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Energy Markets in Transition: Renewables, Bounds and Uncertainty

An Econometric Approach

Evangelos Kyritsis

Dissertation submitted to the Department of Business and Management Science, Norwegian School of Economics, in partial fulfillment of the requirements for the degree of Philosophiae Doctor in Economics

Ἐπεὶ δὲ μετρητική, ἀνάγκη δήπου τέχνη καὶ ἐπιστήμη.
Συμφήσουσιν.

Πλάτων (380 π.Χ.)

Being measurement, it necessarily must be an art and a science. They will assent to this.

Plato (380 B.C.)

Acknowledgments

This PhD journey would neither have started nor been completed without the encouragement and constant support of my supervisor, Jonas Andersson. I am sincerely grateful for his insightful guidance from my very first steps in research as a Master's student until the final steps of my PhD. I would also like to express my deepest gratitude to my co-supervisor, Apostolos Serletis, from the University of Calgary, for providing me with sound and generous advice for my research, and for always being available despite the long physical distance. Without him showing me how to aim high and work even harder, I would be a completely different person. Last, but by no means least, I am grateful to my co-supervisor and PhD coordinator, Leif Sandal, who welcomed me first at NHH, even before I was a student here, and encouraged me to apply for the PhD Programme. His support for and advice on my research career, along with our long interesting discussions, have been invaluable to me.

I have also benefited substantially from my stimulating conversations with Gunnar Eskeland, who has always been encouraging, supportive, and inspiring. Ronald Huisman, from the Erasmus School of Economics, also deserves my special thanks for his sincere interest in my research, helpful advice, and useful discussions. In addition, I am grateful to some of my former professors, namely Constantinos Katrakilidis and Moise Sidiropoulos, from the Aristotle University of Thessaloniki, for introducing me to the world of economics during my undergraduate studies, as well as Panos Pardalos, from the University of Florida, and Athanasios Migdalas and Leonidas Pitsoulis, from the Engineering School of the Aristotle University of Thessaloniki, for their support and guidance during my first graduate studies at the Mediterranean Agronomic Institute of Chania, and later on in my research career.

I am also thankful to my friends and colleagues Erling, Evangelos, Felix, Ingvild, Lars, Lisa, Ole-Andreas, Ondrej, Shiyu, Somayeh, Vit, Yanming, and Yewen, among others for many fruitful discussions, as well as the administrative staff at the department for their commitment to our success.

The final acknowledgements go to my family, Ioannis, Margarita, and Dimitris for their unconditional and continuous support always enabling me to go one step further. Finally, I would like to thank my "samboer" Sandra for her continuous support and for standing by me throughout the entire process. All this would not have been the same without her.

Bergen, February 2018 — Evangelos Kyritsis

Contents

List of Figures

List of Tables

Introduction

For several decades after World War II there were hopes that technology development and in particular nuclear technology evolution would bring a tremendous potential for an abundant, clean, and inexpensive new form of energy, thus rendering economic growth as the major goal of economic policy. And while the so-called 'developed economies' were in a state of full employment, most countries were endeavouring to raise their gross domestic product to the highest possible level. Even the less developed economies set economic growth as their primary economic policy in order to "catch up with the developed countries." Thereby, national programmes that had, as one of their main goals, to increase food production, ended up violating ecological laws, diminishing soil fertility, harming, and finally, reducing biodiversity, through the need for large-scale investments and high energy consumption. Therefore, the concept that technology cannot rush ahead of human needs unless it first identifies them, started being established. Alongside this ascertainment came no indications to convince us that one day this will happen (Ehrlich *et al.*, 1973).

Following these developments, a thirty-member group of scientists, economists, and industrialists, the so-called 'Club of Rome,' was founded in 1968 with the view to a better understanding of the "problematique," as the Club called the interconnected challenges for mankind, which were associated with the predicted economic growth and the depletion of non-renewable natural resources, environmental degradation, industrialisation, population growth, and malnutrition. A group of researchers at the Massachusetts Institute of Technology was thus commissioned by the Club of Rome to investigate these issues. Using a methodology developed by pioneering systems-scientist, Jay Forrester, and under the supervision of Dennis and Donella Meadows, they produced the first study to the Club of Rome, entitled "The Limits to Growth."

Despite the justified limitations of the study, its findings questioned the viability of continued growth in the human ecological footprint and argued that the future quality of life will continue deteriorating as a result of the depletion of natural resources. This broke new ground since at that time it was difficult for the vast majority of people to accept that the consequences of human activities could be sufficiently serious so as to modify the fundamental physical processes on the planet. It focused, therefore, on "how to slow growth" thus raising the rate of economic growth as a major challenge (Meadows *et al.*, 1972).

Almost thirty years later, in 2004, the same research group published a revision of their research, entitled "Limits to Growth: The 30-year Update," concluding that the message for humanity has been changed, and that now it is about bringing the human ecological footprint back down below the earth's limits, with elegance and minimal sacrifice. In fact, they highlighted, through their research findings, that in 1972 the population and economy of humanity may have been below the carrying capacity of the planet, however now this may not be true (Meadows *et al.*, 2004). Consequently, within almost thirty years, not only has the magnitude of scientists' concerns been changing, but the view that the trajectory of humanity is not sustainable, is being established, linking closely the depletion of natural resources to environmental degradation.

Since the 1960's and 1970's, evidence that the concentration of carbon dioxide in the atmosphere has been increasing exponentially, convinced climate scientists in the beginning, and later on, scientists of different disciplines to call for action. In fact it took a remarkably long time until December 1997, when the international community agreed to respond to this call for the first time and take collective action, by signing the Kyoto Protocol and setting internationally binding emission reduction targets. This agreement constituted a 'road map' illustrating the essential actions to avoid major long-term climate change, which had already started taking place due to increased greenhouse-gas emissions caused by human activities. Therefore, during the first commitment period (2008-2012), all the participating countries committed to reduce their greenhouse-gas emissions by an average of 5% compared to the emission levels of the 1990s. From then on several global climate change conferences have taken place under the auspices of the United Nations, with the Paris Agreement in 2016 marking a turning point in the battle against climate change, since for the first time in the history all nations united to legally ratify measures against pollution.

The depletion of natural resources, such as crude oil and natural gas, and environmental concerns, for instance, about the unprecedented increase of carbon dioxide in the atmosphere, together with globalization, growing energy demand, and the deregulation of electricity markets are some of the 'Grand Challenges' that we have been facing within the field of energy markets during the last decades. Alongside these challenges are the issues of energy mix diversification, for instance through the large-scale integration of intermittent renewables, financialization of energy markets, geopolitical change and instability, security of energy supply, and various types of uncertainty from oil prices to energy demand, among other developments which are reshaping the energy markets and rendering their role in the global economy increasingly preeminent, albeit their operations even more challenging. The world is therefore witnessing undeniable evidence that energy markets are going through an era of global transition with new challenges and opportunities.

The transition of electricity markets and in particular the German electricity market, towards a more sustainable energy mix and particularly renewable energy, is one of the main challenges that I have attempted to address in Chapter 1 of this dissertation. Electricity markets play a central role in the global energy scene, but an even more crucial role in the evolving energy market transition. The primary reason for this is that by integrating renewable energy sources into the power generation mix, we manage to adapt, or even respond, to some of the afore-mentioned challenges. That is, the employment of renewables contributes to climate change mitigation, diversification of the energy mix, increase of energy security supply and lastly decoupling economic growth from increasing energy demand. As previously discussed, however, in the case of inexpensive energy or even economic growth, more is not always better, or if it is so, this is true only under specific conditions. Thus, the use of renewables has profound effects on the power systems with which they are integrated, and they challenge the economics and operation of the electricity markets through their intermittent nature. Therefore, the effects of renewables on electricity prices are of great concern, not only to energy market participants such as, for example, risk managers who must have a clear understanding of price dynamics, but also to policymakers who need to adjust the market design based on new challenges in order to improve market efficiency and thus social welfare.

The crude oil market has also been in transition through the process of financialization, thereby establishing a new strand of research attempting to explain the determinants of the oil price by the financialization of the crude oil market. This is in contrast to a large body of literature that traditionally considered that oil prices being determined only by oil-market distinct demand and supply forces. Dramatic oil price fluctuations, for instance from \$140/barrel in the summer of 2008 to \$60/barrel by the end of 2008, support the view that the supply and demand mechanism may not be the only determinants of the oil price, and instead raise the question of whether oil has itself become a financial asset with its price reacting to and influencing other assets in financial markets. The financialization of the crude oil market and interaction with other financial markets is therefore another main topic that I am investigating in Chapter 2 of this dissertation. Motivated by the recent constraints imposed by the zero lower bound on the conventional monetary policy of several central banks, such as the Bank of Canada and the Bank of Japan, I am performring this analysis for the G7 countries and Norway while considering the possible effects of the prolonged episode of zero lower bound.

And while crude oil still is the dominant energy source in the world accounting for 36.9% of the global primary energy consumption in 2016 (EIA, 2017), the renewable energy sector has been experiencing remarkable growth over the past decade, driven by numerous factors, such as reliability and security of energy supply, depletion of natural resources, environmental degradation, and need for decoupling economic growth from energy consumption. Future development, however, of the renewable energy sector depends heavily upon the financial performance of renewable energy companies, since the latter contributes to the success in acquiring private capital for infrastructure investments. Therefore, with the price of other energy products being likely to substitute for renewable energy through positive cross-price elasticities and crude oil being the dominant energy source, Chapter 3 of this dissertation is attempting to investigate the relationship between oil price development and the financial performance of the renewable energy sector, with the aim of shedding some light on the future development of this sector.

Relationships between energy markets, and in particular crude oil, natural gas, and extensively petroleum product prices have been widely investigated in both theoretical and empirical studies. A large number of them explore the relationships among these markets in terms of predictability, through the employment of Granger-causality or other econometric techniques, in order to gain a better understanding of their interactions and improve forecast ability. While Granger non-causality is defined in terms of conditional distribution, most previous studies test non-causality in conditional expectations. Note, however, that a failure to reject the null hypothesis of non-causality in mean does not necessarily preclude the presence of causality at other moments of the distribution. Motivated by these considerations, in Chapter 4 of this dissertation I focus on different ranges of the entire conditional distribution and investigate the dynamic causal relationships between crude oil price and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices within the framework of a dynamic quantile regression model. This reveals a richer set of findings than what is possible by only considering non-causality in a certain moment of the conditional distribution.

This dissertation investigates some of the 'Grand Challenges' that global energy markets are facing during their rapid transition. In doing so, it focuses on some specific energy industries, namely the electricity, renewable energy, and crude oil industries, and it attempts to provide answers to market-oriented questions, for instance, how do intermittent renewable energy sources affect the electricity price formation? What are the corresponding implications for the power system? Does the current energy policy provide the right signals for the envisaged electricity market development? How do financial markets interact with the crude oil market? How does the financial performance of the renewable energy sector respond to oil price shocks? Does their size matter? Does crude oil price Granger-cause the entire conditional distribution of natural gas price or only the tails? Answers to the above questions contribute to a more holistic investigation of these challenges, and therefore facilitate the transition towards a low-carbon and climate-friendly economy.

My thesis is organized into four chapters, each of which is structured as a self contained article. A brief description of the chapters follows.

Chapter 1: Electricity prices, large-scale renewable integration, and policy implications

Co-authored with Jonas Andersson and Apostolos Serletis.
Published in Energy Policy 101, (2017): 550-560.

This chapter investigates the effects of intermittent solar and wind power generation on electricity price formation in Germany. We use daily data from 2010 to 2015, a period with profound modifications in the German electricity market, the most notable being the rapid integration of photovoltaic and wind power sources, as well as the phasing out of nuclear energy. In the context of a GARCH-in-Mean model, we show that both solar and wind power Granger cause electricity prices, that solar power generation reduces the volatility of electricity prices by scaling down the use of peak-load power plants, and that wind power generation increases the volatility of electricity prices by challenging electricity market flexibility.

Chapter 2: The zero lower bound and market spillovers: Evidence from the G7 and Norway

Co-authored with Apostolos Serletis.
Published in Research in International Business and Finance (2017).

In this chapter we investigate mean and volatility spillovers between the crude oil market and three financial markets, namely the debt, stock, and foreign exchange markets, while providing international evidence from each of the seven major advanced economies (G7), and the small open oil-exporting economy of Norway. Using monthly data for the period from May 1987 to March 2016, and a four-variable VARMA-GARCH model with a BEKK variance specification, we find significant spillovers and interactions among the markets, but also absence of a hierarchy of influence from one specific market to the others. We further incorporate a structural break to examine the possible effects of the prolonged episode of zero lower bound in the aftermath of the global financial crisis, and provide evidence of strengthened linkages from all the eight international economies.

Chapter 3: Oil prices and the renewable energy sector

Co-authored with Apostolos Serletis.
Revised and Resubmitted.

Motivated by the fact that energy security, climate change, and growing energy demand issues are moving up on the global political agenda, and contribute to the rapid growth of the renewable energy sector, in this chapter we investigate the effects of oil price shocks, and also of uncertainty about oil prices, on the stock returns of clean energy and technology companies. In doing so, we use monthly data that span the period from May 1983 to December 2016, and a bivariate structural VAR model that is modified to accommodate GARCH-in-mean errors, and it is used to generate impulse response functions. Moreover, we examine the asymmetry of stock responses to oil price shocks and compare them accounting for oil price uncertainty, while effects of oil price shocks of different magnitude are also investigated. Our evidence indicates that oil price uncertainty has no statistically significant effect on stock returns, and that the relationship between oil prices and stock returns is symmetric. Our results are robust to alternative model specifications and stock prices of clean energy companies.

Chapter 4: Dynamic quantile relations in energy markets

Co-authored with Jonas Andersson.
Under Review.

In this chapter we investigate the dynamic relationships between crude oil price and and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices. This is performed by means of Granger causality tests for monthly US data over the period from January 1997 to December 2017. In most previous studies this has been done by testing for the added predictive value of including lagged values of one energy price in predicting the conditional expectation of another. In this study, we instead focus on different ranges of the full conditional distribution. This is done within the framework of a dynamic quantile regression model. The results constitute a richer set of findings than what is possible by just considering a single moment of the conditional distribution. We find several interesting one-directional dynamic relationships between the employed energy prices, especially in the tail quantiles, but also a bi-directional causal relationship between energy prices for which the classical Granger non-causality test suggests otherwise.

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Chapter 1

Electricity Prices, Large-scale Renewable Integration, and Policy Implications

Coauthored with Jonas Andersson and Apostolos Serletis.
Published in Energy Policy 101, (2017): 550-560.

ABSTRACT

This paper investigates the effects of intermittent solar and wind power generation on electricity price formation in Germany. We use daily data from 2010 to 2015, a period with profound modifications in the German electricity market, the most notable being the rapid integration of photovoltaic and wind power sources, as well as the phasing out of nuclear energy. In the context of a GARCH-in-Mean model, we show that both solar and wind power Granger cause electricity prices, that solar power generation reduces the volatility of electricity prices by scaling down the use of peak-load power plants, and that wind power generation increases the volatility of electricity prices by challenging electricity market flexibility.

JEL classification: C22; Q41; Q42.

Keywords: Intermittency, Large-scale integration, Merit-order effect, Volatility, GARCH-in-Mean model.

1.1 Introduction

Electricity markets are gaining increasing importance on the global energy scene. Through adjustments in their market design, electricity markets endeavour to adapt to new challenges and integrate renewable energy sources into the power generation mix. Renewables pledge to mitigate climate change and diversify the energy mix, increase the security of energy supply, and decouple economic growth from increasing energy demand. However, the use of renewables has profound effects on the power systems with which they are integrated, and challenge the economics and operation of the electricity markets through their intermittent nature. See, for example, Pérez-Arriaga and Battle (2012). It is subject to market design whether intermittent power volatility, caused by nature, will penetrate into the power system and pass-through to electricity prices.

Electricity prices reflect the physical peculiarities and economics of the power system as these are captured by supply and demand forces. On the one hand, there is the instantaneous nature of electricity and transmission constraints, and on the other the highly inelastic short-term demand (Sensfuss *et al.*, 2008) and limited economic possibilities of large-scale storage rendering the behavior of electricity prices special and dynamic. Pricing methods that work in the case of financial assets often break down when applied to electricity markets, because the latter are driven by multiple factors and exhibit different underlying data generating processes. Deregulation of electricity markets, which already counts for more than two decades, has provoked fundamental reforms within electricity industries, by introducing increased competition and driving electricity prices to phases of relative tranquility followed by periods of high volatility. In this already challenging power system, intermittent renewables influence electricity prices according to the so-called 'merit-order principle,' which has its origins in the standard microeconomic concept of perfect competition. In line with this, the price of electricity should be equal to the marginal cost of the last needed electricity generation technology, otherwise called marginal plant, to meet electricity demand. Renewables penetrate into the supply curve of the day-ahead market with nearly zero marginal cost and thus get priority dispatch compared to other electricity generation technologies. Accordingly, they shift the supply curve to the right, resulting in a lower electricity price and complex electricity market dynamics.

The effects of renewables on electricity prices are of great concern, not only to energy market participants such as, for example, risk managers who must have a clear understanding of price dynamics, but also to policymakers who need to adjust the market design based on new challenges in order to improve market efficiency and thus social welfare. As Huisman *et al.* (2015, p. 151) recently put it, "an incomplete understanding of these relations could lead to an unintended outcome of the implied policy." Hence, as the role of intermittent renewables increases, it is expected to have remarkable and unprecedented effects on electricity price dynamics, while testing the adequacy and flexibility of electricity market design.

Germany is a pioneer country for renewables integration, and 2015 has been a landmark year, with the growth of renewables in the power generation mix at its highest ever recorded. Agora (2016), a leading energy policy instrument in Germany, points out that "2015 goes down on record as the year in which renewables dominated the power system for the first time ever, becoming by far the most important energy source." The large-scale integration of intermittent renewables has been a natural development in the German electricity industry, especially after its decision in March 2011 to scale down nuclear power plants. This transition of Germany's energy system, known as 'Energiewende,' has been assisted by the German renewable support scheme, which promotes investments in renewable energy generation through the implementation of policy instruments. Accordingly, we can safely argue that the German electricity market has experienced such drastic reforms during the energy transition, that nowadays it constitutes a different electricity market.

This paper contributes to the literature on the effects of renewable power on electricity prices in several ways. First, it fills the gap by disentangling the differential effects of solar and wind power on German day-ahead electricity prices, using daily data, which is as recent as June 2015. Apart from a few studies such as, for example, Clò *et al.* (2015), the majority of the literature focuses on the effects of wind power on electricity prices (because in past years solar power penetration was limited), or treats both solar and wind power as a combination under the name of intermittent renewables. Hence, they ignore the unique features of solar power as well as the corresponding implications for the power system; see Gullì and Balbo (2015). Secondly, since electricity supply nowadays consists largely of stochastic solar and wind power, while electricity demand is captured by electricity load, we are interested in exploring the dynamic relationship between day-ahead electricity prices and supply and demand forces in a multivariate context.

We estimate a univariate GARCH-in-Mean model in order to investigate the effects of solar and wind power on electricity price formation, and therefore explore their different implications in relation to market design. Only a few studies, with the most notable being Ketterer (2014), investigate the effects of renewables on day-ahead electricity price volatility, and most of them do not consider the recent period of high renewable penetration in the German electricity market. Finally, in line with Jónsson *et al.* (2010), we explore the impact of solar and wind power on the distributional properties of German day-ahead electricity prices, under different scenarios of solar and wind power penetration. By doing so, we understand better the effects of solar and wind power on the complex behavior of electricity prices, for instance negative or extreme prices, and consider it in relation to the market design and economics of the German power market.

The paper is structured as follows. In Section 1.2, we give an overview of the deregulation of electricity markets, the subsequent transition towards renewables, as well as the merit-order effect. We also discuss the new challenges of the German electricity market derived from the combination of large-scale integration of intermittent renewables and the limited flexibility of the electricity market. An analysis of negative electricity prices concludes this section. In Section 1.3, we describe the data and investigate their time series properties, while in Section 1.4 the effects of solar and wind power on the distributional properties of electricity prices are investigated. In Section 1.5, we present the GARCH-in-Mean model and discuss the empirical evidence, while in Section 1.6 we conduct a multivariate Granger causality investigation. The last section concludes the paper.

1.2 Challenges in Electricity Markets

Although electricity markets were traditionally designed merely for delivering electricity, nowadays they play numerous important roles in society. For example, sustainable development of energy supply, energy security, environmental protection, climate change mitigation, employment opportunities, and economic efficiency are some of their policy targets. In order to achieve these goals, electricity markets experience profound restructuring, with the most notable being their deregulation and the integration of renewable energy sources into their electricity production mix.

1.2.1 Deregulation and Stylized Facts

The deregulation of electricity markets has provoked fundamental reforms within their industries. Before deregulation, the electricity sector used to be vertically integrated and the public utility commissions set the prices in such a way as to ensure the solvency of the firm. Hence, price variation was minimal and under the rigorous control of regulators (Knittel and Roberts, 2005). After deregulation, however, competition was introduced and price variation rose significantly. Deregulation, in combination with the physical peculiarities and economics of the power system, introduced distinct dynamic properties in electricity prices, which are considerably different from those of financial assets (see Keles *et al.*, 2013). These properties, or stylized facts, have been investigated by a substantial body of literature, including studies by Knittel and Roberts (2005), Higgs and Worthington (2008), Karakatsani and Bunn (2008), Escribano *et al.* (2011), and Fanone *et al.* (2013).

Seasonality is one of the most interesting characteristics of electricity prices, which is predominantly attributed to the highly inelastic short-term electricity demand (see Sensfuss *et al.*, 2008). This can be viewed as a result of the limited efficient storage capabilities that preclude any kind of inventory strategy to be implemented in both the residential and commercial sectors. In combination with the transmission constraints and the instantaneous nature of electricity, any supply and demand shocks will be transmitted immediately to electricity prices, resulting in price spikes and high volatility. Ullrich (2012) investigates the realized volatility and the frequency of price spikes in eight wholesale electricity markets and underlies the need for better understanding of price spikes and volatility. Some other interesting studies on these stylized facts are Huisman and Mahieu (2003), Worthington *et al.* (2005), Karakatsani and Bunn (2010), and Efimova and Serletis (2014). Finally, mean reversion is another specific characteristic of electricity prices, mainly driven by weather conditions (Koopman *et al.*, 2007); it refers to the tendency of electricity prices to revert to a long-run level reflecting the long-run cost of electricity generation.

1.2.2 Transition towards Renewables

Although Germany had not been a pioneer country in the deregulation of electricity markets, as for instance the United Kingdom and Norway, nowadays it attracts special attention as a prominent example of a country integrating renewable energy sources. In fact, 30.1 per cent of its electricity in 2015 came from renewables such as wind and solar, up from 16.6 per cent in 2010 (see Table 1.1). This energy transition, known as Energiewende, is characterized by high growth in renewable energy, and is a natural development in the German electricity industry after the German government's decision in 2011 to phase out nuclear power. Therefore, significant changes have occurred in the German energy mix over the following years with the nuclear power generation falling by 21 per cent during the first year.

Germany achieved this rapid transition through a generous renewable support scheme that relies on three policy instruments: a) fixed-feed in tariffs for renewables accompanied by a take-off obligation, b) a priority dispatch for renewables, and c) very restrictive rules for renewables curtailment that takes place only for security reasons — see Brandstätt *et al.* (2011) and Henriot (2015). Although this support scheme inspired confidence for investors, thus boosting renewable energy investments (Klessmann *et al.*, 2008), it raised a broad discussion related to its high cost that consumers are eventually required to finance (Tveten *et al.*, 2013). Some notable studies that discuss the renewable electricity support instruments are Falconett and Nagasak (2010), Frondel *et al.* (2010), and Verbruggen and Lauber (2012).

1.2.3 Price Formation and the Merit-Order Effect

Similar to every other economic system, the setting of electricity prices is based on the law of supply and demand. Renewables constitute a large part of the current electricity supply in the German electricity market and therefore their influence on electricity prices, through the supply and demand mechanism, should not be disregarded. Economic aspects and pecu-

Table 1.1: Electricity production in Germany by source (%)

Source	2010	2011	2012	2013	2014	2015
Hard coal	18.5	18.3	18.5	19.9	18.9	18.1
Lignite	23.0	24.5	25.5	25.2	24.8	23.8
Nuclear	22.2	17.6	15.8	15.2	15.5	14.1
Natural Gas	14.1	14.0	12.1	10.6	9.7	9.1
Oil	1.4	1.2	1.2	1.1	0.9	0.8
Others	4.2	4.2	4.1	4.1	4.3	4.1
Renewable energies from which	16.6	20.2	22.8	23.9	25.9	30.1
Biomass	4.7	5.3	6.3	6.5	6.9	6.8
Hydro power	3.3	2.9	3.5	3.6	3.1	3.0
Photovoltaic	1.8	3.2	4.2	4.9	5.7	5.9
Waste-to-energy	0.7	0.8	0.8	0.8	1.0	0.9
Wind	6.0	8.0	8.0	8.1	9.1	13.5

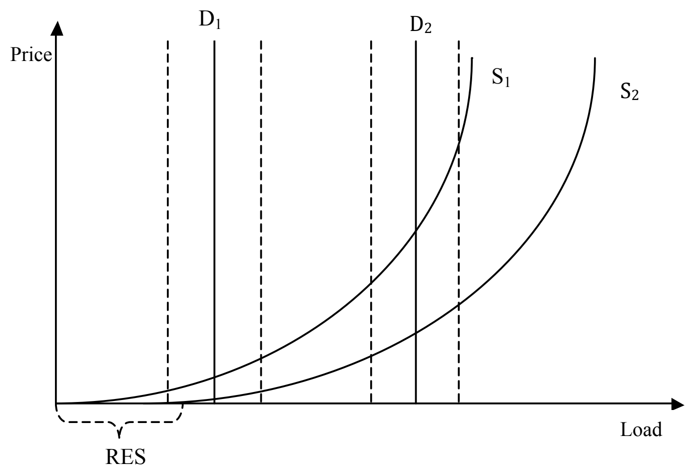
Source: AG Energiebilanzen, 2016.

liarities of electricity markets are actually reflected in the pricing mechanism. That is to say, electricity demand is highly inelastic, capturing the limited ability of consumers to alter their consumption patterns in the short-run, while electricity supply or merit-order curve is discontinuous, convex, and sharply increasing at the high demand level (Karakatsani and Bunn, 2008), indicating the special characteristics of the electricity power generation mix.

The electricity supply curve is constructed based on the aforementioned merit-order principle, according to which supply offers are ranked dependent on their short-run marginal costs (Morales *et al.*, 2014). Therefore, the left part of the curve traditionally consists of supply offers from power plants with low marginal cost such as lignite and hard coal, while the right part of the curve represents the supply offers from electricity generating units with high marginal cost, for instance gas and oil fired power plants. Renewable energy generation faces very low, or even negative marginal cost if renewable support schemes are taken into account, and therefore is usually prioritized in comparison to other electricity generation technologies. Consequently, offers from renewables are located on the left part of the supply curve, thereby replacing more expensive supply offers and shifting the entire curve to the right as illustrated in Figure 1.1. Subject to a specific inelastic demand curve, this results in a lower electricity price and the so-called merit-order effect. The latter simply describes the price diminishing mechanism that is attributed to the renewable electricity generation, which penetrates into the power system.

The magnitude of the merit-order effect depends, predominantly, on three factors: a) the level of electricity demand, b) the slope of the supply curve, which in this context will also be referred to as the merit-order curve, and c) the renewable electricity generation (Sensfus

Figure 1.1: Merit-order effect during peak and off-peak hours



et al., and Keles *et al.*, 2013). Electricity demand and more particularly residual demand, which must be served by conventional power plants, determines the marginal technology that sets the electricity price based on its production cost. The slope of the merit-order curve plays the most important role in the size of the merit-order effect, and depends on numerous factors. Thus, fuel prices influence the value of the merit-order effect, but not all of them have the same impact. Therefore, the prices of the underlying fuels for the base-load power plants are not expected to have a significant impact on the volume of the merit-order effect, since these power plants are rarely substituted by renewables. On the contrary, the prices of fuels that support the mid-load and especially the peak-load power plants, have a greater effect on the size of the price reduction. In fact, Sensfus *et al.* (2008) investigate the merit-order effect on the German electricity market, and conclude through simulation runs with different fuel prices that although a 20 percent price change of the fuels for lignite and nuclear power plants affects the merit-order effect by only 2 percent, a 20 percent price reduction in the price of natural gas reduces the size of the merit-order effect by around 30 percent. Moreover, they underline the significant effect of the ratio of fuel prices, for instance of gas and coal prices on the final result.

Some additional driving factors on the slope of the supply curve are the price of the emission allowances, the capacity of the renewable electricity generation, and the various efficiencies of the power plant portfolio. See Sensfus *et al.* (2008) and Keles *et al.* (2013). Huisman *et al.* (2015) investigate the impact of fuel and emission cost on Nordpool day-ahead electricity prices, and provide empirical evidence of nonlinear dependence. Market power is also an important driving factor for the slope of the merit-order curve, which has seldom been studied in the literature. Gullì and Balbo (2015) investigate the impact of solar production on the Italian electricity prices and analyze the role of the market power in the final outcome. They conclude that solar production can lower the electricity price but only below a specific threshold. The reason is that operators of thermal power plant units may adapt their price strategy based on the expected availability of the renewable power generation in order to offset their reduced revenues which occur during times of renewable penetration. The latter refers primarily for the case of solar power, since it exhibits less intermittent power generation patterns compared to wind. Therefore, renewable power generation does not affect electricity price formation only in a direct way, but also by challenging the economics of the electricity markets with their intermittent nature. Clò *et al.* (2015) provide an interesting literature review of empirical studies regarding the merit-order effect in several countries, including Denmark, Germany, and Spain.

1.2.4 Renewable Energy Intermittency

Although renewable energy sources provide essential benefits for our environment, health, and economy, their intermittent nature challenges the design and operation of electricity markets. As Pérez-Arriaga and Battle (2012, p. 2) put it, "intermittency comprises two separate elements: non-controllable variability and partial unpredictability." Non-controllable variability refers to those situations in which renewable power plants are either unavailable when increased energy requirements occur in the system, or inject substantial amount of energy into the grid irrespective of the electricity demand level. The main reason for this is that renewable energy is determined by weather conditions such as solar radiation or wind speed, contrary to dispatchable generators that adapt their output as a reaction to economic incentives, and therefore the current energy requirements (Hirth, 2013). On the other hand, partial unpredictability describes the limited knowledge about future renewable power generation, due to the stochastic nature of weather conditions.

It is worth noting that similar to other applications, the forecasting horizon is an important factor of precision, and therefore the shorter the time horizon, the more accurate the weather predictions become. Accordingly, electricity markets should be designed in such a way that power systems are getting updated frequently with more accurate forecasts. Although a detailed description of each individual type of electricity market is not within the scope of this paper, it is important to underline that uncontrollable variability effects of renewables impact the day-ahead electricity markets primarily, while unpredictability issues influence the intraday and balancing markets through forecast errors (Morales *et al.*, 2014). This work focuses on the non-controllable variable nature of renewables and its effects on the German day-ahead electricity price, which constitutes a European reference due to its underlying liquidity.

The replacement of dispatchable, conventional power plants with non-controllable variable renewables is a complex procedure, which introduces uncertainty with respect to the market design and particularly for the renewable support mechanism. The main reason is that electricity demand is time-varying and the upstream electricity market should have short-term flexibility to serve the required load. Nicolosi (2010, p. 7257) defines the flexibility of the electricity markets as “their ability to efficiently cover fluctuating electricity demand,” and he adds “this flexibility is influenced by the installed power plant mix and the interaction with other markets.” Traditionally, the German power generation mix consisted of thermal power plants that were designed and scheduled to cover dispatch requirements, which were merely subject to the varying demand forces. However, the integration of renewables increased the variability of residual demand and therefore the operating modes of thermal power plants. Hence, the number of start-ups and shutdowns in thermal production increased significantly in order to balance electrical load and avoid power blackouts. Therefore it can be seen that the role of the conventional power plants is currently twofold; firstly, to adjust to the intermittent renewable power generation, and secondly, to cover the time-varying electricity demand. This significantly increases the call for power system flexibility, as well as the need for the necessary regulatory and operational adjustments. Pérez-Arriaga and Battle (2012) underline the importance of flexibility for the cost of economic dispatch, and comment on their inversely proportional relation. Shutting down and starting up thermal power plants implies increased operation costs due to lower power efficiencies. So the higher the flexibility of the power generation fleet is, the lower the overall cost that is incurred and vice versa.

1.2.5 Negative Prices and their Implications

In the same way that natural resource prices reflect the underlying market scarcities, negative electricity prices represent the limited system’s flexibility. The first negative electricity prices in the European Energy Exchange were observed in October 2008, after the European Energy Exchange (EEX) decided to correct inefficient incidents and more particularly situations when energy oversupply needed to be cut (Nicolosi, 2010). Since then, they have become increasingly common events attracting considerable attention in the literature. Fanone *et al.* (2013) study the case of negative day-ahead electricity prices in the German day-ahead spot market and underline their considerable challenge in energy risk management activities. In a similar study, Genoese *et al.* (2010) show that a sufficient condition for the appearance of negative prices is either a low system load, combined with a moderate wind generation or a moderate system load combined with high wind generation. Besides the other factors, they find wind generation to be the most important influential factor, while they comment on the occurrence of all negative prices during the off-peak period.

Negative electricity prices are not problematic per se, since they are basically efficient for non-storable goods (Nicolosi, 2010). They arise mainly as a result of the large-scale renewable power generation, and the priority dispatch that the renewable support scheme provides them (Brandstätt *et al.*, 2011). Hence in some hours, when the aforementioned sufficient conditions are satisfied, inflexible conventional power plants are forced to ramp-down and give priority to renewables. However, renewables may stop generating electricity only few hours later, and thereby base-load plants need to ramp-up quickly in order to serve the electricity demand. High opportunity costs may occur in these following hours, when prices are above variable costs for conventional power plants, due to their limited flexibility and expensive ramp-ups. This results in the fact that conventional plant operators are willing to bid negative prices into the market in order to avoid these ramp-downs and continue to produce, increasing their revenues. They can follow this pricing strategy as long as the opportunity costs and start-up costs are higher than the negative prices that they need to bid. It is worth mentioning that apart from these costs, long minimum standstill periods and accordingly revenue losses arise for the conventional power plants, before they can start producing again (Genoese *et al.*, 2010). In fact, these long inactive periods threaten the sustainability of the conventional power plants that need high utilization in order to cover their high investment costs (Nicolosi, 2010). Furthermore, they create higher system costs, since a part of demand needs to be produced by other power plants that exhibit lower response time, but more expensive generation.

Another implication of negative electricity prices is the creation of investment incentives for flexible power generation. However, these incentives can be very inefficient and costly to society (Brandstätt *et al.*, 2011). That is to say, although during some hours conventional power plants exhibit negative marginal costs and bid negative electricity prices to avoid their ramp-down, renewables penetrate into the system with zero marginal costs, owing to their priority dispatch. Brandstätt *et al.* (2011) discuss how the operation of renewable energy sources constraints the two leverages of the electricity market, namely prices and quantities; prices are established through fixed-feed in tariffs, while quantities are fixed through priority dispatch and restrictive curtailment. In fact, Brandstätt *et al.* (2011, p. 3736) underline the fact that "market loses degrees of freedom to perform its market-clearing function, at the expense of system-wide economic efficiency." Therefore they suggest voluntary curtailment agreements, as well as maintenance of the priority rule for renewables. Henriot (2015) comments on the limited literature on the economic curtailment, and argues that negative prices are the first market signals for economic curtailment of renewables. Finally, motivated by the aforementioned discussions, we proceed to the next section with the data description.

1.3 The Data

We use daily German electricity spot prices, solar (s_t) and wind (w_t) power generation, and total electricity load (l_t) over the period from January 1, 2010 to June 30, 2015 — a total of 2007 observations. Specifically, we use the day-ahead spot electricity price, Phelix Day Base, which is calculated as the average price of the 24 hours of one day; the Phelix Day Peak, which is the average electricity price of the peak hours; and the average electricity price of the off-peak hours. It is worth mentioning that peak hours cover hours 9 to 20, while off-peak hours cover hours 1 to 8 and hours 21 to 24.[1] The main reason for distinguishing between peak and off-peak hours is the fact that during these hours electricity markets exhibit different characteristics, for instance, flexibility, and economic efficiency, which are accordingly reflected in the electricity price dynamics. In fact, as Ballester and Furió (2015, p. 1606) put it, "the picture has become more informative when peak and off-peak hours are analyzed separately, confirming the fact that these price series should be viewed as different commodities, with different features." All electricity prices and renewable power generation are from the European Energy Exchange, while total electricity load is from the European Network of Transmission System Operators for Electricity (ENTSO-E).

