}-\mu)^2] &= \sigma_y^2 \\ \mathbb{E}[(y_t-\mu)(y_{t-s}-\mu)] = \mathbb{E}[(y_{t-j}-\mu)(y_{t-j-s}-\mu)] &= \gamma_s \end{aligned} \tag{5.1}$$

where μ, σ_y^2 and γ_s are all constants.[3] Simply put, a series is covariance stationary if its mean and autocovariances are unaffected by a change of the time origin.[4]

In practice, data being stationary is the exception rather than the rule. For example, often raw variables have to be transformed by taking natural logarithms to stabilize their variance. Besides, several variables have (deterministic or stochastic) trends that must be explicitly removed or modeled to ensure stationarity.[5]

A typical situation in which the assumption of stationarity does not hold occurs when a time series has a stochastic trend (or unit root). The simplest case of a unit root process is the well-known Random Walk (RW) series

$$y_t = y_{t-1} + u_t \tag{5.3}$$

where u_t is white noise.[6] Rewriting equation (5.3) recursively backward and imposing an initial condition on y_0, we obtain

$$\begin{aligned} y_t &= y_{t-2} + u_{t-1} + u_t \\ &= y_{t-3} + u_{t-2} + u_{t-1} + u_t \\ &= \quad \vdots \\ &= y_0 + \sum_{i=1}^{t} u_i \end{aligned} \tag{5.4}$$

[3]The second and third equations in (5.1) can also be rewritten as

$$\begin{aligned} \mathrm{Var}(y_t) = \mathrm{Var}(y_{t-s}) &= \sigma_y^2 \\ \mathrm{Cov}(y_t, y_{t-s}) = \mathrm{Cov}(y_{t-j}, y_{t-j-s}) &= \gamma_s \end{aligned} \tag{5.2}$$

[4]For a detailed explanation of stationarity, the reader is referred to Enders (2015, pp. 51-55).

[5]A trend in a time series variable can be seen as a systematic upward or downward movement over time (Kilian and Lütkepohl, 2017, p. 20).

[6]A time series is called white noise if it represents a sequence of identically distributed random variables with finite mean, finite variance and no serial correlation (Tsay, 2010, p. 36).

It is easy to note that the variance of equation (5.4) is time-dependent. A shock to the series will have a persistent effect violating the requirements for reliable statistical inference.

Another issue with non-stationary series is related to the concept of spurious regressions. The latter refers to the situation in which two series are significantly correlated, even though a real relationship between the two does not exist (McCallum, 2010, p. 321). Statistical inference based on spurious regressions is misleading. The only case in which two non-stationary series have a meaningful interpretation occurs when these series are cointegrated.

A common technique for tackling a unit root problem is differencing a series until it becomes stationary. A series that needs to be differenced d times in order to achieve stationarity is defined as integrated of order d or, more simply, an $I(d)$ series.

One way to analyze the stationarity properties of a series is the visual inspection of its autocorrelation function (ACF). The lag-k sample autocorrelation function of a y_t series is defined as

$$\rho_k = \frac{\sum_{t=k+1}^{T}(y_t - \mu)(y_{t-k} - \mu)}{\sum_{t=1}^{T}(y_t - \mu)^2} \tag{5.5}$$

where μ denotes the unconditional mean and $0 \leq k < T - 1$ (Tsay, 2010, p. 31). As a rule of thumb, the ACF of a stationary series should converge geometrically to zero, whereas persistence in the ACF is an indicator of a unit root process.

5.1.2 Unit Root Tests

The inspection of the ACF of a series is one useful way for detecting stationarity. Alternatively we can rely on ad hoc tests such the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP) and Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) tests.[7]

The first two tests belong to a broader class of Dickey-Fuller (DF) tests. To understand the essence of a DF test, we start with a simple first-order autoregressive, AR(1), process

$$y_t = \rho y_{t-1} + u_t \tag{5.6}$$

[7] Ideally, the results of all these tests should bring us to the same conclusions. In applied work, however, the results of different stationarity tests may be divergent.

which can be rewritten as

$$\begin{aligned} \Delta y_t &= (\rho - 1)y_{t-1} + u_t \\ &= \delta y_{t-1} + u_t \end{aligned} \tag{5.7}$$

where Δ is the first difference operator. There are three main versions of the DF test,

1. test for a unit root:

$$\Delta y_t = \delta y_{t-1} + u_t \tag{5.8}$$

2. test for a unit root with drift:

$$\Delta y_t = a_0 + \delta y_{t-1} + u_t \tag{5.9}$$

3. test for a unit root with drift and deterministic trend:

$$\Delta y_t = a_0 + a_1 t + \delta y_{t-1} + u_t \tag{5.10}$$

In each case, the null hypothesis is that the y_t series has a unit root, i.e. $H_0 : \delta = 0$.

The main pitfall of these specifications is that they often cannot distinguish between true unit root processes (δ equals zero) and near unit root processes (δ is close to zero). Since the tests are computed on the residual term, it is not possible to use the standard t-distribution for obtaining the critical values. To overcome this issue, Dickey and Fuller (1979) have tabulated an ad hoc distribution whose critical values depend on which of the three versions of the test is used as well as on the sample size.

The ADF test extends the general framework of equation (5.10) to

$$\Delta y_t = a_0 + a_1 t + \delta y_{t-1} + \gamma_1 \Delta y_{t-1} + ... + \gamma_{p-1} \Delta y_{t-p+1} + u_t \tag{5.11}$$

Thanks to the inclusion of lagged values of the dependent variable, the ADF formulation handles possible autocorrelation in the residual term.[8] In the empirical analysis we employ all the three versions of the ADF test.[9]

[8] Note that for brevity we have only reported the equation for the case of a unit root with drift and deterministic trend. However, the same approach applies to the other two cases.

[9] We refer to ADF(τ_1) for the baseline version, to ADF(τ_2) for the version with drift, and to ADF(τ_3) for the version with drift and deterministic trend.

A possible limitation of the ADF test is that it assumes the homoskedasticity of the error term, u_t, in equation (5.6). The PP test of Phillips and Perron (1988) corrects this deficiency by accounting for both autocorrelation and heteroskedasticity in the error term. The main difference compared to the ADF test is that the PP test makes a non-parametric correction to the test statistic by using the Newey and West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimator.

Another prominent test for detecting the presence of a unit root is the KPSS test of Kwiatkowski et al. (1992). The latter is a useful complement to the DF tests since for "economic" reasons we would prefer having the null hypothesis of stationarity.[10] The idea behind this test is best explained using the following equation

$$y_t = \xi_t + u_t \tag{5.12}$$

where u_t is stationary and ξ_t is a RW series such that

$$\xi_t = \xi_{t-1} + v_t \tag{5.13}$$

where $v_t \sim i.i.d.(0, \sigma_v^2)$. If σ_v^2 equals zero, then $\xi_t = \xi_0$ for every t and, thus, y_t is stationary. The null hypothesis of stationarity can be formally stated as

$$H_0 : \sigma_v^2 = 0 \tag{5.14}$$

Similar to the ADF test, the KPSS test can detect stationarity either around a mean or a trend. For future reference, we define the former case as KPSS(c) test and the latter case as KPSS(τ) test. Simulated critical values are also available.

[10] A disadvantage of the DF-like tests is that they require strong evidence to reject the null hypothesis of a series being non-stationary.

5.2 Cointegration

5.2.1 Definition

Cointegration is a fundamental concept in multivariate time series analysis. In econometric terms, cointegration refers to any long-run relationship among non-stationary variables (Enders, 2015, p. 346). Formally, two stochastic processes are cointegrated if they have the same order of integration and share the same stochastic trend. Cointegrated variables generally show similar developments over time. Different statistical methods have been conceived for detecting cointegration. For the purpose of this study, a cointegration analysis is performed to establish the validity of a VAR model over a vector error-correction (VEC) model. To this end, we employ two tests for cointegration: the Engle-Granger methodology and the Johansen procedure.

5.2.2 Engle-Granger Approach

Enders (2015, pp. 360-364) provides a clear illustration of the Engle-Granger approach. For simplicity, suppose that two variables, y_{1t} and y_{2t}, are assumed to be $I(1)$ and we want to determine whether there exists an equilibrium relationship between these series. Engle and Granger (1987) propose a two-step methodology to determine if two $I(1)$ series are cointegrated of order one, i.e. $CI(1,1)$. In the first step, we must test the order of integration of the variables employing, for instance, the unit root tests mentioned above. If both variables are stationary, then it is not necessary to proceed further since standard time series methods apply to stationary variables. If the variables are integrated of different orders, we can conclude that they are not cointegrated. Instead, if the results of the unit root tests suggest that y_{1t} and y_{2t} are $I(1)$ series, we can proceed with the second step in which we derive the long-run equilibrium relationship.

The long-run equilibrium relationship takes the form

$$y_{1t} = \beta_0 + \beta_1 y_{2t} + \varepsilon_t \tag{5.15}$$

where we can denote the residual sequence from equation (5.15) by $\hat{\varepsilon}_t$. As pointed out by Enders (2015, p. 361), the $\hat{\varepsilon}_t$ series contains the estimated values of the deviations from the equilibrium relationship. If $\hat{\varepsilon}_t$ is stationary, then y_{1t} and y_{2t} are cointegrated of order one, i.e. $CI(1,1)$. It is convenient to check whether the residual sequence is stationary by using a DF test of the form

$$\Delta\hat{\varepsilon}_t = \delta\hat{\varepsilon}_{t-1} + \epsilon_t \tag{5.16}$$

in which the null hypothesis is again $H_0 : \delta = 0$. As already mentioned before, if the residuals ϵ_t of equation (5.16) do not appear to be white noise, an ADF test can be implemented instead. More importantly, as we do not observe the actual errors, ε_t, but only their estimates, $\hat{\varepsilon}_t$, we cannot rely on the ordinary DF critical values and instead we should use the critical values interpolated using the response surface of MacKinnon (2010).

Finally, if the null hypothesis of no cointegration is rejected, then the residuals from the long-run equilibrium relationship can be used to estimate the error-correction model (ECM).

5.2.3 Johansen Procedure

An alternative way for detecting cointegration is the well-known Johansen procedure. Enders (2015, p. 374) illustrates that the Johansen procedure can be seen as a multivariate version of the DF test. Recall that in equation (5.7) we test the null hypothesis $H_0 : \delta = 0$ to determine the stationarity of a time series. Using the same logic, if we transform equation (5.7) into a VAR system, then the stationarity of the model itself can be tested. This transformed VAR model is called vector error-correction (VEC) model.[11]

To explain the transformation from a VAR to a VEC model, consider a VAR(1) model including two variables, y_{1t} and y_{2t}, and no deterministic terms. Let y_t be a 2×1 vector containing y_{1t} and y_{2t}, y_{t-1} be a 2×1 vector containing the lagged values of the two series, A_1 be a 2×2 matrix containing the slope coefficients and ε_t

[11] Since the VEC model is not employed in the empirical analysis, we do not describe it thoroughly here. However, the interested reader is referred to Kilian and Lütkepohl (2017, pp. 75-108) for a comprehensive analysis of the topic.

be the 2×1 vector of residuals. This model can be written as

$$y_t = A_1 y_{t-1} + \varepsilon_t \tag{5.17}$$

and subtracting y_{t-1} from both sides, and rearranging terms yields the VEC model

$$\Delta y_t = \Pi y_{t-1} + \varepsilon_t \tag{5.18}$$

where $\Pi = -(I_2 - A_1)$ and I_2 denotes the 2×2 identity matrix. The reader can immediately notice that equations (5.17) and (5.18) are the analogous versions of equations (5.6) and (5.7) in a multivariate fashion. Similar to the DF test, the Johansen methodology tests whether the rank of the matrix Π in equation (5.18) equals zero.[12]

Based on the rank of Π, three scenarios might occur (Zagler, 2004, p. 166). First, if the rank of Π is zero then the system in equation (5.18) has two different stochastic trends and, thus, there is not any cointegrating relationship between the two variables. Second, when Π has full rank, we can define a separate linear long-run relationship for each equation in the VAR system which implies that all variables are stationary (Enders, 2015, p. 359). Third, if Π has reduced rank, then there is cointegration between the two variables.[13]

Generally, the Johansen procedure tests the rank of Π sequentially, starting from the null hypothesis of H_0 : rank $= 0$ and then H_0 : rank ≤ 1 and so forth. The rank of Π indicates the number of cointegrating relationships and, correspondingly, the number of common stochastic trends in the system. For example, a general n-variable system has r cointegrating relationships and $(n - r)$ common trends. As it was the case for the DF test, the critical values of the Johansen procedure are sensitive to the presence of deterministic terms in the model.[14]

[12] The rank of a general matrix A is defined as the maximum number of linearly independent columns of A.

[13] In the example above, with two variables, reduced rank implies a rank equal to one.

[14] For an overview of the different specifications of the Johansen procedure, please consult Enders (2015, pp. 389-393).

5.3 Structural Vector Autoregression

In this section, we present the first stage of our methodology. Along the lines of Kilian (2009), we construct a SVAR model aimed at decomposing the real price of crude oil into three components. In particular, the VAR model of Sims (1980) has the desirable property that the model variables are treated symmetrically so that all variables are jointly endogenous. We begin by outlining the three-variable oil market model. Next, we show the properties of a reduced-form VAR model and its stability conditions. Lastly, we extend the reduced-form VAR model in order to identify the structural innovations of interest.[15]

5.3.1 Model Overview

Let $y_t = (\Delta\text{prod}_t, \text{rea}_t, \Delta\text{rpo}_t)'$ be the vector of monthly observations where Δprod_t denotes the percentage change in global crude oil production, rea_t is a global real economic activity index and Δrpo_t is the first log difference of the real price of oil.[16] Then, the reduced-form VAR representation is

$$y_t = v + \sum_{i=1}^{24} A_i y_{t-i} + \varepsilon_t \tag{5.19}$$

where v is a deterministic term, A_i for $i = 1, \ldots, 24$ are 3×3 parameter matrices and ε_t is a three-dimensional zero mean white noise process. The sample period covered in this study is 1986:2-2017:1.[17]

The general setting of the model in (5.19) is motivated as follows. First, we set 24 lags in order to capture the long cycles of global commodity markets. In this regard, Kilian and Zhou (2017) advise to include at least two years of monthly lags. Underfitting the VAR model could potentially lessen the importance of aggregate demand-driven oil shocks. Consequently, we do not make use of the conventional information criteria in order to establish the lag length of the VAR model.[18] Second,

[15] From this point forward we refer to the terms innovation, shock and disturbance interchangeably.