It is worth mentioning that since we investigate the effects of variable solar and wind power generation on day-ahead electricity prices, the predicted, rather than the actual power generation should be employed in the analysis. The main argument behind this is that the actual power generation does not affect the day-ahead electricity volumes and prices directly, but through their predictions that are placed in the market to be cleared (Morales *et al.*, 2014). However, in this analysis we employ the actual renewable power generation and total load for two reasons. First, the data availability for predicted solar and wind power generation is limited, and second, since the predicted total load data is not available we would have to construct our own prediction model. However, this would render our estimation results subject to the generated regressor problem studied in detail by Pagan (1984), since the estimated predictions of total load would only be a proxy for the market expectations. Hence, we follow Nicolosi (2010) and accordingly use the actual solar and wind power generation, as well as the actual total electricity load. Nicolosi (2010, p. 7261) argues that "since, in this article, the actual market situation is analyzed, the realised values are used." From a similar point of view, Mauritzen (2013), who investigates the effect of wind power production on Danish and Norwegian day-ahead prices, uses the actual wind power generation data, as an approximation of the forecasted wind.

Table 1.2 presents summary statistics for the electricity prices, solar and wind power generation, and total electricity load. Figures 1.2-1.7 depict the development of the series

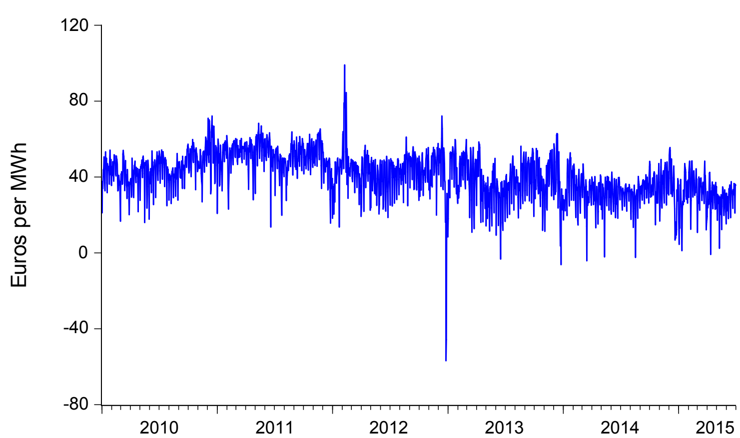
[1] The definition of peak and off-peak hours remains the same during all the months of the year.

Table 1.2: Summary statistics

Variable	Mean	Standard deviation	Skewness	Excess kurtosis	J-B normality
p_t	40.710	12.144	-0.637	6.558	1194.673
$p_{peak,t}$	46.018	14.516	-0.113	4.155	115.817
$p_{off-peak,t}$	35.403	11.130	-2.878	37.184	100490.115
s_t	67090.677	52857.637	0.673	2.433	178.431
w_t	131069.269	110880.605	1.652	6.169	1752.855
l_t	1326660.182	164759.086	-0.390	2.399	81.027

from January 2010 to June 2015. This is the period after the latest profound modification which occurred in Germany's renewable energy policy in 2010. Significant changes followed in the electricity production mix [see Table 1.1], with the most important being the nuclear phase-out, and the rapid integration of photovoltaic and wind power systems. Despite the aggressive renewable energy transition, Germany currently produces more electricity from coal (hard coal and lignite) than renewables, with coal being at a slightly higher level than in 2010. This comes about as a result of the fact that energy transition towards renewables is a long-term and complex process, and therefore the major part of a nuclear power production has to be replaced by other energy sources, such as coal. Natural gas also remains a considerable source of the electricity production mix, despite its decline in recent years, since it supports the flexible peak-load power generation that complements the variable nature of renewables. So in fact, Germany is still strongly dependent on heavily polluting fossil-fuels, and therefore far from meeting the emission reduction target of 40 percent by 2020, compared to 1990 levels.

Figure 1.2: All hours electricity prices



Some stylized facts of electricity prices are discernible from Figure 1.2. A yearly season is present with the price showing a tendency to decrease during the first half of the year and recover gradually by the end of it. The pattern becomes more obvious during the last years of our sample period, possibly due to implications of the energy transition. In addition, we identify a mean reverting behaviour, and a slight tendency for the price to decrease over the last six years, signifying the success of the regulatory changes. Some periods of high volatility followed by periods of relative tranquility can also be identified. Another interesting stylized fact of electricity prices is sudden price spikes. Ullrich (2012) defines price spikes as the combination of an upward jump and a reversal, while he underlines their risky nature for wholesale electricity markets. Electricity price spikes can be attributed to limited economic possibilities of large-scale electricity storage, but should also be investigated in relation to renewable energy sources. Due to these price spikes, the electricity price distributions exhibit high kurtosis and fat tails (see Figures A1.1-A1.3), thus leading to substantial challenges for the operations of energy risk management.

Figures 1.3 and 1.4 show the actual solar and wind power generation during the sample period. We find out that each energy source has its own advantages and areas where compromise is necessary. Wind power production provides the power market with high amounts of energy most of the year, but its output is highly volatile due to its intermittent nature. In contrast, solar power production is more stable than wind power production, and therefore easier to incorporate into medium-term planning (Kovacevic *et al.*, 2013). However, a consistent pattern related to the seasons of the year becomes obvious in the solar production that reaches its maximum during the summer and decreases again gradually during the winter. The inverse seasonal pattern is partly identified in wind power production, thus

Figure 1.3: Solar power production

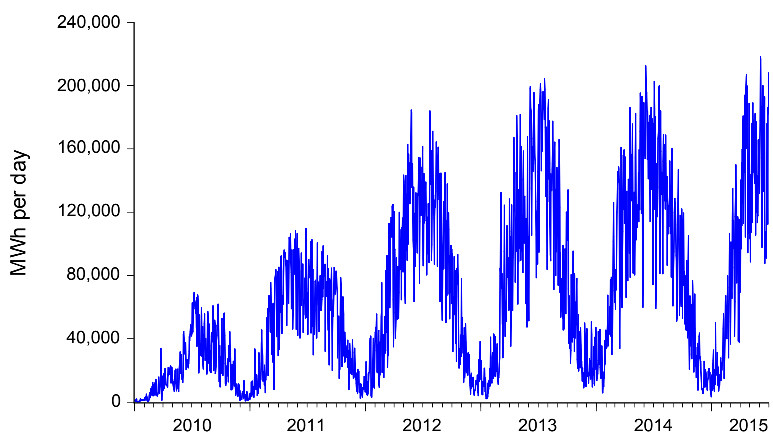
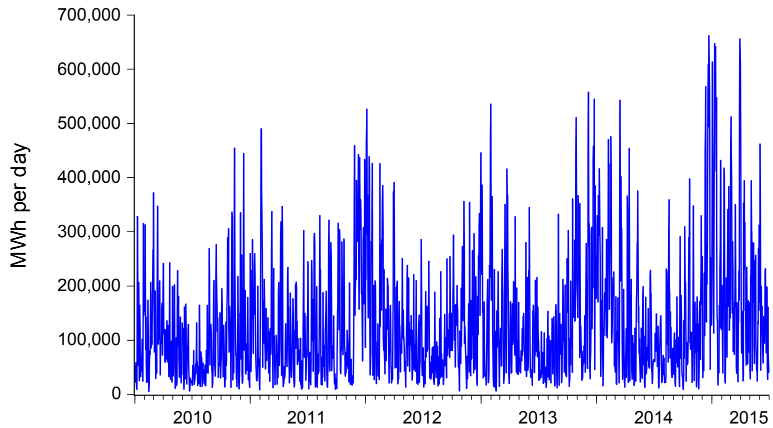


Figure 1.4: Wind power production



indicating the extent to which the complementary nature of the solar and wind power generation can be exploited in the future for a hybrid power generation system. The high penetration rate of solar power into the electricity generation mix is also discernible from Figure 1.3, as a result of generous policy incentives and sharp decline in installation costs.

Electricity demand is an equally important factor in price formation as the electricity supply. In the power systems, it is captured by the total electricity load which is illustrated in Figure 1.5. We can see clearly that electricity demand is well aligned to wind power production, reaching its maximum during the winter, and falling off gradually during the summer. In fact, as Agora (2015, p. 15) puts it, "Germany continues to be a winter peaking country primarily due to the demands of lighting and water and space heating; 6.1 percent of space heating is fueled electrically, including night storage systems and heat pumps."

Figure 1.5: Electricity load

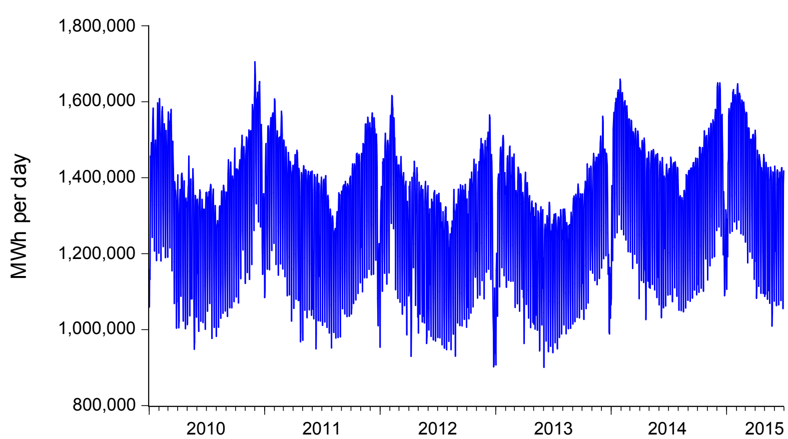
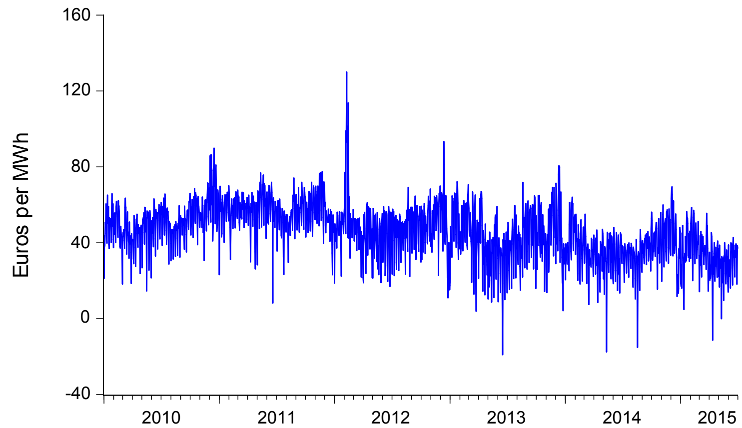


Figure 1.6: Peak electricity prices



In fact, electricity demand follows an inverse seasonal pattern than solar power production, which pushes down the peak electricity price. By looking at Figure 1.3, and Figures 1.6 and 1.7, we notice that peak electricity prices get lower values than off-peak electricity prices during the spring and summer seasons. So, we may conclude that the spread between peak and off-peak electricity prices decreases when solar power generation reaches its maximum and vice versa. However, this conclusion might rely only on some coincidental facts, and therefore additional empirical investigation is necessary.

Before we continue with the empirical analysis, we conduct some necessary unit root and stationary tests in each of the employed series in Table 1.3, in order to test for the presence of a stochastic trend in the autoregressive part of the series. The Augmented Dickey Fuller (ADF) test [see Dickey and Fuller, 1981] and the Dickey-Fuller GLS test [see Elliot, Rothen-

Figure 1.7: Off-peak electricity prices

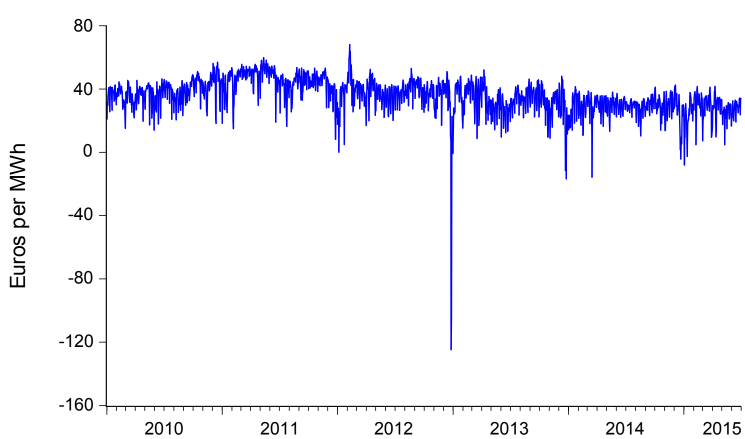


Table 1.3: Unit root and stationarity tests

Variable	ADF τ_μ	DF-GLS μ	KPSS $\hat{\eta}_\mu$	KPSS $\hat{\eta}_\tau$
p_t	-4.458*	-1.894	3.699*	0.408*
$p_{peak,t}$	-3.969*	-1.656	3.455*	0.332*
$p_{off-peak,t}$	-4.845*	-2.340*	3.455*	0.396*
s_t	-2.613	-1.098	1.597*	0.107
w_t	-11.805*	-8.286*	1.107*	0.101
l_t	-4.838*	-1.647	0.399	0.307*

Note: An asterisk indicates significance at the 5% level.

berg, and Stock (1996)] evaluate the null hypothesis of a unit root against an alternative of stationarity. We assume a constant, and select the optimal lag length based on the Bayesian information criterion (BIC). In addition, Kwiatkowski *et al.* (1992) tests are used in order to test the null hypothesis of stationarity (around a constant, for test statistic $\hat{\eta}_\mu$, and around a trend, for $\hat{\eta}_\tau$). We note that electricity prices during all hours and peak hours are not very informative regarding their unit root properties, although they should be stationary based on their mean reverting behavior [see Schwartz (1997), Simonsen *et al.* (2004), Weron *et al.* (2004), and Cartea and Figueroa (2005)], which is also verified by their historical development. Since overdifferencing may be more harmful than including a unit root series in levels, we use the levels of these series alongside the careful checking of the stationarity of the residuals in the model. An examination of the unit root and stationarity tests for the rest of the series, in combination with their historical development in Figures 1.3-1.5, and Figure 1.7, suggest that their levels are stationary, or integrated of order zero, $I(0)$. Last, we check for multicollinearity by using auxiliary regressions, as well as by examining the correlation matrix of the independent variables. Both of them suggest that there is no sign of severe multicollinearity.

1.4 The Effects of Solar and Wind

Having analyzed the descriptive statistics and characteristics of the employed series, the question remains how solar and wind power generation affects day-ahead electricity prices. Therefore, in this section we analyze the way that the main properties of the electricity price distribution react to different amounts of solar and wind power generation, while taking into account total electricity load. We follow Jónsson *et al.* (2010) and divide our data into intervals, according to solar and wind power penetration; penetration here is defined as the ratio of each electric power source to the total electricity load. Tables 1.4 and 1.5 summarize

Table 1.4: Price distribution properties for different solar power penetration levels

	0-7%	7-14%	14-21%
Mean	43.307	36.023	28.031
Standard deviation	12.128	9.725	9.676
Skewness	-1.026	-0.180	-0.757
Kurtosis	5.837	0.472	0.955
Observations	1378	550	79

Table 1.5: Price distribution properties for different wind power penetration levels

	0-5%	5-10%	10-15%	15-20%	20-25%	25-55%
Mean	46.066	42.258	39.312	36.026	32.371	22.866
Standard deviation	10.218	10.578	9.498	9.533	10.938	14.337
Skewness	-0.164	0.264	-0.278	-0.151	0.182	-2.165
Kurtosis	0.350	1.021	0.507	-0.458	-0.414	9.029
Observations	684	562	353	174	100	134

the properties of price distribution for different scenarios of solar and wind power penetration respectively, while Figures 1.8 and 1.9 illustrate the corresponding histograms of electricity prices.

In the case of solar, the first two lines of the table show that both the mean and standard deviation of the electricity price decrease as solar power penetration increases. Moreover, the third and fourth central moments are calculated for each interval. Skewness, which is a measure of the degree of asymmetry of a distribution, takes always negative values indicating the left long tail, while kurtosis is high in the beginning, thus capturing the heavy tails of the distribution, and decreases significantly for solar power penetration higher than 7 percent. Hence, there is statistical evidence that the probability of extremely low electricity prices decreases when solar power penetration gets larger. Figure 1.8 verifies this change in the distributional properties of electricity prices.

The mean of the electricity price also decreases for higher levels of wind power penetration. It is important to state that for wind power penetration higher than 25 percent, the mean of electricity price declines by around 50 percent. However, the standard deviation of the electricity price distribution increases as wind power penetration gets larger, providing some evidence of augmented volatility — see Jónsson *et al.* (2010). Skewness and kurtosis do not provide any obvious pattern, apart from the last interval where electricity price

Figure 1.8: Distribution of prices for different intervals of solar power penetration

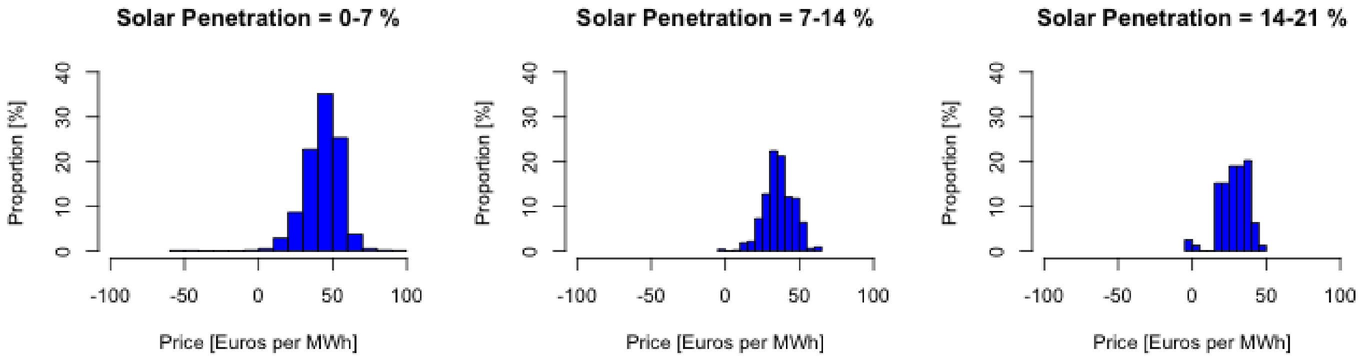
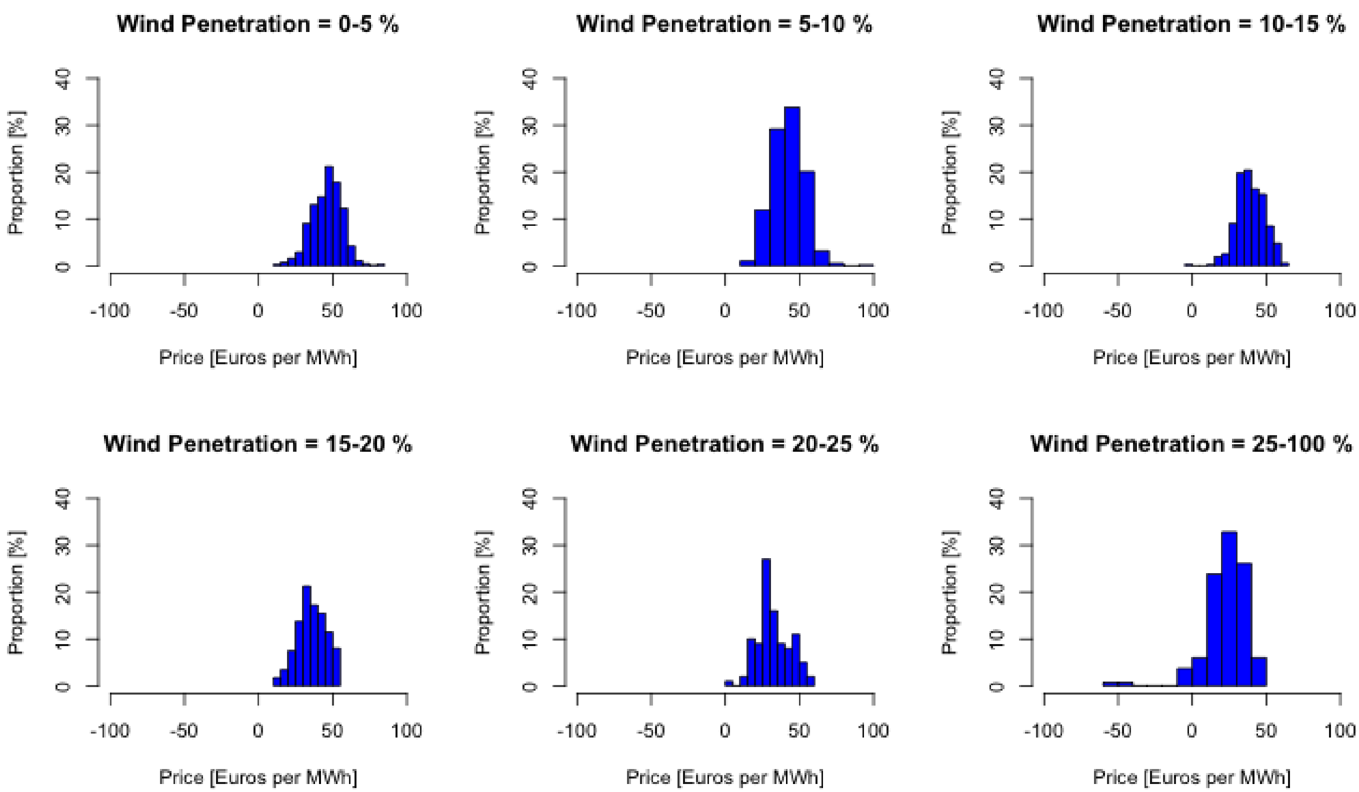


Figure 1.9: Distribution of prices for different intervals of wind power penetration



distribution exhibits negative skewness and high kurtosis. That is to say, the probability of very low electricity prices increases when wind power serves more than 25 percent of the electricity demand. This rapid change of distributional properties during the large interval might be an indication of non-linear effects of wind power generation on electricity prices.

1.5 GARCH Modelling

This section presents three univariate GARCH-in-Mean models for three different electricity prices. In particular, we estimate three GARCH(1,1) models that apply to German day-ahead electricity prices during all hours, peak hours, and off-peak hours. In each case, we specify the mean equation based on the Schwarz Information Criterion (SIC), the Akaike Information Criterion (AIC), and the Hannan-Quin Information Criterion (HQC) (see panels A, B, and C of Table 1.6), which all suggest the AR(7) as the optimal model specification. Accordingly, the three mean equations are represented as

$$p_t = \alpha + \beta_1 \sqrt{h_t} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 s_t + \beta_{10} w_t + \beta_{11} l_t + \varepsilon_t \tag{1.1}$$

$$p_{peak,t} = \alpha + \beta_1 \sqrt{h_t} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 s_t + \beta_{10} w_t + \beta_{11} l_t + \varepsilon_t \tag{1.2}$$

$$p_{off-peak,t} = \alpha + \beta_1 \sqrt{h_t} + \sum_{i=1}^{7} \beta_{1+i} p_{t-i} + \beta_9 s_t + \beta_{10} w_t + \beta_{11} l_t + \varepsilon_t \tag{1.3}$$

where $\sqrt{h_t}$ is the conditional standard deviation, s_t the solar power generation, w_t the wind power generation, and l_t is the total electricity load.

The variance equation of the model is a classic GARCH(1,1) equation augmented with additional regressors — the solar power generation, wind power generation, and the total electricity load. The resulting variance equation is

$$h_t = c_0 + a_1 \varepsilon_{t-1}^2 + b_1 h_{t-1} + b_2 s_t + b_3 w_t + b_4 l_t \tag{1.4}$$

where h_t is the conditional variance and ε_{t-1}^2 are the squared residuals.

It is noteworthy that in contrast to a large part of the literature, we actually include the negative electricity prices in our analysis, since we consider them useful for a better understanding of the market functioning, and also because there is some evidence for a direct relation between them and renewable power generation. The empirical consideration of negative electricity prices for the case of the German/Austrian electricity market is rarely found in the literature since they were not present until 2009 (Ziel*et al.*, 2015). However, Keles

Table 1.6: Optimal AR lag in the mean equation

	A. All prices			B. Peak prices			C. Off-peak prices		
Lag	AIC	SIC	HQ	AIC	SIC	HQ	AIC	SIC	HQ
1	5.558	5.591	5.570	6.095	6.128	6.107	5.464	5.497	5.476
2	6.097	6.134	6.111	6.354	6.390	6.367	5.684	5.720	5.697
3	5.859	5.898	5.873	6.405	6.444	6.419	5.787	5.826	5.802
4	5.753	5.794	5.768	6.164	6.206	6.179	5.643	5.685	5.658
5	5.411	5.456	5.428	5.918	5.963	5.934	5.303	5.348	5.320
6	5.389	5.437	5.407	5.891	5.939	5.909	5.275	5.323	5.293
7	5.363	5.413	5.382	5.848	5.898	5.867	5.259	5.309	5.277
8	5.548	5.601	5.567	5.849	5.903	5.869	5.260	5.313	5.279

et al. (2012) include them in their simulation study and get better results, while Fanone *et al.* (2013) also argue in favor of their inclusion. Therefore, we include the negative prices in our analysis without cutting off or shifting the series. Moreover, we do not apply any extreme value theory, and we merely filter values that exceed, by ten times, the standard deviation of the original price series[2]. We replace the outliers, which arise from the combination of exceptional high wind penetration and low demand, with the median of the respective series, which is a robust statistic.[3]

The empirical estimates for the three models, equations (1.1) and (1.4), equations (1.2) and (1.4), and equations (1.3) and (1.4), are presented in panels A and B of Tables 1.7, 1.8, and 1.9. All autoregressive coefficients, with the exception of the fifth during all hours and off-peak hours, as well as the fourth and fifth during peak hours, are found positive and statistically significant at the 1% level, while GARCH-in-Mean effects are found significant at the 5% level, but only for the case of electricity prices during peak hours. Hence, risk captured by electricity price volatility seems to propagate towards electricity prices during peak hours and affect them in a positive way. The most striking feature in the mean equation is the negative effect of solar and wind power generation on electricity prices, which is in line with the literature. In fact, wind exhibits a more severe effect than solar during all hours of the day, while the solar effect is significant during peak hours, but not during off-peak hours. In contrast, the total electricity load has, as expected, a positive impact on electricity prices throughout all hours of the day, while its effect becomes more prominent during peak hours when the electricity system is tight. Consequently, electricity prices increase with higher demand

[2]It is a common practice in the literature, for outlier detection purposes to filter values that exceed three times the standard deviation of the original series. However, we use the threshold of ten times, so that we solve some potential numerical problems and at the same time include as many observations as possible.

[3]Only 2 observations out of 2007 for the electricity price during off-peak hours are replaced with the median of the series.

Table 1.7: Univariate GARCH base model

A. Conditional mean equation

Constant	10.850 (0.3252)
$\sqrt{h_t}$	0.086 (0.0867)
p_{t-1}	0.463 (0.0000)
p_{t-2}	0.097 (0.0005)
p_{t-3}	0.075 (0.0060)
p_{t-4}	0.068 (0.0081)
p_{t-5}	0.042 (0.0755)
p_{t-6}	0.069 (0.0026)
p_{t-7}	0.162 (0.0000)
s_t	-3.465E-05 (0.0000)
w_t	-4.481E-05 (0.0000)
l_t	4.037E-05 (0.0000)

B. Conditional variance equation

Constant	23.159 (0.0000)
ε^2_{t-1}	0.226 (0.0000)
h_t	0.447 (0.0000)
s_t	-1.483E-05 (0.0000)
w_t	1.385E-05 (0.0000)
l_t	-1.436E-05 (0.0000)

C. Standardized residual diagnostics

$Q(30)$ p-value	0.0001
$Q^2(30)$ p-value	0.9958

and this rise is even greater when demand is high, relative to the other hours of the day and the power system capacity.

In the variance equation, the GARCH coefficient on h_{t-1}, which reflects the persistence of past shocks on the variance, is moderately high (0.552) during peak hours, and low (0.278) during off-peak hours. The ARCH coefficient on ε^2_{t-1}, which captures the impact of new shocks, is always found very low, while total electricity load which reflects the electricity demand profile, surprisingly, decreases electricity price volatility during all hours of the day. Finally, the most interesting feature in the variance equation is the significant effect of solar and wind power generation on electricity price volatility. Specifically, solar power production reduces electricity price volatility in contrast to wind power production that augments it. This finding is in accordance with the previous results from the analysis of distributional properties of electricity prices under different renewable power penetration, where the stand-

Table 1.8: Univariate GARCH peak model

A. Conditional mean equation

Constant	-7.033 (0.3232)
$\sqrt{h_t}$	0.121 (0.0233)
p_{t-1}	0.390 (0.0000)
p_{t-2}	0.124 (0.0000)
p_{t-3}	0.062 (0.0096)
p_{t-4}	0.043 (0.0719)
p_{t-5}	0.057 (0.0116)
p_{t-6}	0.082 (0.0001)
p_{t-7}	0.207 (0.0000)
s_t	-6.838E-05 (0.0000)
w_t	-5.035E-05 (0.0000)
l_t	5.557E-05 (0.0000)

B. Conditional variance equation

Constant	26.318 (0.0000)
ε_{t-1}^2	0.198 (0.0000)
h_t	0.552 (0.0000)
s_t	-1.476E-05 (0.0018)
w_t	1.953E-05 (0.0000)
l_t	-1.656E-05 (0.0000)

C. Standardized residual diagnostics

$Q(30)$ p-value	0.0000
$Q^2(30)$ p-value	0.9011

dard deviation of electricity prices was found to decrease with higher solar power penetration, but to increase with higher wind power penetration.

The effects of solar and wind power generation on electricity price characteristics can be understood better through the analysis of the merit-order effect (see Figure 1.1). First of all, every type of renewable power generation technology induces a merit-order effect, since they can always replace expensive fossil-fuel power generation due to their low, short-run marginal cost and priority dispatch. What really differentiates the effect of each renewable power source on electricity prices, is the relation of its power generation pattern with the special power system characteristics. In the case of solar, it is common knowledge that its greatest amount of production occurs during the same hours of peak electricity demand and therefore expensive peak-load power generation. Hence, solar power generation is expected to exhibit the strongest merit-order effect, compared to different renewable power sources,

Table 1.9: Univariate GARCH off-peak model

A. Conditional mean equation

Constant	3.834 (0.2747)
$\sqrt{h_t}$	-0.054 (0.1417)
p_{t-1}	0.476 (0.0000)
p_{t-2}	0.092 (0.0002)
p_{t-3}	0.070 (0.0024)
p_{t-4}	0.060 (0.0049)
p_{t-5}	0.039 (0.0766)
p_{t-6}	0.099 (0.0000)
p_{t-7}	0.120 (0.0000)
s_t	-1.503E-06 (0.6436)
w_t	-3.861E-05 (0.0000)
l_t	2.552E-05 (0.0000)

B. Conditional variance equation

Constant	22.663 (0.0000)
ε^2_{t-1}	0.143 (0.0000)
h_t	0.278 (0.0000)
s_t	-1.723E-05 (0.0000)
w_t	3.313E-05 (0.0000)
l_t	-1.394E-05 (0.0000)

C. Standardized residual diagnostics

$Q(30)$ p-value	0.0000
$Q^2(30)$ p-value	0.0001

during peak hours. Accordingly, by looking at Figure 1.1, we notice that the new electricity price, after solar power penetration, is set by the intersection of the demand curve D_2 and the new supply curve S_2. What is really noteworthy in this case, is not only the significantly lower system price but also the lower gradient of the new merit-order curve, where the demand curve crosses it. Thus, a new electricity price is set by 'cheaper' power generation, and demand variation can be handled adequately without high cost peak power plants penetrating into the system.

Moreover, solar power generation exhibits low variability, and therefore mid-load power plants can adjust their power production to residual demand efficiently, through their flexibility. In this way, solar power generation manages to reduce electricity price volatility which is characterized by large and frequent price spikes. On the other hand, wind power capacity is more than double that of solar and so, it is expected to induce a larger merit-order effect in total during the day. Combined with high variable power production, wind challenges the operation of power system, and more particularly its flexibility. That is to say, large amounts of wind power penetrate the system with high variability, and alternate the level of residual demand that conventional power plants need to serve. Thus, increased cycle effects and technology switching occur, causing frequent price spikes and increased price volatility. This effect becomes more prominent during off-peak hours, when system flexibility is even lower; base-load power plants, such as lignite or hard coal, bid negative prices in order to avoid ramp-downs, and thereby introduce negative price spikes and increase electricity price volatility.

Finally, Panel C of Tables 1.7, 1.8, and 1.9 reports the Ljung-Box test statistics for the residuals. The Ljung-Box Q test for residual autocorrelation does not pass at conventional significance levels for all the lags; however, autocorrelation plots for residuals show very little autocorrelation and certainly no particular pattern that can be due to non-stationarity or seasonality. Overall, the diagnostic tests suggest that all GARCH models are correctly specified.

1.6 Granger Causality

In this section, we test for Granger causality from solar power generation, wind power generation, and total electricity load to day-ahead electricity prices, within the already specified GARCH framework given by the equations (1.1) and (1.4), equations (1.2) and (1.4), and equations (1.3) and (1.4). In fact, we investigate in the spirit of Granger (1969) whether past information about solar power generation, wind power generation, or total electricity load improves the prediction of electricity prices, beyond predictions that are based merely on past electricity prices.[4] We do that in a multivariate context, and use the Wald (1943) test in order to investigate whether the coefficients of solar, wind, or load, respectively, are zero, thus not Granger-causing electricity prices.

First, we test for Granger causality between electricity prices and solar power generation. Hence, we test the null hypothesis that the set of coefficients of solar, in the mean and variance equations, are jointly zero. If the null hypothesis is rejected, then we can safely conclude that solar Granger-causes the corresponding electricity price distribution. In addition, we explore the same causal relations for the case of wind power generation as well as total electricity load. Table 1.10 reports the results of these tests for electricity prices during all hours, peak hours, and off-peak hours; p-values lower than 0.01 indicate rejection of the null hypothesis of no Granger causality at the 1% significance level. The results clearly indicate

[4]Market forecasts about solar power generation, wind power generation, and total electricity load are provided before daily auction takes place at 12.00 pm.

Table 1.10: p-values for Granger causality

	Electricity price		
Causal variable	All hours	Peak hours	Off-peak hours
Solar	0.0000	0.0000	0.0000
Wind	0.0000	0.0000	0.0000
Load	0.0000	0.0000	0.0000
Solar & wind	0.0000	0.0000	0.0000

that solar power generation, wind power generation, and total electricity load Granger-cause electricity prices at the 1% significance level.

Moreover, we investigate the combined impact of the two most important, intermittent, renewable energy sources in the German electricity market, solar and wind on electricity prices. Hence, we test the null hypothesis that the four coefficients of solar and wind power generation in the mean and variance equations are jointly zero. By looking at Table 1.10, we conclude that their combined impact Granger-causes electricity prices and modifies their distributions. Hence, we arrive at the conclusion that with our data, there is statistically significant evidence for Granger causality from solar power generation, wind power generation, and total electricity load to electricity prices. An interesting direction for future research would be to investigate the same causal relations in the context of non-linear models, while exploring the complex intraday dependence of hourly prices.

1.7 Conclusion

Climate change, environmental degradation, growing energy demand, depletion of natural resources, and limited energy security, all render the deployment of renewable energy sources in the electricity industry of high importance for decades to come. However, despite their many advantages, renewables challenge the operation of electricity markets with their intermittent nature. This paper discusses the ongoing transition of the German electricity market towards renewables, as well as the effects of intermittent solar and wind power generation on electricity price formation through the supply and demand mechanism. More importantly, it provides a study of the relationship between day-ahead electricity prices and solar and wind power generation and total electricity load for all hours, peak hours, and off-peak hours, using data over the period from 2010 to 2015. It also investigates the distributional properties of electricity prices under different scenarios of solar and wind power penetration.

We find that there are causal relationships from solar power generation, wind power generation, and total electricity load to electricity prices during all hours, peak hours, and off-peak hours. We provide evidence that although both solar and wind power generation induce a merit order effect, they have different effects on the volatility of electricity prices and their higher order moments. In particular, solar power generation reduces the volatility of electricity prices while it reduces the probability of electricity price spikes. On the other hand, wind power volatility passes through to electricity prices volatility, and introduces electricity price spikes. While the volatility of renewable power is driven by the stochastic nature of weather conditions, the volatility of electricity prices is also subject to market design.

The findings of this paper underline that effective and sustainable integration of large-scale renewable energy begins with a clear understanding of the distinct properties of each renewable energy source, as well as of its interaction with different parts of the power system. Increased flexibility seems to be the crucial element for addressing different aspects of renewable energy intermittency, such as variability or uncertainty, and rendering renewable energy sources viable and reliable. Hence, flexible conventional power generation, adequate transmission grid, and contribution of renewable energy to system stability are some of the potential ways to increase system flexibility. However, reducing the flexibility requirements through policy measures, such as economic curtailment of renewable generation, energy storage, demand response, and market interconnection can achieve similar results. Lastly, optimal management of renewable resources, for example, through geographic decorrelation, or resource complementarity is another key consideration for future deployment of large-scale renewables.

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1.8 Appendix

Figure A1.1: Histogram of all hours electricity prices

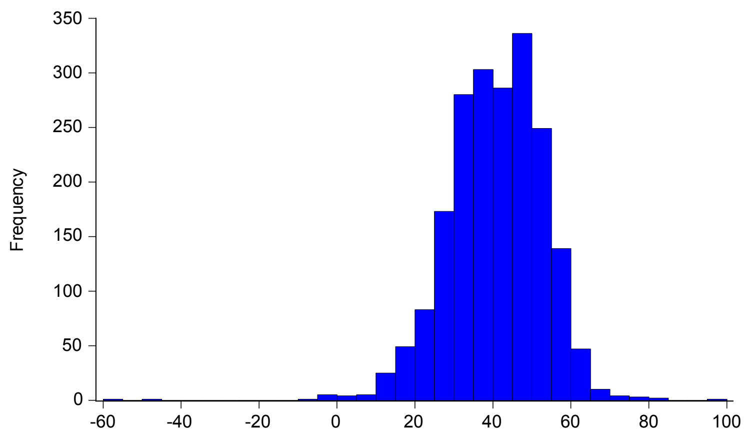


Figure A1.2: Histogram of peak electricity prices

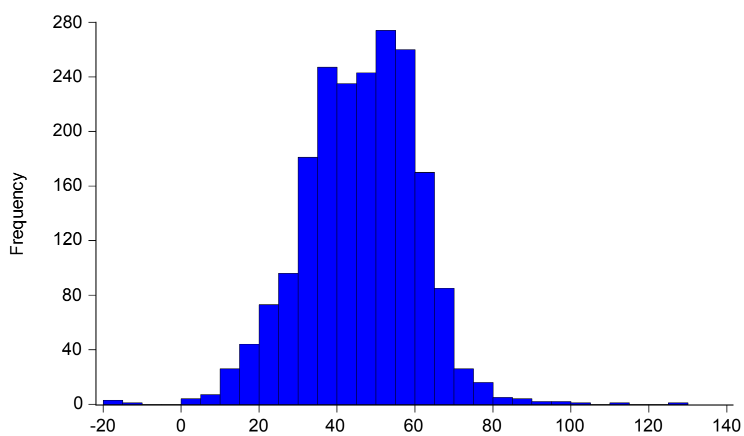
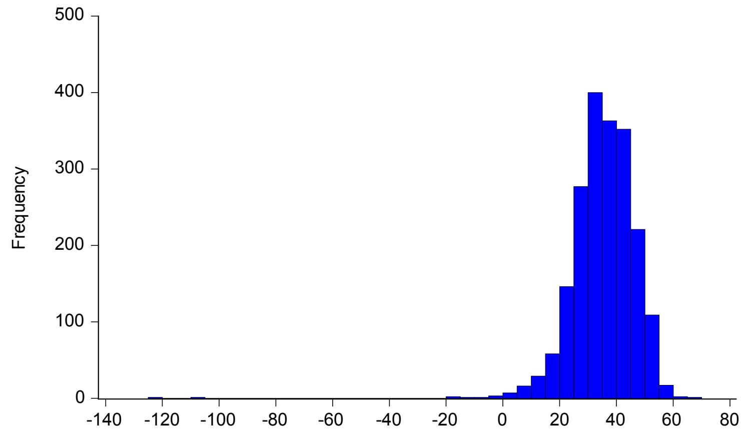


Figure A1.3: Histogram of off-peak electricity prices



Chapter 2

The Zero Lower Bound and Market Spillovers: Evidence from the G7 and Norway

Coauthored with Apostolos Serletis.
Published in Research in International Business and Finance (2017).

ABSTRACT

This paper investigates mean and volatility spillovers between the crude oil market and three financial markets, namely the debt, stock, and foreign exchange markets, while providing international evidence from each of the seven major advanced economies (G7), and the small open oil-exporting economy of Norway. Using monthly data for the period from May 1987 to March 2016, and a four-variable VARMA-GARCH model with a BEKK variance specification, we find significant spillovers and interactions among the markets, but also absence of a hierarchy of influence from one specific market to the others. We further incorporate a structural break to examine the possible effects of the prolonged episode of zero lower bound in the aftermath of the global financial crisis, and provide evidence of strengthened linkages from all the eight international economies.

JEL classification: C32, E32, E52, G15.

Keywords: Crude oil, Financial markets, Mean and volatility spillovers, Structural breaks, VARMA-BEKK model.

2.1 Introduction

Crude oil constitutes one of the world's most important primary energy commodities, and arguably affects the global economy through several different channels or transmission mechanisms. Some notable studies that investigate the effects of crude oil prices on different aspects of the economy are Hamilton (1983), Mork (1989), Lee *et al.* (1995), Elder and Serletis (2010), and Jo (2014). Oil prices were traditionally determined by oil-market distinct demand and supply forces whereas Kilian (2009), in an impressive study, disentangles the determinants of oil price fluctuations, and underlines the importance of global economic activity triggered by the state of the global business cycle. Another strand of the literature, however, attributes the recent dramatic oil price fluctuations to the financialization of commodity markets and speculative activities, which induce oil prices to depart from their fundamental values. See, for example, Singleton (2014) and Juvenal and Petrela (2015). Motivated by these developments and the recent increase of oil price volatility, the aim of this paper is to explore for spillovers and interactions among the crude oil market and the three most important financial markets, namely the bond, stock, and foreign exchange markets. Moreover, in the aftermath of the global financial crisis, we examine the effects of unconventional monetary policy, when the Federal Reserve and other central banks of the G7 countries as well as Norges Bank (the Norwegian Central Bank), cut their policy rates to their effective zero lower bound.

There is a substantial body of literature investigating crude oil price fluctuations, as well as the transmission channels through which they affect different macroeconomic measures, as for instance the GDP — see Hamilton (2003). In recent years, however, a new strand of research has emerged studying and trying to explain the determinants of the price of oil by the financialization of the crude oil market, rather than solely by changes in economic fundamentals. Dramatic oil price fluctuations, for instance from \$140/barrel in the summer of 2008 to \$60/barrel by the end of 2008, support the view that the oil price might not be only determined though its primary supply and demand mechanism, and raise the question of whether oil has itself become a financial asset with its price reacting to and influencing other assets in financial markets. Indeed, since the early 2000s the financialization of commodity markets, and more particularly the oil market, started taking place with financial investors and portfolio managers using energy assets as a means to diversify their portfolios and hedge their exposure against uncertainty risk — see, for example, Ta and Xiong (2012) and Hamilton and Wu (2014). In fact, Alquist and Kilian (2010) comment on the financialization of the oil market, and based on data from the Commodity Futures Trading Commission argue for an unprecedented increase in speculative activities after 2003. Specifically, it is estimated that the total value of assets allocated to commodity index trading strategies increased from \$15 billion at the end of 2003 to \$260 in mid-2008 [see Creti and Nguyen (2015)], while Daskalaki and Skiadopoulos (2011) attribute the financialization of energy markets to different return behavior and low correlation with stock and bond returns.

In this regard, Fattouh *et al.* (2013) examine whether the drastic changes in oil prices during the period from 2003 to 2008 can be viewed as a result of the increased financialization of the oil market, but find evidence that supports the view of economic fundamentals as the main determinant of the oil price. However, this view has been challenged by Juvenal and Petrela (2015), who argue that speculation constituted a major factor in the oil price increase between 2004 and 2008, as well as its subsequent collapse. It is worth noting that several studies investigate the role of speculation in the oil market through different channels. Hamilton (2009) suggests that speculation may occur through the supply side of the market, by speculators purchasing a high number of futures contracts and thereby signalling higher expected prices. In contrast, Kilian and Murphy (2014) look at speculation from the demand side, and more particularly through the demand for oil inventories that are driven by shifts in expectations, not captured by demand and supply factors. Although there is no consensus among academic researchers about how much crude oil financialization and speculative activities are responsible for oil price fluctuations during the past decade, they all agree that participation of financial investors in the oil market has rendered crude oil a financial asset with new stylized facts, as for instance increased price volatility.

The effects of oil price changes on stock prices have been investigated extensively by numerous research papers. Kilian and Park (2009), in an interesting and influential study, treat the price of oil as endogenous, and examine the impact of oil price changes on stock market returns in the United States, by disentangling the supply and demand factors of the oil market. Their empirical results suggest that stock markets react more strongly to changes in global aggregate demand. Recently, and from a similar point of view, Ahmadi *et al.* (2016) investigate the impact of the global oil market on the U.S. stock market taking into account determinant factors from both the crude oil and stock markets. Their findings corroborate the view that a positive global demand shock increases the market return, while a shock to speculative demand for crude oil depreciates the stock market. They also argue that omission of the stock market determinants overestimates the contribution of the oil price shocks in stock market variation. Some more interesting studies on the relationship between oil prices and stock prices using different types of econometric tools are Kling (1985), Jones and Kaul (1996), Sadorsky (1999, 2001, 2012), Cong *et al.* (2008), Park and Ratti (2008), Lee *et al.* (2012), Li *et al.* (2012), Ding *et al.* (2016), and Joo and Park (2017).

Another very interesting relationship with a less extensive yet still growing literature is between oil prices and exchange rates. Oil price changes affect a country's exchange rate primarily through two separate transmission channels, while the impact differs between oil-importing and oil-exporting countries. The first one was initially introduced by Golub (1983) and Krugman (1983), and refers to the wealth effect channel, according to which an oil price increase is related to a wealth transfer from an oil-importing to an oil exporting country, which in turn induces a real depreciation of the exchange rate of the former country, and vice versa. For an empirical application, see Kilian *et al.* (2009). The second transmission mechanism is within the context of the trade balance, based on which higher oil prices result in an improved trade balance of the oil-exporting country, and thereby to a local currency appreciation (vice versa for an oil-importing country). Related empirical evidence is provided by Amano and van Norden (1998), while Buetzer *et al.* (2012) underline the danger of oil price increases to eventually steer the economies of oil-exporting countries towards the Dutch disease. This view, however, has recently been challenged by Bjørland and Thorsrud (2016), who use Australia and Norway as representative cases studies, and argue that booming resource sectors may have significant productivity spillovers to non-resource sectors, while commodity price growth related to global demand is also favourable. In the same study, it is noted that commodity price growth which is unrelated to global activity is less favourable, due to the significant real exchange rate appreciation and reduced competitiveness. In this regard, Basher *et al.* (2016) build upon their previous work and find evidence of nonlinear interaction between oil prices and exchange rates in both oil exporting and importing economies, after they first separate the underlying sources of the oil price movements, according to Kilian's (2009) approach, to an oil supply shock, an oil-market specific demand shock, and a global economic demand shock. Specifically, they find evidence for substantial currency appreciation in oil exporting countries after oil demand shocks whereas global economic demand shocks are found to influence both oil exporting and importing countries, though there is no systematic pattern of appreciating and depreciating exchange rates. Some other interesting studies on this link are Sadorsky (2000), Chen and Chen (2007), and Chen *et al.* (2010).

Moreover, there is an extended literature analyzing the relationship between oil prices and interest rates; a relationship in which the conducted monetary policy, through changes in interest rates and monetary aggregates, plays an important role. In this regard, Krichene (2006) analyzes the link between monetary policy and oil prices, and finds evidence of a two-way relationship contingent on the type of oil shock. Specifically, he finds that during a supply shock, oil price increases cause interest rates to rise whereas falling interest rates cause oil prices to increase during a demand shock. Moreover, the fact that both oil prices and interest rates have increased prior to the majority of postwar U.S. recessions, triggered the intensive interest of literature to explore this relationship in regard to economic activity. Bernanke *et al.* (1997, 2004) try to answer the question of whether those recessions were caused by oil price increases, or by contractionary monetary policy. Using Hamilton's (1996) measure of oil price shocks, they argue that oil price and interest rate increases contribute to the recessions to the same extent, while Hamilton and Herrera (2004) find that oil price shocks have a greater impact on the economy, and that tightening monetary policy does not have such a great effect as implied by Bernanke *et al.* (1997). Hammoudeh and Choi (2006), in contrast, study the impact of oil price and interest rate on the Gulf Cooperation Council's (GCC) stock markets, and provide evidence that only the short-term interest rate has an important, but mixed, effect on the GCC markets. More recently, and within the framework of a dynamic stochastic general equilibrium model, Kormilitsina (2011) shows that tightening monetary policy amplifies the negative effects of the oil price shock.

In the aftermath of the global financial crisis and Great Recession, many central banks, such as the Federal Reserve, the Bank of Japan, the European Central Bank, the Bank of England, the Bank of Canada, and the Norges Bank lowered their policy rates towards, or slightly above, the zero lower bound in order to provide additional monetary stimulus to their economies. Since the monetary policy rate has been used as the primary operating instrument during the last decades and zero was by that time considered the lowest bound, central banks lost their usual ability to signal policy changes via changes in interest rate policy instruments, and attempted further monetary easing by resorting to unconventional measures, such as forward guidance, asset purchase programs, and credit easing. Filardo and Hofmann (2014) investigate the effectiveness of forward guidance by four major central banks, namely, the Federal Reserve, the Bank of Japan, the European Central Bank, and the Bank of England, and conclude that although it has reduced the volatility of near-term expectations about the future path of policy interest rates, the evidence for its impact on expected interest rates has varied significantly, thus making it difficult to draw firm conclusions about their overall effectiveness in reliably stimulating further actual economies. Some more interesting studies on the effectiveness of unconventional monetary policies are Hamilton (2012) and Gambacorta *et al.* (2014). Furthermore, Serletis and Istiak (2016) investigate the relationship between economic activity and Divisia money supply shocks and argue, based on evidence of a symmetric relationship, in favor of monetary aggregates as appropriate policy instruments, since they are measurable, controllable, and have predictable effects on goal variables.

Motivated by the aforementioned discussions, we investigate mean and volatility spillovers between the crude oil market and the three most important financial markets, the bond, stock, and foreign exchange markets, using a multivariate volatility model. This model was first proposed by Bollerslev *et al.* (1998) and has become much more widely used in economics and finance, since it allows for shocks to the variance of one of the variables to 'spill-over' to the others. A recent example is the work by Gilenko and Fedorova (2014) who use a four-dimensional BEKK-GARCH-in-mean model to investigate the spillover effects between the stock markets of BRIC countries (Brazil, Russia, India, and China). In fact, as Bauwens *et al.* (2006, p. 79) put it, "is the volatility of a market leading the volatility of other markets? Is the volatility of an asset transmitted to another asset directly (through its conditional variance) or indirectly (through its conditional covariances)? Does a shock on a market increase the volatility on another market, and by how much? Is the impact the same for negative and positive shocks on the same amplitude?" It is worth mentioning that although there is a substantial body of literature exploring the interactions among the four markets, most of them study each relationship separately rather than in a systems context. Some related studies that investigate up to three markets together are Nadha and Hammoudeh (2007), Akram (2009), Basher *et al.* (2012), and Diaz *et al.* (2016). Here, we follow Serletis and Xu (2018) and examine the possible effects of monetary policy at the zero lower bound in the aftermath of the global financial crisis, while providing international evidence from each of the seven major advanced economies (G7) and the small open oil-exporting economy of Norway. The main argument behind this is that spillovers and interactions among the four markets might vary across different international economies, since the latter exhibit different characteristics, such as oil dependency or conducted monetary policy.

The rest of the paper is structured as follows. In Section 2.2, we describe the data and investigate their time series properties. In Section 2.3, we present the VARMA-GARCH model with a BEKK representation and structural break, while in Sections 2.4 and 2.5 the empirical evidence is presented, discussed, and summarized. Some concluding remarks are given in Section 2.6.

2.2 Data and Basic Properties

We use monthly data for each of the G7 countries, namely Canada, France, Germany, Italy, Japan, the U.K., and the U.S., as well as for the significantly smaller and oil-exporting country of Norway, for the period from May 1987 to March 2016. Other papers also use monthly data to study the interaction between the crude oil and stock market [see Park and Ratti (2008), Miller and Ratti (2009), and Ahmadi *et al.* (2016)], and the relationship between oil prices and exchange rates [see Chen and Chen (2007), and Atems *et al.* (2015)].

For the oil price series (o_t), we use the world's most commonly referenced crude oil price benchmark, the spot British price of oil (Brent) published by the U.S. Energy Information Administration. The main argument behind this is the fact that around two-thirds of the global physical oil-trading uses the Brent as a reference price, primarily due to the "light" and "sweet" properties of Brent oil which render it ideal for transportation to distant locations.[1] In order to take fluctuations of exchange rates and inflation into account, we follow Güntner

[1] These properties refer to the low sulfur concentration of crude oil (less than 0.5%).

(2014) and accordingly construct the national real oil price of each country. In doing so, we convert the Brent oil price from U.S dollars to national currency using the corresponding bilateral exchange rate as reported by the St. Louis Federal Reserve Economic Database (FRED), and then deflate it using the domestic consumer price index (CPI), available from OECD. In the case of the euro area countries, namely France, Germany, and Italy, we also use the irreversible parity rates with the euro, obtained from the exchanging national cash archives of the European Central Bank, in order to convert to national currency for the period after the introduction of the euro in January 2002.

For the interest rate series, i_t, we use the short-term interest rate from IMF International Financial Statistics and OECD.[2] Moreover, we employ the monthly average share price indices from OECD for the stock price series, s_t, after deflating them using the corresponding CPI. Last, the bilateral exchange rates between the U.S dollar and the different national currencies are used for the exchange rate series, e_t, while for the case of the U.S. we use the nominal effective exchange rate, available from the IMF International Financial Statistics. Tables A2.1-A2.8 present summary statistics of each individual series of each of the eight countries, namely the log levels, $\ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$, and logarithmic first differences, $\Delta \ln o_t$, $\Delta \ln i_t$, $\Delta \ln s_t$, and $\Delta \ln e_t$. It is worth noting that in the cases of negative short-term interest rate such as in France and Italy, the levels, rather than the logarithms of the short-term interest rate are examined, while from a similar point of view in the case of Germany and Japan we employ the levels, and not the logarithms, of all the series. In general, the p-values for skewness and kurtosis underline significant deviations from symmetry and normality with both the logged series and the first differences of the logs. Moreover, the Jarque-Bera (1980) test statistic, distributed as $x^2(2)$ under the null hypothesis of normality, rejects the null hypothesis with nearly all the series. It is to be noted that all series are scaled up by a factor of 100, except for the case of Japan where the stock price series and exchange rate are scaled down by a factor of 0.01, and the oil price by a factor of 0.001; the main reason for doing so is to make all four series be in the same range.

In the first step of volatility modeling, we test for the presence of a unit root (a stochastic trend) in the autoregressive representation of each individual series of each of the eight countries. Panel A of Tables 2.1-2.3 reports the results of unit root and stationary tests in log levels, $\ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$, and logarithmic first differences, $\Delta \ln o_t$, $\Delta \ln i_t$, $\Delta \ln s_t$, and $\Delta \ln e_t$. Specifically, we use the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller (1981)] and the Dickey-Fuller GLS (DF-GLS) test [see Elliot *et al.* (1996)] which evaluate the null hypothesis of a unit root against an alternative of stationarity, assuming both a constant and trend. We select the optimal lag length based on the parsimonious

[2] These refer either to three month interbank offer rate or the rate associated with Treasury Bills, Certificates of Deposit or comparable instruments, each with a three month maturity.

Table 2.1: Unit Root and Stationary Tests

	Canada			France			Germany		
Series	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
				A. Levels					
lno_t	-3.477	-2.157	0.521	-3.021	-2.035	0.627	-2.803	-2.077	0.627
lni_t	-3.768	-3.065	0.179	-2.695	-2.218	0.519	-2.680	-1.630	0.228
lns_t	-3.032	-2.333	0.433	-2.167	-2.332	0.796	-2.676	-2.661	0.339
lne_t	-1.494	-1.738	1.047	-2.509	-2.340	0.492	-2.637	-2.478	0.478
				B. First differences					
Δlno_t	-14.590	-8.687	0.071	-14.712	-8.130	0.076	-13.971	-8.306	0.085
Δlni_t	-7.553	-6.086	0.036	-13.869	-6.878	0.052	-11.801	-5.626	0.133
Δlns_t	-14.843	-7.580	0.056	-15.216	-4.742	0.049	-13.451	-6.951	0.042
Δlne_t	-13.329	-6.215	0.158	-13.497	-6.920	0.060	-13.441	-7.232	0.055

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Table 2.2: Unit Root and Stationary Tests

	Italy			Japan			Norway		
Series	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
				A. Levels					
$\ln o_t$	-3.342	-2.163	0.520	-3.318	-2.378	0.664	-3.262	-2.028	0.624
i_t	-2.827	-2.467	0.687	-1.643	-1.639	0.911	-3.171	-2.900	0.190
$\ln s_t$	-1.901	-1.907	0.894	-2.413	-2.035	0.658	-3.118	-3.041	0.142
$\ln e_t$	-1.904	-1.880	1.050	-2.820	-2.346	0.244	-2.300	-2.114	0.622
				B. First differences					
Δlno_t	-14.548	-8.119	0.070	-12.847	-8.158	0.065	-14.816	-8.394	0.073
Δi_t	-10.317	-5.230	0.055	-5.251	-5.252	0.155	-12.015	-6.259	0.053
Δlns_t	-14.792	-6.443	0.090	-13.959	-6.331	0.033	-14.818	-7.618	0.031
Δlne_t	-12.293	-6.956	0.073	-13.666	-5.987	0.040	-12.572	-7.808	0.087

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Table 2.3: Unit Root and Stationary Tests

	United Kingdom			United States		
Series	ADF	DF-GLS	KPSS	ADF	DF-GLS	KPSS
A. Levels						
$\ln o_t$	-2.726	-1.817	0.737	-2.688	-1.951	0.745
$\ln i_t$	-2.363	-2.286	0.835	-2.039	-1.960	0.790
$\ln s_t$	-2.042	-1.914	0.988	-2.104	-2.089	1.037
$\ln e_t$	-3.285	-3.311	0.354	-2.187	-0.801	1.463
B. First differences						
Δlno_t	-15.090	-7.631	0.092	-14.081	-8.142	0.090
Δlni_t	-8.727	-5.069	0.062	-11.691	-5.923	0.098
Δlns_t	-13.708	-5.014	0.056	-14.000	-5.812	0.052
Δlne_t	-13.592	-6.350	0.034	-11.638	-5.616	0.169

Note: Sample period, monthly observations, 1987:5-2016:3. The 1% (and 5%) critical values for the ADF, DF-GLS, and KPSS tests are -3.989, -3.484, and 0.216 (-3.425, -2.891, and 0.146), respectively.

Bayesian information criterion (BIC) assuming a maximum lag length of four for each series. In addition, the KPSS test [see Kwiatkowski *et al.* (1992)] is used in order to test the null hypothesis of stationarity around a trend. As shown in Panel A of Tables 2.1-2.3, the null hypothesis of a unit root cannot in general be rejected for most of the series at conventional significance levels by both the ADF and DF-GLS test statistics. Furthermore, the null hypothesis of trend stationarity can be rejected at conventional significance levels by the KPSS test. Accordingly, we conclude that each of the four series in all countries is non-stationary, or integrated of order one, $I(1)$. We repeat the unit root and stationary tests in Panel B of Tables 2.1-2.3 using the first differences of the series. The null hypotheses of the ADF and DF-GLS tests are in general rejected at conventional significance levels, while the null hypothesis of the KPSS test cannot be rejected. Hence, we can safely argue that the first differences of the series are integrated of order zero, $I(0)$.

Most of the literature perceives this property of 'difference stationary' [see Nelson and Plosser (1982)] as a suggestion for using first differences as the appropriate representation of the data in the model. However, in the case of Canada and Japan, evidence of cointegration among the four series is found based on Johansen's (1988) maximum likelihood method. Such a cointegrated system with $I(1)$ variables normally encourages the use of vector error correction (VEC) models, since the latter allow for the explicit investigation of the cointegrating relations. However a VAR in levels is also adequate provided that the cointegrating relations are not the primary goal of study, as in our case. In fact, Lütkepohl (2004) demonstrates that VAR and VEC models are equivalent. Therefore, in the case of Canada and Japan we estimate the model using the series in levels. Finally, motivated by all previous discussions, we proceed to the next section which describes our econometric model.

2.3 The Econometric Model

In this section, we estimate a four-variable VARMA-GARCH model with a Baba, Engle, Kraft, and Kroner (BEKK) representation [see Baba *et al.* (1991) and Engle and Kroner (1995) for more details], which models in a systems context the levels and volatilities of the crude oil price, interest rate, stock price, and exchange rate in each of the G7 countries and Norway. The main reason for selecting a VARMA framework is the fact that it allows us to capture the features of the data generating process in a parsimonious way, without the need for additional number of parameters. In fact, Inoue and Kilian (2002, p.322) argue that "the existence of finite-lag order VAR models is highly implausible in practice and often inconsistent with the assumptions of the macroeconomic model underlying the empirical analysis."

It is also noteworthy that in contrast to a large part of the literature, we abandon the assumption of normally distributed errors, and instead assume a student-t distribution with the shape parameter being estimated together with the other parameters. The main argument behind this is the fact that financial series have empirical distributions that exhibit fatter tails than the normal distribution. See Jansen and de Vries (1991), Koedijk *et al.* (1992), Koedijk and Kool (1994), Loretan and Phillips (1994), Kearns and Pagan (1997), Corsi (2009), and Huisman *et al.* (1998). The latter is of high importance since underestimation of fat tails could lead to an erroneous assessment of the extreme events. Moreover, Aghababa and Barnett (2016) assess the dynamic structure of the spot price of crude oil and find evidence of nonlinear dependence, which is however moderated by time aggregation, as for instance in monthly observations that we actually use here.

We follow Serletis and Xu (2018) and for the mean equation, we use a VARMA(1,1) model specification with a break to capture the possible effects of monetary policy at the zero lower bound

$$z_t = \Phi + (\Gamma + \tilde{\Gamma} \times D)z_{t-1} + (\Psi + \tilde{\Psi} \times D)\epsilon_{t-1} + \epsilon_t \tag{2.1}$$

where

$$\epsilon_t|\Omega_{t-1} \sim t_v(0, H_t); \qquad H_t = \begin{bmatrix} h_{oo,t} & h_{oi,t} & h_{os,t} & h_{oe,t} \\ h_{io,t} & h_{ii,t} & h_{is,t} & h_{ie,t} \\ h_{so,t} & h_{si,t} & h_{ss,t} & h_{se,t} \\ h_{eo,t} & h_{ei,t} & h_{es,t} & h_{ee,t} \end{bmatrix}$$

and

$$z_t = \begin{bmatrix} ln : o_t \\ ln : i_t \\ ln : s_t \\ ln : e_t \end{bmatrix}; \epsilon_t = \begin{bmatrix} \epsilon_{o,t} \\ \epsilon_{i,t} \\ \epsilon_{s,t} \\ \epsilon_{e,t} \end{bmatrix}; \Gamma = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{13} & \gamma_{14} \\ \gamma_{21} & \gamma_{22} & \gamma_{23} & \gamma_{24} \\ \gamma_{31} & \gamma_{32} & \gamma_{33} & \gamma_{34} \\ \gamma_{41} & \gamma_{42} & \gamma_{43} & \gamma_{44} \end{bmatrix}; \tilde{\Gamma} = \begin{bmatrix} \tilde{\gamma}_{11} & \tilde{\gamma}_{12} & \tilde{\gamma}_{13} & \tilde{\gamma}_{14} \\ \tilde{\gamma}_{21} & \tilde{\gamma}_{22} & \tilde{\gamma}_{23} & \tilde{\gamma}_{24} \\ \tilde{\gamma}_{31} & \tilde{\gamma}_{32} & \tilde{\gamma}_{33} & \tilde{\gamma}_{34} \\ \tilde{\gamma}_{41} & \tilde{\gamma}_{42} & \tilde{\gamma}_{43} & \tilde{\gamma}_{44} \end{bmatrix};$$

$$\Psi = \begin{bmatrix} \psi_{11} & \psi_{12} & \psi_{13} & \psi_{14} \\ \psi_{21} & \psi_{22} & \psi_{23} & \psi_{24} \\ \psi_{31} & \psi_{32} & \psi_{33} & \psi_{34} \\ \psi_{41} & \psi_{42} & \psi_{43} & \psi_{44} \end{bmatrix}; \tilde{\Psi} = \begin{bmatrix} \tilde{\psi}_{11} & \tilde{\psi}_{12} & \tilde{\psi}_{13} & \tilde{\psi}_{14} \\ \tilde{\psi}_{21} & \tilde{\psi}_{22} & \tilde{\psi}_{23} & \tilde{\psi}_{24} \\ \tilde{\psi}_{31} & \tilde{\psi}_{32} & \tilde{\psi}_{33} & \tilde{\psi}_{34} \\ \tilde{\psi}_{41} & \tilde{\psi}_{42} & \tilde{\psi}_{43} & \tilde{\psi}_{44} \end{bmatrix},$$

where D is a dummy variable being always equal to zero, except for the time that the policy rate in the United States hits the zero lower bound and takes the value of one; Ω_{t-1} is the information set available in period $t-1$, and v a parameter that characterizes the shape of the student-t distribution. The last parameter, also called shape parameter, describes the level of the tail fatness in the error distribution and equals the number of existing moments. Actually, the lower the value of the shape parameter is, the fatter the tails of the error distribution become.

For the variance equation, the BEKK model specification is preferred for a number of reasons over other models, such as the dynamic conditional correlation (DCC) model or the asymmetric dynamic conditional correlation (ADCC) model, developed by Engle (2002) and Cappiello *et al.* (2004), respectively. First, the BEKK model forces all the parameters to enter the model via quadratic forms, ensuring that all the conditional variances are positive, while the positive definiteness of the conditional variance-covariance matrix H_t is guaranteed, by construction, without imposing any restrictions on the parameters. Secondly, the parameter estimation of the BEKK model is more accurate than that provided by the DCC model [see Huang *et al.* (2010)], whereas it allows for more rich dynamics in the variance-covariance structure of time series. For instance, a shortcoming of the DCC model is that imposes a common dynamic structure (persistence) on all conditional correlations. Finally, grounded on the fact that the crucial decision in MGARCH modelling is between flexibility and parsimony, we prefer the BEKK model specification that is flexible enough to provide a realistic representation, while also being parsimonious for such a system of four elements (Bauwens *et al.* 2006).

More precisely, we use the BEKK (1,1,1) specification which can be regarded a multivariate generalization of GARCH(1,1) model. The resulting variance equation with a dummy variable is

$$\begin{aligned} H_t = C'C + (B + \tilde{B} \times D)' H_{t-1} (B + \tilde{B} \times D) \\ + (A + \tilde{A} \times D)' \epsilon_{t-1} \epsilon'_{t-1} (A + \tilde{A} \times D) \end{aligned} \tag{2.2}$$

where

$$A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}; \tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \tilde{a}_{13} & \tilde{a}_{14} \\ \tilde{a}_{21} & \tilde{a}_{22} & \tilde{a}_{23} & \tilde{a}_{24} \\ \tilde{a}_{31} & \tilde{a}_{32} & \tilde{a}_{33} & \tilde{a}_{34} \\ \tilde{a}_{41} & \tilde{a}_{42} & \tilde{a}_{43} & \tilde{a}_{44} \end{bmatrix};$$

$$B = \begin{bmatrix} \beta_{11} & \beta_{12} & \beta_{13} & \beta_{14} \\ \beta_{21} & \beta_{22} & \beta_{23} & \beta_{24} \\ \beta_{31} & \beta_{32} & \beta_{33} & \beta_{34} \\ \beta_{41} & \beta_{42} & \beta_{43} & \beta_{44} \end{bmatrix}; \tilde{B} = \begin{bmatrix} \tilde{\beta}_{11} & \tilde{\beta}_{12} & \tilde{\beta}_{13} & \tilde{\beta}_{14} \\ \tilde{\beta}_{21} & \tilde{\beta}_{22} & \tilde{\beta}_{23} & \tilde{\beta}_{24} \\ \tilde{\beta}_{31} & \tilde{\beta}_{32} & \tilde{\beta}_{33} & \tilde{\beta}_{34} \\ \tilde{\beta}_{41} & \tilde{\beta}_{42} & \tilde{\beta}_{43} & \tilde{\beta}_{44} \end{bmatrix}$$

where $C'C$, B, $\tilde{B}$, A and $\tilde{A}$ are 4×4 matrices with C being a triangular matrix to ensure positive definiteness of H_t. The variance equation allows every conditional variance and covariance to be a function of all lagged conditional variances and covariances, as well as of all lagged squared residuals and cross-products of residuals. Assuming that the H matrix is symmetric, the model produces ten unique equations modeling the dynamic variances of oil, interest rate, stock price, and exchange rate, as well as the covariances between them.

We forgo employing additional explanatory variables, since our model already contains 68 mean equation parameters, 74 variance equation parameters, and the distribution shape parameter v, for a total 143 parameters. Last, the following restriction is imposed on our model $\tilde{\gamma}_{11} = \tilde{\psi}_{11} = \tilde{\alpha}_{11} = \tilde{\beta}_{11} = 0$, thus not allowing the crude oil price to be affected by the zero lower bound constraint.