[16] The only difference compared to Kilian (2009) is that we utilise the changes in the real price of oil rather than its level form since we want a VAR model composed of stationary series only.

[17] However the model results are available from 1988:2 since we lose 24 observations from lagging the three variables.

[18] For our data, the Akaike Information Criterion (AIC) points toward a VAR(2) model. The latter specification would be clearly improper for the study of the oil market.

we include monthly dummy variables to capture seasonal effects which are usually present in energy markets (Back, Prokopczuk, and Rudolf, 2012). Third, we include roughly 30 years of data which should be able to capture the different types of oil market shocks over time. As explained by Kilian and Zhou (2017), the identification of a structural VAR model rests on the presence of sufficient variation in the data driven by each shock. This assumption may not hold if a too short sample is chosen.

5.3.2 Reduced-form Model

A general form of the model in (5.19) with p lags and no deterministic terms can be represented as

$$y_t = \sum_{i=1}^{p} A_i y_{t-i} + \varepsilon_t \tag{5.20}$$

where y_t, for $t = 1, \ldots, T$, denotes a K-dimensional vector of time series data, A_i is a $K \times K$ matrix of autoregressive slope coefficients, and ε_t is the K-dimensional vector of zero mean innovations. The innovations are assumed to be serially uncorrelated, granted the correct lag length has been chosen, but are allowed to be mutually correlated with variance-covariance matrix

$$\Sigma_\varepsilon = \mathbb{E}(\varepsilon_t \varepsilon_t') \tag{5.21}$$

Consequently, the error term is a white noise process $\varepsilon_t \sim i.i.d.(0, \Sigma_\varepsilon)$. The main point of the VAR(p) model in (5.20) is that it expresses the current values of the data as a linear function *only* of its own lagged values and lagged values of the other model variables up to some prespecified maximum lag order p (Kilian and Lütkepohl, 2017, p. 2).

In order to test the hypothesis of no serial correlation in the estimated reduced-form residuals $\hat{\varepsilon}_t$, a Breusch-Godfrey Lagrange Multiplier (LM) test can be implemented.[19] The Breusch-Godfrey LM statistic is based upon the auxiliary regression

$$\hat{\varepsilon}_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + B_1 \hat{\varepsilon}_{t-1} + \ldots + B_h \hat{\varepsilon}_{t-h} + u_t^* \tag{5.22}$$

[19] For a better description of this test, the reader is referred to Breusch (1978) and Godfrey (1978).

where the $\hat{\varepsilon}_t$ with $t \leq 0$ are replaced by zero and u_t^* is an auxiliary error term (Kilian and Lütkepohl, 2017, pp. 53-54). The null hypothesis is defined as

$$H_0: \quad B_1 = \ldots = B_h = 0 \tag{5.23}$$

and correspondingly the alternative hypothesis implies that at least one of these coefficients differs from zero. As an additional check, we also test for serial correlation of the reduced-form residuals using a small sample correction of the Breusch-Godfrey LM test which was proposed by Edgerton and Shukur (1999).

Finally, we must say that the simple model in (5.20) has little power for the purpose of this study. A transformation to a structural form of (5.20) is therefore needed.

5.3.3 Stability

As pointed out by Kilian and Lütkepohl (2017, p. 2), SVAR analysis hinges on the presumption that the data generating process (DGP) is well approximated by a reduced-form VAR. In applied work, a key feature for assessing the appropriateness of a reduced-form VAR model is its stability. In loose terms, a stable process is one that does not diverge to infinity (i.e. an explosive process). The concept of stability is well illustrated by Lütkepohl (2007, pp. 12-18). Consider the simple VAR(1) model:

$$y_t = v + A_1 y_{t-1} + \varepsilon_t \tag{5.24}$$

where v is a deterministic term. Then, imposing an initial condition on y_0 and iterating forward in (5.24) yields

$$\begin{aligned}
y_1 &= v + A_1 y_0 + \varepsilon_1 \\
y_2 &= v + A_1(v + A_1 y_0 + \varepsilon_1) + \varepsilon_2 \\
y_2 &= (I_K + A_1)v + A_1^2 y_0 + A_1 \varepsilon_1 + \varepsilon_2 \\
&= \quad \vdots \\
y_t &= (I_K + A_1 + \ldots + A_1^{t-1})v + A_1^t y_0 + \sum_{j=0}^{t-1} A^j \varepsilon_{t-j}
\end{aligned} \tag{5.25}$$

where I_K denotes the $K \times K$ identity matrix. All the y_t, for $t > 0$, are a function of just y_0 and the error terms. The reader can immediately recognize that equation (5.25) resembles equation (5.4) in a multivariate framework.[20]

Notice that if all the eigenvalues, λ, of matrix A_1 are smaller than one in absolute value, substitution in (5.25) can continue and y_t can be written as

$$y_t = \frac{v}{(I_K - A_1)} + \sum_{j=0}^{\infty} A_1^j \varepsilon_{t-j} \tag{5.26}$$

$$= \mu + \sum_{j=0}^{\infty} A_1^j \varepsilon_{t-j} \tag{5.27}$$

where μ denotes the unconditional mean of the model. Hence, a VAR(1) model is called stable if and only if all the eigenvalues of A_1 are smaller than one in modulus or equivalently

$$\det(I_K - A_1 z) \neq 0 \qquad \text{for } |z| \leq 1 \tag{5.28}$$

where $\det(\cdot)$ is the determinant of the matrix in parenthesis. The inequality in (5.28) can be generalized to a VAR(p) model whose stability condition is defined as

$$\det(I_K - A_1 z - A_2 z^2 - \ldots - A_p z^p) \neq 0 \qquad \text{for } |z| \leq 1 \tag{5.29}$$

and is called the reverse characteristic polynomial of the VAR(p) process. If the roots of the reverse characteristic polynomial do not lie in and on the complex unit circle then the VAR(p) process is stable (Lütkepohl, 2007, p. 16). Lastly, it is worth mentioning that in a VAR(p) model with K variables there are Kp roots.[21]

5.3.4 Structural Model

Going back to the reduced-form VAR in (5.20), we can estimate the model parameters by least squares (LS) methods applied separately to each of the model equations (Pfaff, 2008). In fact, the ordinary least squares (OLS) estimators are both consistent and efficient under the assumption of $\varepsilon_t \sim i.i.d.(0, \Sigma_\varepsilon)$.

[20] The only difference is that here we have introduced the deterministic term v, however the conclusions would have not changed if we had omitted it.

[21] We have provided an overview of the topic. For the mathematical derivation of the stability conditions, please consult Lütkepohl (2007, pp. 12-18).

Nevertheless, the properties of a reduced-form model may be unsatisfactory for two reasons. First, the model in (5.20) allows for an unrestricted number of lags but does not allow for contemporaneous relationships among the variables. Since economic theory often links variables contemporaneously, the model in (5.20) must be adjusted accordingly.[22] The second deficiency of the reduced-form VAR is that its error terms are in general mutually correlated. Hence, we would like to decompose these error terms into mutually orthogonal innovations. Orthogonality is important, for instance, when we try to quantify the effect of a shock to one equation, holding all other shocks constant.[23] If the error terms are correlated, then a shock to one equation is associated with shocks to other equations and, thus, the *ceteris paribus* assumption is violated. In a regression context, like the one in the second stage of our methodology, it is essential that the constructed oil market shocks are orthogonal variables. As illustrated by Basher, Haug, and Sadorsky (2016), if orthogonality holds, the innovation series are uncorrelated with other included and omitted variables in the regression model and their estimated coefficients are unbiased.[24]

To overcome these two limitations, we can model the instantaneous relations between the system variables by means of a SVAR model. A conventional approach is to convert the reduced-form model in (5.20) into its structural representation,

$$\begin{aligned} \mathbf{A}y_t =& A_1^* y_{t-1} + \ldots + A_p^* y_{t-p} + \mathbf{A}\varepsilon_t \\ A_j^* =& \mathbf{A}A_j \end{aligned} \tag{5.30}$$

for $j = 1, \ldots, p$ and

$$\mathbf{A}\varepsilon_t = \mathbf{B}e_t \tag{5.31}$$

where $e_t \sim i.i.d.(0, I_K)$ and, $\mathbf{A}$ and $\mathbf{B}$ are two $K \times K$ invertible matrices. From (5.31) we can infer that there are as many structural innovations as variables in the model

[22] Alternatively, we can think of the instantaneous relationships as naturally hidden in the correlation structure of Σ_ε (Amisano and Giannini, 1997, p. 15).

[23] What econometricians call impulse-response analysis (IRA).

[24] Under this scenario, the only consequence of the omitted variable bias is an increase in the residual variance in the regression.

and that the structural innovations are, by definition, orthogonal (Kilian and Lütkepohl, 2017, p. 109). The SVAR model in (5.30) can also be rewritten as

$$\mathbf{A}y_t(I_K - A_1L - A_2L^2 - \ldots - A_pL^p) = \mathbf{A}\varepsilon_t = \mathbf{B}e_t \tag{5.32}$$

where L is the lag operator.[25]

The so-called **AB**-model of Amisano and Giannini (1997) is a common approach for "orthogonalizing" the innovations in a short-run VAR model.[26] The **AB**-model suits well our purpose since the simultaneous equation system in (5.31) is postulated for the reduced-form errors ε_t directly rather than for the observable variables y_t (Lütkepohl, 2007, p. 364).[27]

Solving for the reduced-form errors

$$\varepsilon_t = \mathbf{A}^{-1}\mathbf{B}e_t \tag{5.33}$$

and substituting for (5.21), we then obtain the variance-covariance matrix of ε_t:

$$\begin{aligned}
\Sigma_\varepsilon &= \mathbb{E}[(\mathbf{A}^{-1}\mathbf{B}e_t)(\mathbf{A}^{-1}\mathbf{B}e_t)'] && (5.34)\\
&= \mathbb{E}[(\mathbf{A}^{-1}\mathbf{B}e_t)e_t'\mathbf{B}'(\mathbf{A}^{-1})'] && (5.35)\\
&= \mathbf{A}^{-1}\mathbf{B}\mathbb{E}(e_te_t')\mathbf{B}'(\mathbf{A}^{-1})' && (5.36)\\
&= \mathbf{A}^{-1}\mathbf{B}\Sigma_e\mathbf{B}'(\mathbf{A}^{-1})' && (5.37)\\
&= \mathbf{A}^{-1}\mathbf{B}I_K\mathbf{B}'(\mathbf{A}^{-1})' && (5.38)\\
&= \mathbf{A}^{-1}\mathbf{B}\mathbf{B}'(\mathbf{A}^{-1})' && (5.39)
\end{aligned}$$

For notational convenience, we also define

$$\mathbf{P} = \mathbf{A}^{-1}\mathbf{B} \tag{5.40}$$

[25]The lag operator is defined to be a linear operator such that for any value of a time series y_t, $L^iy_t \equiv y_{t-i}$ and for any constant c, $Lc \equiv c$.

[26]The terminology short-run stems from the fact that we impose restrictions on the contemporaneous responses among the variables. Alternatively, we could have estimated a long-run SVAR model along the lines of Blanchard and Quah (1989).

[27]Indeed, all we care about for the estimation in the second stage is the set of orthogonal innovations.

and obtain the final version of the variance-covariance matrix as

$$\Sigma_\varepsilon = \mathbf{P}\mathbf{P}' \tag{5.41}$$

Recall that, as we employ three variables ($K = 3$) in our VAR(24) model, the variance-covariance matrix in (5.41) has a 3×3 structure of the form

$$\begin{aligned}\Sigma_\varepsilon = \begin{bmatrix} \sigma_{11} & \sigma_{12} & \sigma_{13} \\ \sigma_{21} & \sigma_{22} & \sigma_{23} \\ \sigma_{31} & \sigma_{32} & \sigma_{33} \end{bmatrix} &= \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix}' \\ &= \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} p_{11} & p_{21} & p_{31} \\ p_{12} & p_{22} & p_{32} \\ p_{13} & p_{23} & p_{33} \end{bmatrix}\end{aligned} \tag{5.42}$$

where σ_{ij} and p_{ij}, for $i, j = 1, 2, 3$, are the parameters of matrices Σ_ε and $\mathbf{P}$, respectively.