2.4 Individual country estimates

The four-variable VARMA(1,1)-BEKK(1,1,1) model with a structural break described above is estimated individually for each country in Estima RATS 9.0 using the Maximum Likelihood method. In doing so, we use the BFGS (Broyden, Fletcher, Goldfarb, & Shanno) estimation algorithm, which is recommended for GARCH models, along with the derivative-free Simplex pre-estimation method. Tables 2.4-2.11 report the estimated coefficients (with significance levels in parentheses), as well as the student-t distribution shape parameter estimate, v, and the key diagnostics for the standardized residuals

$$\hat{z}_{jt} = \frac{\hat{e}_{jt}}{\sqrt{\hat{h}_{jt}}} \tag{2.3}$$

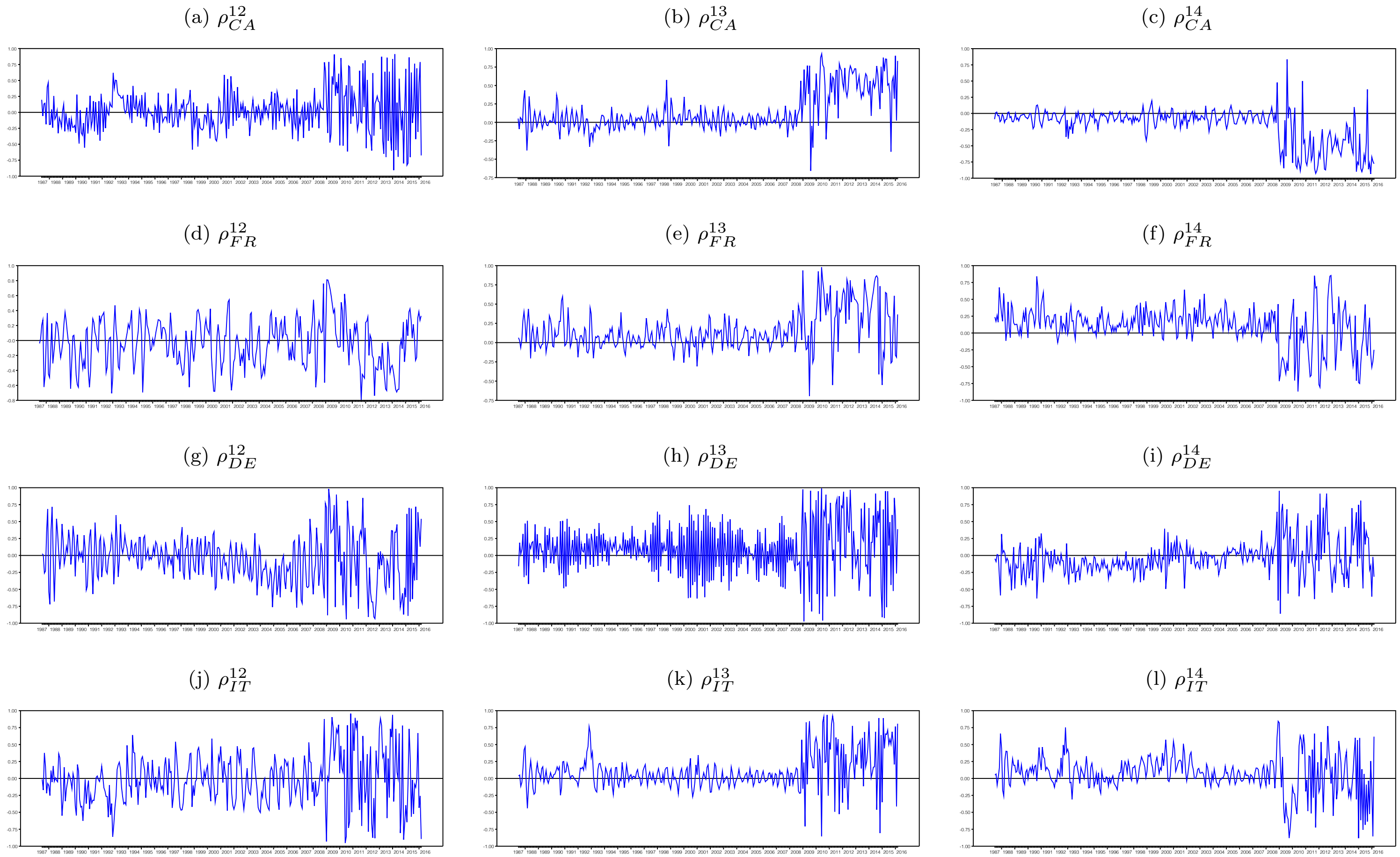
for $j = \ln o_t$, $\ln i_t$, $\ln s_t$, and $\ln e_t$. In fact, Panel B of Tables 2.4-2.11 reports some descriptive statistics for the standardized residuals, as well as the p-values of the Ljung-Box Q test for residual autocorrelation, and the McLeod-Li Q^2 test for squared residual autocorrelation. Both tests evaluate the null hypothesis of independently distributed data against an alternative of autocorrelation.

In order to answer our research question, we need to capture and discuss the dynamics of the system, given by the Γ, Ψ, A, and B coefficient matrices for the period before the zero lower bound was reached, and by $\Gamma + \tilde{\Gamma}$, $\Psi + \tilde{\Psi}$, $A + \tilde{A}$, and $B + \tilde{B}$ for the time that the zero lower bound constraint is binding. It is to be noted that we focus only on the estimation results that are statistically significant at the 95% level, as well as that our discussion takes place in terms of predictability and not as implying an underlying structural economic relationship. Moreover, we do not identify the source of shocks since this is not within the scope of this paper, and present the estimation results for each country individually. Finally, the conditional correlation coefficients can be easily computed from the BEKK model, as follows:

$$\rho_{12,t} = \frac{h_{12,t}}{\sqrt{h_{11,t}\ h_{22,t}}} \tag{2.4}$$

Figures 2.1 and 2.2 depict the development of the conditional correlation coefficients between the crude oil market and each of the three financial markets, in each of the G7 countries and

Figure 2.1: Cross-market conditional correlations in Canada, France, Germany, and Italy



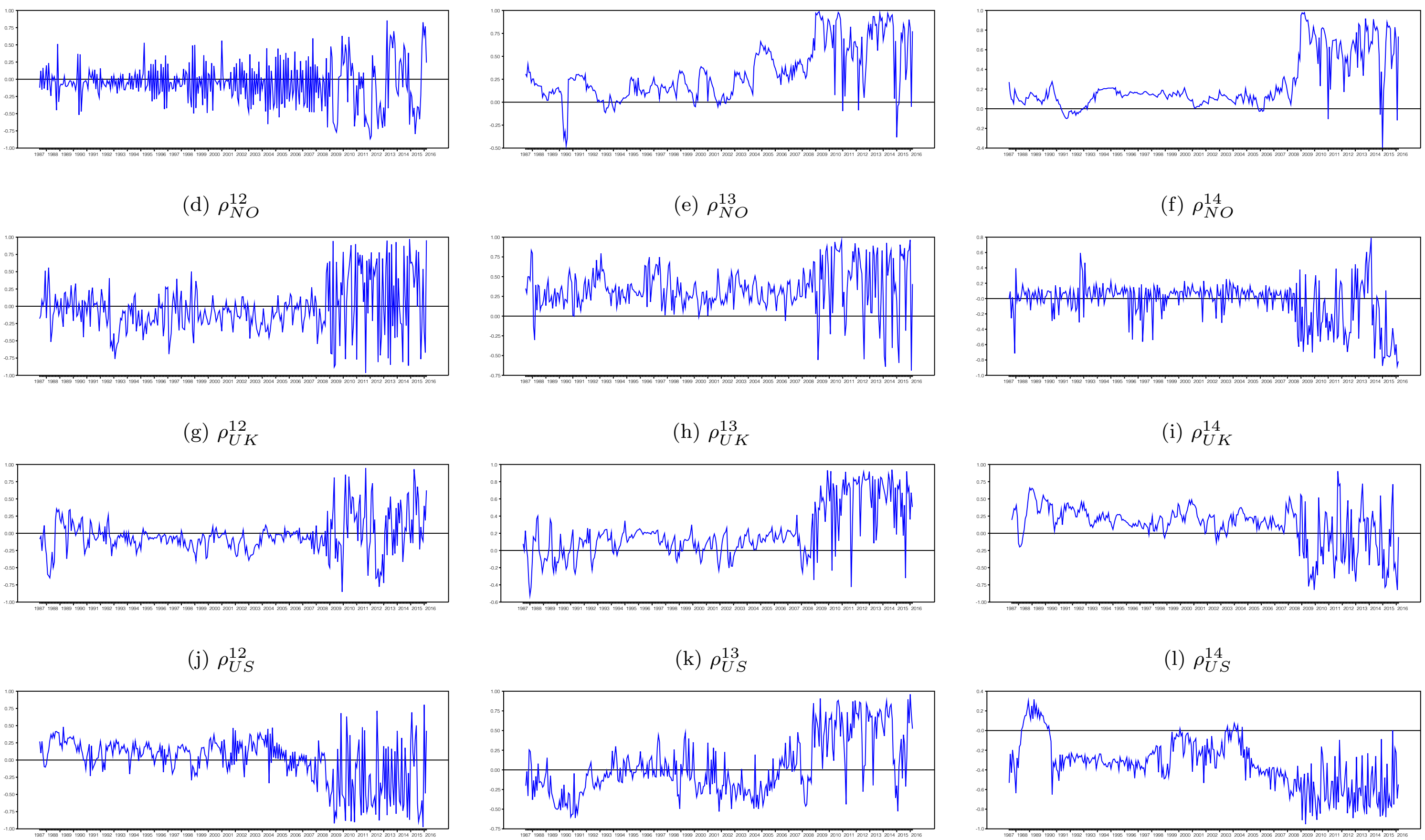
(a) ρ^{12}_{CA} (b) ρ^{13}_{CA} (c) ρ^{14}_{CA}

(d) ρ^{12}_{FR} (e) ρ^{13}_{FR} (f) ρ^{14}_{FR}

(g) ρ^{12}_{DE} (h) ρ^{13}_{DE} (i) ρ^{14}_{DE}

(j) ρ^{12}_{IT} (k) ρ^{13}_{IT} (l) ρ^{14}_{IT}

Figure 2.2: Cross-market conditional correlations in Japan, Norway, United Kingdom, and United States



(a) ρ^{12}_{JP} (b) ρ^{13}_{JP} (c) ρ^{14}_{JP}

(d) ρ^{12}_{NO} (e) ρ^{13}_{NO} (f) ρ^{14}_{NO}

(g) ρ^{12}_{UK} (h) ρ^{13}_{UK} (i) ρ^{14}_{UK}

(j) ρ^{12}_{US} (k) ρ^{13}_{US} (l) ρ^{14}_{US}

Norway. The evolution of the market interactions is illustrated, for the period before and after the zero lower bound was reached, while differences across countries are detected and discussed in the following sections.

2.4.1 Canada

As can be seen in Table 2.4, in the oil-dependent Canadian economy, we find that the autoregressive coefficients along the main diagonal in the Γ matrix are all significant and close to one. That is to say, for each of the four markets, today's performance is a good predictor of tomorrow's performance. Moreover, the off-diagonal elements of the Γ matrix suggest significant spillover effects affecting the crude oil, bond, and foreign exchange markets, but not the stock market. Specifically, the current price of crude oil is affected by last period's interest rate, stock price, and exchange rate; a higher interest rate leads to a decrease in the price of oil ($\gamma_{12} = -0.046$ with a p-value of 0.000), whereas a higher stock market index leads to an increase in the price of oil ($\gamma_{13} = 0.102$ with a p-value of 0.000), and an appreciation of the U.S. dollar relative to the Canadian dollar leads to a decline in the price of oil ($\gamma_{14} = -0.248$ with a p-value of 0.000). Last, we find evidence of spillovers from the crude oil market to the debt and foreign exchange markets, since $\gamma_{21} = -0.018$ (with a p-value of 0.014) and $\gamma_{41} = -0.011$ (with a p-value of 0.008).

However, some spillover effects change or new ones occur when the zero bound is reached in the U.S. policy rate, as is indicated by the $\tilde{\Gamma}$ matrix. In particular, we find that an increase in the price of oil today will lead to a higher stock price tomorrow, since $\tilde{\gamma}_{31} = 0.056$ (with a p-value of 0.000). Moreover, the intertemporal correlation between the oil price and the interest rate changes when the zero lower bound constraint is binding, since in that case an increase in the interest rate leads to a higher oil price (as $\gamma_{12}+\tilde{\gamma}_{12} = -0.046+0.080 = 0.034$). Overall, we find that some new spillovers are created across the markets, while some intertemporal relationships change after the zero lower bound occurs.

On the other hand, the moving average coefficients along the diagonal of the Ψ matrix are moderate and significant, except for the case of the stock price, implying that each of the crude oil price, interest rate, and exchange rate series is consistent with a typical ARMA process. In addition, a single spillover effect in the moving average terms, otherwise called shock spillover, is found propagating from the stock market towards the debt market, while affecting it in a negative way ($\gamma_{23} = -0.137$ with a p-value of 0.008). Furthermore, new shock spillovers are found for the case of the crude oil market when the zero lower bound occurs. In particular, negative shock spillovers occur from the debt and foreign exchange markets towards the crude oil market, since $\tilde{\gamma}_{12} = -0.379$ (with a p-value of 0.000), and $\tilde{\gamma}_{14} = -1.342$ (with a p-value of 0.009).

Regarding volatility spillovers, all the 'own-market' coefficients in the A and B matrices

Table 2.4: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Canada

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.857(0.000) & -0.046(0.000) & 0.102(0.000) & -0.248(0.000) \\ -0.018(0.014) & 0.991(0.000) & 0.025(0.000) & -0.031(0.331) \\ -0.005(0.261) & -0.005(0.282) & 0.994(0.000) & -0.020(0.317) \\ -0.011(0.008) & -0.006(0.003) & 0.007(0.113) & 0.971(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.080(0.000) & -0.015(0.005) & 0.048(0.599) \\ 0.045(0.000) & -0.116(0.000) & -0.047(0.000) & 0.054(0.118) \\ 0.056(0.000) & -0.002(0.849) & -0.059(0.000) & 0.231(0.000) \\ 0.016(0.097) & 0.008(0.286) & -0.017(0.094) & -0.038(0.273) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.279(0.000) & 0.103(0.170) & -0.136(0.352) & 0.079(0.829) \\ -0.001(0.980) & 0.422(0.000) & -0.137(0.008) & 0.196(0.254) \\ -0.006(0.797) & -0.039(0.296) & 0.050(0.402) & 0.049(0.747) \\ 0.000(0.981) & -0.012(0.380) & -0.041(0.061) & 0.213(0.001) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.379(0.000) & -0.233(0.403) & -1.342(0.009) \\ 0.002(0.938) & -0.148(0.064) & 0.164(0.019) & -0.022(0.911) \\ 0.001(0.983) & 0.067(0.124) & -0.036(0.723) & -0.835(0.000) \\ -0.013(0.585) & 0.020(0.349) & 0.045(0.407) & 0.288(0.014) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.047	0.879	0.070	0.483
z_{i_t}	-0.158	1.088	0.000	0.962
z_{s_t}	-0.052	0.976	0.028	0.548
z_{e_t}	0.083	0.856	0.103	0.530

C. Student's t distribution shape

$v = 6.812(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.177(0.019) & -0.008(0.825) & 0.055(0.454) & -0.002(0.890) \\ 0.134(0.090) & 0.491(0.000) & -0.043(0.233) & -0.013(0.361) \\ 0.634(0.001) & 0.074(0.174) & 0.191(0.006) & -0.009(0.587) \\ 0.199(0.642) & -0.865(0.000) & 0.125(0.478) & -0.153(0.000) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.151(0.001) & -0.078(0.480) & -0.048(0.261) \\ -0.071(0.552) & 0.247(0.085) & -0.105(0.114) & 0.161(0.000) \\ 1.405(0.000) & -0.412(0.000) & -0.066(0.673) & -0.133(0.135) \\ 1.668(0.021) & 0.644(0.005) & 0.153(0.701) & 0.334(0.102) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.637(0.000) & -0.094(0.083) & 0.254(0.000) & 0.000(0.998) \\ -0.384(0.035) & -0.824(0.000) & 0.089(0.327) & 0.054(0.191) \\ -1.435(0.000) & 0.166(0.200) & 0.653(0.000) & 0.008(0.759) \\ -1.118(0.057) & 0.484(0.325) & -0.288(0.226) & 0.985(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.110(0.095) & -0.269(0.000) & -0.015(0.566) \\ 0.234(0.258) & 0.155(0.028) & -0.032(0.763) & -0.064(0.277) \\ 0.631(0.069) & -0.140(0.340) & -0.988(0.000) & 0.430(0.000) \\ 0.113(0.866) & -0.665(0.210) & -1.111(0.000) & 0.037(0.708) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

are found statistically significant whereas the estimates suggest a high degree of persistence. There is no evidence for spillover ARCH effects from the oil market to any of the three financial markets, but we find statistically significant spillover ARCH effects when the zero lower bound is reached. In particular, an unexpected shock in the crude oil market increases the volatility of the debt market when the zero lower bound occurs, since $\tilde{a}_{12} = 0.151$ with a p-value of 0.001. On the other hand, an unexpected shock in the stock market increases the volatility in the crude oil market (as $a_{31} = 0.634$ with a p-value of 0.001), and this spillover ARCH effect is strengthened further when the zero lower bound constraint on the policy rate is binding, since $\tilde{a}_{31} = 1.405$ (with a p-value of 0.000), implying an ARCH effect of $(0.634 + 1.405)^2$. Moreover, a new significant spillover ARCH effect propagates from the foreign exchange market to the crude oil market when the zero lower bound occurs (as $\tilde{a}_{41} = 1.668$ with a p-value of 0.021).

Furthermore, statistically significant spillover GARCH effects occur between the four markets. In particular, we find volatility spillovers running from the crude oil market to the stock market (as $\beta_{13} = 0.254$ with a p-value of 0.000), as well as from the debt and stock markets to the crude oil market, since $\beta_{21} = -0.384$ (with a p-value of 0.035) and $\beta_{31} = -1.435$ (with a p-value of 0.000). Moreover, we find that the spillover GARCH effect from the oil market on the stock market increases when the zero lower bound is reached, since $\tilde{\beta}_{13} = -0.269$ (with a p-value of 0.000), implying a GARCH effect of $(0.254+0.269)^2$. Overall, we find that monetary policy at the zero lower bound strengthens already existing volatility spillovers, or even creates some new ones between the crude oil and financial markets.

2.4.2 France

In the case of France (see Table 2.5), which is the 6th largest export economy in the world and the 9th largest oil-importing economy (IEA, 2016), we find that the autoregressive coefficients of debt and stock markets along the main diagonal in the Γ matrix are moderate and statistically significant, suggesting that for both of them, today's performance could be a useful predictor of tomorrow's performance. Regarding spillover effects between the oil and financial markets, there is empirical evidence only for the case of crude oil and stock markets. In particular, we find that the current price of oil is affected by last period's stock price in a positive way ($\gamma_{13} = 1.083$ with a p-value of 0.000) whereas a higher oil price leads to an increase in the stock price ($\gamma_{31} = 0.356$ with a p-value of 0.000). Moreover, we do not find significant interactions between the three financial markets, except for the spillover effect propagating from the debt and foreign exchange markets to the stock market. Hence, we find that a higher interest rate leads to a lower stock price, since $\gamma_{32} = -0.035$ (with a p-value of 0.044), while a stronger U.S. dollar relative to the French franc leads also to a decline in stock prices, since $\gamma_{34} = -0.265$ (with a p-value of 0.032).

Table 2.5: The four-variable VARMA(1,1)-BEKK(1,1,1) model for France

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.212(0.074) & 0.024(0.532) & 1.083(0.000) & 0.118(0.743) \\ 0.236(0.311) & 0.762(0.000) & -0.082(0.764) & -0.726(0.197) \\ 0.356(0.000) & -0.035(0.044) & 0.412(0.000) & -0.265(0.032) \\ -0.073(0.160) & -0.021(0.081) & 0.014(0.886) & -0.113(0.284) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.790(0.096) & -91.567(0.000) & -4.080(0.310) \\ -0.848(0.043) & 0.331(0.061) & -38.899(0.000) & -2.297(0.172) \\ -0.373(0.000) & 0.047(0.008) & -1.020(0.000) & 0.234(0.038) \\ 0.462(0.000) & 0.057(0.001) & 0.171(0.515) & 0.261(0.058) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.318(0.012) & -0.014(0.699) & -1.150(0.000) & 0.124(0.642) \\ -0.128(0.606) & -0.460(0.000) & 0.507(0.126) & 1.340(0.047) \\ -0.445(0.000) & 0.047(0.007) & -0.206(0.059) & 0.389(0.000) \\ 0.080(0.113) & 0.016(0.145) & 0.017(0.861) & 0.568(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.893(0.069) & 91.548(0.000) & 4.034(0.309) \\ 0.834(0.050) & -0.034(0.877) & 38.132(0.000) & 1.797(0.306) \\ 0.466(0.000) & -0.053(0.002) & 0.814(0.000) & -0.361(0.000) \\ -0.519(0.000) & -0.052(0.028) & -0.271(0.313) & -0.674(0.000) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.078	0.752	0.317	0.639
z_{i_t}	0.008	1.550	0.195	0.987
z_{s_t}	-0.054	0.843	0.317	0.001
z_{e_t}	-0.018	0.777	0.735	0.722

C. Student's t distribution shape

$v = 3.983(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.426(0.000) & -0.305(0.002) & 0.030(0.554) & -0.090(0.004) \\ -0.015(0.370) & 0.612(0.000) & -0.002(0.823) & -0.006(0.223) \\ 0.377(0.004) & -0.732(0.000) & 0.051(0.456) & 0.115(0.001) \\ 0.753(0.008) & 0.162(0.690) & 0.580(0.000) & -0.099(0.180) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.278(0.013) & 0.204(0.009) & 0.275(0.000) \\ 0.356(0.014) & -0.638(0.000) & 0.546(0.000) & -0.101(0.026) \\ -0.286(0.121) & 0.535(0.019) & -0.678(0.000) & 0.026(0.659) \\ 1.837(0.001) & 0.267(0.607) & 0.538(0.158) & -0.289(0.069) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.656(0.000) & -0.055(0.297) & 0.073(0.104) & -0.113(0.000) \\ 0.001(0.941) & 0.813(0.000) & -0.002(0.686) & 0.003(0.336) \\ -0.923(0.000) & 0.166(0.057) & 0.701(0.000) & -0.015(0.809) \\ 1.377(0.000) & -0.261(0.132) & 0.459(0.020) & 0.932(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.045(0.454) & -0.113(0.061) & 0.090(0.000) \\ 0.273(0.000) & 0.017(0.737) & -0.003(0.961) & -0.011(0.427) \\ 0.766(0.000) & 0.010(0.939) & -0.282(0.042) & 0.014(0.835) \\ -0.146(0.671) & 0.219(0.303) & -0.165(0.485) & -0.180(0.037) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

However, the spillover effects change after the zero lower bound constraint is binding, as indicated by the $\tilde{\Gamma}$ matrix. Specifically, we find that an increase in the price of oil could affect negatively the interest rate, since $\tilde{\gamma}_{21} = -0.848$ (with a p-value of 0.043), and ambiguously the stock market, since $\gamma_{31} = 0.356$ (with a p-value of 0.000) and $\tilde{\gamma}_{31} = -0.373$ (with a p-value of 0.000). Moreover, a new spillover effect is found from the crude oil market to the foreign exchange market, since $\tilde{\gamma}_{41} = 0.462$ (with a p-value of 0.000). On the other hand, the intertemporal correlation between the stock price and the oil price changes when the zero lower bound is reached, since an increase in stock market price could lead to a decline in the price of oil (as $\gamma_{13} + \tilde{\gamma}_{13} = 1.083 - 91.567 = -90.484$). Last, the debt and foreign exchange markets are found to affect the stock price in an uncertain way when the zero lower bound occurs, since $\gamma_{32} = -0.035$ and $\tilde{\gamma}_{32} = 0.047$ (with a p-value of 0.044 and 0.008, respectively), whereas $\gamma_{34} = -0.265$ and $\tilde{\gamma}_{34} = 0.234$ (with a p-value of 0.032 and 0.038, respectively). Overall, we find that spillover effects between the crude oil market and the financial markets are mainly strengthened when the zero lower bound constraint is binding, while the financial markets interact with each other in an ambiguous way.

Regarding volatility linkages, we find significant spillover ARCH effects from the oil market to the debt and foreign exchange market (as $\alpha_{12} = -0.305$ with a p-value of 0.002 and $\alpha_{14} = -0.090$ with a p-value of 0.004) whereas these are further strengthened after the zero lower bound occurs, since $\tilde{\alpha}_{12} = 0.278$ (with a p-value of 0.013) and $\tilde{\alpha}_{14} = 0.275$ (with a p-value of 0.000), implying ARCH effects of $(0.305 + 0.278)^2$ and $(0.090 + 0.275)^2$, respectively. Moreover, a new spillover ARCH effect is found from the crude oil market to the stock market when the zero lower bound is reached. In particular, an unexpected shock in the crude oil price increases the volatility of the stock price when the zero lower bound constraint is binding, since $\tilde{\alpha}_{13} = 0.204$ (with a p-value of 0.009).

In addition, we find that all the 'own-market' coefficients in the B matrix are statistically significant and the estimates suggest a high degree of persistence. There are also volatility spillovers from the crude oil market to the foreign exchange market, with $\beta_{14} = -0.113$ (with a p-value of 0.000), as well as from the stock and foreign exchange markets to the crude oil market, since $\beta_{31} = -0.923$ (with a p-value of 0.000) and $\beta_{41} = 1.377$ (with a p-value of 0.000). We also find a new volatility spillover propagating from the debt market to the crude oil market, as $\tilde{\beta}_{21} = 0.273$ (with a p-value of 0.000).

2.4.3 Germany

In the case of Germany, as can be seen in Table 2.6, we find that all the autoregressive coefficients in the Γ matrix, except that for the foreign exchange market, are moderate and significant along the main diagonal. Hence, for each of the three markets, today's performance is a good predictor of tomorrow's performance. Moreover, we find significant

Table 2.6: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Germany

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.177(0.000) & -0.281(0.921) & 0.131(0.009) & 43.545(0.048) \\ 0.009(0.000) & 0.725(0.000) & 0.015(0.000) & 2.851(0.000) \\ 0.035(0.082) & 4.077(0.016) & 0.471(0.000) & 16.796(0.477) \\ 0.002(0.000) & 0.005(0.670) & 0.001(0.018) & 0.023(0.821) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -8.635(0.136) & 1.756(0.000) & -92.506(0.000) \\ 0.011(0.000) & 0.124(0.000) & -0.036(0.000) & -10.643(0.000) \\ -0.270(0.000) & 2.831(0.246) & 0.147(0.000) & -6.779(0.828) \\ 0.000(0.455) & -0.002(0.888) & -0.001(0.000) & -0.520(0.001) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.456(0.000) & 0.621(0.817) & -0.299(0.000) & -28.656(0.152) \\ -0.009(0.000) & -0.468(0.000) & -0.015(0.000) & -4.012(0.000) \\ -0.133(0.000) & -6.357(0.001) & -0.235(0.000) & -62.564(0.025) \\ -0.002(0.000) & -0.006(0.570) & -0.001(0.023) & 0.391(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 40.184(0.000) & -1.514(0.000) & 150.582(0.000) \\ -0.011(0.000) & 0.442(0.000) & 0.035(0.000) & 11.902(0.000) \\ 0.512(0.000) & 20.976(0.000) & -0.362(0.000) & 77.346(0.023) \\ 0.000(0.000) & 0.029(0.095) & 0.001(0.000) & 0.319(0.024) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.005	0.926	0.282	0.693
z_{i_t}	-0.004	0.981	0.349	0.240
z_{s_t}	-0.036	0.929	0.235	0.032
z_{e_t}	0.060	0.886	0.793	0.144

C. Student's t distribution shape

$v = 6.490(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.416(0.000) & -0.003(0.002) & -0.131(0.030) & 0.000(0.750) \\ 2.061(0.100) & 0.406(0.000) & 2.569(0.047) & -0.030(0.000) \\ -0.043(0.556) & -0.003(0.040) & -0.411(0.000) & 0.001(0.001) \\ 39.401(0.024) & 0.243(0.621) & -33.554(0.040) & 0.087(0.366) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.000(0.887) & -0.130(0.117) & 0.001(0.013) \\ -146.568(0.000) & -0.494(0.001) & -136.227(0.000) & -0.091(0.034) \\ 0.277(0.103) & -0.002(0.383) & 0.648(0.000) & 0.000(0.451) \\ 373.555(0.000) & 0.199(0.746) & 323.245(0.000) & -0.300(0.061) \end{bmatrix};$$

$$B = \begin{bmatrix} -0.091(0.071) & -0.003(0.063) & 0.734(0.000) & 0.000(0.099) \\ -3.110(0.071) & -0.900(0.000) & 1.123(0.407) & -0.004(0.361) \\ -1.084(0.000) & 0.001(0.443) & -0.204(0.000) & -0.000(0.863) \\ -116.547(0.000) & 1.053(0.015) & 22.984(0.443) & -0.455(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.005(0.001) & -0.709(0.000) & 0.000(0.352) \\ 73.597(0.000) & 1.426(0.000) & 1.575(0.793) & 0.044(0.053) \\ 0.573(0.000) & 0.000(0.808) & 0.562(0.000) & 0.000(0.302) \\ -25.313(0.657) & -0.479(0.459) & -156.196(0.000) & 0.444(0.004) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

spillover effects propagating from the stock and foreign exchange markets to the crude oil market since $\gamma_{13} = 0.131$ (with a p-value of 0.009) and $\gamma_{14} = 43.545$ (with a p-value of 0.048). On the other hand, there is also evidence of spillovers from the crude oil market to the debt and foreign exchange markets, since $\gamma_{21} = 0.009$ (with a p-value of 0.000) and $\gamma_{41} = 0.002$ (with a p-value of 0.000).

In addition, we find that spillover effects change after the policy rate hits the zero lower bound, as indicated in the $\tilde{\Gamma}$ matrix. In particular, we find that a higher stock price today leads to an even larger increase in the price of oil tomorrow (as $\tilde{\gamma}_{13} = 1.756$ with a p-value of 0.000), while the intertemporal correlation between the foreign exchange market and the crude oil market changes when the zero lower bound constraint is binding (as $\gamma_{14} + \tilde{\gamma}_{14} = 43.545 - 92.506 = -48.961$). Moreover, there is evidence of a strengthened spillover effect from the crude oil market to the debt market (as $\tilde{\gamma}_{21} = 0.011$ with a p-value of 0.000), as well as of a new spillover effect running from the crude oil market to the stock market, since $\tilde{\gamma}_{31} = -0.270$ (with a p-value of 0.000).

The moving average coefficients along the diagonal of the Ψ matrix are moderate and significant, implying that each of the four markets are consistent with a typical ARMA process, while the off-diagonal elements indicate the spillover effects across the four markets. Regarding the oil price equation, we find that stock market shocks affect the crude oil market negatively at normal times (as $\psi_{13} = -0.299$ with a p-value of 0.000), and even stronger when the zero lower bound is reached (as $\tilde{\psi}_{13} = -1.514$ with a p-value of 0.000). Moreover, we find evidence of shock spillovers running from the crude oil market to all the financial markets, and influencing them in a negative way, since $\psi_{21} = -0.009$ (with a p-value of 0.000), $\psi_{31} = -0.133$ (with a p-value of 0.000), and $\psi_{41} = -0.002$ (with a p-value of 0.000). In addition, we find a new shock spillover propagating from the debt market towards the crude oil market, and affecting it in a positive way when the zero lower bound occurs (as $\tilde{\psi}_{12} = 40.184$ with a p-value of 0.000).

Furthermore, we find statistically significant spillover ARCH effects from the crude oil market to the debt and stock markets, implying that an unexpected shock in the crude oil market increases the volatility of the bond and stock markets, since $\alpha_{12} = -0.003$ (with a p-value of 0.002) and $\alpha_{13} = -0.131$ (with a p-value of 0.030). In addition, there is evidence of a new spillover ARCH effect propagating from the debt market to the crude oil market when the zero lower bound is reached. In particular, an unexpected shock in the debt market increases the volatility of the crude oil market when the zero lower bound occurs, since $\tilde{\alpha}_{21} = -146.568$ (with a p-value of 0.000). Moreover, the spillover ARCH effect from the foreign exchange market to the crude oil market increases when the zero lower constraint is binding, since $\tilde{\alpha}_{41} = 373.555$ (with a p-value of 0.000), implying an ARCH effect of $(39.401 + 373.555)^2$.

Regarding volatility linkages, all the 'own-market' coefficients in the B and $\tilde{B}$ matrices are statistically significant, except that for the crude oil market, while the estimates imply a high degree of persistence. Moreover, we find statistically significant spillover GARCH effects running from the crude oil market to the stock market ($\beta_{13} = 0.734$ with a p-value of 0.000), as well as a new one from the crude oil market to the bond market after the zero lower bound is reached, since $\tilde{\beta}_{12} = 0.005$ (with a p-value of 0.001). Overall, we find that unconventional monetary policy at the zero lower bound establishes stronger first- and second- moment linkages between the markets.

2.4.4 Italy

In the case of Italy (see Table 2.7), we find that all the autoregressive coefficients in the Γ matrix, except that for the foreign exchange market, are moderate and significant along the main diagonal. This indicates that, for each of the three markets, today's performance provides high predictive power for tomorrow's performance. Furthermore, we find significant spillover effects from the crude oil market to the bond and stock markets, and vice versa, while there is no evidence of interaction between the crude oil and the foreign exchange markets. In particular, a higher interest rate leads to an increase in the price of oil (as $\alpha_{12} = 0.066$ with a p-value of 0.029) whereas a higher stock price leads also to an increase of the crude oil price (as $\alpha_{13} = 1.137$ with a p-value of 0.005). On the other hand, a higher oil price leads to an increase of the interest rate ($\alpha_{21} = 0.908$ with a p-value of 0.004) and the stock price ($\alpha_{31} = 0.221$ with a p-value of 0.008). However, the intertemporal correlation between the crude oil market and the debt market changes after the zero lower bound occurs. In particular, a higher oil price leads to a decrease of the interest rate when the zero lower bound is reached, since $\tilde{\alpha}_{21} = -1.106$ (with a p-value of 0.002).

On the other hand, the moving-average coefficients along the diagonal of the Ψ matrix are moderate and significant, suggesting that the dynamics of all markets are consistent with a typical ARMA process. Another interesting result is that there are also shock spillovers across the markets. In particular, there is a significant impact of a surprise change in the oil price on the interest rate, stock price, and foreign exchange market in the next period. For instance, an unexpected increase in the oil price will affect the interest rate and the stock market in a negative way ($\psi_{21} = -0.930$ with a p-value of 0.003 and $\psi_{31} = -0.921$ with a p-value of 0.008), while it will increase the foreign exchange of the U.S. dollar to Italian lira (as $\psi_{41} = 0.103$ with a p-value of 0.020). Moreover, we find shock spillovers running from the bond market towards the crude oil market, since $\psi_{12} = -0.056$ (with a p-value of 0.023), whereas this is further strengthened when the zero lower bound constraint is binding as $\tilde{\psi}_{12} = -0.302$ (with a p-value of 0.005).

The estimates for the variance equation show moderate and significant ARCH coefficients

Table 2.7: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Italy

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.264(0.018) & 0.066(0.029) & 1.137(0.005) & 0.250(0.541) \\ 0.908(0.004) & 0.322(0.000) & 2.299(0.001) & -0.741(0.331) \\ 0.221(0.008) & 0.011(0.424) & 0.408(0.002) & -0.137(0.481) \\ -0.082(0.065) & -0.019(0.019) & -0.172(0.124) & 0.063(0.564) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -0.007(0.921) & -0.835(0.060) & 1.088(0.402) \\ -1.106(0.002) & 0.560(0.000) & -2.452(0.001) & -0.783(0.382) \\ 0.151(0.540) & -0.043(0.540) & -0.148(0.534) & 4.106(0.000) \\ -0.055(0.335) & 0.036(0.017) & 0.183(0.117) & 0.026(0.903) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.494(0.000) & -0.056(0.023) & -1.174(0.002) & -0.197(0.595) \\ -0.930(0.003) & 0.282(0.001) & -2.183(0.002) & 1.407(0.071) \\ -0.291(0.002) & -0.029(0.039) & -0.292(0.028) & 0.408(0.103) \\ 0.103(0.020) & 0.007(0.291) & 0.131(0.234) & 0.388(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.302(0.005) & 0.779(0.072) & -1.791(0.160) \\ 1.149(0.001) & -0.596(0.000) & 2.322(0.001) & 0.131(0.886) \\ 0.113(0.638) & -0.034(0.705) & 0.334(0.155) & -4.957(0.000) \\ 0.016(0.788) & 0.018(0.371) & -0.251(0.035) & -0.424(0.050) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.049	0.772	0.494	0.671
z_{i_t}	0.035	1.216	0.215	0.956
z_{s_t}	-0.125	0.872	0.343	0.649
z_{e_t}	-0.056	0.853	0.630	0.489

C. Student's t distribution shape

$v = 5.034(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.315(0.000) & -0.237(0.005) & 0.060(0.093) & -0.016(0.463) \\ -0.029(0.026) & 0.789(0.000) & -0.028(0.001) & -0.019(0.000) \\ -0.502(0.000) & -1.276(0.000) & -0.062(0.360) & -0.085(0.017) \\ 0.656(0.028) & -1.004(0.009) & -0.137(0.382) & -0.070(0.333) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.235(0.007) & -0.040(0.622) & 0.094(0.006) \\ 0.020(0.901) & -2.079(0.000) & -0.720(0.000) & 0.107(0.017) \\ 0.648(0.000) & 1.163(0.000) & 0.713(0.000) & 0.302(0.000) \\ 2.142(0.000) & 0.732(0.064) & 0.577(0.067) & 0.500(0.003) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.555(0.000) & -0.055(0.434) & 0.051(0.430) & 0.198(0.000) \\ -0.035(0.008) & 0.706(0.000) & 0.001(0.896) & 0.004(0.470) \\ -1.256(0.000) & 0.164(0.217) & 0.284(0.077) & 0.241(0.000) \\ 0.977(0.042) & -0.248(0.562) & 1.467(0.000) & -0.106(0.610) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.000(0.999) & 0.244(0.004) & -0.244(0.000) \\ -0.089(0.203) & -0.159(0.008) & -0.173(0.010) & -0.047(0.137) \\ 0.767(0.000) & -0.047(0.726) & -0.229(0.288) & -0.441(0.000) \\ -2.715(0.000) & 0.191(0.660) & -1.752(0.000) & 0.407(0.089) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

along the main diagonal of the A matrix, for the case of the crude oil and bond market (since $\alpha_{11} = -0.315$ and $\alpha_{22} = 0.789$, both with a p-value of 0.000), suggesting that volatility is persistent in both these markets. Moreover, we find statistically significant spillover ARCH effects from the crude oil market to the bond market (as $\alpha_{12} = -0.237$ with a p-value of 0.005), which is further strengthened when the zero lower bound occurs (since $\tilde{\alpha}_{12} = 0.235$ with a p-value of 0.007). Moreover, there is evidence of new spillover ARCH effects, for instance propagating from the crude oil market towards the foreign exchange market. Hence, an unexpected shock in the price of oil will increase the volatility of the foreign exchange rate of U.S. dollar to Italian lira, since $\tilde{\alpha}_{14} = 0.094$ with a p-value of 0.006.

Finally, the main diagonal coefficients of the B matrix indicate that there are statistically significant GARCH effects for the crude oil and debt markets, since $\beta_{11} = 0.555$ (with a p-value of 0.000) and $\beta_{22} = 0.706$ (with a p-value of 0.000). Moreover, there are significant spillover GARCH effects across the four markets. For instance, there is evidence for volatility spillovers from all three financial markets towards the crude oil market, since $\beta_{21} = -0.035$ (with a p-value of 0.008), $\beta_{31} = -1.256$ (with a p-value of 0.000), and $\beta_{41} = 0.977$ (with a p-value of 0.042), while the latter two spillover GARCH effects are further strengthened after the zero lower bound is reached, since $\tilde{\beta}_{31} = 0.767$ (with a p-value of 0.000) and $\tilde{\beta}_{41} = -2.715$ (with a p-value of 0.000). Hence, we find evidence of strengthened volatility spillovers across markets when the zero lower bound occurs.

2.4.5 Japan

In the case of Japan (see Table 2.8), we find all the autoregressive coefficients in the Γ matrix to be statistically significant and close to one along the main diagonal, suggesting that today's performance is a useful predictor of tomorrow's performance. In addition, we find evidence of significant spillover effects to the crude oil and stock markets, but not to the debt and foreign exchange markets. For instance, the current price of crude oil is affected by last period's interest rate and stock price; a higher interest rate leads to a decline in the price of oil ($\gamma_{12} = -0.029$ with a p-value of 0.023) whereas a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 0.076$ with a p-value of 0.049). In addition, an appreciation of the U.S. dollar relative to the Japanese yen leads to an increase in the price of the stock market, since $\gamma_{34} = 0.163$ (with a p-value of 0.000). Last, we find that although the interactions between the crude oil and the three financial markets do not change when the zero lower bound occurs, spillovers across the financial markets become stronger. In fact, there is evidence of an increased spillover effect propagating from the foreign exchange market towards the stock market, since $\tilde{\gamma}_{34} = 0.540$ (with a p-value of 0.000), as well as from the stock market to the bond market as $\tilde{\gamma}_{23} = -0.093$ (with a p-value of 0.000).

The moving average coefficients along the diagonal of the Ψ matrix are moderate and

Table 2.8: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Japan

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.957(0.000) & -0.029(0.023) & 0.076(0.049) & -0.014(0.907) \\ 0.001(0.059) & 1.000(0.000) & 0.000(0.858) & -0.010(0.057) \\ 0.002(0.436) & -0.006(0.288) & 1.014(0.000) & 0.163(0.000) \\ 0.000(0.876) & -0.001(0.431) & 0.007(0.090) & 0.944(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -1.374(0.391) & -0.888(0.227) & 1.406(0.169) \\ -0.001(0.077) & -0.229(0.000) & -0.093(0.000) & 0.133(0.000) \\ 0.001(0.843) & -0.434(0.002) & -0.385(0.000) & 0.540(0.000) \\ -0.001(0.678) & 0.006(0.920) & 0.107(0.000) & -0.140(0.000) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.379(0.000) & -0.015(0.776) & -0.164(0.187) & 0.039(0.918) \\ 0.002(0.560) & 0.055(0.220) & -0.003(0.641) & 0.021(0.366) \\ -0.004(0.720) & -0.069(0.029) & 0.298(0.000) & 0.038(0.803) \\ 0.001(0.883) & -0.010(0.367) & -0.006(0.777) & 0.233(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 13.127(0.000) & -1.582(0.157) & 4.219(0.108) \\ -0.003(0.356) & -0.548(0.000) & 0.193(0.000) & -0.390(0.000) \\ 0.028(0.012) & 1.445(0.000) & -0.298(0.010) & 0.830(0.002) \\ 0.006(0.202) & 0.358(0.000) & -0.216(0.000) & 0.642(0.000) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	0.033	0.096	0.074	0.811
z_{i_t}	-0.144	4.680	0.811	0.996
z_{s_t}	-0.016	0.114	0.201	0.424
z_{e_t}	0.000	0.112	0.239	0.002

C. Student's t distribution shape

$v = 2.123(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} -0.853(0.020) & 0.087(0.033) & -0.104(0.048) & -0.026(0.139) \\ -0.131(0.753) & 1.149(0.015) & -0.348(0.112) & -0.040(0.485) \\ -0.927(0.101) & 0.070(0.189) & 0.467(0.094) & -0.058(0.413) \\ -1.310(0.225) & -0.554(0.045) & -0.928(0.079) & 0.036(0.849) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & -0.041(0.100) & 0.227(0.042) & 0.057(0.085) \\ 43.201(0.041) & -1.705(0.022) & 7.157(0.029) & 2.584(0.033) \\ -20.498(0.051) & -0.428(0.050) & -1.439(0.146) & -0.248(0.340) \\ 67.791(0.039) & -1.419(0.053) & 4.946(0.063) & 1.142(0.159) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.963(0.000) & -0.001(0.797) & -0.004(0.093) & -0.001(0.357) \\ 0.172(0.755) & -0.615(0.000) & 0.379(0.082) & -0.006(0.938) \\ 0.026(0.554) & 0.019(0.180) & 0.967(0.000) & -0.022(0.016) \\ 0.103(0.587) & 0.005(0.879) & 0.035(0.446) & 0.914(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.000(0.951) & 0.038(0.000) & 0.015(0.000) \\ 7.764(0.006) & 1.103(0.000) & 1.117(0.002) & 0.239(0.068) \\ -1.249(0.225) & -0.045(0.037) & -0.480(0.000) & -0.033(0.566) \\ -2.027(0.528) & 0.024(0.659) & -0.179(0.589) & -0.451(0.015) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

statistically significant, except for the case of the debt market, implying that each of the crude oil price, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix indicate the spillover effects across the four markets. There is no evidence of shock spillovers from each of the financial markets towards the crude oil market, except for the case of the debt market and when the zero lower bound is reached, since $\tilde{\psi}_{12} = 13.127$ (with a p-value of 0.000). On the other hand, oil price shocks affect the stock market positively when the zero lower bound occurs, since $\tilde{\psi}_{31} = 0.028$ (with a p-value of 0.012).

Moreover, we find statistically significant spillover ARCH effects running from the crude oil market to the debt and stock markets, since $\alpha_{12} = 0.087$ (with a p-value of 0.033) and $\alpha_{13} = -0.104$ (with a p-value of 0.048). In fact, the latter spillover ARCH effect is found to be strengthened after the zero lower bound is reached, since $\tilde{\alpha}_{13} = 0.227$ (with a p-value of 0.042), implying an ARCH effect of $(0.104 + 0.227)^2$. Although we do not find significant spillover ARCH effects propagating from the financial markets towards the crude oil market at normal times, there is evidence for new spillover ARCH effects running separately from the debt and foreign exchange markets to the crude oil market, when the zero lower bound occurs ($\tilde{\alpha}_{21} = 43.201$ with a p-value of 0.041 and $\tilde{\alpha}_{41} = 67.791$ with a p-value of 0.039).

Regarding volatility linkages, all the 'own-market' coefficients in the B and $\tilde{B}$ matrices are statistically significant and the estimate coefficients suggest a high degree of persistence. Moreover, we find significant spillover GARCH effects across the markets when the zero lower bound occurs. In particular, there is evidence for volatility spillovers from the crude oil market to the stock and foreign exchange markets, with $\tilde{\beta}_{13} = 0.038$ (with a p-value of 0.000) and $\tilde{\beta}_{14} = 0.015$ (with a p-value of 0.000). Last, the past volatility of the interest rate has a positive effect on the volatility of the crude oil price, since $\tilde{\beta}_{21} = 7.764$ (with a p-value of 0.006).

2.4.6 Norway

The Norwegian economy is a small and open economy highly dependent on oil-exports, and thereby on the price of oil. In Table 2.9, we find that all the autoregressive coefficients in the Γ matrix, except those for the crude oil and foreign exchange markets, are moderate and significant along the main diagonal. This indicates that, for both the debt and stock markets, today's performance provides high predictive power for tomorrow's performance. Moreover, we find significant spillover effects to the crude oil, debt, and stock markets, but there is no evidence of spillovers from the crude oil, debt, and stock markets to the foreign exchange market. In fact, the current price of crude oil is affected by last period's interest rate and stock price. Specifically, a higher value of each of the interest rate and stock price leads to an increase in the price of oil, since $\gamma_{12} = 0.662$ (with a p-value of 0.000) and $\gamma_{13} = 1.206$

(with a p-value of 0.000), respectively.

However, the spillover effects across the markets are found to change after the zero lower bound occurs. Hence, we find that the intertemporal correlation between the crude oil market and each of the debt and stock markets change after the zero lower bound is reached, since in those cases a higher interest rate leads to a decline in the price of oil ($\gamma_{12} + \tilde{\gamma}_{12} = 0.662 - 1.572 = -0.910$), while a higher stock price also leads to a decline in the price of oil ($\gamma_{13} + \tilde{\gamma}_{13} = 1.206 - 2.094 = -0.888$).

On the other hand, the moving-average coefficients along the diagonal of the Ψ matrix are all moderate and significant, except for the case of the bond market, suggesting that each of the crude oil price, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix capture the shock spillovers across the four markets, and suggest negative and significant shock spillovers from the debt and stock markets to the crude oil market ($\psi_{12} = -0.785$ with a p-value of 0.000 and $\psi_{13} = -1.269$ with a p-value of 0.000), and vice versa ($\psi_{21} = -0.669$ with a p-value of 0.000 and $\psi_{31} = -0.085$ with a p-value of 0.029). Furthermore, we find evidence of new shock spillovers, such as from the stock market to the foreign exchange market (as $\tilde{\psi}_{43} = -0.262$ with a p-vale of 0.011), as well as strengthened spillover effects, for instance from the crude oil market to the stock market (as $\psi_{31} + \tilde{\psi}_{31} = -0.085 - 0.250 = -0.335$) when the zero lower bound is reached.

Furthermore, we find significant spillover ARCH effects propagating from the crude oil market to the stock market at normal times ($\alpha_{13} = 0.288$ with a p-value of 0.000), and even further increased when the zero lower bound occurs ($\tilde{\alpha}_{13} = -0.853$ with a p-value of 0.000), implying an ARCH effect of $(0.288 + 0.853)^2$. Moreover, the spillover ARCH effect from the stock market on the crude oil market is statistically significant, and increases further when the zero lower bound is reached, since $\tilde{\alpha}_{31} = 1.020$ (with a p-value of 0.000), implying ARCH effects of $(0.488 + 1.020)^2$. In addition, there is evidence for a new spillover ARCH effect running from the foreign exchange market to the crude oil market. In particular, an unexpected change in the bilateral exchange rate between the U.S. dollar and the Norwegian krone will increase the volatility of the crude oil price, since $\tilde{\alpha}_{41} = -2.866$ (with a p-value of 0.000).

Finally, all the main diagonal coefficients of the B matrix, except that for the foreign exchange market, are statistically significant suggesting GARCH effects in all three markets. Furthermore, there are significant spillover GARCH effects from the crude oil market to all the financial markets, implying that past oil price volatility has a positive effect on the volatility of the interest rate (as $\beta_{12} = 0.127$ with a p-value of 0.002), the stock price (as $\beta_{13} = 0.484$ with a p-value of 0.000), and the bilateral exchange rate between the U.S. dollar and the Norwegian krone (as $\beta_{14} = 0.084$ with a p-value of 0.026), respectively. Last, there is evidence for increased spillover GARCH effects from the crude oil market on the stock and

Table 2.9: The four-variable VARMA(1,1)-BEKK(1,1,1) model for Norway

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} -0.089(0.219) & 0.662(0.000) & 1.206(0.000) & 0.207(0.520) \\ 0.668(0.000) & 0.589(0.000) & 0.581(0.000) & -0.459(0.109) \\ 0.022(0.609) & -0.172(0.033) & -0.183(0.013) & -0.242(0.075) \\ -0.035(0.334) & -0.064(0.199) & 0.116(0.070) & -0.178(0.129) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -1.572(0.000) & -2.094(0.000) & -0.402(0.398) \\ -0.310(0.067) & -0.305(0.061) & -1.810(0.000) & -1.241(0.010) \\ 0.188(0.000) & -0.196(0.139) & -0.433(0.000) & 0.849(0.002) \\ -0.179(0.001) & 0.049(0.389) & 0.231(0.046) & 0.491(0.003) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.190(0.005) & -0.785(0.000) & -1.269(0.000) & -0.108(0.737) \\ -0.669(0.000) & -0.159(0.155) & -0.547(0.000) & 0.485(0.085) \\ -0.085(0.029) & -0.024(0.730) & 0.364(0.000) & 0.290(0.016) \\ 0.046(0.219) & 0.020(0.680) & -0.094(0.118) & 0.529(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 1.330(0.000) & 2.230(0.000) & -0.447(0.316) \\ 0.433(0.011) & 0.236(0.185) & 1.548(0.000) & 1.638(0.001) \\ -0.250(0.000) & 0.218(0.067) & 0.545(0.000) & -1.467(0.000) \\ 0.128(0.034) & 0.124(0.044) & -0.262(0.011) & -0.522(0.001) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.011	0.973	0.081	0.469
z_{i_t}	-0.049	1.043	0.281	0.938
z_{s_t}	0.009	0.965	0.558	0.350
z_{e_t}	0.088	0.913	0.661	0.021

C. Student's t distribution shape

$v = 10.497(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.055(0.406) & 0.029(0.505) & 0.288(0.000) & -0.052(0.027) \\ -0.299(0.009) & 0.657(0.000) & -0.395(0.000) & -0.073(0.024) \\ -0.488(0.000) & -0.024(0.684) & -0.466(0.000) & 0.134(0.000) \\ 0.083(0.692) & 0.110(0.401) & -0.248(0.157) & -0.105(0.128) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.309(0.000) & -0.853(0.000) & -0.041(0.519) \\ 0.095(0.545) & -0.599(0.000) & 0.328(0.016) & -0.093(0.272) \\ 1.020(0.000) & -0.925(0.000) & 0.731(0.000) & -0.277(0.003) \\ -2.866(0.000) & -0.839(0.000) & -1.089(0.001) & 0.345(0.049) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.443(0.000) & 0.127(0.002) & 0.484(0.000) & 0.084(0.026) \\ -0.524(0.000) & 0.601(0.000) & 0.093(0.441) & 0.055(0.077) \\ -0.334(0.039) & -0.299(0.000) & 0.435(0.000) & 0.016(0.697) \\ -2.987(0.000) & 0.133(0.432) & -0.128(0.582) & 0.128(0.226) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.015(0.821) & -0.191(0.017) & -0.155(0.000) \\ 0.308(0.070) & -1.191(0.000) & -0.019(0.908) & 0.015(0.819) \\ 0.225(0.160) & 0.235(0.031) & -0.248(0.086) & 0.006(0.921) \\ 2.647(0.000) & 0.190(0.378) & 0.522(0.094) & 0.021(0.910) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

foreign exchange markets, since $\tilde{\beta}_{13} = -0.191$ (with a p-value of 0.017) and $\tilde{\beta}_{14} = -0.155$ (with a p-value of 0.000), implying spillover GARCH effects of $(0.484 + 0.191)^2$ and $(0.084 + 0.155)^2$, respectively.

2.4.7 United Kingdom

In the case of the U.K. (see Table 2.10), we find the autoregressive coefficients of the stock and foreign exchange markets in the Γ matrix significant and close to one along the main diagonal, suggesting that for both of them, today's performance is a useful predictor of tomorrow's performance. In addition, all four markets experience significant spillover effects from each other. In fact, the current price of crude oil is affected by last period's stock price and exchange rate; a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 1.226$ with a p-value of 0.000) whereas a stronger U.S. dollar relative to the British pound leads to a decline in the price of oil ($\gamma_{14} = -1.395$ with a p-value of 0.007). Moreover, we find that at normal times the performance of all the financial markets is influenced by last period's oil price, suggesting that a higher oil price could lead to an increase in the interest rate and stock price, respectively, since $\gamma_{21} = 0.681$ (with a p-value of 0.002) and $\gamma_{31} = 0.998$ (with a p-value of 0.000), as well as to an appreciation of the U.S. dollar compared to the British pound, since $\gamma_{41} = 0.421$ (with a p-value of 0.000).

However, the spillover effects change after the zero lower bound is reached. For instance, we find that the intertemporal correlation between the crude oil market and the three financial markets changes when the zero lower bound constraint on the policy rate is binding; an increase in the crude oil price could lead to a decrease of the interest rate and stock price, respectively, since $\tilde{\gamma}_{21} = -0.975$ (with a p-value of 0.002) and $\tilde{\gamma}_{31} = -1.501$ (with a p-value of 0.000), as well as to a depreciation of the U.S. dollar compared to the British pound ($\tilde{\gamma}_{31} = -0.993$ with a p-value of 0.000).

Furthermore, the moving average coefficients along the main diagonal of the Ψ matrix are all singificant, except for the case of the oil market, implying that each of the interest rate, stock price, and exchange rate series is consistent with a typical ARMA process. Another interesting result is that there are shock spillovers from both the stock and foreign exchange markets towards the crude oil market, since $\psi_{13} = -1.378$ (with a p-value of 0.000) and $\psi_{14} = 1.384$ (with a p-value of 0.006), and vice versa (as $\psi_{31} = -1.062$ with a p-value of 0.000 and $\psi_{41} = -0.421$ with a p-value of 0.000). We also find evidence of a new shock spillover propagating from the debt market towards the crude oil market when the zero lower bound occurs, since $\tilde{\psi}_{12} = -0.464$ (with a p-value of 0.023).

Moreover, the estimates for the variance equation show significant ARCH coefficients along the main diagonal of the A matrix, except that for the crude oil market, suggesting that volatility is persistent in all three markets. The off-diagonal elements of the A matrix

Table 2.10: The four-variable VARMA(1,1)-BEKK(1,1,1) model for United Kingdom

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.177(0.192) & 0.127(0.426) & 1.226(0.000) & -1.395(0.007) \\ 0.681(0.002) & -0.091(0.601) & 1.413(0.000) & -1.188(0.020) \\ 0.998(0.000) & -0.618(0.000) & 0.772(0.000) & -1.547(0.000) \\ 0.421(0.000) & -0.324(0.000) & 0.508(0.000) & -1.099(0.000) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & 0.130(0.442) & 1.141(0.000) & 1.067(0.131) \\ -0.975(0.002) & 1.039(0.000) & -0.214(0.654) & -0.182(0.728) \\ -1.501(0.000) & 0.710(0.000) & 1.252(0.000) & 0.599(0.000) \\ -0.993(0.000) & 0.422(0.000) & 0.939(0.000) & 0.326(0.064) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} -0.086(0.525) & -0.005(0.977) & -1.378(0.000) & 1.384(0.006) \\ -0.636(0.003) & 0.662(0.000) & -1.334(0.000) & 0.976(0.053) \\ -1.062(0.000) & 0.635(0.000) & -0.583(0.000) & 1.719(0.000) \\ -0.421(0.000) & 0.227(0.001) & -0.498(0.000) & 1.324(0.000) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & -0.464(0.023) & -0.502(0.087) & -1.152(0.059) \\ 0.862(0.008) & -1.005(0.000) & 0.006(0.990) & 0.069(0.896) \\ 1.556(0.000) & -0.793(0.000) & -1.343(0.000) & -0.568(0.000) \\ 0.951(0.000) & -0.261(0.001) & -1.090(0.000) & -0.408(0.011) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.031	0.921	0.227	0.047
z_{i_t}	0.004	1.025	0.956	0.974
z_{s_t}	-0.153	0.970	0.982	0.255
z_{e_t}	0.019	0.929	0.461	0.511

C. Student's t distribution shape

$v = 7.442(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.048(0.563) & 0.086(0.006) & -0.020(0.587) & -0.049(0.016) \\ -0.347(0.077) & 0.650(0.000) & -0.121(0.162) & -0.181(0.000) \\ 0.093(0.562) & 0.042(0.432) & 0.363(0.000) & 0.010(0.774) \\ -0.292(0.315) & -0.395(0.000) & -0.283(0.017) & 0.390(0.000) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 0.025(0.671) & 0.229(0.000) & 0.085(0.003) \\ -0.560(0.028) & -0.035(0.778) & -0.100(0.422) & 0.166(0.003) \\ -1.681(0.000) & -0.355(0.014) & -0.547(0.000) & -0.229(0.001) \\ 1.377(0.011) & 0.431(0.060) & 1.510(0.000) & -1.097(0.000) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.721(0.000) & -0.168(0.000) & 0.039(0.344) & 0.080(0.000) \\ 0.086(0.732) & 0.377(0.001) & -0.041(0.609) & 0.302(0.000) \\ -1.179(0.000) & -0.202(0.005) & 0.732(0.000) & 0.073(0.102) \\ -0.033(0.910) & 0.481(0.000) & -0.045(0.577) & 0.713(0.000) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & 0.095(0.009) & 0.069(0.288) & -0.133(0.000) \\ -0.499(0.100) & 0.192(0.157) & -0.510(0.000) & -0.262(0.000) \\ -0.366(0.365) & 0.109(0.512) & -1.270(0.000) & -0.132(0.076) \\ -0.357(0.458) & -1.263(0.000) & 0.143(0.565) & -0.112(0.223) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

also indicate significant spillover ARCH effects across the four markets. For example, an unexpected shock in the crude oil market increases the volatility of the exchange rate between the U.S. dollar and the British pound at normal times (as $\alpha_{14} = -0.049$ with a p-value of 0.016), while this effect becomes stronger when the zero lower bound occurs, since $\tilde{\alpha}_{14} = 0.085$ (with a p-value of 0.003), implying an ARCH effect of $(0.049 + 0.085)^2$.

Finally, all the 'own-market' coefficients in the B matrix are statistically significant and the estimates suggest a high degree of persistence. There is also evidence for volatility spillovers from the crude oil market to the debt and foreign exchange markets, with $\beta_{12} = -0.168$ (with a p-value of 0.000) and $\beta_{14} = 0.080$ (with a p-value of 0.000). In addition, we find that some spillover GARCH effects become stronger when the zero lower bound occurs; past volatility of the crude oil price has a bigger effect on the volatility of the interest rate and exchange rate series when the zero lower bound occurs, since $\tilde{\beta}_{12} = 0.095$ (with a p-value of 0.009) and $\tilde{\beta}_{14} = -0.133$ (with a p-value of 0.000).

2.4.8 United States

As can be seen in Table 2.11, the autoregressive coefficients in the Γ matrix suggest spillover effects from the stock and foreign exchange markets to the crude oil market. In particular, the current price of crude oil is affected by last period's stock price and exchange rate; a higher stock price leads to an increase in the price of oil ($\gamma_{13} = 2.357$ with a p-value of 0.000), while a stronger U.S. dollar leads to a decline in the price of oil ($\gamma_{14} = -1.912$ with a p-value of 0.033). Moreover, there is no evidence of significant spillovers to the three financial markets at normal times; however, new spillover effects run across the financial markets when the zero lower bound is reached. Hence, we find that a higher stock price could lead to an increase in the interest rate, since $\tilde{\gamma}_{23} = 11.241$ (with a p-value of 0.000), whereas a stronger U.S. dollar could affect the interest rate in a negative way, since $\tilde{\gamma}_{24} = -15.660$ (with a p-value of 0.000).

On the other hand, the moving average coefficients along the main diagonal of the Ψ matrix are all significant, except that for the crude oil market, suggesting that each of the interest rate, stock price, and exchange rate series is consistent with a typical ARMA process. The off-diagonal elements of the Ψ matrix indicate the spillover effects across the four markets. For instance, there is evidence of shock spillovers propagating from the stock market towards the crude oil market, since $\psi_{13} = -2.483$ (with a p-value of 0.000), as well as from the debt market towards the stock market, since $\psi_{32} = 0.086$ (with a p-value of 0.049). However, all financial markets shocks affect the crude oil market significantly after the zero lower bound constraint is binding. Hence, an unexpected shock in each of the bond and stock markets is associated with an increase in the price of oil (as $\tilde{\psi}_{12} = 0.589$ with a p-value

Table 2.11: The four-variable VARMA(1,1)-BEKK(1,1,1) model for United States

A. Conditional mean equation

$$\Gamma = \begin{bmatrix} 0.066(0.637) & 0.245(0.136) & 2.357(0.000) & -1.912(0.033) \\ 0.178(0.069) & 0.777(0.000) & 0.034(0.892) & -0.062(0.871) \\ -0.011(0.802) & -0.082(0.088) & -0.111(0.469) & 0.009(0.968) \\ 0.046(0.154) & -0.049(0.065) & 0.171(0.070) & 0.117(0.315) \end{bmatrix}; \quad \tilde{\Gamma} = \begin{bmatrix} 0.000 & -0.918(0.000) & -6.673(0.000) & 6.325(0.000) \\ -0.238(0.643) & 1.019(0.003) & 11.241(0.000) & -15.660(0.000) \\ 0.043(0.490) & -0.084(0.232) & -1.708(0.001) & 0.497(0.000) \\ -0.095(0.055) & 0.232(0.000) & 1.712(0.000) & -0.826(0.020) \end{bmatrix};$$

$$\Psi = \begin{bmatrix} 0.016(0.905) & -0.050(0.763) & -2.483(0.000) & 0.974(0.289) \\ -0.148(0.118) & -0.340(0.002) & 0.098(0.717) & 0.125(0.792) \\ -0.056(0.214) & 0.086(0.049) & 0.325(0.025) & 0.069(0.708) \\ -0.042(0.205) & 0.051(0.041) & -0.142(0.111) & 0.325(0.002) \end{bmatrix}; \quad \tilde{\Psi} = \begin{bmatrix} 0.000 & 0.589(0.007) & 6.561(0.000) & -5.711(0.001) \\ 0.345(0.507) & -0.922(0.011) & -11.544(0.000) & 18.986(0.000) \\ 0.011(0.864) & 0.043(0.469) & 1.521(0.004) & -0.868(0.000) \\ 0.112(0.026) & -0.203(0.000) & -1.778(0.000) & 0.591(0.085) \end{bmatrix}.$$

B. Residual diagnostics

	Mean	Variance	$Q(4)$	$Q^2(4)$
z_{o_t}	-0.015	0.809	0.191	0.726
z_{i_t}	0.020	1.087	0.024	0.782
z_{s_t}	-0.088	0.876	0.996	0.751
z_{e_t}	-0.016	0.835	0.909	0.978

C. Student's t distribution shape

$v = 5.535(0.000)$

D. Conditional variance-covariance structure

$$A = \begin{bmatrix} 0.341(0.000) & -0.009(0.779) & 0.119(0.000) & -0.036(0.005) \\ -0.159(0.055) & 0.304(0.000) & -0.169(0.000) & -0.003(0.878) \\ 0.036(0.851) & -0.055(0.561) & 0.497(0.000) & 0.026(0.432) \\ 0.191(0.720) & -0.020(0.921) & 0.437(0.095) & 0.061(0.550) \end{bmatrix}; \quad \tilde{A} = \begin{bmatrix} 0.000 & 2.304(0.000) & -0.430(0.000) & -0.023(0.397) \\ 0.055(0.625) & 1.108(0.000) & 0.089(0.071) & -0.020(0.408) \\ -0.465(0.132) & 1.785(0.000) & -0.330(0.015) & -0.157(0.006) \\ -4.639(0.000) & 15.714(0.000) & -1.120(0.034) & -0.035(0.867) \end{bmatrix};$$

$$B = \begin{bmatrix} 0.639(0.000) & 0.148(0.014) & -0.222(0.000) & 0.050(0.003) \\ -0.546(0.026) & -0.531(0.001) & 0.312(0.000) & 0.189(0.000) \\ -1.100(0.000) & 0.649(0.000) & 0.120(0.425) & 0.184(0.000) \\ 2.855(0.001) & 2.315(0.000) & -0.001(0.997) & 0.397(0.040) \end{bmatrix}; \quad \tilde{B} = \begin{bmatrix} 0.000 & -0.738(0.000) & 0.470(0.000) & -0.130(0.000) \\ 0.538(0.029) & 0.187(0.284) & -0.355(0.000) & -0.216(0.000) \\ 0.849(0.024) & -1.434(0.000) & -0.259(0.154) & -0.335(0.000) \\ -0.796(0.526) & -5.726(0.000) & 2.212(0.000) & -1.225(0.000) \end{bmatrix}.$$

Note: Sample period, monthly observations, 1987:5-2016:3. Numbers in parentheses are p-values.

of 0.007 and $\psi_{13} + \tilde{\psi}_{13} = -2.483 + 6.561 = 4.078$), while an unexpected appreciation of the U.S. dollar influences the crude oil market negatively, since $\tilde{\psi}_{14} = -5.711$ (with a p-value of 0.001).

The estimates for the variance equation show significant ARCH coefficients along the main diagonal of the A matrix, except that for the foreign exchange market, suggesting that volatility is persistent in all three markets. Moreover, we find significant spillover ARCH effects running from the crude oil market towards the stock and foreign exchange markets, since $\alpha_{13} = 0.119$ (with a p-value of 0.000) and $\alpha_{14} = -0.036$ (with a p-value of 0.005). In particular, the spillover ARCH effect from the oil market on the stock market increases when the zero lower bound is reached, since $\tilde{\alpha}_{13} = -0.430$ (with a p-value of 0.000), implying an ARCH effect of $(0.119 + 0.430)^2$. Furthermore, a new spillover ARCH effect is found from the foreign exchange market to the oil market when the zero lower bound is reached, since $\tilde{\alpha}_{41} = -4.639$ (with a p-value of 0.000). Hence, an unexpected appreciation of the U.S. dollar will increase the volatility of the crude oil market.

Finally, the main diagonal coefficients of the B matrix, except that for the stock market, indicate that there are statistically significant GARCH effects in all three markets. Moreover, there are significant spillover GARCH effects from the crude oil market towards all the financial markets, since $\beta_{12} = 0.148$ (with a p-value of 0.014), $\beta_{13} = -0.222$ (with a p-value of 0.000), and $\beta_{14} = 0.050$ (with a p-value of 0.003). Moreover, all these spillovers are further strengthened when the zero lower bound constraint on the policy rate is binding, since $\tilde{\beta}_{12} = -0.738$ (with a p-value of 0.000), $\tilde{\beta}_{13} = 0.470$ (with a p-value of 0.000), and $\tilde{\beta}_{14} = -0.130$ (with a p-value of 0.000). Overall, we find that the volatility spillovers across the markets increase when the zero lower bound is reached.

2.5 Summary of Key Results

In this section we summarize the results paying special attention to systematic patterns of market spillovers across countries. In this regard, for each of the eight countries, we find a significant spillover effect propagating from the stock market towards the crude oil market; a higher stock price leads to an increase in the price of oil during normal times. On the contrary, when the zero lower bound constraint on the U.S. policy rate is binding, we find that the same spillover effect is strengthened further in Germany and the United Kingdom, whereas it becomes negative in France, Norway, and the United States, and weakens slightly in the case of Canada. With respect to spillovers between the financial markets, we find evidence that in Canada, Germany, Italy, and Norway, a higher stock price leads to an increase of the interest rate at normal times, and a decline of the interest rate when the zero lower bound is reached.

However, a surprise change in the stock market affects the debt market in the opposite way. We find that in Canada, Germany, Italy, and Norway, an unexpected increase in the stock market is associated with a decline of the interest rate at normal times, and an increase of it when the zero lower bound occurs. Moreover, we notice that an unexpected increase in the price of oil affects the stock price in a negative way during normal times, in France, Germany, Italy, Norway, and United Kingdom, and in a positive way in France, Germany, and the United Kingdom when the zero lower bound is reached. It is worth noting that, when the zero lower bound occurs, a new positive shock spillover is running from the crude oil market to the stock market in Japan, while in Norway the previously negative shock spillover between the two markets is further increased.

Finally, with respect to second-moment linkages, we find that in France, Germany, and Italy, there is a significant spillover ARCH effect running from the foreign exchange market to the crude oil market, suggesting that an unexpected shock in the foreign exchange market increases the volatility of the crude oil price, while this effect increases further in these countries and starts running in the rest of them when the zero lower bound is reached. In addition, we find at normal times a significant spillover ARCH effect propagating from the crude oil market towards the debt market in all three eurozone countries, namely, France, Germany, and Italy, as well as in Japan and the United Kingdom. Furthermore, there is evidence that this spillover ARCH effect increases further in France and Italy, and start occurring in Canada, the United States, and Norway, when the zero lower bound is reached. Finally, we find a statistically significant spillover GARCH effect running at normal times from the crude oil market towards the stock market in Canada, Germany, Norway, and the United States, while increasing further in all these countries and starts running in Italy and Japan, when the zero lower bound is reached. Last, based on the estimated cross-market conditional correlations, we do not find any evidence to support the view of a different underlying structure in the spillover mechanism, in each of the studied Eurozone countries, France, Germany, and Italy, in the two periods, before and after the introduction of the Euro. The employment of a more parsimonious model, however, would provide the opportunity to investigate the two periods, separately, and extract more information about any possible change in the interaction mechanism.

2.6 Concluding Remarks

Motivated by the financialization of the crude oil market over the past decade, and the speculative activities that induce oil prices to depart from their fundamental values due to several financial factors, in this paper we explore for mean and volatility spillovers among the crude oil market and the three most important financial markets, namely, the debt, stock, and foreign exchange markets, in each of the seven major advanced economies (G7), and the small open oil-exporting economy of Norway. Using monthly data that span from the first Brent oil price in May 1987 up to March 2016, and a four-variable VARMA-GARCH model with a BEKK variance specification, we find that in all the G7 countries, as well as in Norway, significant spillovers occur among the four markets, both in terms of volatility and mean estimates. Moreover, we find evidence for strengthened market relationships after the zero lower bound is reached and unconventional monetary measures are employed. Yet, a few individual country results are worth highlighting; with respect to the spillovers between the crude oil market and each of the financial markets, we can notice that these are more tightened in the oil-dependent economies of Norway and Germany, while they are significantly weaker in the case of Japan.