At this point, however, we encounter a problem. Given its symmetric nature, the variance-covariance matrix Σ_ε has $\frac{3(3+1)}{2}$ free parameters.[28] On the other hand, the right-hand side (RHS) of equation (5.42) presents nine unknown parameters. To illustrate the point that it is not possible to uniquely solve equation (5.41), we write

[28]Trivially, the symmetry of Σ_ε comes from the fact that $\sigma_{12} = \sigma_{21}$, $\sigma_{13} = \sigma_{31}$ and $\sigma_{23} = \sigma_{32}$.

down the nine equations from the system in (5.42) as

$$\sigma_{11} = p_{11}^2 + p_{12}^2 + p_{13}^2 \tag{5.43}$$

$$\sigma_{12} = p_{11}p_{21} + p_{12}p_{22} + p_{13}p_{23} \tag{5.44}$$

$$\sigma_{13} = p_{11}p_{31} + p_{12}p_{32} + p_{13}p_{33} \tag{5.45}$$

$$\sigma_{21} = p_{21}p_{11} + p_{22}p_{12} + p_{23}p_{13} \tag{5.46}$$

$$\sigma_{22} = p_{21}^2 + p_{22}^2 + p_{23}^2 \tag{5.47}$$

$$\sigma_{23} = p_{21}p_{31} + p_{22}p_{32} + p_{23}p_{33} \tag{5.48}$$

$$\sigma_{31} = p_{31}p_{11} + p_{32}p_{12} + p_{33}p_{13} \tag{5.49}$$

$$\sigma_{32} = p_{31}p_{21} + p_{32}p_{22} + p_{33}p_{23} \tag{5.50}$$

$$\sigma_{33} = p_{31}^2 + p_{32}^2 + p_{33}^2 \tag{5.51}$$

In the system above, there are three sets of equations which are identical, namely equations (5.44) and (5.46), equations (5.45) and (5.49), and equations (5.48) and (5.50). Since we have six independent equations to solve for nine unknown parameters, the system is not identified unless some restrictions on the **P** matrix are imposed.

5.3.5 Identification

Even though there exists a variety of alternative strategies for achieving identification, we follow Kilian (2009) and employ a recursively identified SVAR model. More specifically, this model is identified by means of short-run exclusion restrictions on the model variables. Imposing exclusion restrictions is the most common approach for reducing the number of parameters to estimate in a SVAR model. In simple words, this identification strategy limits the contemporaneous feedback among some of the model variables.

Imposing restrictions on the **P** matrix implies reducing the number of free parameters of both the **A** and **B** matrices. Recall that the **A** and **B** matrices have nine elements each whereas the matrix Σ_ε has six free parameters only. Therefore the order condition for identification requires

$$2 * 9 - 6 = 12$$

total restrictions to be placed on the **A** and **B** matrices.[29] Following Amisano and Giannini (1997, pp. 18-19) we define the two matrices of interest as

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 \\ a_{21} & 1 & 0 \\ a_{31} & a_{32} & 1 \end{bmatrix} \tag{5.52}$$

and

$$\mathbf{B} = \begin{bmatrix} b_{11} & 0 & 0 \\ 0 & b_{22} & 0 \\ 0 & 0 & b_{33} \end{bmatrix} \tag{5.53}$$

The form of the **A** matrix provides the recursive structure, while the diagonal matrix **B** "orthogonalizes" the effects of the innovations.[30] Most importantly, we have restricted six parameters in each matrix, fulfilling the order condition for identification. The **P** matrix resulting from (5.40) is lower triangular (i.e. the three elements above the principal diagonal are equal to zero) and therefore the variance-covariance Σ_ε in (5.41) can be uniquely identified. By imposing the minimum amount of restrictions, we obtain what is called a short-run just-identified SVAR model.[31]

Amisano and Giannini (1997, p. 20) show that the parameters in the matrices **A** and **B** can be estimated by minimizing the negative of the concentrated log-likelihood function,

$$\ln L_c(\mathbf{A}, \mathbf{B}) = -\frac{KT}{2}\ln(2\pi) + \frac{T}{2}\ln|\mathbf{A}|^2 - \frac{T}{2}\ln|\mathbf{B}|^2 - \frac{T}{2}\mathrm{tr}(\mathbf{A}'\mathbf{B}'^{-1}\mathbf{B}^{-1}\mathbf{A}\tilde{\Sigma}_\varepsilon) \tag{5.54}$$

[29]For a VAR model containing K variables the order condition can be generalized to include

$$2K^2 - \frac{K(K+1)}{2}$$

restrictions.

[30]Notice that this identification scheme reproduces the effects of a Choleski decomposition.

[31]We could have imposed more restrictions than the ones dictated by the order condition, resulting in an overidentified model.

where K is the number of parameters in the model, T is the sample size, $\mathrm{tr}(\cdot)$ is the trace of the matrix in parenthesis and $\tilde{\Sigma}_\varepsilon$ is the estimate of the reduced-form variance-covariance matrix. The log-likelihood function in (5.54) can be estimated using numerical methods. More specifically, we employ the scoring algorithm which is embedded in the "vars" R package of Pfaff (2008).[32]

The final step consists of retrieving the structural shocks by combining the reduced-form errors, estimated with LS methods, and the parameters of the **A** and **B** matrices, estimated with numerical methods. Then by substituting for **P** in (5.33), we obtain

$$\varepsilon_t = \mathbf{P} e_t \tag{5.55}$$

which is the final equation relating the reduced-form and structural errors. Using the terminology of Kilian and Lütkepohl (2017, p. 109), **P** is defined as the structural impact multiplier matrix as it includes the short-run restrictions imposed to the SVAR model.

Since our interest lies in the structural errors, we rearrange equation (5.55) into

$$e_t = \mathbf{P}^{-1} \varepsilon_t \tag{5.56}$$

and obtain the desired orthogonal innovations.

5.3.6 Ordering

In the context of this study, equation (5.55) can be formally represented as

$$\varepsilon_t = \begin{pmatrix} \varepsilon_t^{\Delta \text{prod}} \\ \varepsilon_t^{\text{rea}} \\ \varepsilon_t^{\Delta \text{rpo}} \end{pmatrix} = \begin{bmatrix} p_{11} & 0 & 0 \\ p_{21} & p_{22} & 0 \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{pmatrix} e_t^{\text{oil supply shock}} \\ e_t^{\text{aggregate demand shock}} \\ e_t^{\text{oil-specific demand shock}} \end{pmatrix} \tag{5.57}$$

[32] For a more detailed description of the **AB**-model, the interested reader is referred to Amisano and Giannini (1997, pp. 48-59).

The representation in (5.57) matches with the oil market model of Kilian (2009, p. 1058). For simplicity, we rename the elements of the vector of structural innovations to

$$e_t = [e_t^{\mathrm{s}}, e_t^{\mathrm{d}}, e_t^{\mathrm{idi}}]'$$

where e_t^{idi} refers to a residual shock designed to capture idiosyncratic oil demand shocks (Kilian and Murphy, 2010).

Each row of the system in (5.57) can be viewed as an equation by multiplying each term on the RHS such that

$$\varepsilon_t^{\Delta\mathrm{prod}} = p_{11}e_t^{\mathrm{s}} \tag{5.58}$$

$$\varepsilon_t^{\mathrm{rea}} = p_{21}e_t^{\mathrm{s}} + p_{22}e_t^{\mathrm{d}} \tag{5.59}$$

$$\varepsilon_t^{\Delta\mathrm{rpo}} = p_{31}e_t^{\mathrm{s}} + p_{32}e_t^{\mathrm{d}} + p_{33}e_t^{\mathrm{idi}} \tag{5.60}$$

The reduced-form errors, ε_t, are expressed as weighted averages of the mutually uncorrelated innovations, e_t, with the elements of matrix **P** serving as weights.

Along the lines of Kilian (2009), the three structural shocks in (5.57) are interpreted as follows: e_t^s represents unexpected innovations to the global supply of crude oil; e_t^d captures disturbances to oil demand due to changes in global demand for industrial commodities; and e_t^{idi} seizes the innovations which cannot be explained by the first two shocks. Hence, the residual shock e_t^{idi} should primarily capture the movements in precautionary demand for crude oil driven by the uncertainty regarding future oil supply.[33]

A rationale for the ordering of the variables in (5.57) is given as follows. First, global supply of crude oil does not respond to innovations in the demand for oil within the same month (i.e. a vertical short-run oil supply curve) due to the high adjustment costs of oil production and uncertainty about the future state of the oil market. This assumption seems reasonable because supply decisions are made based on expectations of medium-term demand.[34] Second, while aggregate demand responds to oil supply shocks within the same month, it takes more than a month for the global

[33] To a lower extent, e_t^{idi} can also capture changes in oil demand which are not explained by variations in present demand for industrial commodities. For instance, an increased preference for more fuel-efficient cars would result in lower demand for oil, given the same level of global economic activity.

[34] Theoretical support for this assumption is provided by Anderson, Kellogg, and Salant (2018).

economic activity to react to oil-specific demand shocks.[35] This conjecture is in line with the sluggish adjustments of global real economic activity following movements in oil prices (Kilian, 2009, p. 1059).[36] Third, the real price of oil responds to shocks to both oil supply and global real economic activity within the same month. This assumption seems plausible as any exogenous changes in oil production or aggregate demand are immediately transmitted to oil prices (Basher, Haug, and Sadorsky, 2016).[37]

5.4 Linear Regression Models

The second stage of our analysis consists of specifying a set of linear regression models aimed at disentangling the effects of the structural shocks on stock markets.

To address the question of how stock returns respond to different oil market shocks, a linear regression model is estimated for each stock market,

$$sr_{i,t} = \beta_{0,i} + \beta_{1,i} e^{s}_{i,t} + \beta_{2,i} e^{d}_{i,t} + \beta_{3,i} e^{idi}_{i,t} + \beta_{4,i} W_{i,t} + u_{i,t} \tag{5.61}$$

where $sr_{i,t}$ is the real stock return for country i at time t. The shock variables come from the previously estimated SVAR model. We also include the log returns of a world stock market index, W, to control for influences on stock returns other than oil shocks. We do not include lagged values of the structural shocks as extra explanatory variables because we assume a certain degree of efficiency of the stock markets. For the U.S., we adjust the model in (5.61) such that

$$sr_{i,t} = \beta_{0,i} + \beta_{1,i} e^{s}_{i,t} + \beta_{2,i} e^{d}_{i,t} + \beta_{3,i} e^{idi}_{i,t} + \beta_{4,i} W_{i,t-1} + u_{i,t} \tag{5.62}$$

where the only difference consists of lagging by one period the variable that controls for global stock market returns. This choice is motivated by the fact that a large share

[35] Kilian and Zhou (2017) establish the validity of this assumption for the business cycle index employed in this study.

[36] Given that changes in global real activity are sluggish, one could also restrict the contemporaneous response of aggregate demand to oil supply innovations, i.e. imposing $p_{21} = 0$ in the system in (5.57). However, Kilian and Lütkepohl (2017, pp. 225-226) argue that the estimate of p_{21} is empirically close to zero, even though the parameter is left unrestricted.

[37] The oil price collapse amid the COVID-19 outbreak is a real-life example that supports this conjecture.

of the MSCI World Index is composed of U.S. stocks and ignoring endogeneity in a regression model could potentially lead to invalid statistical inference.[38]

With the second regression model we try to understand whether the oil shocks increase the stock market co-movement among oil-exporting countries, and analogously, among oil-importing countries. Stock market co-movement is a relevant subject in finance, mainly due to its role for asset allocation, portfolio diversification and risk management (Jach, 2017). In our context, the term co-movement refers to the phenomenon in which two (or more) time series tend to move in sync. The literature provides several quantitative methods for computing the degree of stock market co-movement. We follow Yang, Wang, and Wu (2013, p. 1237) and use the degree of market dispersion to measure how closely different stock markets fluctuate together. In order to proxy the degree of market dispersion, we employ the cross-sectional standard deviation (CSSD) index of Christie and Huang (1995). The latter is formally defined as

$$CSSD_{j,t} = \sqrt{\frac{\sum_{i=1}^{N}(sr_{i,t} - \overline{sr}_{j,t})^2}{N-1}} \tag{5.63}$$

where sr_i is defined above and $\overline{sr}_{j,t}$ is the cross-sectional average of the N returns in the aggregate portfolio j at time t.[39] As described by Christie and Huang (1995), this index quantifies the degree to which stock returns of different countries tend to plunge and surge together. The main intuition behind equation (5.63) is that the larger the level of market dispersion (CSSD), the lower the degree of stock market co-movement. To study how oil market shocks affect the stock market co-movement of a group of country, we specify the following linear regression model,

$$CSSD_{j,t} = \beta_{0,j} + \beta_{1,j}e^{s}_{j,t} + \beta_{2,j}e^{d}_{j,t} + \beta_{3,j}e^{idi}_{j,t} + u_{j,t} \tag{5.64}$$

where $CSSD_{j,t}$ denotes the stock market dispersion proxy for portfolio j at time t.

All the regression models are estimated by OLS methods using the Newey and

[38] As of 2020 the U.S. has a weight of 64,34% on the composition of the MSCI World Index. Also, the decision of using lagged world stock returns is driven by the absence of suitable alternatives. The best option would have been the MSCI World excluding USA Index which is not accessible. On the other hand, time series of Exchange Traded Funds (ETFs) tracking the performance of developed stock markets, excluding the U.S., are not long enough to cover the sample period of interest.

[39] The portfolio includes the stock returns of either oil-exporting countries or oil-importing countries.

West (1987) heteroskedasticity and autocorrelation consistent (HAC) covariance matrix estimator.[40].

More importantly, we assume that the oil market shocks are predetermined variables with respect to changes in stock prices. This assumption is crucial to rule out any feedback effects from stock returns to oil shocks within the same month, since including explanatory variables which are not strictly exogenous would invalid statistical inference. The assumption of predetermined oil market shocks with respect to macroeconomic and financial variables is supported in Kilian (2009). In addition, Kilian and Vega (2011) show that there are no contemporaneous responses from U.S. macroeconomic aggregates to innovations in oil prices at daily and monthly horizons.[41] Given the leading role of the U.S. within the global economy, we believe it is fair to assume that the results of Kilian and Vega (2011) can be extended to the other countries in our sample.

Finally, it is worth noting that most of the stock return series do not cover the full estimation period (1986:2-2017:1). In order to deal with this issue, we follow the recommendation of Kilian and Zhou (2017) and recover the shocks from the SVAR model estimated on the full sample, but fit the linear regression models on the country-specific subsamples.