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2.7 Appendix

Table A2.1: Summary Statistics for Canada

Series	Mean	Variance	*p*-values Skewness	Kurtosis	Normality
			A. Levels		
$\ln o_t$	3.918	0.235	0.044	0.000	0.000
$\ln i_t$	1.201	0.758	0.000	0.076	0.000
$\ln s_t$	4.271	0.131	0.043	0.000	0.000
$\ln e_t$	0.217	0.019	0.707	0.000	0.000
			B. First differences		
Δlno_t	0.000	0.007	0.876	0.000	0.000
Δlni_t	-0.007	0.006	0.003	0.000	0.000
Δlns_t	0.002	0.002	0.000	0.000	0.000
Δlne_t	0.000	0.000	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.2: Summary Statistics for France

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
lno_t	5.382	0.296	0.106	0.000	0.000
i_t	4.255	10.559	0.000	0.009	0.000
lns_t	4.504	0.130	0.322	0.001	0.002
lne_t	1.708	0.017	0.000	0.729	0.001
			B. First differences		
Δlno_t	0.001	0.008	0.315	0.000	0.000
Δi_t	-0.024	0.101	0.313	0.000	0.000
Δlns_t	0.002	0.003	0.000	0.000	0.000
Δlne_t	0.000	0.001	0.464	0.567	0.645

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.3: Summary Statistics for Germany

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
o_t	75.093	1753.321	0.000	0.026	0.000
i_t	3.688	7.001	0.000	0.400	0.000
s_t	97.314	926.107	0.001	0.004	0.000
e_t	0.616	0.006	0.083	0.233	0.107
			B. First differences		
Δo_t	0.029	43.007	0.000	0.000	0.000
Δi_t	-0.012	0.040	0.122	0.000	0.000
Δs_t	0.193	25.126	0.000	0.000	0.000
Δe_t	0.000	0.000	0.305	0.018	0.033

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.4: Summary Statistics for Italy

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
lno_t	11.091	0.271	0.050	0.000	0.000
i_t	5.433	19.853	0.000	0.000	0.000
lns_t	4.748	0.117	0.005	0.001	0.000
lne_t	7.340	0.025	0.002	0.731	0.009
			B. First differences		
Δlno_t	0.001	0.008	0.352	0.000	0.000
Δi_t	-0.031	0.152	0.000	0.000	0.000
Δlns_t	-0.001	0.003	0.001	0.000	0.000
Δlne_t	0.001	0.001	0.013	0.007	0.001

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.5: Summary Statistics for Japan

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
o_t	4677.788	9269802.685	0.000	0.090	0.000
i_t	1.008	2.339	0.000	0.000	0.000
s_t	160.058	3189.314	0.000	0.000	0.000
e_t	113.050	298.191	0.624	0.269	0.475
			B. First differences		
Δo_t	3.644	241490.380	0.000	0.000	0.000
Δi_t	-0.007	0.018	0.013	0.000	0.000
Δs_t	-0.351	66.214	0.000	0.000	0.000
Δe_t	-0.080	9.243	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.6: Summary Statistics for Norway

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
$\ln o_t$	5.627	0.266	0.083	0.000	0.000
$\ln i_t$	1.528	0.480	0.284	0.000	0.000
$\ln s_t$	3.974	0.470	0.786	0.000	0.000
$\ln e_t$	1.906	0.018	0.000	0.714	0.000
			B. First differences		
Δlno_t	0.001	0.007	0.903	0.000	0.000
Δlni_t	-0.008	0.004	0.000	0.000	0.000
Δlns_t	0.006	0.004	0.000	0.000	0.000
Δlne_t	0.001	0.001	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.7: Summary Statistics for UK

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
$\ln o_t$	3.223	0.316	0.006	0.000	0.000
$\ln i_t$	1.317	1.103	0.000	0.023	0.000
$\ln s_t$	4.553	0.061	0.091	0.002	0.002
$\ln e_t$	-0.498	0.008	0.000	0.171	0.000
			B. First differences		
Δlno_t	0.000	0.008	0.731	0.000	0.000
Δlni_t	-0.008	0.003	0.000	0.000	0.000
Δlns_t	0.001	0.002	0.000	0.000	0.000
Δlne_t	0.000	0.001	0.000	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Table A2.8: Summary Statistics for US

			p-values		
Series	Mean	Variance	Skewness	Kurtosis	Normality
			A. Levels		
lno_t	3.747	0.308	0.003	0.000	0.000
lni_t	0.746	1.848	0.000	0.014	0.000
lns_t	4.448	0.156	0.000	0.000	0.000
lne_t	4.595	0.032	0.000	0.001	0.000
			B. First differences		
Δlno_t	0.000	0.008	0.380	0.000	0.000
Δlni_t	-0.007	0.011	0.000	0.000	0.000
Δlns_t	0.003	0.001	0.000	0.000	0.000
Δlne_t	0.002	0.000	0.008	0.000	0.000

Note: Sample Period, monthly observations, 1987:05-2016:03.

Chapter 3

Oil Prices and the Renewable Energy Sector

Coauthored with Apostolos Serletis.
Under Revision.

ABSTRACT

Energy security, climate change, and growing energy demand issues are moving up on the global political agenda, and contribute to the rapid growth of the renewable energy sector. In this paper we investigate the effects of oil price shocks, and also of uncertainty about oil prices, on the stock returns of clean energy and technology companies. In doing so, we use monthly data that span the period from May 1983 to December 2016, and a bivariate structural VAR model that is modified to accommodate GARCH-in-mean errors, and it is used to generate impulse response functions. Moreover, we examine the asymmetry of stock responses to oil price shocks and compare them accounting for oil price uncertainty, while effects of oil price shocks of different magnitude are also investigated. Our evidence indicates that oil price uncertainty has no statistically significant effect on stock returns, and that the relationship between oil prices and stock returns is symmetric. Our results are robust to alternative model specifications and stock prices of clean energy companies.

JEL classification: C32, G15, Q42.

Keywords: Renewable energy, Transition, Oil prices, Uncertainty, GARCH-in-Mean model, Asymmetric responses.

3.1 Introduction

The renewable energy sector has been experiencing remarkable growth over the past decade. Worldwide installations of renewable power capacity reached a new high record of 138.5 GW[1] in 2016 (New Energy Finance, 2017), and expectations for large-scale deployment of renewables have also been raised for years to come. This development, however, is not a result of a single factor or event, but rather a combination of economic and societal concerns associated with the reliability and security of energy supply, the depletion of natural resources, extreme weather events triggered by environmental degradation, and decoupling of economic growth from energy consumption. Alongside these the financial performance of renewable energy companies also has a critical influence on the future development of the renewable energy sector, since companies' profitability is positively related to their success in acquiring private capital for infrastructure investments. Therefore, a better understanding of the underlying driving forces is of high interest, not only to investors who need to assess the risk exposure assumed by their firms, and construct hedge ratios and portfolio weights accordingly, but also to policymakers who must evaluate and adjust the renewable energy policy landscape, in order to facilitate the transition towards a sustainable energy system.

Financial performance of renewable energy companies is contingent upon numerous factors, and in fact prices of other energy products that are likely to substitute for renewable energy, for instance, through their positive cross-price elasticities, are considered to be among the most important determinants. Hence, with crude oil being the dominant energy source in the world, accounting for 36.9% of the global primary energy consumption in 2016 (EIA, 2017),[2] it is essential to investigate the relationship between the oil price development and the financial performance of the renewable energy sector. Apart from the vast majority of the literature that investigates the effects of oil prices on the economy, the aggregate stock market activity, or even other energy prices such as, for example, the natural gas price, only a few studies pay particular attention to the impact of oil prices on the financial performance of the renewable energy sector; the most noticeable being Henriques and Sadorsky (2008), Kumar *et al.* (2012), Broadstock *et al.* (2012), Sadorsky (2012a), Managi and Okimoto (2013), Wen *et al.* (2014), Inchauspe *et al.* (2015), and more recently Reboredo (2017).

All of these studies, however, ignore the potentially important effect of oil price uncertainty on renewable energy companies, and more particularly on their financial performance. Since the outset of the global financial crisis in 2008-2009, the crude oil market has experienced dramatic oil price fluctuations, for instance from \$140/barrel in the summer of 2008 to \$60/barrel by the end of 2008, which were followed, after the sharp downturn in

[1] This includes global new investments in wind, solar, biomass and waste-to-energy, geothermal, small hydro and marine sources.

[2] Oil supply of 35.942 quadrillion Btu satisfied 97.394 quadrillion Btu of demand (EIA, 2017).

the mid-2014, by low and remarkably volatile oil prices (see Figure 3.1). Increased oil price volatility translates into significant uncertainty in the crude oil market, and its overall impact should accelerate future transition towards renewable energy. The main argument behind this statement is that with renewable energy considered as a substitute for crude oil, increases in oil price uncertainty should encourage a substitution effect away from crude oil towards renewable energy sources, thus improving the financial performance of renewable energy companies. However, despite some anecdotal evidence that rising oil price uncertainty strengthens the dominance of the renewable energy industry in the global energy scene, and therefore its financial performance, an up-to-date empirical evidence is imperative to confirm or invalidate the hypothesis.

This paper contributes to the literature on the relationship between the price of oil and the stock returns of clean energy and technology companies in several ways. First, we use monthly data over the period from May 1983 to December 2016, and estimate a bivariate GARCH-in-Mean structural VAR model by full information maximum likelihood, thus avoiding Pagan's (1984) generated regressor problems. By doing so, we directly investigate the effect of oil price uncertainty on the response of the renewable energy and technology stock returns. Second, we generate the impulse response functions to assess whether the response of stock returns is symmetric or asymmetric to positive and negative oil price shocks, after accounting for the effect of oil price uncertainty. As an additional contribution to the literature, the use of a test, recently introduced by Kilian and Vigfusson (2011), over the same data set allows us to investigate whether the renewable energy and technology stock returns respond symmetrically or asymmetrically to positive and negative oil price shocks of different magnitude.

The rest of the paper is structured as follows. In Section 3.2, we review and discuss the empirical literature related to the effects of oil price on the aggregate and industry-specific stock returns, while paying special attention to the relationship between oil prices and stock returns of clean energy and technology companies. Section 3.3 presents the bivariate GARCH-in-Mean structural VAR model, which is employed to investigate the direct effects of oil price uncertainty on the employed stock returns. In Section 3.4 we present the data and discuss the empirical findings, while in Section 3.5 we investigate the robustness of our results to the use of a formal symmetry test based on a nonlinear structural VAR model, recently proposed by Kilian and Vigfusson (2011). The last section discusses the findings and concludes the paper.

3.2 Review of the literature

3.2.1 Oil prices and stock market activity

Given the indispensable role of crude oil as an energy commodity in the world economy, but also as a financial asset since the early 2000s, there is a substantial and growing body of literature investigating the relationship between oil price shocks and stock market returns. On theoretical grounds, stock prices reflect the value of expected future earnings of companies that contingent on several factors, such as relative sensitivity to changes in oil prices or dissimilar dependence on the oil industry, might be driven by oil price shocks. In regard to this, Chen *et al.* (1986) and Hamao (1988) study the effects of oil price changes on the U.S. and Japanese stock markets, respectively, and find no compelling evidence that supports such a relationship. Kling (1985) and Jones and Kaul (1996), in contrast, argue that changes in oil prices have a detrimental effect on stock market returns, while Sadorsky (1999) confirms that oil price fluctuations are imperative for understanding stock market development. Huang *et al.* (1996), however, find no negative relationship between changes in the price of oil futures and the returns of various stock indices; while Wei (2003) reports that the decline in the U.S. stock market in 1974 cannot be attributed to the 1973-1974 oil price increase. In fact, he suggests other possible factors, including the tightening of monetary policy. This view also receives strong support from Bjørnland (2009), who examines the small and open oil-exporting country of Norway, and argues that oil prices affect stock market returns indirectly, through monetary policy.

A possible explanation for all the aforementioned studies not reaching a general consensus is that none of them, apart from Bjørnland (2009), differentiates oil-exporting from oil-importing countries. Wang *et al.* (2013) compare the relationship of oil price shocks and stock returns in several countries with different oil-dependence, and find that the explanatory power of oil prices shocks to stock return variations is stronger in oil-exporting than oil-importing countries, as well as the evidence of different magnitudes, durations, and directions of stock response. Arouri and Rault (2012) support this view through their study, with particular reference in the Gulf Corporation Countries, finding a positive relationship between oil price shocks and stock prices. From a similar point of view, Park and Ratti (2008) examine this relationship in the United States and 13 European countries, and report that a positive oil price shock has a statistically significant and negative effect on stock prices of all the oil-importing countries, but positive in the case of the oil-exporting country of Norway.

Another strand of literature focuses on the effects of oil price shocks on the stock markets of emerging economies, since the latter are less energy efficient, and therefore more exposed to oil price changes. Papapetrou (2001) uses a multivariate vector autoregression model to investigate the dynamic relationship between oil prices, real stock prices, interest rates, and real economic activity, and underlines the important role of oil price movements in the Greek stock price development. From a similar point of view, Basher and Sadorsky (2006) employ a multifactor model and find strong evidence that oil price risk drives stock price returns in emerging markets, while Cong *et al.* (2008) find evidence against such a positive relationship for most Chinese stock returns, except for those of the manufacturing and oil sectors.

In a different study, Kilian and Park (2009) follow Kilian's (2009) approach and decompose oil price fluctuations into structural shocks, in order to study their effects on the U.S. stock market returns. In doing so, they treat the price of crude oil as endogenous, and report that the response of stock prices to oil price shocks depends on the nature of oil price shocks. Some notable studies that build upon this framework are Apergis and Miller (2009), Güntner (2014), and Ahmadi *et al.* (2016). Nor do all the industry sectors respond in a similar way to oil price shocks [see Lee *et al.* (1995), Davis and Haltiwanger (2001), and Lee and Ni (2002)], and therefore sectoral-based investigation is imperative for a better understanding of this relationship. The oil and gas sectors, as well as the technology sector, are investigated by Sadorsky (2001, 2003), while a large number of industries in the U.S. and China are explored by Elyasiani *et al.* (2011) and Caporale (2015), respectively. All their findings underline the necessity of studying the various industries separately, mainly due to their different dependence on the oil industry.

A less extensive yet substantial body of literature investigates the impact of oil price volatility, which is also a measure of uncertainty, on economic activity and stock market returns. Elder and Serletis (2010) were the first to examine the direct effects of oil price uncertainty on real economic activity, and provide evidence of a negative and significant relationship. In addition, they find that increased oil price volatility amplifies the negative response of real economic activity to an unexpected increase in the real price of oil, while diminishing the positive response to an unexpected drop in the real price of oil. Lee *et al.* (1995) and Ferderer (1996) also underline the important role of oil price volatility in economic activity, while Sadorsky (1999) first explores its impact on the U.S. stock returns, and reports a statistically significant negative association. From a similar point of view, Park and Ratti (2008) show that increased oil price volatility depresses real stock returns in the oil-importing European countries, while they document little evidence of asymmetric effects. Masih *et al.* (2011) also indicate the dominance of oil price volatility on real stock returns in South Korea, and comment on the need of firms for adjusting their risk management procedures accordingly. Diaz *et al.* (2016), from an international point of view, examine the relationship between oil price volatility and stock returns in the G7 economies, and provide evidence in favor of a negative association. This negative relationship, however, does not receive support by Alsalman (2016), who reports that uncertainty about the real price of oil has no statistically significant effect on U.S. real stock returns across all the investigated industries, except in the case of the coal sector. Moreover, she finds that aggregate stock returns respond symmetrically to positive and negative oil price shocks, but this symmetry does not hold across all sectors, thus highlighting the importance of studying each sector separately. Alsalman and Herrera (2015) provide further evidence in favor of symmetric response for aggregate stock returns, while Herrera *et al.* (2015) explain symmetric (asymmetric) responses through the statistically insignificant (significant) effect of oil price uncertainty on investments.

3.2.2 Oil prices and the renewable energy sector

Despite the rapid growth of the renewable energy sector over the past decade in the face of rising oil prices and environmental concerns, little attention has been devoted to the relationship between oil prices and stock prices of renewable (or alternative) energy sector.[3] To the best of our knowledge, Henriques and Sadorsky (2008) first discuss this gap in the literature, and investigate the dynamic relationships between alternative energy stock prices, technology stock prices, oil prices, and interest rates, through a four variable vector autoregression model. They find causality effects, in the spirit of Granger, propagating from both technology stock prices and oil prices towards stock prices of alternative energy companies, listed on major U.S. stock exchanges, while the latter stock prices are found to be more strongly correlated with stock prices of technology companies, rather than with oil prices. In fact, they find that oil prices have only a limited impact on renewable energy stock returns. However, Kumar *et al.* (2012) investigate this relationship, considering also the prices for carbon allowances, and provide evidence that rising oil prices have a significant positive impact on clean energy stock prices, contrary to carbon market prices. Similar to Henriques and Sadorsky (2008), they also support the view that clean energy and technology companies are considered by investors as similar asset classes. Broadstock *et al.* (2012) adopt time-varying conditional correlation and asset pricing models to explore how the dynamics of international oil prices affect Chinese energy-related stock price returns. Specifically, they study the response of a composite energy index, as well as three sub-indices for oil and natural gas, coal and electricity, and new energy sector, to international oil price shocks, and report that oil price changes are a significant factor in energy-related stock price movements, especially after the 2008 financial crisis, whereas the new energy stocks are found to be the most resilient to oil price shocks.

Building upon the vector autoregressive analysis of Henriques and Sadorsky (2008), Managi and Okimoto (2013) consider a Markov-switching model in order to explore possible struc-

[3] The terms alternative energy, clean energy, renewable energy, and sustainable energy are used interchangeably when the discussion comes around to tracking stock indices or investment assets.

tural changes and asymmetric effects among oil prices, technology stock prices, and clean energy stock prices. They provide evidence in favor of a structural change in the market in late 2007, and a positive relationship between oil prices and clean energy prices thereafter. Furthermore, they support the view of Henriques and Sadorsky (2008) and Kumar *et al.* (2012) for similarity between clean energy stock prices and technology stock prices, by arguing that technologies related to storage and other forms of clean energy benefit from a number of government policies. More recently, Reboredo (2015) investigates the dependence structure and conditional value-at-risk (CoVaR) measure of systemic risk between oil prices and a set of global and sectoral renewable energy indices, through the employment of copulas for the period from December 2005 to December 2013. His empirical findings display that a time-varying average and symmetric tail dependence exists between oil returns and several global and sectoral renewable energy indices, while oil price dynamics contribute around 30% to downsize and upside risk of renewable energy companies.

From a different point of view, Inchaupse *et al.* (2015) examine the dynamics of excess returns for the WilderHill New Energy Global Innovation Index (NEX), which constitutes a major international benchmark index for renewable energy, through the use of a multi-factor asset pricing model with time-varying coefficients. They report a weak influence of oil price, relatively to the MSCI World Index and technology stocks, on NEX returns, altough this effect becomes more influential after 2007. In fact, they find that NEX Index yields negative active returns after the financial crisis in 2009, and attribute this poor performance to the increased market uncertainty triggered by low oil price and government subsidy cuts. Bürer and Wüstenhagen (2009) also underline the important contribution of supportive policy environments to renewable energy investments, while Hofman and Huisman (2012) show that, after the financial crisis, 11 out of 12 renewable energy policies decreased significantly in popularity by venture capital and private equity investors. Decreased risk tolerance, higher capital demand and increased borrowing costs are mentioned as some of the contributing factors.

In recent years, a new strand of literature has emerged studying volatility spillovers between oil prices and renewable energy stock prices. Specifically, Sadorsky (2012a) employs different multivariate GARCH models (BEKK, Diagonal, CCC, and DCC) to examine conditional correlations and volatility spillovers between oil prices and the stock prices of clean energy and technology companies. He finds that stock prices of clean energy companies correlate more strongly with technology stock prices than with oil prices, that significant volatility spillovers exist among them, and that oil is a useful hedge for clean energy stocks. Extending this framework to include asymmetric effects, Wen *et al.* (2014) use a bivariate asymmetric BEKK model to investigate mean and volatility spillover effects between renewable energy and fossil fuel stock prices in China. They provide evidence that negative news about new energy and fossil fuel stock returns lead to larger return changes in their counter assets than positive news, that significant mean and volatility spillovers occur among them, and that new energy stocks are more speculative and riskier than fossil fuel stocks. Sadorsky (2012b) provides a comprehensive study on different factors of renewable energy company risk and highlights that renewable energy companies can be among the riskiest types of companies to invest in. In fact, he shows that oil price increases have a positive effect on company risk, whereas increases in company sales growth reduce systematic risk. Very recently, Reboredo *et al.* (2017) investigate dependence and causal effects between oil price dynamics and renewable energy returns for the period 2006-2015. Through the use of continuous and discrete wavelets and linear and non-linear Granger causality tests, they find evidence of non-linear causality running from renewable energy indices to oil prices, and mixed evidence of causality propagating from oil prices to renewable energy prices.

Yet, no study has investigated the relationship between oil price uncertainty and the stock prices of renewable energy companies, to the best of our knowledge. The purpose of the paper is to fill this void. A better understanding of the relationship between oil price uncertainty and financial performance of the renewable energy sector is imperative for understanding and foreseeing the evolution of the renewable energy sector in the years to come.

3.3 The structural GARCH-in-Mean VAR

In this paper we employ a bivariate monthly structural VAR model, modified to accommodate GARCH-in-Mean errors as in Elder (2004) and Elder and Serletis (2010), in logarithmic oil price changes and stock returns. The structural system is represented as follows

$$\boldsymbol{B}\boldsymbol{y}_t = \boldsymbol{\alpha} + \sum_{i=1}^{p} \boldsymbol{\Gamma}_i \boldsymbol{y}_{t-i} + \boldsymbol{\Lambda}\boldsymbol{H}^{1/2}_{\boldsymbol{\Delta} lno_t} + \boldsymbol{\epsilon}_t \tag{3.1}$$

$$\epsilon_t|\Omega_{t-1} \sim iid\, N(0, \boldsymbol{H}_t) \tag{3.2}$$

where the vector $\boldsymbol{y}_t$ includes the change in the price of oil (Δlno_t) and the stock returns (Δlnz_t), $\boldsymbol{\alpha}$ is a parameter vector, $\boldsymbol{B}$ and $\boldsymbol{\Gamma}_i$ are 2 × 2 matrices representing the contemporaneous and lagged effects, and $\boldsymbol{\epsilon}_t$ denotes a vector of serially and mutually uncorrelated structural shocks. Moreover, $\boldsymbol{\Lambda}$ is a vector of coefficients that measures the effect of oil price volatility on the conditional mean of the employed series, $\boldsymbol{H}^{1/2}_{\boldsymbol{\Delta} lno_t}$ is the conditional standard deviation of oil, Ω_{t-1} denotes the information set at time $t-1$, and $\boldsymbol{H}_t$ is the covariance matrix. The system is identified by assuming that the diagonal elements of $\boldsymbol{B}$ are equal to unity, that $\boldsymbol{B}$ is a lower triangular matrix, and that the structural disturbances, $\boldsymbol{\epsilon}_t$, are contemporaneously uncorrelated. Therefore, we allow the stock returns to respond to contemporaneous innovations in the change in the price of oil, as in Edelstein and Kilian (2007).

The conditional variance is modeled as bivariate GARCH

$$diag(\boldsymbol{H}_t) = \boldsymbol{A} + \sum_{j=1}^{s} \boldsymbol{F}_j diag(\boldsymbol{\epsilon}_{t-j}\boldsymbol{\epsilon}'_{t-j}) + \sum_{i=1}^{r} \boldsymbol{G}_i diag(\boldsymbol{H}_{t-i}) \tag{3.3}$$

where *diag* is the operator that extracts the diagonal from a square matrix. In fact, we assume that the conditional variance of $y_{i,t}$ depends only on its own past squared errors and its own past conditional variances, so that parameter matrices $\boldsymbol{F}_j$ and $\boldsymbol{G}_i$ are also diagonal. Moreover, we estimate the variance equation (3.3) with $s = r = 1$, since the parsimonious GARCH(1,1) model has been found to outperform other GARCH configurations, under the most general conditions [see Hansen and Lunde (2005)]. Low-order GARCH models, and particularly GARCH (1,1), receive also support by Bollerslev *et al.* (1992).

We estimate the model by full information maximum likelihood, thus avoiding Pagan's (1984) generated regressor problems associated with estimating the variance function parameters separately from the conditional mean parameters. Consistent with Elder (2004) and Elder and Serletis (2010), we estimate the bivariate GARCH-in-Mean VAR model described by equations (1)-(3), by full information maximum likelihood, and by numerically maximizing the log likelihood function

$$l_t = -\frac{n}{2} ln(2\pi) + \frac{1}{2} ln|\boldsymbol{B}|^2 - \frac{1}{2} ln|H_t| - \frac{1}{2}(\boldsymbol{\epsilon}'_t \boldsymbol{H}_t^{-1} \boldsymbol{\epsilon}_t) \tag{3.4}$$

with respect to the structural parameters $\boldsymbol{B}, \alpha, \boldsymbol{\Gamma}, \boldsymbol{\Lambda}, \boldsymbol{A}, \boldsymbol{F}$, and $\boldsymbol{G}$.

In doing so, we set the pre-sample values of the conditional variance matrix $\boldsymbol{H}_0$ to their unconditional expectation and condition on the pre-sample values of $\boldsymbol{y}_t$. To ensure that $\boldsymbol{H}_t$ is positive definite, we restrict $\boldsymbol{A} > 0$, $\boldsymbol{F} \geq 0$, and $\boldsymbol{G} \geq 0$, as in Engle and Kroner (1995). By satisfying the standard regularity conditions, full information maximum likelihood estimates are asymptotically normal and efficient, with the asymptotic covariance matrix given by the inverse of Fisher's information matrix. For mode details, see Elder (2004) or Elder and Serletis (2010).

To evaluate the effect of oil price uncertainty on the response of stock returns to an oil price shock, we generate impulse response functions. These are based on an oil price shock equal to the unconditional standard deviation of the change in the price of oil and are calculated for the GARCH-in-Mean VAR as in Elder (2003)

$$\frac{\partial E(y_{j,t+k}\,|\,\varepsilon_{i,t}\,,\Omega_{t-1})}{\partial \varepsilon_{i,t}} = \sum_{\tau=0}^{k-1} \left[\boldsymbol{\Theta}_\tau \boldsymbol{B}^{-1} \boldsymbol{\Lambda} \left(\boldsymbol{F} + \boldsymbol{G}\right)^{k-\tau-1} \boldsymbol{F}\right] \boldsymbol{\iota}_1 + \left(\boldsymbol{\Theta}_k \boldsymbol{B}^{-1}\right) \boldsymbol{\iota}_0. \tag{3.5}$$

where $\boldsymbol{\iota}_1$ denotes $\partial E\left[vec\left(\boldsymbol{\epsilon}'_t \boldsymbol{\epsilon}_t\right)|\,\varepsilon_{i,t}\,,\Omega_{t-1}\right]/\,\partial \varepsilon_{i,t}$, which is an $N^2 \times 1$ vector with $2\varepsilon_{i,t}$ in the $N(i-1)+i$ spot and 0s elsewhere. Moreover, $\boldsymbol{\iota}_0$ denotes $\partial \boldsymbol{\epsilon}_t / \partial \varepsilon_{i,t}$, which is an $N \times 1$

vector with $\varepsilon_{i,t}$ in the ith spot and 0s elsewhere. In fact, Elder (2003) notes that equation (5) is analogous to the impulse response function of an orthogonalized VAR. The second term on the right side of the equation captures the usual direct effect of a shock $\varepsilon_{i,t}$ on the conditional forecast of $y_{j,t+k}$ while the first term captures the effect on the conditional forecast of $y_{j,t+k}$ through the forecasted effect on the conditional variance. It is noteworthy that as the horizon increases the first term shrinks to the zero matrix since the eigenvalues of $\boldsymbol{F} + \boldsymbol{G}$ are constrained to be lower than one. See Elder (2003) for more details.

In particular, the impulse responses are calculated from the maximum likelihood estimates of the model's parameters, while the one-standard error bands are generated by the Monte Carlo method described in Hamilton (1994, p. 337). The responses are constructed based on parameter values drawn randomly from the sampling distribution of the maximum likelihood parameter estimates, where the covariance matrix of the maximum likelihood estimates is derived from an estimate of Fisher's information matrix. Finally, we plot the impulse responses of stock returns to positive and negative oil price shocks, after accounting for oil price uncertainty, thus gaining a better insight into whether responses are symmetric or asymmetric.

3.4 The data and empirical evidence

This study uses monthly closing prices of three clean energy indices, namely, WilderHill Clean Energy Index (ECO), WilderHill New Energy Global Innovation Index (NEX), and S&P Global Clean Energy Index (SPGCE), as well as the technology index, NYSE Arca Technology Index (PSE). Specifically, ECO is a modified equal dollar-weighted index comprised of 52 companies which are active in the renewable energy sector, and whose activities stand to benefit substantially from a societal transition toward the use of cleaner energy and conservation. This index is the oldest index devoted merely to tracking clean (renewable) energy companies, and it is disseminated by the American Stock Exchange (AMEX). NEX is a modified dollar-weighted index comprised of publicly traded companies whose businesses focus on renewable energy and climate change mitigation technologies. Most of the stocks are listed on exchanges outside the United States, and therefore the index is weakly correlated with ECO. NEX constitutes the first and leading global index for clean, alternative, and renewable energy. SPGCE is a weighted index of 30 companies from around the world that are engaged in clean energy production, and clean energy equipment and technology business.

Investments in renewable energy companies, however, may be considered to be similar to those of other high technology companies (Henriques and Sadorsky, 2008), an argument actually supported by the stock market behavior in the late 1990s. Therefore, we also employ in our analysis the NYSE Arca Technology Index which is a price weighted index devoted solely to technology. In particular, it is composed of 100 leading technology companies that are active in 15 different industries, including computer hardware, software, data storage and processing, electronics, semiconductors, telecommunications, and biotechnology. Figures 3.1-3.5 illustrate the development of each of the indices alongside with its squared returns. Unlike the PSE index that fully recovers from the losses associated with the global financial crisis in 2008-2009, while exhibiting a clear upward trend for the rest of the investigated period, all three clean energy indices remain at historically low levels. In particular their significant drop in value during the financial crisis is partly reversed in the next year, before another, but smaller, plunge occurs between 2011 and 2012. Since this last decline, only the NEX index rebounds completely and continues fluctuating at the post-financial crisis levels. All stock indices exhibit low price volatility, at least compared to the oil futures price.

Figure 3.1: WTI crude oil price and its squared returns

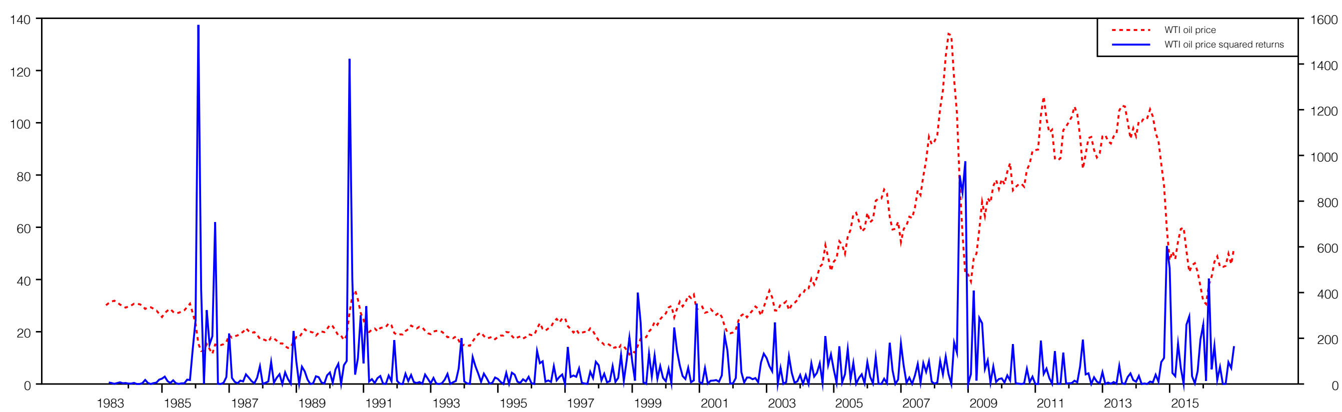


Figure 3.2: ECO index and its squared returns

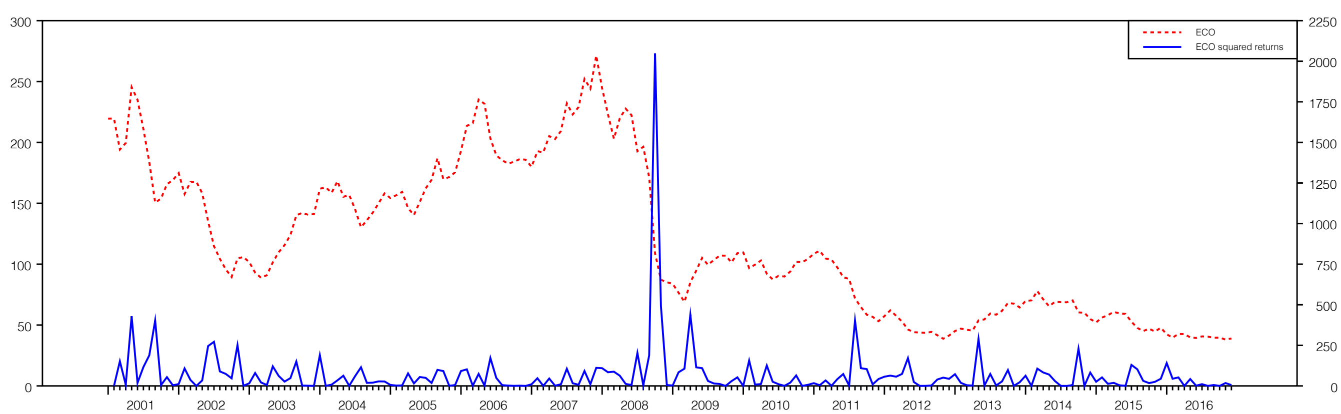


Figure 3.3: NEX index and its squared returns

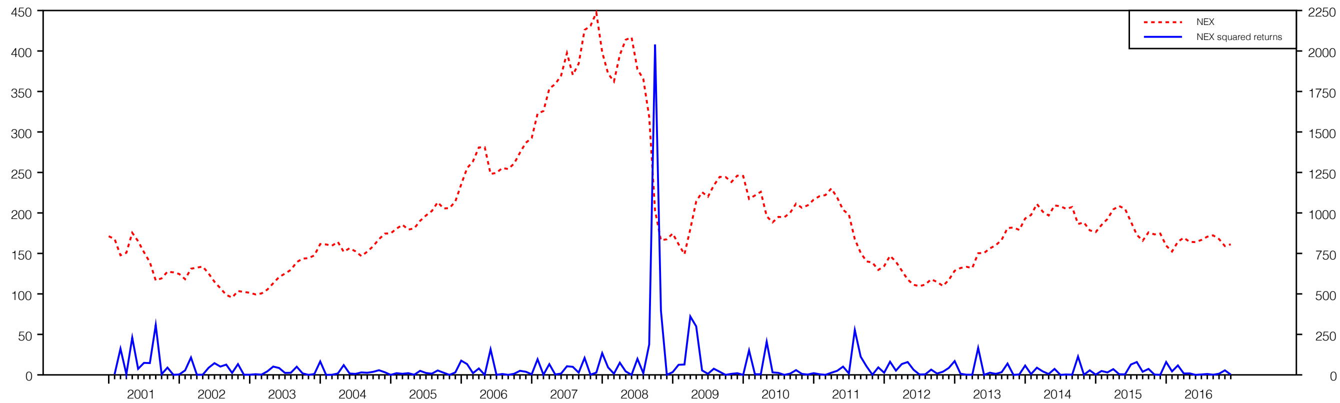


Figure 3.4: PSE index and its squared returns

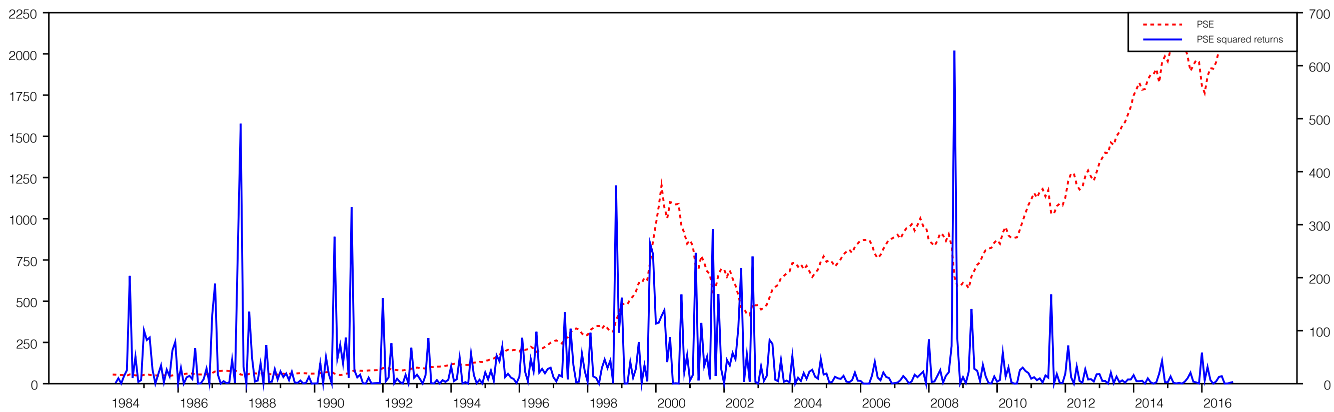
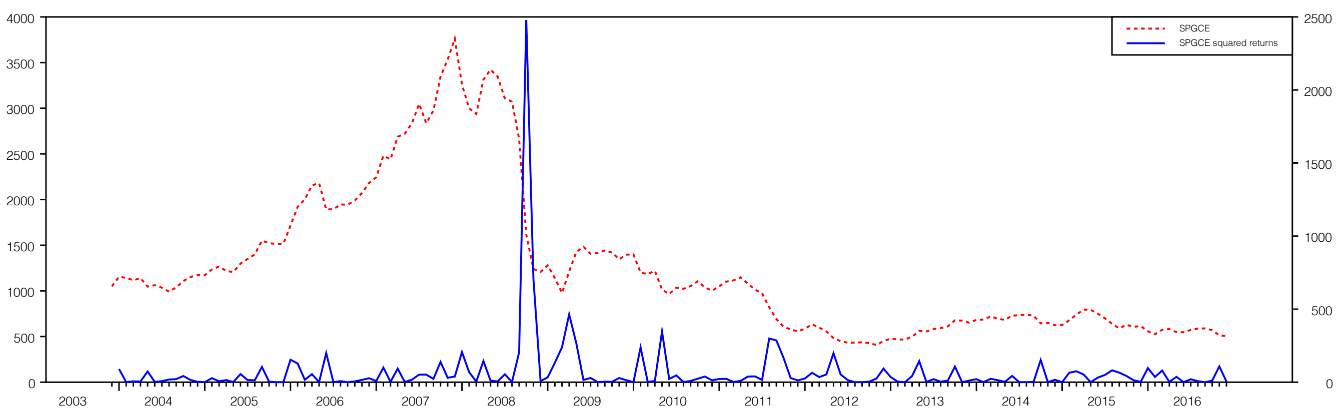


Figure 3.5: SPGCE index and its squared returns



In addition, the excess return on the market, which is defined as the value-weighted return on all NYSE, AMEX, and NASDAQ stocks from the Center for Research in Security Prices (CSRP) minus the 1-month Treasury bill rate, is employed as a proxy for the aggregate U.S. stock return. For the price of oil, we use the nearest futures contract to maturity on the West Texas Intermediate crude oil futures contract, for a number of reasons. Firstly, due to temporary shortages or surpluses, spot prices are more affected by short-run price fluctuations than futures prices (Sadorsky, 2001). Secondly, the effectiveness of firms' hedging activities is evaluated by the variability of futures oil prices (Elyasiani *et al.*, 2011). Lastly, it is the most extensively traded oil futures contract in the world, and therefore constitutes a benchmark for the oil market and commodity portfolio diversification (Sadorsky, 2012). Our data sample covers the period from May 1983, which coincides with the availability of our proxy for the oil price, to December 2016. For each data series, we calculate the continuously compounded monthly returns as $100 \times ln(p_t/p_{t-1})$ as in Sadorsky (2012), and we plot the returns of each of the stock indices alongside with the price of oil futures in Figure 3.6.

It is worth mentioning here an interesting feature of the data related to the contemporaneous correlation between the different price series. We present these correlations in Table 3.1 for log levels (in panel A) and for first differences of log levels (in panel B). In order to determine whether these correlations are statistically significant, we follow Pindyck and Rotemberg (1990) and we perform a likelihood ratio test of the hypotheses that the correlation matrices are equal to the identity matrix. The test statistic is

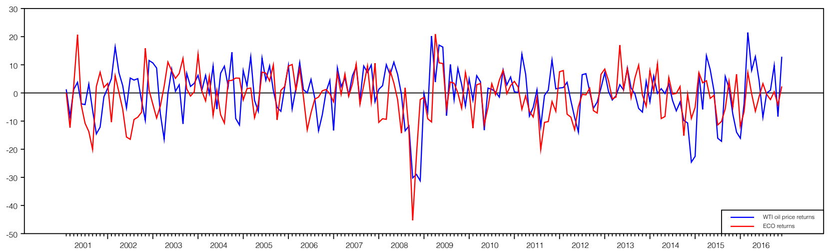
$$-2ln(|R|^{N/2})$$

where $|R|$ is the determinant of the correlation matrix and N is the number of observations. The test statistic is distributed as χ^2 with $q(q-1)/2$ degrees of freedom, where q is the number of series. Although the test statistic is 0.000 for the logged prices, it is equal to 939.001 with a p-value of 0.000 for the first differences of the logs, and therefore we can clearly reject the hypothesis that these series are uncorrelated. In addition, we notice that some of the correlation patterns documented in Table 3.1 also manifest in the graphical presentation of the employed series in Figure 3.6.

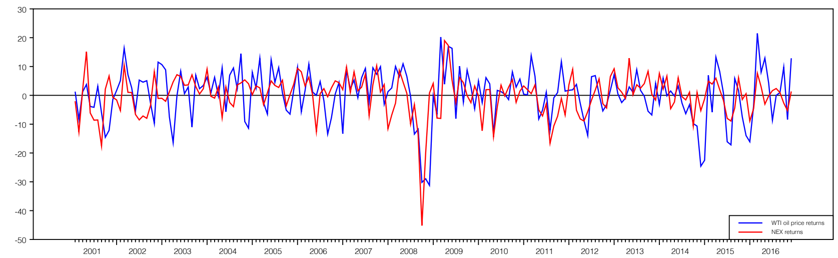
Before we continue to the next step of modeling, we conduct some unit root and stationary tests in each of the employed series in Table 3.2, in order to test for the presence of a stochastic trend in the autoregressive representation of the series. All three tests, namely, the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller, 1981], the Dickey-Fuller GLS (DF-GLS) test [see Elliot *et al.*, 1996] and the KPSS test [see Kwiatkowski *et al.*, 1992] provide evidence that all series are stationary, or integrated of order zero, $I(0)$. It should be noted that the Schwarz information criterion (SIC) is used to select the lag length in both the ADF and DF-GLS regressions, assuming a maximum lag length of 4 months for each

Figure 3.6: WTI crude oil price returns and returns of sub-indices

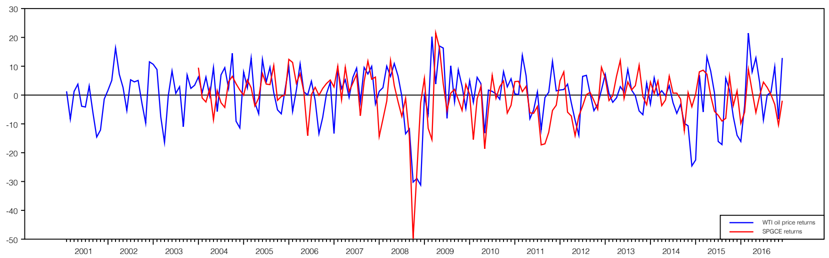
(a) WTI and ECO Index



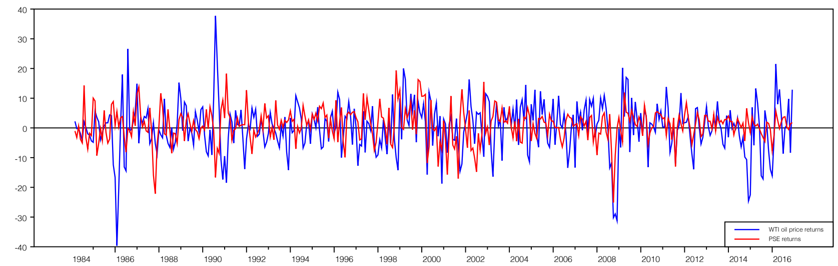
(b) WTI and NEX Index



(c) WTI and PSE Index



(d) WTI and SPGCE Index



(e) WTI and Aggregate Index

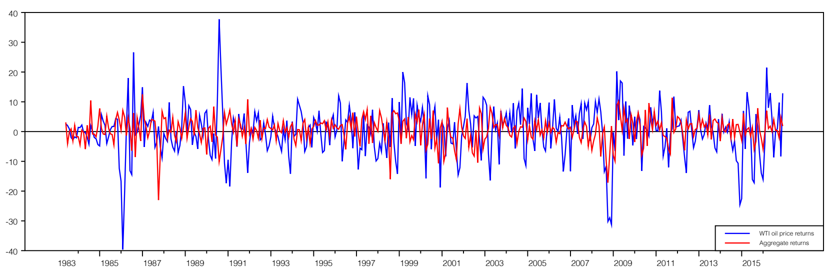


Table 3.1: Contemporaneous correlations

	A. Log levels					B. First differences of log levels				
Series	ECO	NEX	PSE	SPGCE	WTI	ECO	NEX	PSE	SPGCE	WTI
ECO	1	0.996	0.985	0.998	0.989	1	0.931	0.767	0.907	0.434
NEX	0.996	1	0.996	0.999	0.996	0.931	1	0.798	0.959	0.490
PSE	0.985	0.996	1	0.992	0.996	0.767	0.798	1	0.721	0.328
SPGCE	0.998	0.999	0.992	1	0.994	0.907	0.959	0.721	1	0.440
WTI	0.989	0.996	0.996	0.994	1	0.434	0.490	0.328	0.440	1
	$x^2(10) = 0.000$					$x^2(10) = 939.001$				

Note: Monthly data from 2003:12 to 2016:12.

series, while the Bartlett kernel for the KPSS regressions is determined using the Newey-West bandwidth (NWBW). Moreover, in Table 3.3 we conduct a series of Ljung-Box (1979) tests for serial correlation, in which the Q-statistics are asymptotically distributed as $\chi^2(4)$ on the null hypothesis of no autocorrelation. Certainly, there is significant serial dependence in the data. In addition, a Ljung-Box test for serial correlation in the squared data provides evidence in favor of conditional heteroscedasticity, which is also confirmed by an ARCH test, distributed as a $\chi^2(4)$ on the null hypothesis of no ARCH effects.

Motivated by the aforementioned discussions and the dynamic properties of the employed data, we estimate the bivariate GARCH-in-Mean structural VAR model given by equations (3.1)-(3.3), with one lag as suggested by the Schwarz information criterion (SIC), and using monthly observations on the log change in the price of oil and the log change in the price of each of the indices examined in this paper. To evaluate the efficiency of the model specification in terms of predictability, and its consistency with the data, we calculate and compare the SIC for the GARCH-in-Mean VAR model and the conventional homoskedastic VAR model. Based on the values of the Schwarz information criterion in Table 3.4, the bivariate GARCH-in-Mean VAR model is preferred over the homoskedastic VAR model in most of the cases.

The parameter estimates of the mean and variance functions, for the different sectors, are reported in Tables A3.1-A3.5, with t-statistics in parentheses. We find statistically significant evidence of ARCH effects in the price of oil and GARCH effects in the stock returns, which provide further support for our proposed model. Specifically, in the case of the aggregate stock returns (see Table A3.5), the coefficients on the lagged squared errors and lagged conditional variance for both the price of oil and stock returns are highly significant, while their sum is equal to (0.268+0.603)=0.871 and (0.118+0.852)=0.970, respectively. These results provide evidence that the volatility process for the crude oil price, and also

Table 3.2: Unit roots and stationary tests

	Test			
Series	ADF	DF-GLS	KPSS	Decision
AGG	-18.717*	-5.676*	0.057	$I(0)$
ECO	-10.154*	-10.107*	0.063	$I(0)$
NEX	-9.351*	-9.070*	0.080	$I(0)$
PSE	-14.638*	-13.708*	0.077	$I(0)$
SPGCE	-8.264*	-3.282*	0.182	$I(0)$
WTI	-14.600*	-13.821*	0.075	$I(0)$

Note: An asterisk indicates significance at the 5% level.

Table 3.3: Tests for serial correlation and conditional heteroskedasticity

Series	Q(4)	$Q^2(4)$	ARCH(4)
AGG	2.777 (0.596)	13.527 (0.009)	10.762 (0.029)
ECO	17.059 (0.002)	8.926 (0.063)	10.445 (0.034)
NEX	27.908 (0.000)	9.577 (0.048)	10.718 (0.030)
PSE	37.651 (0.000)	17.017 (0.002)	13.515 (0.009)
SPGCE	25.909 (0.000)	14.220 (0.007)	15.616 (0.004)
WTI	42.656 (0.000)	69.517 (0.000)	52.134 (0.000)

Note: Numbers in parentheses are marginal significance levels.

that for the aggregate stock returns, is very persistent. The primary coefficient of interest, however, from the bivariate GARCH-in-Mean VAR relates to the effect of uncertainty about the change in the price of oil on stock returns. This is the coefficient on the conditional standard deviation of the log change in the price of oil in the stock return equation, λ_{21}, and the null hypothesis is that the value of it is equal to zero. The point estimates for the coefficient on oil price uncertainty are reported in Tables A3.1-A3.5, and show that there is not enough statistical evidence to reject the null hypothesis that the value of λ_{21} is zero. This finding holds across all industry sectors, with the coefficient on oil price uncertainty having a positive but statistically insignificant effect on the renewable and technology industries, and insignificant negative effect on the aggregate stock market.

In order to investigate the effect of incorporating oil price uncertainty on the dynamic response of stock returns to an oil price shock, we plot the impulse responses for positive and negative oil price shocks in Figures A3.1-A3.5, over a horizon of twelve months. These are generated from the maximum likelihood estimates of the model's parameters. Accounting for the effect of oil price uncertainty, we find that a positive shock in oil prices tends to increase the stock returns of the three renewable energy indices, namely ECO, NEX, and SPGCE,

Table 3.4: Model specification tests with WTI crude oil price

Model	Homoskedastic VAR	Bivariate GARCH-M VAR
AGG - WTI	5203.715	5143.391
ECO - WTI	2696.742	2704.585
NEX - WTI	2614.204	2615.708
PSE - WTI	5265.364	5208.170
SPGCE - WTI	2191.582	2194.203

Note: This table computes the Schwartz Information Criterion for the conventional homoskedastic VAR and the bivariate GARCH-in-Mean VAR.

immediately, while this positive effect decreases sharply within the first two months (see the first panel of Figures A3.1, A3.2, and A3.4). Specifically, the SPGCE index experiences an increase in its monthly rate of change of about 130 basis points after one month, followed by a decline in the second month by about 70 basis points. It is worth mentioning that the positive effect is quite similar but less prominent for both the NEX and ECO indices. The dynamic effects of the positive oil price shock on the SPGCE and NEX indices are statistically significant for the first two and a half and one and a half months, respectively, while for the ECO index it is statistically significant only for the first month.

In the second panel of Figures A3.1, A3.2, and A3.4 we report the impulse responses of the same three indices to a negative oil price shock, again accounting for the effects of oil price uncertainty. As can be seen, the dynamic effect of the negative oil price shock on the ECO index is not statistically significantly different from zero after one month. However, a negative oil price shock induces a positive effect on the NEX index of about 20 basis points the first month, followed by a slight increase the second month. After that, it gradually fades out approaching zero. In a similar way, the SPGCE index undergoes a jump in its monthly rate of change of about 50 basis points after two months, and decreases slowly towards zero in the following months. Both NEX and SPGCE indices are not statistically significantly different from zero after two and four months, respectively.

The impulse responses of technology stock returns (PSE), however, are more similar to those of the aggregate stock returns. As can be seen in the first panel of Figures A3.3 and A3.5, a positive oil price shock leads to a decline in both stock returns after one month, followed by an increase in the second month. Impulse responses of aggregate stock returns are found to have a more rapid recovery rate than technology stock returns. However, the dynamic effects of the positive oil price shock on both technology and aggregate stock returns are not statistically significantly different from zero at all horizons. In contrast, a negative oil price shock tends to induce a jump in both technology and aggregate stock returns after one month, which is followed by a slow decline (see the second panel of Figures A3.3 and

A3.5). The dynamic effects of the negative oil price shock on both returns are however not statistically significantly different from zero. Finally, a visual comparison of the impulse responses in Figures A3.1-A3.5 does not provide us clear evidence on whether the responses of the three renewable energy stock market returns to positive and negative oil price shocks are symmetric or asymmetric, while those of the technology and aggregate returns are more likely to be symmetric.

Next, we compare the impulse responses of the different stock returns to a positive oil price shock as estimated by our model with that from a model in which oil price uncertainty is restricted from entering the stock return equation (that is, λ_{21}=0). We compare these responses in the third panel of Figures A3.1-A3.5, with the error bands being suppressed for clarity, and conclude that accounting for oil price uncertainty tends to enhance the positive dynamic responses of the three renewable energy indices to a positive oil price shock, while it amplifies the negative dynamic response of the aggregate returns to a positive oil price shock. Finally, the response of technology index returns from the two models are found identical, thus providing evidence that uncertainty about the price of oil does not disturb the dynamic response of technology returns to a positive oil price shock.

3.5 Robustness

We have performed an impulse response analysis to assess whether the relationship between crude oil prices and stock returns of clean energy and technology companies is symmetric or asymmetric, and we have provided evidence in favor of symmetric impulse responses of stock returns to oil price shocks. To investigate the robustness of these results, we employ an impulse response based test, recently introduced by Kilian and Vigfusson (2011). One of the main arguments for doing so is the fact that Kilian and Vigfusson (2011) question, through their investigation of the effects of oil price shocks, the use of slope-based tests to test for asymmetries and nonlinearities, and therefore propose a test of symmetric impulse responses to shocks of different signs and magnitudes, based on impulse response functions. In fact, they demonstrate that slope-based tests are not informative with regards to whether the asymmetry in the impulse responses is economically or statistically significant, as well as that slope based tests cannot allow for the possibility that the degree of asymmetry of the response functions by construction depends on the magnitude of the shock.

The Kilian and Vigfusson (2011) symmetry test, based on impulse response functions, involves estimating the following nonlinear structural VAR model

Table 3.5: p-values for $H_0 : I_g(h, \delta) = -I_g(h, -\delta), h = 0, 1, ..., 12$

	ECO		NEX		PSE		SPGCE		AGG	
h	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$	$\hat{\sigma}$	$2\hat{\sigma}$
0	0.306	0.299	0.460	0.465	0.221	0.224	0.253	0.250	0.714	0.719
1	0.325	0.310	0.222	0.202	0.089	0.088	0.173	0.155	0.781	0.779
2	0.522	0.505	0.352	0.341	0.183	0.179	0.255	0.240	0.919	0.917
3	0.675	0.656	0.508	0.493	0.205	0.222	0.255	0.249	0.932	0.926
4	0.791	0.781	0.636	0.630	0.314	0.332	0.355	0.345	0.974	0.971
5	0.819	0.827	0.683	0.670	0.368	0.390	0.457	0.444	0.988	0.985
6	0.872	0.880	0.785	0.773	0.433	0.418	0.567	0.556	0.995	0.993
7	0.904	0.907	0.861	0.852	0.541	0.525	0.654	0.645	0.998	0.997
8	0.944	0.946	0.886	0.866	0.632	0.604	0.739	0.736	0.999	0.999
9	0.916	0.949	0.901	0.889	0.721	0.695	0.800	0.804	1.000	1.000
10	0.921	0.971	0.917	0.918	0.772	0.714	0.829	0.841	1.000	1.000
11	0.853	0.885	0.938	0.947	0.835	0.786	0.849	0.876	1.000	1.000
12	0.898	0.923	0.961	0.954	0.884	0.844	0.874	0.866	1.000	1.000

Note: p-values are based on the χ^2_{h+1} distribution.

$$\Delta lno_t = \alpha_{10} + \sum_{j=1}^{p} \beta_{11}(j) \Delta lno_{t-j} + \sum_{j=1}^{p} \beta_{12}(j) \Delta lnz_{t-j} + u_{1t} \tag{3.6}$$

$$\Delta lnz_t = \alpha_{20} + \sum_{j=0}^{p} \beta_{21}(j) \Delta lno_{t-j} + \sum_{j=1}^{p} \beta_{22}(j) \Delta lnz_{t-j} + \sum_{j=0}^{p} \delta_{21}(j) \tilde{o}_{t-j} + u_{2t} \tag{3.7}$$

where $\tilde{o}_t$ is Hamilton's (2003) net oil price increase over the previous twelve months, defined as

$$\tilde{o}_t = \max\big[0, lno_t - \max\{lno_{t-1}, lno_{t-2}, ..., lno_{t-12}\}\big]$$

where o_t denotes the price of oil.

The null hypothesis of symmetric impulse responses of Δlnz_t to positive and negative oil price shocks of the same size is

$$H_0 : I_g(h, \delta) = -I_g(h, -\delta) \quad \text{for } h = 0, 1, ..., H. \tag{3.8}$$

It tests whether the responses of Δlnz_t to a positive shock in the oil price growth rate of size δ is equal to the negative of the response of Δlnz_t to a negative shock in the oil price growth rate of the same size, $-\delta$, for horizons $h = 0, 1, ..., H$. See Kilian and Vigfusson (2011) for a more detailed discussion of the methodology.

Since the Kilian and Vigfusson (2011) test depends on the size of the shock, δ, we illustrate in Figure A3.6 the empirical responses of the different logarithmic stock returns to one- and two-standard-deviation oil price shocks of positive and negative signs, in a model with one lag and considering the twelve-month net oil price increase. Hence, the figure depicts the response of the logarithmic stock returns to a positive shock $I_g(h, \delta)$, and the negative of the response to a negative shock, $-I_g(h, -\delta)$. The impulse responses are derived for twelve months based on $10,000$ simulations and 50 histories.

As can been seen from the different plots in Figure A3.6, the responses of the different logarithmic stock returns to positive shocks are not significantly different than those to negative shocks, for both small (one-standard-deviation) and big (two-standard-deviation) oil price shocks. In addition, we report the p-values of the null hypothesis (3.8) in Table 3.5, for both small shocks ($\delta = \hat{\sigma}$) and large shocks ($\delta = 2\hat{\sigma}$). By looking at the results, we conclude that the null hypothesis of a symmetric relationship between the oil prices and each of the examined stock returns cannot be rejected at the 5% significance level.

3.6 Conclusion

In the context of a bivariate structural VAR model, which is modified to accommodate GARCH-in-Mean errors, we investigate the relationship between oil prices and stock returns of clean energy and technology companies. Specifically, we employ monthly data over the period from May 1983 to December 2016, and estimate the model taking a full information maximum likelihood approach, thus avoiding Pagan's (1984) generated regressor problems. Furthermore, we conduct an impulse response analysis to assess whether the relationship between crude oil prices and stock returns of clean energy and technology companies is symmetric or asymmetric, and provide evidence of symmetric stock responses to oil price shocks. More importantly, we investigate the effects of uncertainty about the change in the price of oil on the employed stock returns, and we find that oil price uncertainty has a positive but statistically insignificant effect on the renewable energy and technology stock returns, and an insignificant negative effect on the aggregate stock returns. Our results are robust to alternative model specifications and stock prices of clean energy companies.

The resilience of renewable energy stock returns to oil price uncertainty effects may stem from the fact that the economics of the renewable energy sector have become very competitive in recent years, and therefore renewables can compete successfully with oil, even when the price of oil fluctuates around the recent low levels. Another possible explanation might be the fact that oil is not predominantly used in electricity generation, while any possible spillover effect from oil to other primary sources of electricity generation such as, for example, coal and gas, seem not to be prominent enough in order to affect renewables indirectly. Furthermore, resilience of renewable energy sector can be explained by the fact that developing countries such as, for instance, China, India, and Middle East countries, experience rapid economic growth that is accompanied by growing energy demand, and finally, severe environmental externalities. Hence, under different pressures of environmental pollution, such as, air pollution and water contamination, they endeavor to reduce fossil fuel consumption and expand their renewable energy industry. Finally, the insignificant effect of oil price uncertainty on the employed stock returns might be a possible explanation for the symmetric stock responses.

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3.7 Appendix

Table A3.1: Parameter estimates of the ECO and WTI structural VAR

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ \\ -0.291\ (-5.047) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} 0.182\ (2.113) \\ \\ 0.002\ (0.027) \end{bmatrix};\ \boldsymbol{\Lambda} = \begin{bmatrix} 0 \\ \\ 0.154\ (0.459) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.109\ (1.502) \\ \\ 0.200\ (2.673) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.782\ (1.336) \\ \\ -1.696\ (-0.612) \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 11.842\ (1.545) \\ \\ 5.295\ (1.396) \end{bmatrix};\ diag\boldsymbol{F} = \begin{bmatrix} 0.176\ (1.907) \\ \\ 0.116\ (1.817) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.652\ (3.917) \\ \\ 0.798\ (8.561) \end{bmatrix}.$$

Note: Monthly data from 2001:01 to 2016:12. Numbers in parentheses are t-statistics.

Table A3.2: Parameter estimates of the NEX and WTI structural VAR

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.253\ (-5.185) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} 0.169\ (1.983) \\ -0.029\ (-0.530) \end{bmatrix};\ \boldsymbol{\Lambda} = \begin{bmatrix} 0 \\ 0.341\ (1.010) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.135\ (1.451) \\ 0.283\ (3.637) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.761\ (1.328) \\ -2.486\ (-0.922) \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 14.668\ (1.832) \\ 5.349\ (0.914) \end{bmatrix};\ diag\boldsymbol{F} = \begin{bmatrix} 0.193\ (2.292) \\ 0.177\ (1.577) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.593\ (4.058) \\ 0.694\ (2.954) \end{bmatrix}.$$

Note: Monthly data from 2001:01 to 2016:12. Numbers in parentheses are t-statistics.

Table A3.3: Parameter estimates of the PSE and WTI structural VAR

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.024\ (-0.750) & 1 \end{bmatrix};\ \boldsymbol{C} = \begin{bmatrix} 0.216\ (3.983) \\ -0.019\ (-0.580) \end{bmatrix};\ \boldsymbol{\Lambda} = \begin{bmatrix} 0 \\ 0.002\ (0.016) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.048\ (0.755) \\ 0.268\ (5.058) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.265\ (0.757) \\ 0.828\ (0.971) \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 11.191\ (2.938) \\ 1.483\ (1.586) \end{bmatrix};\ diag\boldsymbol{F} = \begin{bmatrix} 0.264\ (4.276) \\ 0.156\ (2.940) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.578\ (7.102) \\ 0.808\ (12.720) \end{bmatrix}.$$

Note: Monthly data from 1984:02 to 2016:12. Numbers in parentheses are t-statistics.

Table A3.4: Parameter estimates of the SPGCE and WTI structural VAR

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ -0.309\ (-4.865) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} 0.119\ (1.224) \\ 0.011\ (0.154) \end{bmatrix}; \boldsymbol{\Lambda} = \begin{bmatrix} 0 \\ 0.287\ (0.940) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.106\ (1.200) \\ 0.325\ (3.850) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 1.021\ (1.617) \\ -2.570\ (-1.009) \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 14.415\ (1.861) \\ 4.323\ (1.183) \end{bmatrix};\ diag\boldsymbol{F} = \begin{bmatrix} 0.242\ (2.561) \\ 0.086\ (1.566) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.560\ (3.731) \\ 0.824\ (8.172) \end{bmatrix}.$$

Note: Monthly data from 2003:12 to 2016:12. Numbers in parentheses are t-statistics.

Table A3.5: Parameter estimates of the Aggregate and WTI structural VAR

A. Conditional mean equation

$$\boldsymbol{B} = \begin{bmatrix} 1 & 0 \\ 0.010\ (0.388) & 1 \end{bmatrix}; \boldsymbol{C} = \begin{bmatrix} 0.219\ (3.920) \\ -0.013\ (-0.506) \end{bmatrix}; \boldsymbol{\Lambda} = \begin{bmatrix} 0 \\ -0.040\ (-0.483) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_1 = \begin{bmatrix} 0.067\ (0.933) \\ 0.018\ (0.314) \end{bmatrix};$$

$$\boldsymbol{\Gamma}_2 = \begin{bmatrix} 0.203\ (0.615) \\ 1.009\ (1.567) \end{bmatrix}.$$

B. Conditional variance equation

$$\boldsymbol{C}_v = \begin{bmatrix} 9.119\ (2.768) \\ 0.675\ (1.865) \end{bmatrix};\ diag\boldsymbol{F} = \begin{bmatrix} 0.268\ (4.509) \\ 0.118\ (3.587) \end{bmatrix};\ diag\boldsymbol{G} = \begin{bmatrix} 0.603\ (7.662) \\ 0.852\ (23.804) \end{bmatrix}.$$

Note: Monthly data from 1983:05 to 2016:12. Numbers in parentheses are t-statistics.