5.5 Structural Breaks

The issue of detecting structural breaks in time series is very relevant. Many macroeconomic and financial time series regularly present structural changes. The latter may arise for several reasons. For instance, breaks may occur following new market regulations, financial crisis, changes in central banks' targets etc.

[40] As long as the independent variables are strictly exogenous, heteroskedasticity or autocorrelation in the errors does not cause bias or inconsistency in time series regressions. Nevertheless, OLS standard errors and tests statistics are no longer valid, even asymptotically, in the presence of serial correlation (Wooldridge, 2009, pp. 412-414)

[41] Also, several authors have placed financial variables below the oil market variables in their recursively identified SVAR models, indicating no feedback effects from the financial markets to the oil market (see, e.g., Kilian and Park (2009) and Kang, Ratti, and Yoon (2014)).

To better understand the concept of structural breaks, we follow Zeileis et al. (2002) and consider the standard linear regression model

$$y_i = x_i' \beta_i + u_i \tag{5.65}$$

where $i = 1, \ldots, n$ and $u_i \sim i.i.d.(0, \sigma^2)$.[42] Moreover, $x_i = (1, x_{i2}, \ldots, x_{ik})'$ denotes a $K \times 1$ vector of observations of the explanatory variables, with the first component equal to unity, and β_i is the $K \times 1$ vector of regression coefficients. A test for structural breaks establishes whether the vector of coefficients β_i is time invariant. The null hypothesis of no structural changes is formally stated as

$$H_0 : \quad \beta_i = \beta_0 \tag{5.66}$$

for $i = 1, \ldots, n$. Correspondingly, the alternative hypothesis implies that the coefficient vector varies over time.

In what follows, let $\hat{\beta}^{(n)}$ be the OLS estimate of the regression coefficients based on all the n available observations so that the OLS residuals can be denoted as

$$\hat{u}_i = y_i - x_i' \hat{\beta}^{(n)} \tag{5.67}$$

with the variance estimate

$$\hat{\sigma}^2 = \frac{1}{n-K} \sum_{i=1}^{n} \hat{u}_i^2 \tag{5.68}$$

There are various statistical methods for testing the null hypothesis in (5.66) building upon the OLS residuals in (5.67). The most common way for detecting structural breaks in a time series regression is the Chow test. One way to perform the Chow test is to divide the dataset in two subsets and check the equality of parameters in the following way:

$$\frac{(SSR - (SSR_1 + SSR_2))/K}{(SSR_1 + SSR_2)/(n - 2K)} \tag{5.69}$$

where SSR is the sum of squared OLS residuals (Enders, 2015, p. 103).

However, this procedure presents three main shortcomings. First, we need to

[42] Notice that we have changed the time subscript from t to i.

have enough observations to create two separate subsamples. This is a main concern in our case, as some of the stock return series present no more than ten years of data. Splitting an already short sample would strongly undermine statistical inference. Second, the Chow test assumes that we know the timing of the structural break. This assumption is, of course, hard to be met in practice. Our sample presents a number of events which could potentially be responsible for structural breaks. Third, the test speculates that the models in the two subsamples have the same variance. This equality assumption should be itself tested.

In light of these drawbacks, we rule out the possibility of using the Chow test for our analysis. A much easier and more efficient way for detecting structural changes is to test for the presence of endogenous breaks. An endogenous break is described as a change occurring at a not prespecified date (Enders, 2015, p. 104). More specifically, we employ a statistical method which has gained increasing success in recent years: the OLS-CUSUM test. The latter belongs to the generalized fluctuation test framework of Kuan and Hornik (1995). The OLS-CUSUM test, first proposed by Ploberger, Krämer, and Kontrus (1989), is meant to capture structural breaks in the linear regression model based on the cumulative sums of the error terms. More precisely, it builds upon an empirical fluctuation process (efp) that captures the movements in the OLS residuals.

The OLS-CUSUM type empirical fluctuation process is defined as

$$W_n^0(t) = \frac{1}{\hat{\sigma}\sqrt{n}} \sum_{i=1}^{\lfloor nt \rfloor} \hat{u}_i \tag{5.70}$$

where $W(t)$, for $0 \leq t \leq 1$, is the Standard Brownian Motion (or Wiener Process), $\lfloor nt \rfloor$ is the integer part of nt, and $\hat{u}_i$ and $\hat{\sigma}$ come from equations (5.67) and (5.68), respectively. The limiting process for $W_n^0(t)$ starts in zero at $t = 0$ and goes back to zero at $t = 1$. Zeileis et al. (2002, pp. 4-5) point out that the limiting process of the efp in (5.70) is known and consequently the critical boundaries can be computed. The probability of crossing these boundaries under (5.66) is α. If the OLS-CUSUM efp exceeds, at some point in time, these boundaries then the fluctuation is improbably large and hence (5.66) should be rejected at the significance level α.[43]

[43]For more details about the generalized fluctuation tests, the reader is referred to Zeileis et al. (2002).

Chapter 6

Empirical Results

In this chapter, we outline the results of the two-stage procedure. We start by showing the outcome of the preliminary tests. Next, we describe the estimation results of the first stage and make sure that the VAR model is well-specified. We proceed by showing the results of the linear regression models and assess the stability of their parameters over time. We conclude with a robustness test in which we employ an alternative proxy for global oil prices.

6.1 Preliminary Tests

6.1.1 Unit Root Test Results

Before estimating the VAR model, it is appropriate to test for the unit root properties of the series. As explained before, a VAR model containing nonstationary data might lead to a spurious regression problem, resulting in unreliable estimates.

Table 6.1 shows the test statistics of the unit root tests conducted on the original and differenced series. As explained in Chapter 4, the global oil production and the real oil price series were originally transformed by taking natural logarithms. The optimal lag length of the ADF test is chosen based on the Akaike Information Criterion (AIC).[1]

The global oil production series shows mild indications of trend stationarity, as displayed by the test statistic of ADF(τ_3). The PP test barely rejects the unit root hypothesis at the 10% significance level. However, the null hypothesis of stationarity

[1] The formula for the AIC is

$$AIC = T * \ln{(SSR)} + 2n$$

where T is the number of usable observations and n is the number of parameters estimated.

TABLE (6.1) Results of the Unit Root Tests for the Oil Market Variables

Panel A: Original series						
	ADF(τ_1)	ADF(τ_2)	ADF(τ_3)	PP	KPSS(c)	KPSS(τ)
prod_t	1.153	-0.858	-3.446^b	-3.397^c	2.573^a	0.300^a
rea_t	-4.123^a	-4.114^a	-4.118^a	-3.477^b	0.168	0.150^b
rpo_t	-0.021	-2.296	-2.888	-2.790	1.426^a	0.239^a

Panel B: Differenced series						
	ADF(τ_1)	ADF(τ_2)	ADF(τ_3)	PP	KPSS(c)	KPSS(τ)
prod_t	-18.072^a	-18.125^a	-18.122^a	-26.406^a	0.071	0.034
rea_t	-15.329^a	-15.322^a	-15.309^a	-16.054^a	0.058	0.056
rpo_t	-12.469^a	-12.456^a	-12.445^a	-14.855^a	0.083	0.079

Notes: Test statistics of the unit root tests outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

is firmly rejected at the 1% level using the KPSS tests. Conversely, the stationarity of the differenced series is supported by the results of all the six tests.

The ADF tests support the stationarity of the real economic activity series as the null hypothesis is rejected at the 1% significance level in all three cases. The KPSS test version with a trend, KPSS(τ), provides only weak evidence against stationarity (rejection at the 5% level). Another reason to support the $I(0)$ nature of the series is the fact that the real economic activity index is already detrended and, according to Kilian and Murphy (2010), stationary by construction. For completeness, we provide the unit root test results for the differenced series in Panel B of Table 6.1.

The real oil price series is clearly nonstationary since oil prices have dramatically fluctuated over the sample considered (see Figure 4.1c). In fact, the ADF and PP tests cannot reject the null hypothesis at any levels, whereas the KPSS tests suggest the presence of a unit root in the series (rejection at the 1% level). The last row of Panel B of Table 6.1 reveals that rpo_t is indeed an $I(1)$ series.

6.1.2 Cointegration Test Results

Next, we test for cointegration between the two $I(1)$ series. If global crude oil production (prod_t) and the real price of oil (rpo_t) were cointegrated, then we would need to include the error-correction term in the VAR model.[2]

First, we conduct the Engle-Granger methodology. We regress the crude oil production series on the real price of oil series and save the residuals.[3] The ACF of the estimated residuals is displayed in Figure B.1 in Appendix B. The residuals show a high degree of persistence that is confirmed by the results of the ADF test. In fact, the test statistic of the ADF test is -2.303 which is not smaller than the corresponding critical values of MacKinnon (2010). In our case, with more than 300 observations, the 10% critical value is equal to -3.067 (see Table B.1 in Appendix B).[4]

As an additional check, we also perform the Johansen procedure for cointegration. Table 6.2 illustrates that the null hypothesis of no cointegration between the two variables cannot be rejected at the 10% significance level.

Since both the Engle-Granger methodology and the Johansen procedure do not provide evidence of cointegration, we rule out the possibility of a VEC model.

6.2 Oil Market Model

6.2.1 Preliminary Checks

In light of the results of the unit root and cointegration tests we proceed by estimating the VAR model in (5.19). The latter is composed of three $I(0)$ series: $\Delta prod_t$, rea_t and Δrpo_t.

Each of the three equations in the VAR system contains 24 lags, a constant and seasonal dummy variables. We do not report the OLS estimates for the VAR equations since they are not of direct interest for the purpose of this study.[5] However, it is interesting to report that the monthly dummy variables are statistically significant. This basic point underscores the importance of considering seasonality in oil market models as claimed by Hamilton and Herrera (2004).

Turning to the analysis of the error terms, we see that the ACFs of the reduced-form residuals indicate absence of autocorrelation (see Figures B.2a-B.2c in Appendix

[2]The vector error-correction (VEC) model can be seen as a restricted VAR model.

[3]As noted by Enders (2015, pp. 360-364), either prod_t or rpo_t can be used as the dependent variable.

[4]Notice that using the critical values of the Dickey-Fuller table would be very misleading (Enders, 2015, pp. 360-364). In the present case, for instance, we would reject the null hypothesis of nonstationary residuals at the 5% significance level.

[5]We omit the results also for a matter of space since each of the three equations includes 84 parameters.

TABLE (6.2) Results of the Johansen Procedure for prod_t and rpo_t

Type	Rank	Test Statistic	90% Confidence Level
λ_{trace}	R=0	11.36	15.66
	R≤1	1.32	6.50
λ_{max}	R=0	10.03	12.91
	R≤1	1.32	6.50

Notes: λ_{trace} and λ_{max} denote the trace statistic and max-eigenvalue statistic, respectively.

B). In fact, all the spikes lie within the two blue dashed lines which denote the significance threshold. Only Figure B.2a presents a significant spike at lag 18 which is most likely spurious and, thus, not relevant. In addition, Table 6.3 displays the results of two multivariate tests for no serial correlation in the reduced-form residuals. Neither the Breusch-Godfrey test nor the Edgerton-Shukur test can reject the null hypothesis of no serial correlation.

TABLE (6.3) Results of the Multivariate Tests for Serial Correlation in the Reduced-form Residuals

Type	Test Statistic	p-value
BG	53.962	0.169
ES	0.900	0.660

Notes: BG and ES denote the Breusch-Godfrey and the Edgerton-Shukur tests, respectively.

The absence of serial correlation in the reduced-form residuals does not imply, however, lack of mutual correlation among them. Table 6.4 shows that the reduced-form residuals are indeed correlated with each other. This highlights the importance of estimating the structural form of a VAR model. Including the reduced-form residuals in the second stage would be clearly wrong since the explanatory variables in the regression models should be independent.

The reduced-form VAR model also meets the stability condition since the reverse characteristic polynomial of the process has no roots in and on the complex unit circle (Lütkepohl, 2007, p. 16). As a final check for the reduced-form VAR model, we check whether its parameters are time invariant. Kilian and Lütkepohl (2017, pp. 69-72) point out that the stationarity of a VAR model is violated not only if the stability

TABLE (6.4) Correlation Matrix of the Reduced-form Residuals

	Δprod	rea	Δrpo
Δprod	1.000		
rea	−0.021	1.000	
Δrpo	−0.106	0.151	1.000

condition does not hold but also if the model parameters change over time. It turns out that the OLS-CUSUM test for structural breaks outlined in Chapter 5 can also be adopted in a multivariate framework.[6] Figure B.3 in Appendix B provides clear evidence for the time invariance of the model parameters since in none of the three cases the empirical fluctuation processes exceed the 5% critical boundaries.

6.2.2 Structural Oil Market Shocks

The reduced-form VAR model appears to be well-specified as it passes all the diagnostic checks: no serial correlation in the residuals, stability of the process and time invariance of the model parameters. The next step consists of estimating the structural form using the **AB**-model of Amisano and Giannini (1997) and obtain the orthogonal innovations.

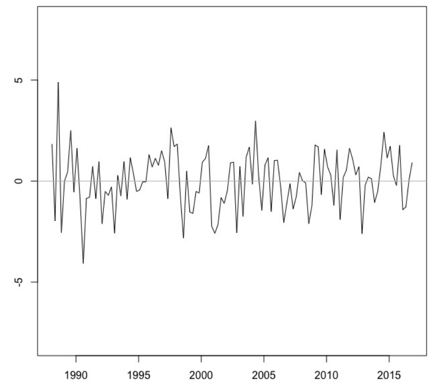
Figures 6.1a-6.1c plot the time paths of the oil market structural shocks. The latter have been summed up by quarters to improve readability. The first thing we notice is that the oil supply shock series presents higher volatility in the very first part of the sample. On the other hand, the aggregate demand shock series fluctuate more in the second part of the sample, especially after the 2008-2009 global economic recession. Figures 6.1a-6.1c show that, at any point in time, the real price of oil responds to a multitude of oil market shocks.

A historical explanation of the different shocks is given as follows.

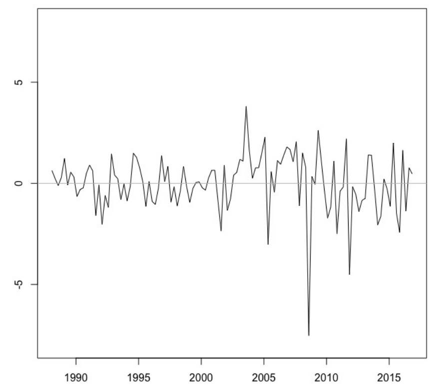
In 1985, amid a dispute among OPEC members, Saudi Arabia decided it would no longer attempt to sustain the price of oil by diminishing production and, conversely, began producing at full capacity. This turbulent period, in the mid to late

[6] The CUSUM test was originally proposed for linear regression models, however Ploberger, Krämer, and Kontrus (1989) establish its validity in dynamic models.

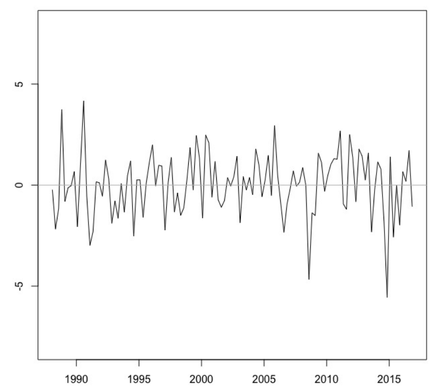
FIGURE (6.1) Historical Evolution of the Oil Market Shocks



(A) Oil Supply Shock (e_t^s)



(B) Aggregate Demand Shock (e_t^d)



(C) Oil-specific Demand Shock (e_t^{idi})

Notes: Monthly innovations summed up by quarters.

1980s, is reflected by wide swings in oil supply shocks. More specifically, we can see in Figure 6.1a a large positive oil supply shock just at the end of 1988.

In 1990, Iraq invaded Kuwait and started the Gulf War. Oil prices rose by more than 50% from the prewar time to the end of 1990. From Figure 6.1c, we note a significant positive oil-specific demand shock in this period. In the same time frame, we also report a noticeable disruption in oil supply. These findings have important implications for understanding oil price fluctuations. When exogenous political events occur, oil prices are not only affected by current physical supply disruptions, but also by expectations regarding future oil supply shortfalls. Indeed, the oil-specific demand shock series reflects increases (or decreases) in the precautionary demand for oil, which are fuelled by the degree of uncertainty over future oil supply.

In the 21^{st} century, demand-side shocks have played a more prominent role compared to supply-side shocks. In the early 2000s, demand from Asian countries contributed to a dramatic increase in oil prices. These findings are supported in Figure 6.1b, which shows that the persistent upward trend of global aggregate demand was responsible for the oil price increase. The fact that a booming aggregate demand fostered the oil price surge of the early 2000s helps explaining why the global economy proved to be resilient in that period.[7]

The substantial decrease in oil prices following the Great Recession is again associated with adverse aggregate demand shocks and, to a lower extent, negative oil-demand specific shocks. Note, in particular, that the aggregate demand shock series shows a sharp decline at the time of the bankruptcy of Lehman Brothers in 2008.

The most recent years have been characterized by the U.S. shale oil boom and by a reduced influence of the OPEC in the geopolitical equilibrium (Paltseva, 2019). In this environment, oil prices plummeted from $100.26 per barrel in June 2014 to $27.48 per barrel in January 2016. Figures 6.1a and 6.1c tell us that the plunge of oil prices in this period can be attributed to both positive supply shocks and adverse oil-specific demand shocks.

[7] Kilian and Park (2009) corroborate this conjecture in a study of the U.S. stock market for the period 2000-2007.

Overall, Figures 6.1a-6.1c underscore the importance of identifying the sources of oil price changes in order to track the major oil events.

6.3 Oil Market Shocks and Stock Returns

In the second step of our methodology, we examine the relationship between structural oil market shocks and stock returns in major oil-exporting and oil-importing countries.

In order to correctly run the regressions in (5.61) and (5.62), we must first ensure that the structural shock and stock return series are covariance stationary. From a visual inspection of Figures 6.1a-6.1c, we see that the shock series fluctuate around a mean of zero. Some concerns may arise for changes in the variance across time, especially for the supply shock and aggregate demand shock series. The results of the unit root tests in Table 6.5 provide evidence in favor of stationarity of the three series. Likewise, all the stock return series are covariance stationary as shown in Table 6.6.

TABLE (6.5) Results of the Unit Root Tests for the Oil Market Shock Series

	ADF(τ_1)	ADF(τ_2)	ADF(τ_3)	PP	KPSS(c)	KPSS(τ)
e^{s}	-13.037^{a}	-13.018^{a}	-13.020^{a}	-18.446^{a}	0.080	0.046
e^{d}	-13.099^{a}	-13.080^{a}	-13.085^{a}	-18.734^{a}	0.147	0.114
e^{idi}	-13.191^{a}	-13.172^{a}	-13.155^{a}	-18.549^{a}	0.076	0.066

Notes: Test statistics of the unit root tests outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

We proceed by estimating the linear regression models and ensure that they do not present any structural breaks. Figures B.4a-B.5d in Appendix B show that none of the ten empirical fluctuation processes exceed the 5% critical boundaries.

Table 6.7 shows the results of the OLS-CUSUM test. The null hypothesis of no structural breaks cannot be rejected at any levels for eight regression models, whereas only for the GCC countries there is weak evidence of structural breaks (i.e. the null hypothesis of no structural breaks is rejected at the 10% significance level).

TABLE (6.6) Results of the Unit Root Tests for the Stock Return Series

	ADF(τ_1)	ADF(τ_2)	ADF(τ_3)	PP	KPSS(c)	KPSS(τ)
CAN	-12.651^a	-12.694^a	-12.677^a	-16.188^a	0.039	0.039
MEX	-12.298^a	-12.344^a	-12.329^a	-16.873^a	0.082	0.076
NOR	-12.285^a	-12.369^a	-12.352^a	-15.545^a	0.029	0.027
RUS	-9.142^a	-9.175^a	-9.247^a	-10.868^a	0.103	0.057
SAU	-7.467^a	-7.443^a	-7.441^a	-10.508^a	0.106	0.085
UAE	-6.162^a	-6.159^a	-6.302^a	-8.969^a	0.281	0.070
CHN	-9.092^a	-9.089^a	-9.079^a	-13.948^a	0.040	0.034
GER	-13.125^a	-13.266^a	-13.258^a	-17.350^a	0.060	0.047
IND	-9.969^a	-9.972^a	-9.951^a	-14.282^a	0.084	0.083
USA	-13.970^a	-14.112^a	-14.096^a	-18.320^a	0.103	0.071
World	-15.905^a	-15.951^a	-15.937^a	-20.598^a	0.070	0.073

Notes: Test statistics of the unit root tests outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

The estimation results for the linear regression models are displayed in Table 6.8. As a first look at the impact of oil shocks on stock returns, we notice that the R^2 values for the ten regressions range from a low of 0.006 (U.S.) to a high of 0.483 (Norway).[8] For Mexico, Norway, Saudi Arabia, China and India increases in world stock returns have a highly statistically significant and positive effect on stock market returns meaning that the stock indices of these countries tend to go hand-in-hand with movements in global financial markets. Past changes in world stock returns do not have any explanatory power for the U.S. current stock returns.

By looking at Panel A of Table 6.8, we notice that oil market shocks have an impact on the stock returns of all the oil-exporting countries in the sample.

Unanticipated oil-supply shocks (e^s), do not exert any significant effect on stock returns for most of the countries. Mexico is the only country in our sample showing a negative effect at the 5% significance level. The latter finding is consistent with the view for which positive oil supply shocks reduce oil prices and, therefore, adversely affect firms' revenues in an economy that depends on oil exports.

[8]However, the fact that for all the countries but the U.S. we have included the contemporaneous effect of world stock returns might explain the low R^2 for this country.

TABLE (6.7) Results of the OLS-CUSUM Test of the Linear Regression Model of Stock Returns on Oil Market Shocks

Panel A: Oil-exporting countries		
	Test statistic	p-value
CAN	0.698	0.714
MEX	1.003	0.267
NOR	0.723	0.672
RUS	0.781	0.575
SAU	1.241	0.092^{c}
UAE	1.284	0.074^{c}

Panel B: Oil-importing countries		
	Test statistic	p-value
CHN	0.795	0.552
GER	0.845	0.472
IND	0.755	0.618
USA	0.993	0.278

Notes: OLS-CUSUM test outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

On the other hand, an unanticipated shock driven by a change in global aggregate demand (ε^{d}) exerts a positive effect on the stock markets of Canada and Norway. The positive relationship for Canada is statistically significant at the 5% level, whereas for Norway is significant at the 1% level. These results are intuitive since an aggregate demand shock generates upward pressures on the price of oil, which eventually leads to higher firms' revenues and, thus, higher stock prices. Also, higher oil prices, in times of economic expansion, could result in a transfer of wealth from oil-importing to oil-exporting countries. On the other hand, the absence of any effects for the other oil-exporting economies could be related to the fact that positive aggregate demand shocks may lead to higher crude oil domestic consumption for these countries.[9] Therefore, following an economic upturn, a rise in domestic consumption of oil could partially offset the increase in revenues from oil exports.

Next, the impact of an oil-specific demand shock ($\varepsilon^{\mathrm{idi}}$) is significant for Norway, Russia and the GCC countries. The positive sign of the coefficients is consistent with

[9]This is especially true for the GCC countries which rank in the first positions for oil consumption per capita (`https://www.indexmundi.com/g/r.aspx?v=91000`).

TABLE (6.8) OLS Estimates of the Linear Regression Model of Stock Returns on Oil Market Shocks

Panel A: Oil-exporting countries								
	Const	e^s	e^d	e^{idi}	W	W_{-1}	R^2	Obs
CAN	0.265 (1.129)	0.052 (0.230)	0.729^b (2.133)	0.395 (1.533)	0.052 (0.945)		0.036	348
MEX	0.255 (0.728)	- 1.054^b (−2.530)	0.183 (0.740)	0.112 (0.297)	0.893^a (9.812)		0.315	302
NOR	0.440 (1.572)	0.208 (0.673)	0.796^a (2.829)	0.625^b (2.368)	0.970^a (12.993)		0.483	348
RUS	0.366 (0.590)	0.371 (0.397)	1.366 (1.571)	2.217^a (2.796)	0.126 (0.802)		0.099	195
SAU	0.047 (0.067)	1.080 (1.627)	0.871 (1.541)	1.223^c (1.872)	0.238^b (2.396)		0.070	155
UAE	- 0.613 (−0.625)	- 0.460 (−0.376)	0.583 (1.024)	1.754^c (1.942)	0.083 (0.459)		0.041	132

Panel B: Oil-importing countries								
	Const	e^s	e^d	e^{idi}	W	W_{-1}	R^2	Obs
CHN	0.206 (0.366)	- 0.085 (−0.125)	0.683 (1.533)	0.347 (0.516)	0.522^a (4.449)		0.103	234
GER	0.547 (1.618)	0.174 (0.498)	0.316 (0.823)	0.462 (1.265)	0.062 (0.909)		0.010	348
IND	0.181 (0.487)	- 0.122 (−0.262)	1.291^a (3.692)	0.620 (1.479)	0.821^a (8.862)		0.332	234
USA	0.407^c (1.738)	0.137 (0.538)	0.268 (0.626)	0.043 (0.134)		0.032 (0.553)	0.006	348

Notes The t statistics (in parentheses) are calculated using the Newey and West (1987) heteroskedasticity-consistent robust standard errors. The dependent variable is real stock market returns. Const is the intercept, W_{-1} is the lagged return of the world stock index, R^2 is the coefficient of determination and Obs is the number of observations used in the regressions. a, b and c denote significance at the 1%, 5%, and 10% level of significance respectively.

the assumption for which positive shifts in precautionary demand for oil generate increases in the price of this commodity and thus increases in stock prices of these countries. It is not surprising to acknowledge that such economies are very sensitive to this type of shock. Figure 3.4 shows that oil rents (as a percentage of GDP) in Norway, Russia, Saudi Arabia and the U.A.E. have been consistently higher compared to oil rents in Canada and Mexico.

It is worth noting that the magnitude of the oil-specific demand shock is particularly high for Russia and the Arab economies. The fact that Russia's stock market returns are highly sensitive to idiosyncratic oil demand shocks is motivated by the fact that economic growth in this country over the past years has been primarily driven by energy exports as documented by Zhu et al. (2016). The results for Saudi Arabia and the U.A.E. underscore the crucial point about the heavy reliance of the GCC countries on oil exports as a driving force for economic growth (Basher, Haug, and Sadorsky, 2018).

Also, the statistical significance of both aggregate and oil-specific demand shocks for Norway corroborates the findings of previous literature. For instance, Bjørnland (2008) reports that Norway' stock returns increase by 2.5% following a 10% increase in oil prices.

Turning now to the oil-importing countries (Panel B of Table 6.8), we notice that oil shocks have only an effect on stock returns in India. An aggregate demand shock generates an appreciation of Indian stocks which is statistically significant at the 1% level. It may seem puzzling, at first, that positive aggregate demand shocks, which drive up oil prices, would be capable of increasing stock returns in this country. However, as discussed in Kilian and Park (2009), an unanticipated increase in global demand for industrial commodities has two effects on the stock returns of an oil-importing country. One effect is a direct stimulus for the national economy and hence for its stock market. The indirect effect is that a positive aggregate demand shock raises the price of oil (and other industrial commodities), slowing down economic activity and depressing stock returns. In practice, it is unclear which effect dominates the other.[10] For India, we can infer that the direct effect more than offsets the indirect one. Another argument which supports this hypothesis is the fact that India has experienced a higher economic growth rate compared to most of the other countries in the sample, during the time under consideration. Oil supply shocks and oil-specific demand shocks, on the other hand, are not statistically significant in either of the four oil-importing countries.

The absence of effects for China and Germany can be reconciled with the findings of Cong et al. (2008) and Cueppers and Smeets (2015). Cong et al. (2008) report that oil shocks do not show a statistically significant impact on major Chinese stock market indices but they do have an effect on stock returns of Chinese manufacturing and oil companies. For Germany, Cueppers and Smeets (2015) find that only certain

[10]For the U.S., Kilian and Park (2009) find that the stimulating effect tends to dominate in the first twelve months following the shock, whereas the depressing effect reaches its full strength only with a delay.

industries are affected by oil shocks, whereas others remain unaffected. Finally, the fact that U.S. stock returns do not react to the structural innovations can be explained by the large size of the oil and gas sector in this country which includes leading companies such as Chevron and ExxonMobil. Another possible explanation is that U.S. net imports of crude oil have steadily decreased since 2006.[11]

Overall, the results in Table 6.8 support the importance of disentangling the different sources of oil price changes in order to understand the stock markets' responses (Kilian and Park, 2009). In line with previous literature, oil supply shocks do not seem to play a significant role in relationship with stock returns as demand-driven shocks do. A plausible explanation is that supply shocks do not have a substantial impact on oil prices in the first place. Several papers claim that the effect of supply-side shocks on oil prices is minimal and has diminished over time (see, e.g., Kilian and Park (2009, p. 1274)).

Lastly, it is important to remark that oil shocks exert an influence on all the six oil-exporting countries but they only affect one oil-importing country. It could be the case that while oil represents just a production input in an oil-importing economy, it represents a crucial source of economic growth in an economy that depends on oil exports. Hence, oil market shocks may not only have a direct impact on the oil sector of an oil-exporting country but they could also generate spillover effects to other sectors of the economy.[12] This argument is especially valid for countries such as Russia, Saudi Arabia and the U.A.E, which have not yet been able to diversify their economies away from oil dependence.

6.4 Oil Market Shocks and Stock Market Co-movement

In this section, we examine whether the three structural shocks have an effect on the stock market co-movement among the countries in our sample.

Our point of departure is the hypothesis that the stock markets of countries which share a common net oil position should react similarly to oil market shocks. Therefore, the three oil shocks should increase the connectedness of stock returns

[11] The historical evolution of U.S. net oil imports can be seen at `https://www.eia.gov/dnav/pet/hist/LeafHandler.ashx?n=pet&s=mttntus2&f=m`.

[12] Also, recall from Chapter 3 that the effects of oil shocks in an oil-exporting country may be amplified by the actions taken by the government via the fiscal channel.

among oil-exporting countries, and analogously, among oil-importing countries. To possibly capture extra relationships within a subset of countries, we also split the oil-exporting (EXP) and oil-importing (IMP) countries into developed and emerging markets according to the classification of the MSCI.[13] Formally, the subsets are defined as:

1. developed oil-exporting countries (DE-EXP): Canada and Norway;
2. emerging oil-exporting countries (EM-EXP): Mexico, Russia, Saudi Arabia and the U.A.E.;
3. developed oil-importing countries (DE-IMP): Germany and the U.S.;
4. emerging oil-importing countries (EM-IMP): China and India.

We begin by computing the cross-sectional standard deviation ($CSSD_t$) index series in (5.63) for each of the six groups of countries. As usual, we check whether the series are covariance stationary. The results of the unit root tests are displayed in Table 6.9. Both the ADF and PP tests reject the null hypothesis at the 1% significance level. On the other hand, the KPSS tests only provide mild evidence against the null hypothesis of stationarity for five series. In light of these results, we conclude that all the series are covariance stationary.

TABLE (6.9) Results of the Unit Root Tests for the CSSD Series

	ADF(τ_1)	ADF(τ_2)	ADF(τ_3)	PP	KPSS(c)	KPSS(τ)
EXP	-2.186^b	-5.994^a	-7.487^a	-10.308^a	0.732^b	0.091
DE-EXP	-5.195^a	-10.464^a	-10.825^a	-17.006^a	0.441^c	0.140^c
EM-EXP	-2.514^b	-6.796^a	-8.209^a	-10.397^a	0.675^b	0.086
IMP	-2.943^a	-8.483^a	-9.050^a	-15.352^a	0.495^b	0.073
DE-IMP	-5.522^a	-10.774^a	-10.756^a	-16.615^a	0.093	0.090
EM-IMP	-4.460^a	-10.938^a	-11.379^a	-15.724^a	0.568^b	0.0418

Notes: Test statistics of the unit root tests outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

Next, we run the six regression models and check if these present any structural breaks. As reported on the left-hand side of Table 6.10, the null hypothesis of

[13]The classification of markets currently in use can be found at `https://www.msci.com/market-classification`.

no structural breaks is firmly rejected for five regression models. By looking at the plots of the OLS-CUSUM tests in Figures B.6a-B.6f in Appendix B, we notice that the empirical fluctuation processes, for these five models, exceed the 5% critical boundaries around the period of the 2007-2008 financial crisis. As a structural break could provide unreliable estimates of the regression coefficients, we adjust the regression model in (5.64) to

$$CSSD_{j,t} = \beta_{0,j} + \beta_{1,j} e^{s}_{j,t} + \beta_{2,j} e^{d}_{j,t} + \beta_{3,i} e^{idi}_{j,t} + DV_t + u_{j,t} \tag{6.1}$$

where DV_t is a dummy variable which equals zero until 2008:11 and equals one thereafter.[14] We set the dummy variable in this way as it seizes the dynamics before and after the financial crisis.[15]

Introducing the dummy variable in the regression models is very effective. Figures B.7a-B.7e in Appendix B show that none of the processes for the regression models including the dummy variable exceed the 5% critical boundaries. The visual inspection is in line with the results of the tests for no structural breaks as displayed on the right-hand side of Table 6.10.

TABLE (6.10) Results of the OLS-CUSUM Test of the Linear Regression Model of CSSD on Oil Market Shocks

	Without dummy		With dummy	
	Test statistic	p-value	Test statistic	p-value
EXP	2.829	0.000^a	1.205	0.109
DE-EXP	2.003	0.001^a	0.909	0.380
EM-EXP	2.592	0.000^a	1.130	0.155
IMP	2.231	0.000^a	0.967	0.306
DE-IMP	1.019	0.249		
EM-IMP	1.610	0.011^b	0.760	0.609

Notes: OLS-CUSUM test outlined in Chapter 5. a, b and c denote statistical significance at the 1%, 5%, and 10% level, respectively.

The estimation results of the linear regression models are presented in Table 6.11. First, we note that the dummy variable is statistically significant in all the cases.

[14]Clearly, for the linear regression model (DE-IMP) which does not present structural breaks we do not include the dummy variable.

[15]On November 25, 2008 the Federal Reserve (FED) began the first round of Quantitative Easing (QE1) to tackle the negative consequences of the financial crisis.

Also, we note that oil market shocks help to explain a much larger portion of the stock market dispersion among oil-exporting countries ($R^2 = 0.166$) compared to the one among oil-importing countries ($R^2 = 0.049$).

TABLE (6.11) OLS Estimates of the Linear Regression Model of CSSD on Oil Market Shocks

Panel A: Oil-exporting countries							
	Const	ϵ^{s}	ϵ^{d}	ϵ^{idi}	DV	R^2	Obs
EXP	7.192^a (15.516)	0.230 (0.665)	-0.330^b (-2.071)	-0.052 (-0.252)	-2.730^a (-4.798)	0.166	132
DE-EXP	4.146^a (18.349)	-0.336^c (-1.820)	-0.268 (-1.031)	-0.174 (-0.937)	-1.463^a (-3.706)	0.060	348
EM-EXP	7.627^a (11.235)	0.364 (1.164)	-0.281 (-1.480)	0.077 (0.351)	-2.771^a (-3.538)	0.142	132

Panel B: Oil-importing countries							
	Const	ϵ^{s}	ϵ^{d}	ϵ^{idi}	DV	R^2	Obs
IMP	5.813^a (22.803)	0.069 (0.310)	-0.172 (-1.046)	-0.195 (-1.083)	-1.163^a (2.891)	0.049	234
DE-IMP	3.852^a (17.394)	-0.004 (-0.020)	-0.031 (-0.146)	0.091 (0.535)		0.001	348
EM-IMP	5.560^a (22.931)	0.061 (0.171)	-0.084 (-0.299)	-0.399 (-1.379)	-1.019^c (-1.860)	0.026	234

Notes The t statistics (in parentheses) are calculated using the Newey and West (1987) heteroskedasticity-consistent robust standard errors. The dependent variable is the CSSD index. Const is the intercept, DV is a dummy variable which equals zero until 2008:11 and equals one thereafter, R^2 is the coefficient of determination and Obs is the number of observations used in the regressions. a, b and c denote significance at the 1%, 5%, and 10% level of significance respectively.

From Panel A of Table 6.11, an unanticipated aggregate demand shock (ε^{d}) exerts a negative effect on the CSSD of oil-exporting countries (EXP) which is statistically significant at the 5% level. This result implies that an increase in oil prices, propelled by rising aggregate demand, is followed by more stock market co-movement among the oil-exporting countries.[16] These results are in line with the findings of Yang, Wang, and Wu (2013, p. 1237) who study a different set of oil-exporting countries. In addition, a positive oil supply shock (ε^{s}) induces more co-movement between the Canadian and Norwegian (DE-EXP) stock returns at the 10% significance level. The latter finding is particularly interesting since neither Canada nor Norway present

[16] Recall from Chapter 5 that a higher value of the CSSD implies higher dispersion in stock returns.

statistically significant responses to oil supply shocks in the country-specific regression models (see Panel A of Table 6.8). This implies that an oil shock which does not affect stock returns of single countries might still explain the co-movement of a set of stock markets.

Conversely, oil market shocks do not have any statistically significant effects on the stock market co-movement among oil-importing countries. This finding is in line with the previous results which show the weak role of oil market shocks for these countries (see Panel B of Table 6.8).

6.5 Alternative Proxy of Global Oil Prices

In the last section, we perform a robustness check to evaluate the sensitivity of the regression results to an alternative proxy for global oil prices. More specifically, we employ the Brent Crude price in place of the WTI price.[17] As shown in Figure 6.2, the Brent price has been, on average, lower than the WTI price for most of the sample period. As outlined in Chapter 3, at the beginning of 2011, the spread started to grow reaching a peak of $28.53 per barrel in September 2011.

The spread in recent years could potentially provide different insights for the analysis of Saudi Arabia and the U.A.E. since the regression models for these countries are estimated only in the most recent part of the sample.[18]

Table C.1 in Appendix C shows the estimation results of the linear regression model of stock returns on oil market shocks.[19]

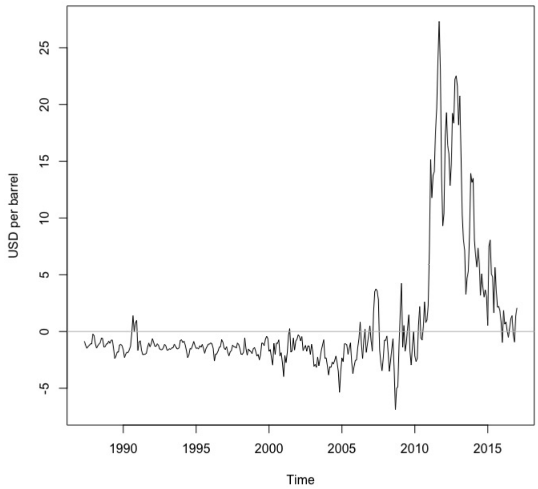
Compared to the results of Table 6.8, the magnitude of an oil-specific demand shock increases for Russia and the Arab countries. A possible explanation for this lies in the fact that Brent is the main benchmark for Europe and Middle East. Hence, the stock markets in these regions could be more sensitive to changes in Brent prices compared to WTI prices. Also, a shock to the precautionary demand for oil now

[17] The series is sourced from the FRED for the period 1987:5-2017:1. This is the longest data span available. Compared to the WTI series, we lose 16 observations. However, this difference should not affect the main conclusions given the large size of our sample.

[18] The estimation results for Saudi Arabia and the U.A.E. are available from 2004:3 and 2006:2, respectively.

[19] We have carried out the same two-stage procedure followed for the WTI series. For the sake of brevity, we omit the results of the preliminary tests and diagnostic checks of the VAR model since these are qualitatively similar to the ones obtained for the WTI series.

FIGURE (6.2) Spread Brent-WTI



Difference between the Price of Brent Crude and WTI in U.S. Dollar per Barrel for the Period 1987:5-2017:1

exerts a positive and statistically significant effect on the Canadian stock returns. Finally, Russia's stock market responds positively to an aggregate demand shock and this is reflected by a substantially higher R^2 (0.144 compared to 0.099 in Table 6.8). In general, the signs of the coefficients are consistent with our underlying hypothesis.

For the oil-importing countries, the situation is unchanged compared to the previous results as only India responds positively to an aggregate demand shock.

Table C.2 in Appendix C shows the responses of the CSSD series to oil market shocks. The results are largely unaffected by the change of the proxy of global oil prices. The only noticeable difference is that now both positive supply and oil-specific demand shocks increase the degree of co-movement between the Canadian and Norwegian stock markets (DE-EXP).

Overall, the results obtained using Brent as a proxy for global oil prices validate the main findings outlined above.

Chapter 7

Conclusions

In this thesis, we seek to explain possible different reactions of stock markets in six oil-exporting countries (Canada, Mexico, Norway, Russia, Saudi Arabia and the U.A.E.) and four oil-importing countries (China, Germany, India and the U.S.) to oil market shocks.

The results of our empirical analysis point toward heterogeneous responses of these two group of countries to oil market shocks.

First, for the oil-exporting countries, positive demand-side oil shocks increase stock returns in Canada, Norway, Russia, Saudi Arabia and the U.A.E whereas positive oil supply shocks decrease stock returns in Mexico. On the other hand, among the oil-importing countries, only India reacts to oil market shocks. An unanticipated aggregate demand shock, which raises oil prices, has a positive effect on Indian stock returns. Even though this finding might seem at odds with the theory linking oil price changes and stock returns in an oil-importing economy, it can be explained by the fact that economic growth in India tends to dominate the negative impact of higher oil prices.

Second, we find that positive aggregate demand shocks induce more stock market co-movement among oil-exporting countries. Conversely, none of the three structural shocks have an effect on the stock market co-movement among oil-importing countries. These findings are in line with the results of Yang, Wang, and Wu (2013) and consistent with the results of the regressions relating country-specific stock returns with the structural shocks. Besides, we find that positive supply shocks, which reduce the price of oil, increase the co-movement between the Canadian and Norwegian stock markets.

Finally, employing an alternative proxy for global oil prices does not undermine our results and, if anything, supports them.

Our results suggest some relevant implications.

We show that both developed and emerging economies which rely on oil exports are sensitive to oil market shocks even after controlling for movements in global stock markets. This finding provides useful information to policymakers in these countries who should be aware of the negative economic consequences of oil price decreases following an oil market shock. For instance, if oil prices fall due to a decline in global activity, these economies may be quite severely affected, as both demand for oil, other goods and services decline. This argument is particularly relevant for Russia, Saudi Arabia and the U.A.E. as the magnitude of demand-driven oil shocks is particularly high for these countries. These economies should attempt to diversify away from oil in order to promote the stability of their stock markets.[1]

Besides, market participants should acknowledge that the performance of the stock markets in the oil-exporting countries studied is related to the trends in the oil market. Hence, investors in these markets should protect themselves against the risk of falling oil prices caused by oil market shocks.

Lastly, our results have implications for global portfolio management. We show that oil shocks affect the stock market co-movement among oil-exporting countries only. Hence, a portfolio composed of stocks in oil-importing countries would be a better pick than a portfolio composed of stocks in oil-exporting countries, in terms of diversification.

Future research, which could eliminate some of the limitations of this thesis, should follow two directions.

First, it would be interesting to examine what are the effects of oil shocks on stock returns across industries in the countries included in our sample.

Second, we could estimate a time-varying parameter vector autoregression (TVP-VAR) which includes both oil and stock market variables. For example, this model could provide useful insights for the U.S. which is gradually switching its net position in the global oil market.

[1] In this regard, it is worth mentioning that in 2016 Saudi Arabia announced a long-term plan (Saudi Vision 2030) aimed at reducing its dependence on oil.

Appendix A

Stock Market Data

TABLE (A.1) Stock Market Indices

Country	Index	Currency	Sample Period	Source
CAN	S&P/TSX Composite	CAD	1986:1-2017:1	Yahoo Finance
MEX	IPC Mexico	MXN	1991:11-2017:1	Yahoo Finance
NOR	OSEBX	NOK	1986:1-2017:1	Yahoo Finance
RUS	MOEX Russia	RUB	2000:10-2017:1	Investing.com
SAU	TASI	USD	2004:2-2017:1	Bloomberg
UAE	DFMGI	USD	2006:1-2017:1	Bloomberg
CHN	SSE Composite	CNY	1997:7-2017:1	Yahoo Finance
GER	GDAXI	EUR	1987:12-2017:1	Yahoo Finance
IND	S&P BSE SENSEX	INR	1997:7-2017:1	Yahoo Finance
USA	S&P 500	USD	1986:1-2017:1	Yahoo Finance
World	MSCI World	USD	1986:1-2017:1	GitHub

Appendix B

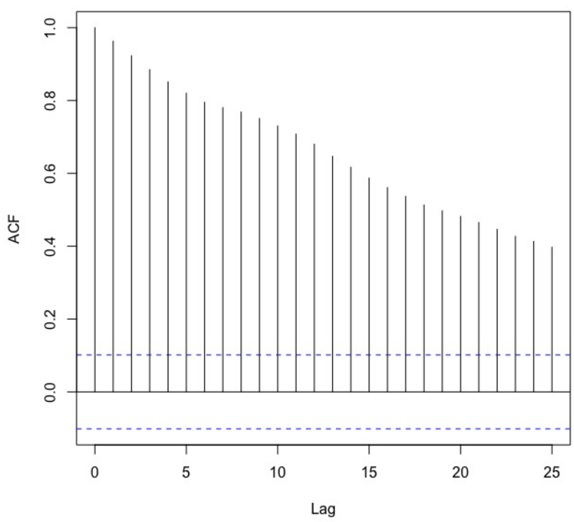
Diagnostic Checks

TABLE (B.1) Critical Values for the Engle-Granger Cointegration Test

T	1%	5%	10%
50	-4.123	-3.461	-3.130
100	-4.008	-3.398	-3.087
200	-3.954	-3.368	-3.067
500	-3.921	-3.350	-3.054

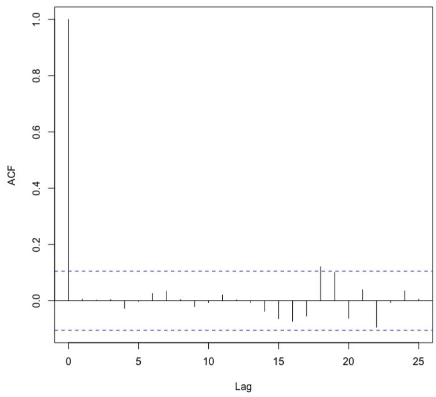
Notes: Critical values for the cointegrating relationship between two variables estimated using the Engle-Granger methodology where T refers to size of the sample. Table sourced from the Instructor's Resource Guide to accompany Enders (2015).

FIGURE (B.1) ACF of the Residuals from the Engle-Granger Approach

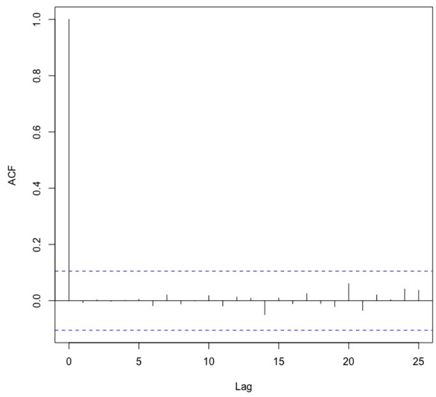


Notes: The blue dashed lines denote the significance threshold.

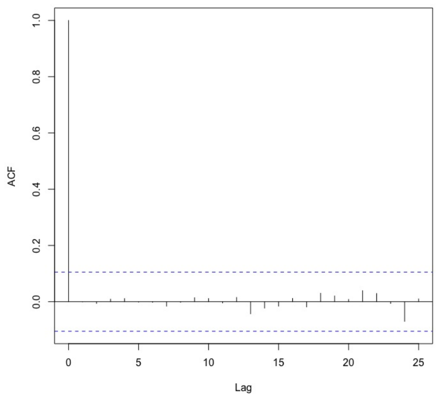
FIGURE (B.2) ACF of the VAR Residuals



(A) Δprod_t



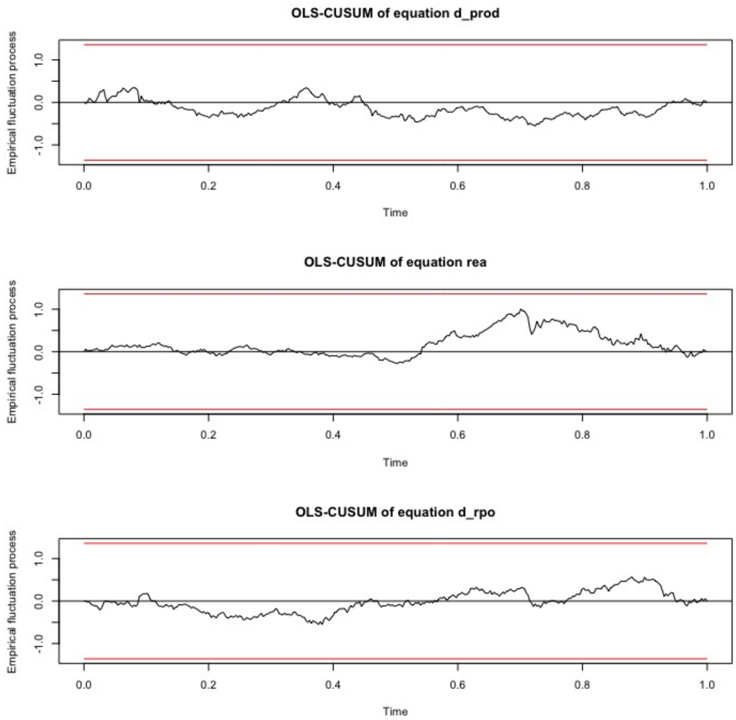
(B) rea_t



(C) Δrpo_t

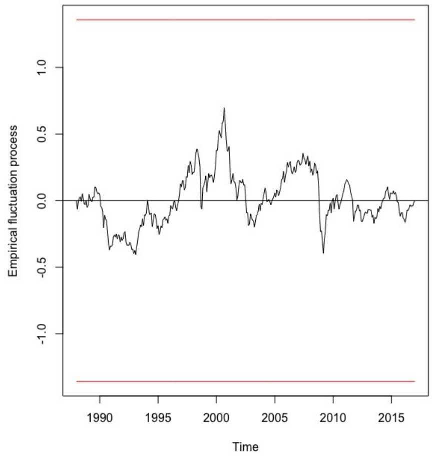
Notes: The blue dashed lines denote the significance threshold.

FIGURE (B.3) OLS-CUSUM of the VAR Model Equations

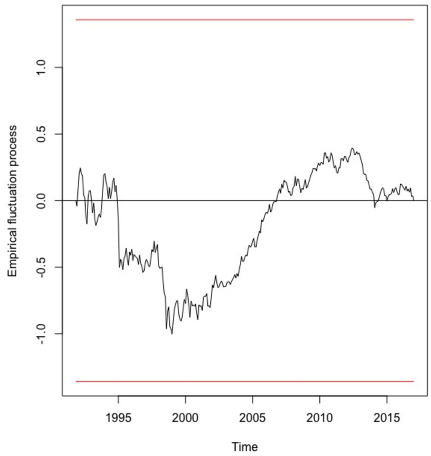


Notes: d_prod refers to $\Delta prod$ and d_rpo refers to Δrpo. Empirical fluctuation processes of the OLS-CUSUM test described in Chapter 5. The red lines denote the significance threshold at 5% level.

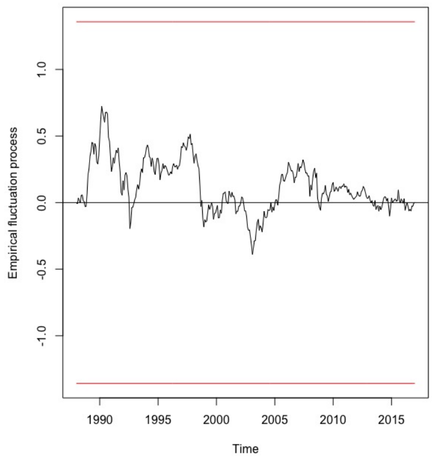
FIGURE (B.4) OLS-CUSUM of the Linear Regression Model of Stock Returns on Oil Market Shocks (Oil-exporting Countries)



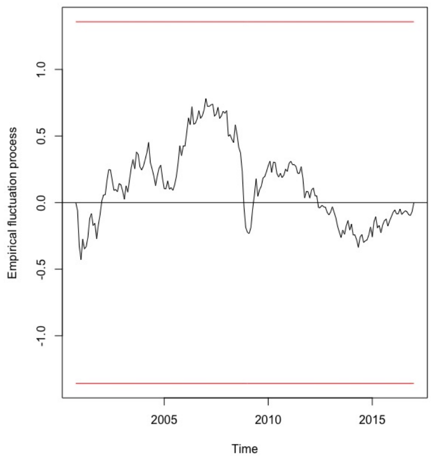
(A) CAN



(B) MEX

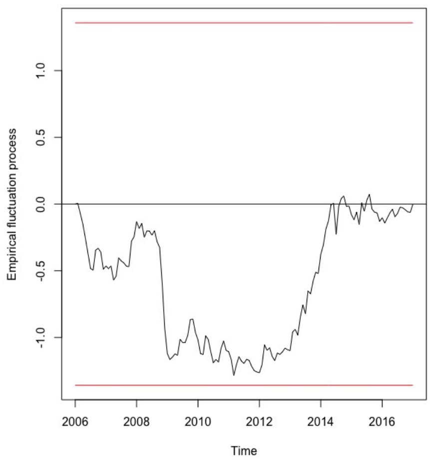


(C) NOR



(D) RUS

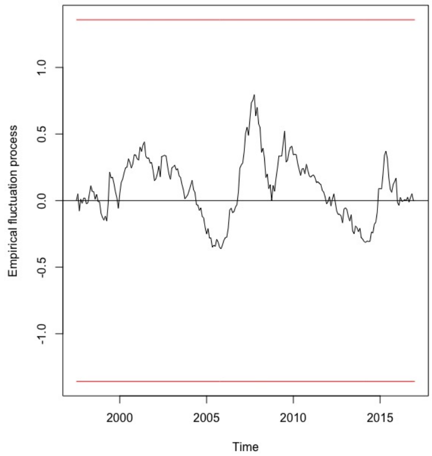
(E) SAU



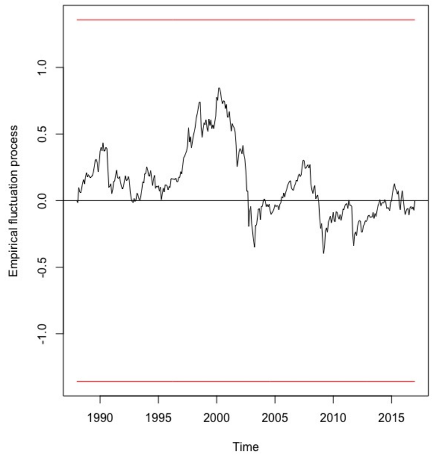
(F) UAE

Note: Empirical fluctuation processes of the OLS-CUSUM test described in Chapter 5. The red lines denote the significance threshold at 5% level.

FIGURE (B.5) OLS-CUSUM of the Linear Regression Model of Stock Returns on Oil Market Shocks (Oil-importing Countries)

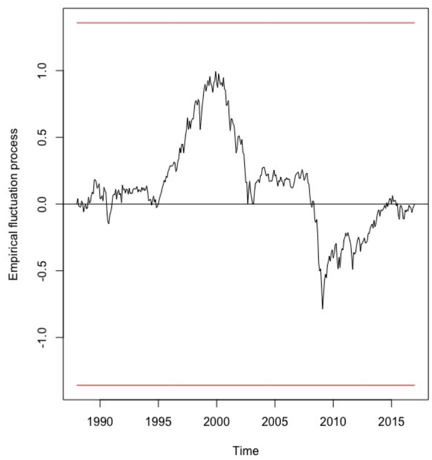


(A) CHN



(B) GER

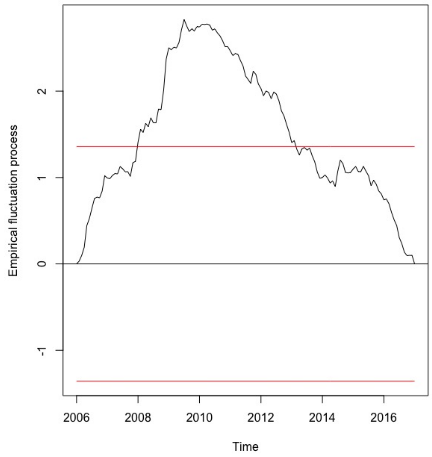
(C) IND



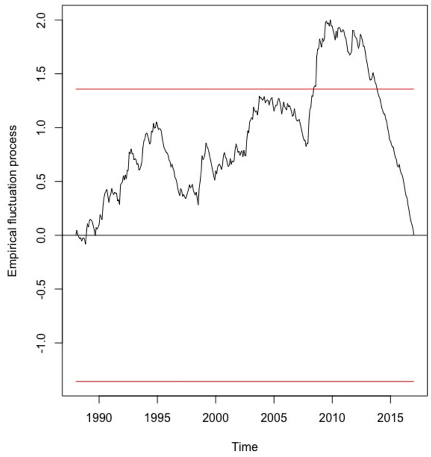
(D) USA

Note: Empirical fluctuation processes of the OLS-CUSUM test described in Chapter 5. The red lines denote the significance threshold at 5% level.

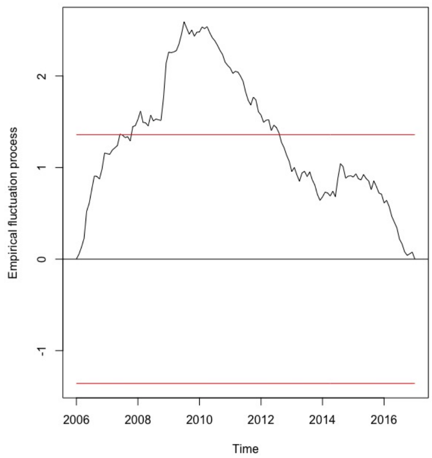
FIGURE (B.6) OLS-CUSUM of the Linear Regression Model of CSSD on Oil Market Shocks



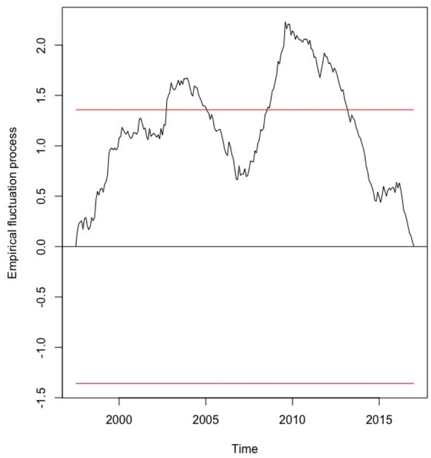
(A) EXP



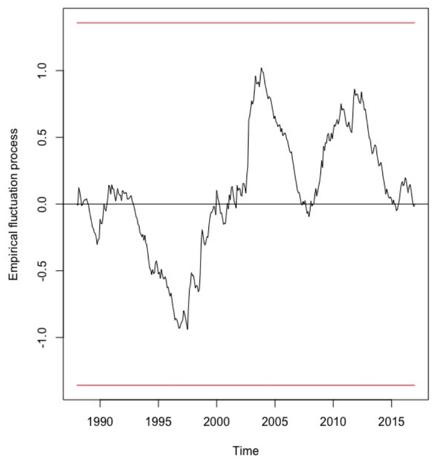
(B) DE-EXP



(C) EM-EXP



(D) IMP

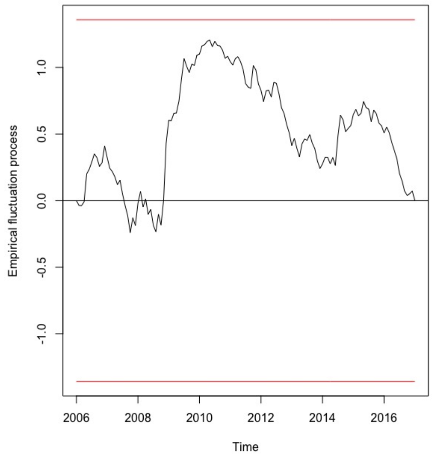


(E) DE-IMP

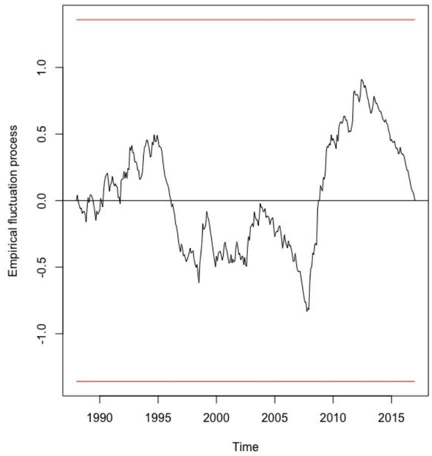
(F) EM-IMP

Note: Empirical fluctuation processes of the OLS-CUSUM test described in Chapter 5. The red lines denote the significance threshold at 5% level.

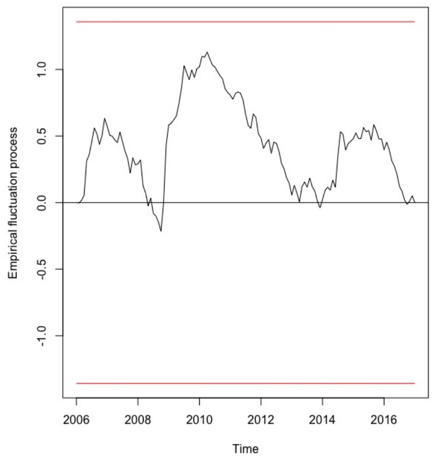
FIGURE (B.7) OLS-CUSUM of the Linear Regression Model of CSSD on Oil Market Shocks (with Dummy)



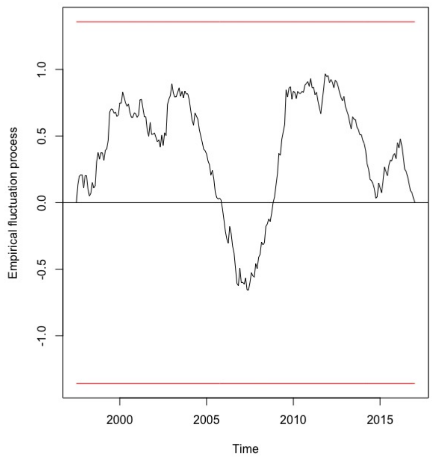
(A) EXP



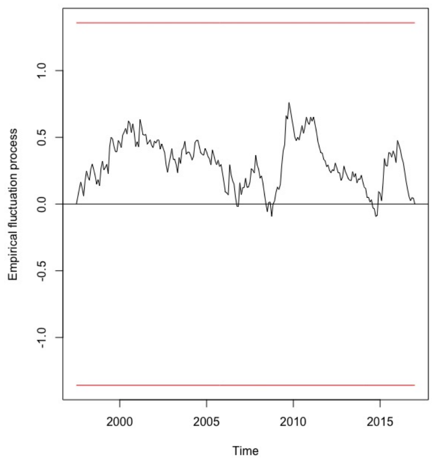
(B) DE-EXP



(C) EM-EXP



(D) IMP



(E) EM-IMP

Note: Empirical fluctuation processes of the OLS-CUSUM test described in Chapter 5. The red lines denote the significance threshold at 5% level.

Appendix C

Robustness Checks

TABLE (C.1) OLS Estimates of the Linear Regression Model of Stock Returns on Oil Market Shocks (Brent)

Panel A: Oil-exporting countries								
	Const	e^s	e^d	e^{idi}	W	W_{-1}	R^2	Obs
CAN	0.261 (1.064)	0.217 (0.937)	0.801^b (2.451)	0.622^b (2.239)	0.052 (0.958)		0.052	332
MEX	0.260 (0.736)	−0.881^b (−2.137)	0.213 (0.791)	0.114 (0.332)	0.893^a (9.869)		0.312	302
NOR	0.316 (1.155)	0.333 (1.167)	0.727^a (2.759)	0.634^b (2.236)	0.973^a (12.889)		0.491	332
RUS	0.348 (0.577)	0.066 (0.095)	1.355^c (1.780)	3.023^a (3.346)	0.130 (0.918)		0.144	195
SAU	0.052 (0.071)	0.520 (1.000)	0.890 (1.550)	1.719^b (2.270)	0.222^b (2.171)		0.080	155
UAE	−0.592 (−0.616)	−0.691 (−0.611)	0.580 (1.092)	2.582^a (2.618)	0.064 (0.358)		0.070	132

Panel B: Oil-importing countries								
	Const	e^s	e^d	e^{idi}	W	W_{-1}	R^2	Obs
CHN	0.204 (0.369)	−0.143 (−0.244)	0.482 (1.093)	0.248 (0.427)	0.532^a (4.391)		0.099	234
GER	0.482 (1.361)	0.132 (0.366)	0.381 (0.998)	0.636 (1.562)	0.055 (0.816)		0.013	332
IND	0.172 (0.458)	−0.045 (−0.104)	1.230^a (3.272)	0.520 (1.139)	0.832^a (9.015)		0.327	234
USA	0.380 (1.583)	0.231 (0.980)	0.162 (0.376)	−0.055 (−0.163)		0.049 (0.825)	0.006	332

Notes The t statistics (in parentheses) are calculated using the Newey and West (1987) heteroskedasticity-consistent robust standard errors. The dependent variable is real stock market returns. Const is the intercept, W_{-1} is the lagged return of the world stock index, R^2 is the coefficient of determination and Obs is the number of observations used in the regressions. a, b and c denote significance at the 1%, 5%, and 10% level of significance respectively.

TABLE (C.2) OLS Estimates of the Linear Regression Model of CSSD on Oil Market Shocks (Brent)

Panel A: Oil-exporting countries							
	Const	ε^{s}	ε^{d}	ε^{idi}	DV_t	R^2	Obs
EXP	7.151^{a} (16.234)	0.025 (0.102)	-0.300^{c} (-1.765)	-0.054 (-0.230)	-2.667^{a} (-4.594)	0.184	132
DE-EXP	4.144^{a} (16.379)	-0.346^{c} (-1.756)	-0.323 (-1.498)	-0.372^{c} (-1.702)	-1.455^{a} (-3.351)	0.072	332
EM-EXP	7.614^{a} (11.447)	0.297 (1.118)	-0.269 (-1.377)	0.093 (0.360)	-2.752^{a} (-3.616)	0.140	132

Panel B: Oil-importing countries							
	Const	e^{s}	e^{d}	e^{idi}	DV	R^2	Obs
IMP	5.820^{a} (22.703)	0.133 (0.632)	-0.237 (-1.416)	-0.153 (-0.832)	-1.180^{a} (-2.933)	0.052	234
DE-IMP	3.885^{a} (16.348)	-0.052 (-0.221)	0.015 (0.067)	-0.258 (-0.041)		0.000	332
EM-IMP	5.569^{a} (24.015)	0.245 (0.821)	-0.187 (-0.640)	-0.231 (-0.741)	-1.056^{c} (-1.900)	0.024	234

Notes The t statistics (in parentheses) are calculated using the Newey and West (1987) heteroskedasticity-consistent robust standard errors. The dependent variable is the CSSD index. Const is the intercept, DV is a dummy variable which equals zero until 2008:11 and equals one thereafter, R^2 is the coefficient of determination and Obs is the number of observations used in the regressions. a, b and c denote significance at the 1%, 5%, and 10% level of significance respectively.

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