Figure A3.1: Impulse response functions of the WTI-ECO structural VAR

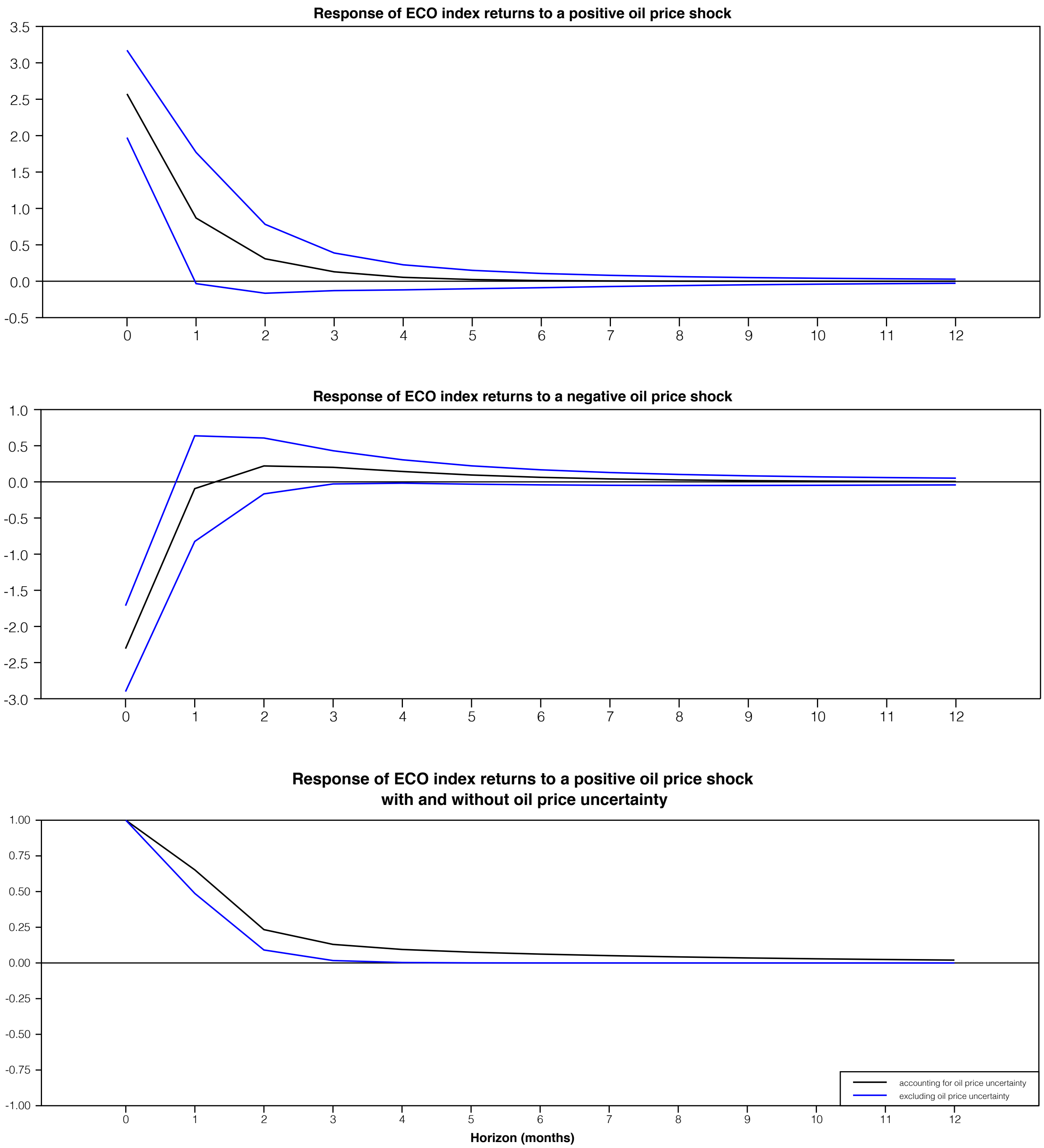


Figure A3.2: Impulse response functions of the WTI-NEX structural VAR

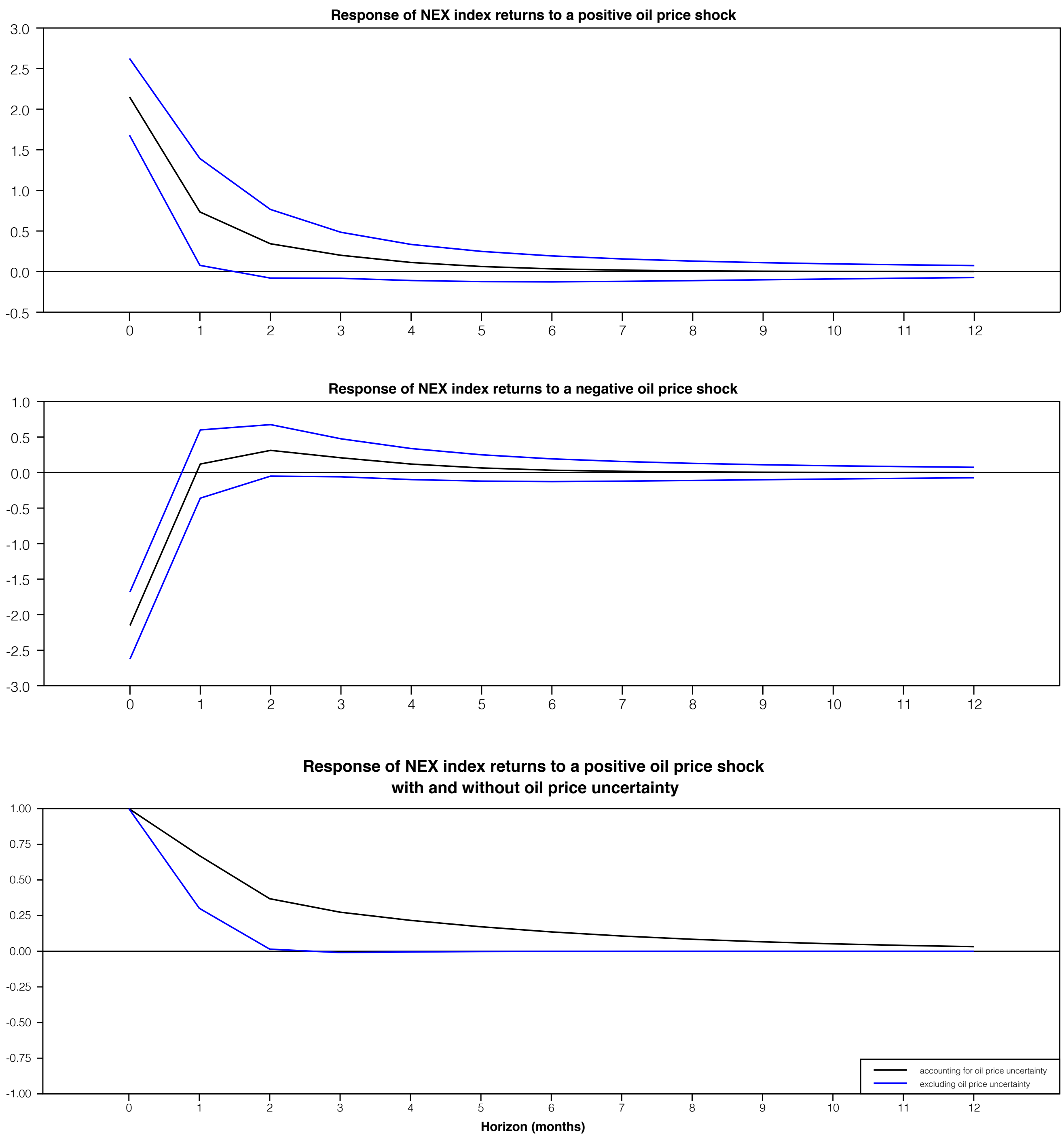


Figure A3.3: Impulse response functions of the WTI-PSE structural VAR

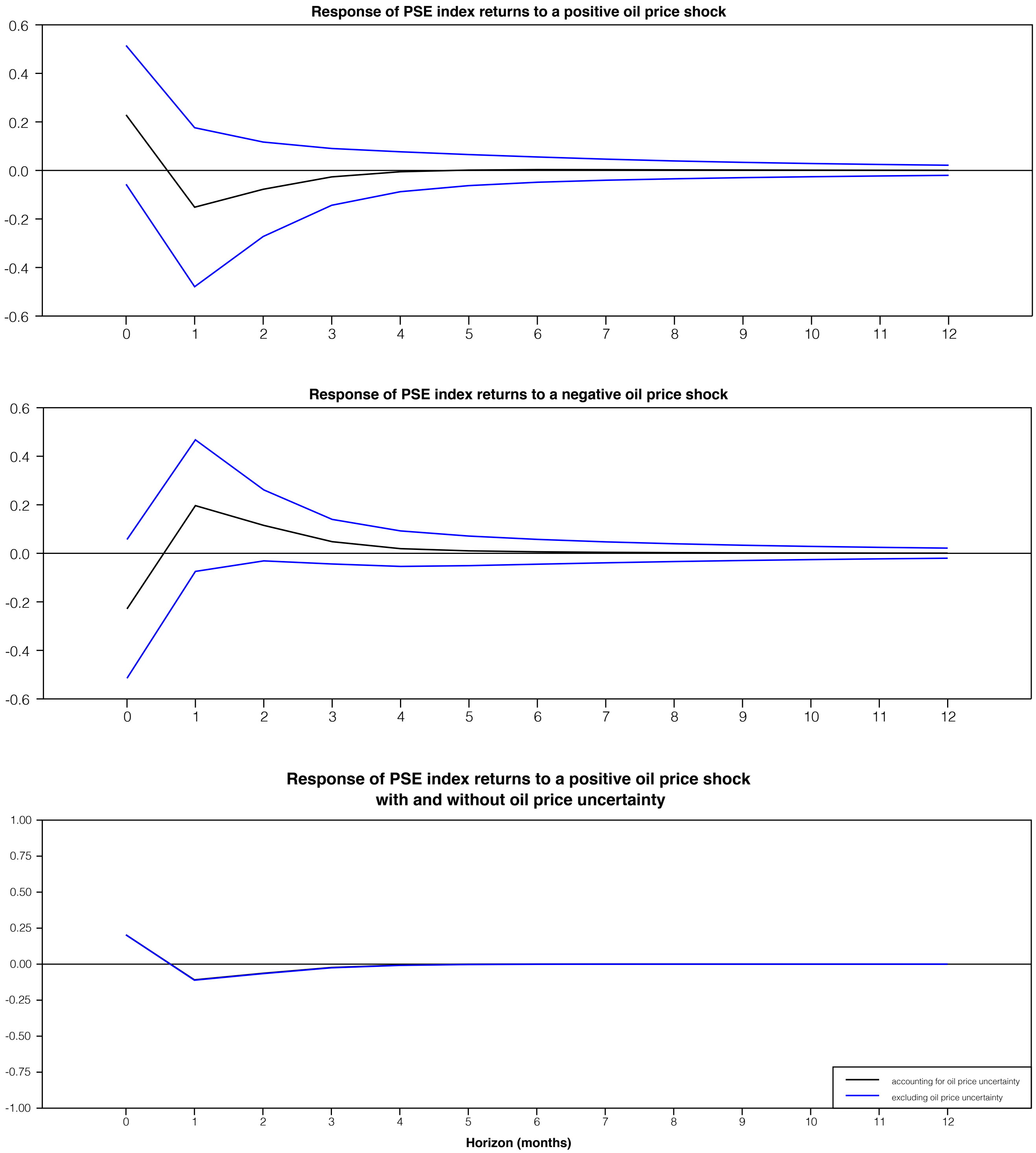


Figure A3.4: Impulse response functions of the WTI-SPGCE structural VAR

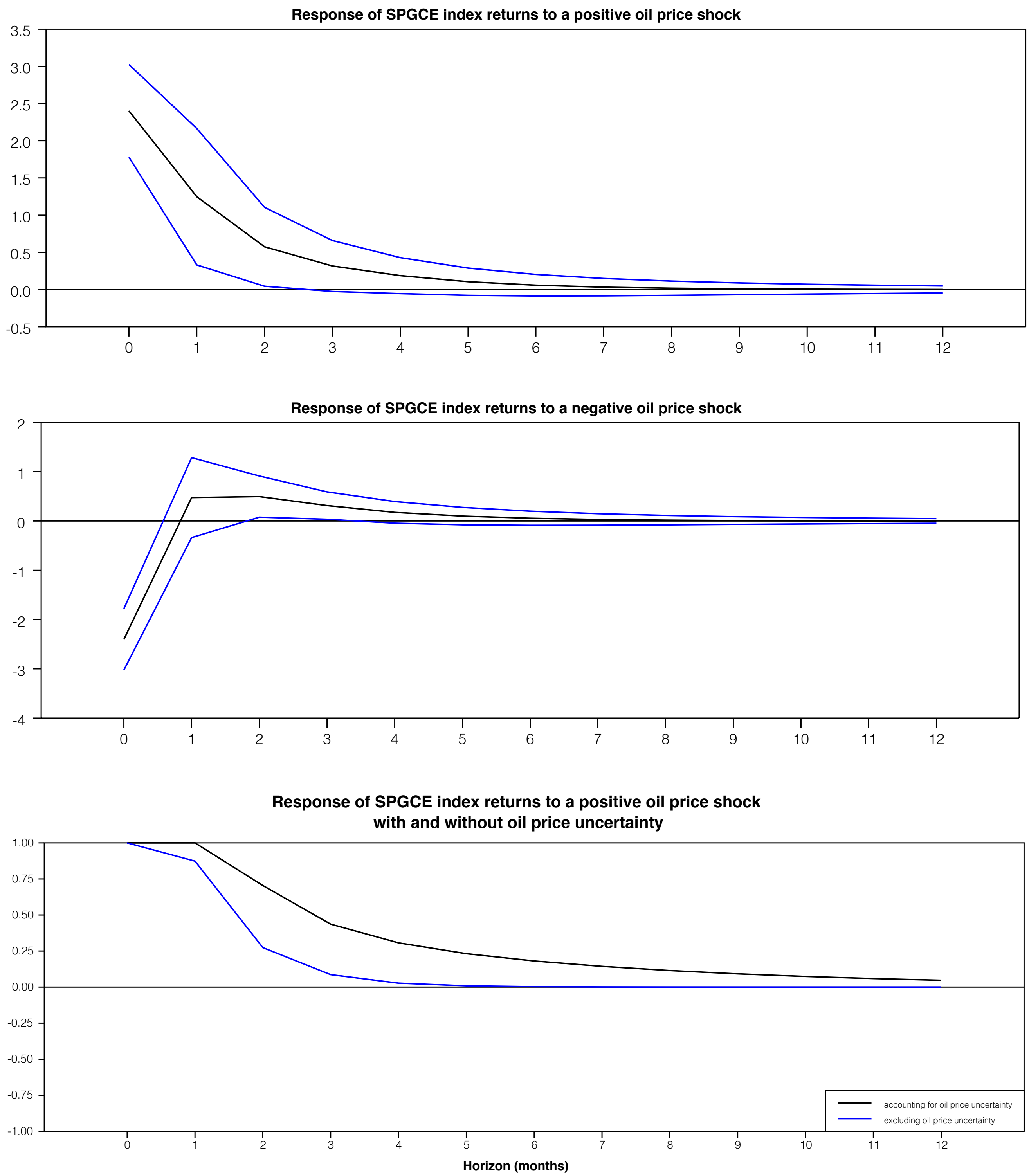


Figure A3.5: Impulse response functions of the WTI-Aggregate structural VAR

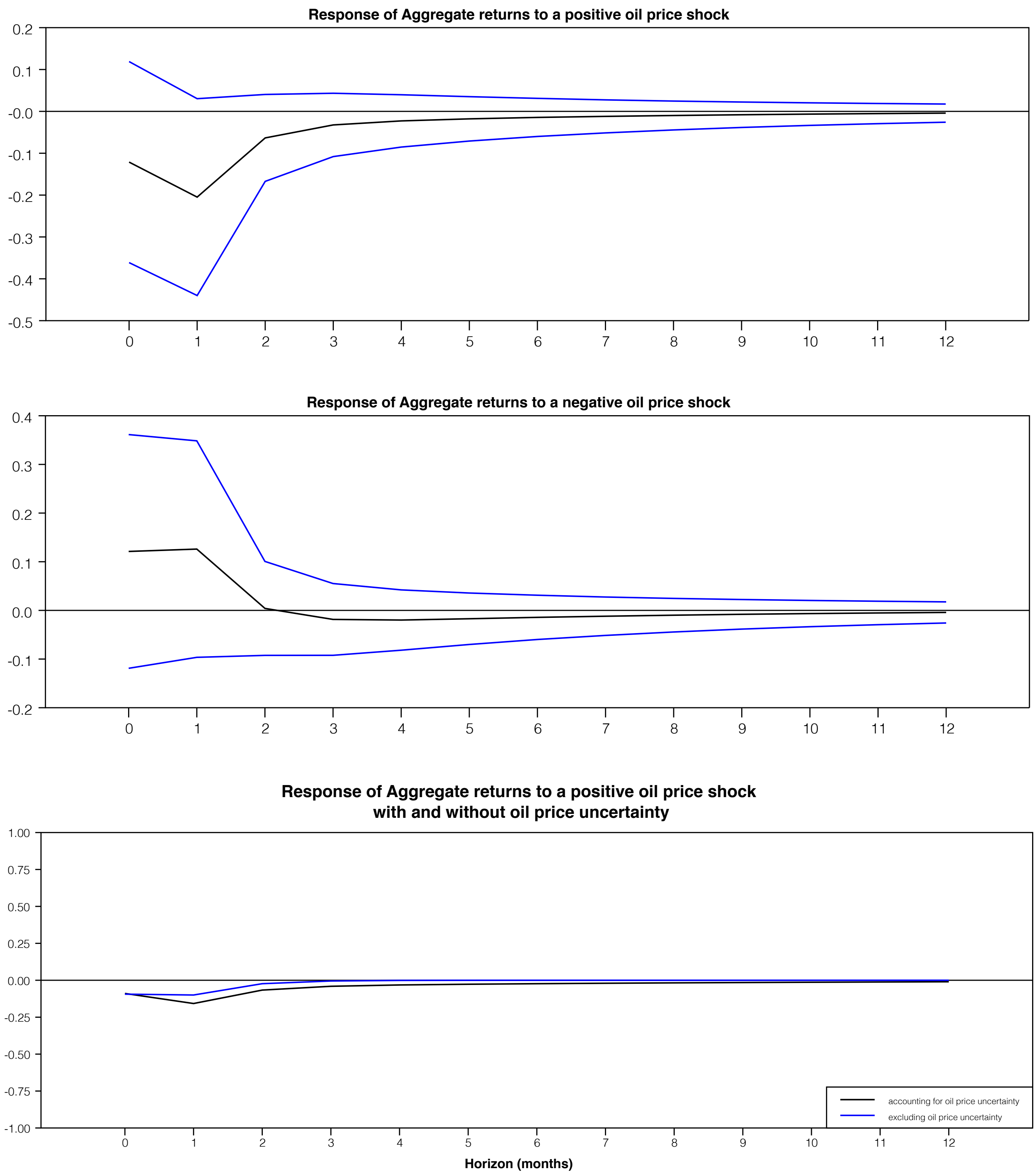
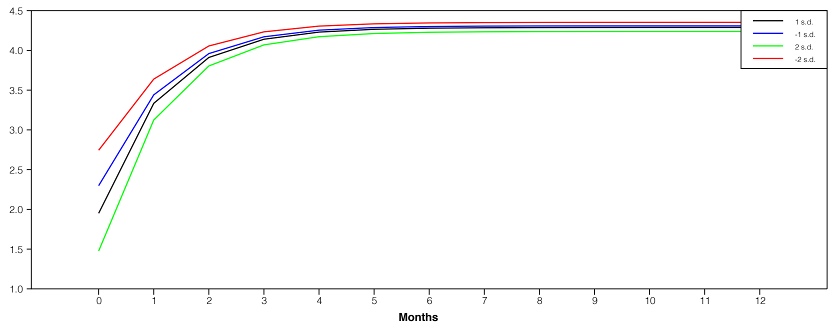
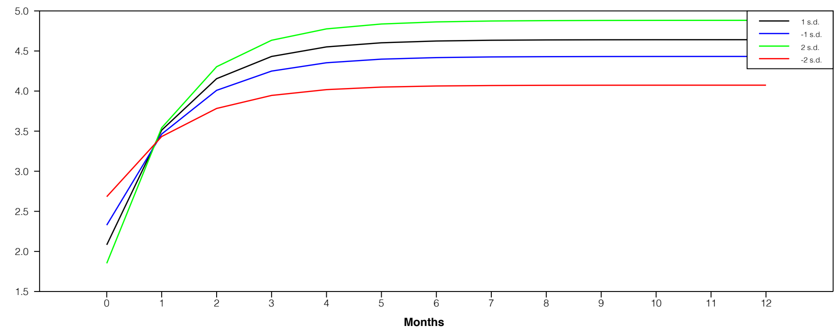


Figure A3.6: Indices responses to oil price shocks by shock size

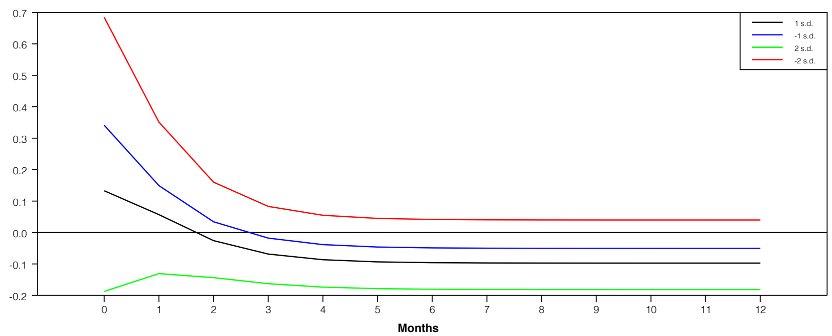
(a) ECO Index



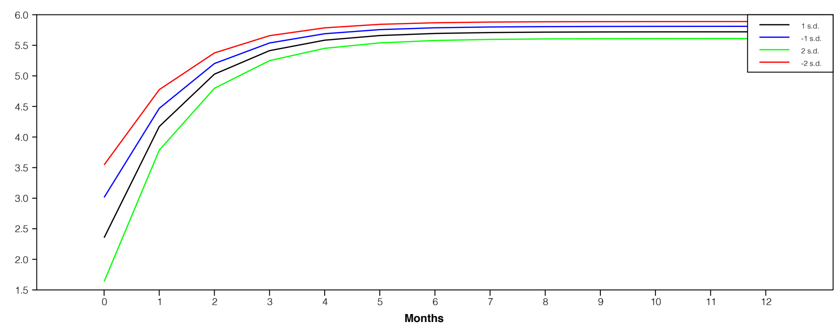
(b) NEX Index



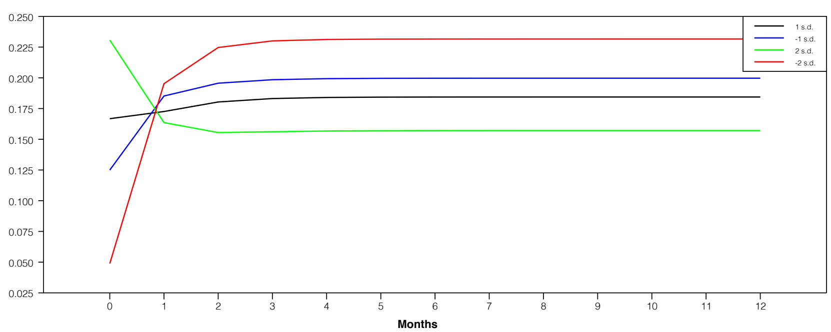
(c) PSE Index



(d) SPGCE Index



(e) Aggregate Index



Chapter 4

Dynamic Quantile Relations in Energy Markets

Coauthored with Jonas Andersson.

ABSTRACT

In this paper we investigate the dynamic relationships between crude oil price and and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices. This is performed by means of Granger non-causality tests for monthly US data over the period from January 1997 to December 2017. In most previous studies this has been done by testing for the added predictive value of including lagged values of one energy price in predicting the conditional expectation of another. In this study, we instead focus on different ranges of the full conditional distribution. This is done within the framework of a dynamic quantile regression model. The results constitute a richer set of findings than what is possible by just considering a single moment of the conditional distribution. We find several interesting one-directional dynamic relationships between the employed energy prices, especially in the tail quantiles, but also a bi-directional causal relationship between energy prices for which the classical Granger non-causality test suggests otherwise.

JEL classification: C22; Q41; Q42.

Keywords: Energy prices, Granger non-causality, Quantile regression.

4.1 Introduction

In this paper we study the relationship between crude oil price and a set of energy prices, namely diesel, gasoline, heating, and natural gas prices in the spirit of Granger causality. As Bauwens *et al.* (2006, p. 306) put it, "the time-series notion of Granger (-Sims) causality is based on the idea that cause must precede effect, and that a factor cannot cause another variable if it doesn't contribute to the conditional distribution (or expectation) of that variable given the past. This concept has become very influential in time series and macroeconometric modelling." In the present paper we analyze the causal relationships, not only in the expectations, but also in the conditional quantiles of the employed energy price series, by estimating quantile regressions [see Koenker and Bassett (1978) and Basset and Koenker (1982)] and testing the null hypothesis of Granger non-causality in quantiles using the sup-Wald test, as suggested by Koenker and Machado (1999).

Several advantages apply to the quantile Granger non-causality test compared to the classical Granger non-causality test in mean. First, the quantile test considers different locations of the conditional distribution, and therefore it provides a more complete description of the true dynamic relationship than the traditional Granger non-causality test which only investigates average relationships (in the center of the conditional distribution). This advantage is important for our study, since we have reason to believe that one energy price will affect different parts of the future distribution of another energy price to different degrees. In economic terms, this is interpreted as a different dynamic relationship in different market conditions. Thus, we avoid the need for sample splitting when we study various market situations, and therefore we do not reduce the sample size nor loose the time dependence structure in the original data.

The relationship between crude oil and energy prices has been investigated extensively in numerous research papers. Serletis and Herbert (1999) explore the existence of common trends in Henry Hub and Transco Zone 6 natural gas prices, the fuel oil price for New York Harbor, and the PJM power market for electricity prices. They find shared trends among the prices, and therefore evidence of effective arbitraging mechanisms for these prices across these markets, as well as causality and a feedback relationship between any two price pairs. Other empirical studies, such as for instance, Yücel and Guo (1994), employ rigorous econometric techniques and find evidence of the existence of a long-run relationship between coal, natural gas, and oil prices, while Villar and Joutz (2006) confirm the stable long-run cointegrating relationship between crude oil and natural gas prices, also suggesting that oil price is exogenous to natural gas price. Finally, Brown and Yücel (2009), similar to Asche *et al.* (2006), find cointegration between natural gas and crude oil prices and discuss substitutability and competition between the two fuels in electric power generation. In addition, they find oil price movements explaining natural gas price quite satisfactorily, as well as evidence for natural gas price Granger causing crude oil price, but only to a marginal extent.

Furthermore, there is an extended literature exploring the existence of asymmetry in the relationship between oil and energy prices. Bacon (1991), in a seminal study for the crude oil and gasoline markets in the United Kingdom, describes the asymmetric mechanism as 'rockets and feathers,' thus referring to the fact that gasoline prices rise rapidly like rockets in response to crude oil price increases, but fall slowly like feathers in response to crude oil price declines. Balke *et al.* (1998) investigate the asymmetric relationship between crude oil and gasoline prices in the United States and provide mixed evidence of asymmetry. In doing so, they consider two identical model specifications, which differ only in the specification of asymmetry, and find evidence for rare and small, but also large and pervasive asymmetry. More recently, Chang and Serletis (2016) investigate the relationship between crude oil and gasoline prices for the United States and confirm the asymmetric effects, while providing evidence in support of the 'rockets and feathers' behaviour.

Motivated by growing environmental concerns about climate change and costly fossil fuels, Reboredo *et al.* (2017) use continuous and discrete wavelet methods, and linear and non-linear Granger causality tests, to study co-movement and causality between oil price variation and renewable energy stock returns. Their findings indicate weak, but in the long run gradually strengthened, dependence between oil and renewable energy returns. They also find evidence of non-linear causality running from renewable energy indices to oil prices at different time horizons, as well as mixed evidence of Granger causality running from oil to renewable energy prices. From a different point of view, Atil *et al.* (2014) use the nonlinear autoregressive distributed lags model to examine the pass-though of crude oil prices into gasoline and natural gas prices, and they conclude that oil prices affect gasoline prices and natural gas prices in an asymmetric and non-linear transmission way. Lahiani *et al.* (2017) extend the analysis of Atil *et al.* (2014), by considering additional fuel prices and using a more advanced methodology, thereby providing evidence of a stationary equilibrium relationship between these prices.

This research adds to the extant literature related to causal relationships between crude oil price and a set of energy prices by providing empirical evidence regarding Granger causality between these prices. To the best of our knowledge, no such study has investigated Granger causality in the entire conditional distribution between these energy prices. Our study contributes to the existing literature by filling this void. The quantile approach enables us to test for non-causality between the employed monthly energy prices in different quantiles of each variable, and therefore to reveal possible non-linear causal effects between them. The same methodological approach has previously been followed by Chuang *et al.*

(2009) and Ding *et al.* (2014), who investigate causal relationships between stock returns and volume and stock returns and real estate property, respectively. Our results indicate significant dynamic effects between the employed price series, particularly in the tail quantiles. We also see a bi-directional causal relationship between heating and crude oil prices, for which the classical Granger non-causality test suggests otherwise.

This rest of the paper is structured as follows. In Section 4.2 we introduce the classical Granger causality test and the sup-Wald test of causality in quantiles. In Section 4.3 we describe the data we use and present the empirical evidence, while in Section 4.4 we conclude with a brief discussion of our findings and their implications for an effective and sustainable energy risk management.

4.2 Empirical analysis

4.2.1 Classical Granger causality test

When a variable x does not Granger-cause another variable y, it suggests that

$$F_{y_t}(z|(y,x)_{t-1}) = F_{y_t}(z|y_{t-1}), \quad \forall z \in \mathbb{R}, \tag{4.1}$$

holds where $F_{y_t}(.|\Omega)$ is the conditional distribution of y_t with Ω denoting the information set available at time $t-1$, and $(y,x)_{t-1}$ denotes the information set generated by y_t and x_t up to time $t-1$ (Granger, 1969). On the contrary, when Equation (4.1) fails to hold, the variable x is said to Granger-cause y. A necessary condition for Equation (4.1) is that

$$\mathbb{E}(y_t|(y,x)_{t-1}) = \mathbb{E}(y_t|y_{t-1}) \tag{4.2}$$

where $\mathbb{E}(y_t|(y,x)_{t-1})$ is the conditional mean of the variable y_t. Usually Equation (4.2) is used as the starting point for tests of Granger causality. There could be, at least, two reasons for this. Firstly, the test is sometimes used to investigate if a variable is worthwhile using in forecasting another. Modelling the conditional mean rather than the entire conditional distribution is then a natural starting point. Secondly, estimating the full conditional distributions is more cumbersome than implementing the classical Granger causality test, which can be done by means of a vector autoregressive (VAR) model. The estimation can even be done by ordinary least squares. As an example, if crude oil is denoted y_t and gasoline prices x_t, the classical test could be performed within the framework of the bivariate VAR-model

$$y_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{j=1}^{q} \beta_j x_{t-j} + \epsilon_{y,t} \tag{4.3}$$

$$x_t = \gamma_0 + \sum_{i=1}^{p} \gamma_i x_{t-i} + \sum_{j=1}^{q} \delta_j y_{t-j} + \epsilon_{x,t}, \tag{4.4}$$

where $\epsilon_t = (\epsilon_{y,t}, \epsilon_{x,t})'$ is a vector of i.i.d random disturbances. The null hypothesis of Granger non-causality in mean from x_t to y_t is rejected if the coefficients of $x_{t-1}, x_{t-2}, ..., x_{t-q}$ in Equation (4.3) are jointly significantly different from zero. In the same way, if the coefficients of lagged y_t, thus $\delta_1, \delta_2, ..., \delta_q$, in Equation (4.4) are significantly different from zero, then we conclude that y_t Granger-causes x_t in mean. Note, however, that this notion of non-causality is not sufficient for Granger non-causality in distribution. Therefore, although a failure to reject the null hypothesis means that x does not Granger-cause y in the mean, it does not preclude causality in other moments or distribution characteristics.

4.2.2 Quantile causality test

As discussed earlier, for many cases the conditional mean approach may not describe the complete causal relationship between two time series variables. Given the fact that a distribution is completely determined by its quantiles, Lee and Yang (2006) first considered Granger non-causality in terms of the conditional quantiles of the distribution. Hence, Equation (4.1) is equivalent to

$$Q_{y_t}(\tau|(y,x)_{t-1}) = Q_{y_t}(\tau|y_{t-1}), \quad \forall\tau \in (0,1), \tag{4.5}$$

where $Q_{y_t}(\tau|\Omega)$ denotes the $\tau - th$ quantile of $F_{y_t}(\cdot|\Omega)$. Thus, we say that x does not Granger-cause y in all quantiles if Equation (4.5) holds. Note, however, that in this case non-causality is tested only in a particular quantile level, and not quantile intervals.

Rather than testing non-causality in a moment (mean or variance) or in a fixed quantile level τ, in this study we are interested in investigating causal relations in different quantile intervals by testing Equation (4.1). In doing so, we follow Chuang *et al.* (2009) who, in an interesting and influential study, investigate the causal relations between stock return and volume and define Granger non-causality in the quantile range [a, b] $\subset$ (0,1) as

$$Q_{y_t}(\tau|(y,x)_{t-1}) = Q_{y_t}(\tau|y_{t-1}), \quad \forall\tau \in [a,b], \tag{4.6}$$

where $Q_{y_t}(\tau|\Omega)$ denotes the quantile of $F_{y_t}(\cdot|\Omega)$ for $\tau \in [a,b]$. The quantile causality test is performed considering several quantile ranges $[a,b] \subset (0,1)$ for $\tau \in [a,b]$, using the quantile regression method proposed by Koenker and Bassett (1978) and Basset and Koenker (1982), and the sup-Wald statistic test suggested by Koenker and Machado (1999); see also Koenker (2005) for a more comprehensive study of quantile regression. To test for Granger-non causality in quantiles, we consider the following conditional quantile versions of Equations (4.3) and (4.4)

$$Q_{y_t}(\tau|\Omega_{t-1}) = \phi_0(\tau) + \sum_{j=1}^{p} \phi_j(\tau) y_{t-j} + \sum_{h=1}^{q} \psi_h(\tau) x_{t-h} \tag{4.7}$$

$$Q_{x_t}(\tau|\Omega_{t-1}) = \omega_0(\tau) + \sum_{j=1}^{p} \omega_j(\tau) x_{t-j} + \sum_{h=1}^{q} \xi_h(\tau) y_{t-h}, \tag{4.8}$$

where Ω_{t-1} denotes the information set generated by past values of y_t and x_t. The null hypothesis of non-causality in quantiles is

$$H_0 : \psi(\tau) = 0, \quad \forall \tau \in [a, b], \tag{4.9}$$

for Equation (4.7). Hence, if the parameter vector $\psi(\tau) = [\psi_1(\tau), \psi_2(\tau), ..., \psi_q(\tau)]'$ is equal to zero, it implies that x_t does not Granger-cause y_t at the quantile interval $\tau \in [a, b]$. In a similar way, if $\xi(\tau) = [\xi_1(\tau), \xi_2(\tau), ..., \xi_q(\tau)]'$ is equal to zero, then we can say that y_t does not Granger-cause x_t at the quantile interval $\tau \in [a, b]$.

In order to determine the significance level of the sup-Wald test, for each range and each lag order, we generate 100,000 independent simulations approximating the standard Brownian motion through the use of a Gaussian random walk with 3,000 i.i.d. $N(0, 1)$ innovations to identify the critical values at the 1%, 5%, and 10% significance levels.[1] Furthermore, since we need to select the optimal lag for each quantile range in order to conduct the sup-Wald test, we use the sequential lag selection method to determine the optimal lag truncation order [see Chuang *et al.* (2009) and Ding *et al.* (2014)]. For instance, if the null hypothesis $\psi_q(\tau) = 0$ for [0.05, 0.5] is not rejected for the lag-q model but the null $\psi_{q-1}(\tau) = 0$ for [0.05, 0.5] is rejected for the lag-$(q-1)$ model, then we set the desired lag order as $q^* = q - 1$ for the quantile interval [0.05, 0.5]. If no test statistic, however, is significant over that interval, we select the lag length of order one. We calculate the sup-Wald test statistics to check the joint significance of all coefficients of lagged past values for each quantile interval. Hence, if the selected lag order is q^*, then the null hypothesis is $H_0 : \psi_1(\tau) = \psi_2(\tau) = \psi_q(\tau) = 0$ for [0.05, 0.5].[2] For simplicity, we do not assume different lag orders, hence $p = q$. Therefore, by employing the methodology of quantile Granger non-causality while considering various quantile ranges $[a, b]$, we can capture the quantile range from which the true causal relationships arise.

[1] The table of critical values is available on request. Some critical values of the sup-Wald test have also been tabulated in De Long (1981) and Andrews (1993).

[2] The results for lag order selection of the quantile causality tests are not reported here in order to preserve space, but they can be provided upon request.

4.3 The data and empirical evidence

This study uses energy prices, namely crude oil, diesel, gasoline, heating, and natural gas prices for the United States. We use the U.S. refiner's acquisition cost (RAC)[3] for a composite of domestic and imported crude oil as a proxy for the price of crude oil, the Los Angeles ultra-low sulfur No 2 diesel price for the diesel price, the New York Harbour conventional gasoline price for the price of gasoline, the New York Harbour No 2 heating oil price for the price of heating, and the Henry Hub natural gas price for the price of natural gas. All prices are obtained from the U.S. Energy Information Administration (EIA) on a monthly basis, over the period from January 1997 to December 2017.

Table A4.1 presents the summary statistics of the five price series. The average monthly prices range from \$1.591 per gallon for gasoline to \$53.968 per barrel of crude oil. On a monthly basis, the commodity prices reach their maximum values in June 2008 for diesel (\$3.894), gasoline (\$3.292), and heating (\$3.801). The highest peak in natural gas price (\$13.420) and crude oil price (\$129.03) was observed in October 2005 and July 2008, respectively. It is worth mentioning that during the first half of 2008 all energy prices increased from 41.05% for the case of gasoline to 58.82% for natural gas, with crude oil increasing by 47.22%, while during the second half of 2008 all of them experienced a remarkable drop of more than 47%, thus providing evidence for a strong price relationship. Table A4.1 also shows that all the series are positively skewed and deviate from normality, while natural gas price exhibits excess kurtosis indicating fatter tails, and in particular longer right tail than a normal distribution.

We present in Table A4.2 an interesting feature of the data related to the contemporaneous correlations across the logarithmic first differences[4] of the energy price series. In order to determine whether these correlations are statistically significant, we follow Pindyck and Rotemberg (1990) and we perform a likelihood ratio test of the hypotheses that the correlation matrices are equal to the identity matrix. The test statistic is

$$-2ln(|R|^{N/2})$$

where $|R|$ is the determinant of the correlation matrix and N is the number of observations. The test statistic is distributed as χ^2 with $q(q-1)/2$ degrees of freedom, where q is the number of series. The test statistic is equal to 888.782 with a p-value of 0.000 for the first differences of the logs, and therefore we can clearly reject the null hypothesis that these series are uncorrelated. We also notice the relatively weak price correlation between the crude oil

[3] The U.S. refiner's acquisition cost (RAC) for composite crude oil is a weighted average of domestic and imported crude oil costs. It includes transportation and other fees paid by refiners, but does not include the cost of crude oil purchased for the Strategic Petroleum Reserve.

[4] The terms logarithmic first differences and logarithmic returns are used interchangeably.

and natural gas price series, a fact that has been expected since diesel, gasoline, and heating are refined petroleum products, and therefore more dependent on oil price development. Crude oil and natural gas prices, however, are also related to each other since they are both substitutes in direct consumption, and competitors in production of other energy sources such as cooking, heating, and electricity generation. The correlation patterns documented in Table A4.2 also manifest in Figures A4.1 - A4.5, which depict the development of the employed series over the investigated period.

Before we continue with our main analysis, we conduct some necessary unit root and stationary tests in the logarithmic first differences of each of the employed series, in order to test for the presence of a stochastic trend (a unit root) in the autoregressive representation of each individual series. Our motivation stems from the fact that existence of a unit root in a series invalidates the standard assumptions for an asymptotic analysis, as for instance the usual asymptotic properties of estimators, based on which statistical inference is performed. As shown in Table A4.3, all three tests, namely, the Augmented Dickey-Fuller (ADF) test [see Dickey and Fuller, 1981], the Dickey-Fuller GLS (DF-GLS) test [see Elliot *et al.*, 1996] and the KPSS test [see Kwiatkowski *et al.*, 1992] provide evidence that all series are stationary, or integrated of order zero, $I(0)$, and therefore we continue our analysis employing all price series in first logarithmic differences. The Bayesian information criterion (BIC) is used for the lag length selection in both the ADF and DF-GLS regressions, while the Bartlett kernel for the KPSS regressions is determined using the Newey-West bandwidth (NWBW). The stationarity of the logarithmic first differences of each of the price series is also verified by their historical development, depicted in Figures A4.1 - A4.5.

In the next step we use the Wald test to conduct the Granger non-causality test in mean, and in doing so, we test the null hypothesis that $\beta_j = 0$ (or $\delta_j = 0$) for $j = 1, 2, ..., q$, in the two linear regression models described in Equations (4.3) and (4.4). Rejection of the null hypothesis implies that knowledge of past values of x_t improves the prediction of future energy price of y_t, beyond predictions that are based on past prices of the energy product alone, $y_{t-1}, y_{t-2}, ..., y_{t-q}$. We select the optimal lag truncation order by the Bayesian Information Criterion (BIC) and report the estimation results in Table 4.1.

No linear causal relationship is found propagating from any employed energy price to crude oil price, while the latter is found to Granger-cause the diesel, gasoline, and heating prices. We also notice that the selected lag order varies from one to two months, contingent on the particular investigated causal relationship between the employed fuel prices. After performing this test to all the relationships between the crude oil price and each of the other fuel prices, we conclude that the price of crude oil from the last two months improves the prediction of each of the diesel and gasoline prices, beyond predictions that are based on past prices of diesel or gasoline alone. Knowledge of the price of crude oil from only the

Table 4.1: Tests for Granger causality in the mean

The null	p-value	Decision
Crude oil $\nRightarrow$ Diesel	0.000 (2)	Causality
Diesel $\nRightarrow$ Crude oil	0.456 (2)	No causality
Crude oil $\nRightarrow$ Gasoline	0.000 (2)	Causality
Gasoline $\nRightarrow$ Crude oil	0.270 (2)	No causality
Crude oil $\nRightarrow$ Heating	0.015 (1)	Causality
Heating $\nRightarrow$ Crude oil	0.376 (1)	No causality
Crude oil $\nRightarrow$ Natural gas	0.227 (1)	No causality
Natural gas$\nRightarrow$ Crude oil	0.963 (1)	No causality

Notes: Sample Period, monthly observations, 1997:01-2017:12. The symbol $\nRightarrow$ denotes the null hypothesis of Granger non-causality. The entry "Causality" indicates that the null hypothesis is rejected at the 5% significance level, while the entry "No causality" indicates that the null hypothesis of Granger non-causality could not be rejected at the 5% significance level. Numbers in parentheses indicate the selected lag order based on the Bayesian information criterion.

last month improves the prediction of future heating price, compared to predictions that are based only on past prices of heating price, but it does not improve the prediction of natural gas price. In the opposite direction, past information of neither diesel, gasoline, or natural gas prices improves the prediction of future crude oil price beyond predictions that are based on past prices of crude oil alone. Although the afore-mentioned results, which are based on the conditional mean represented by Equation (4.2), are useful to learn about causal relationships, they may not reveal all the information that describe the complete causal relationship between two time-series variables.

Motivated by these considerations, we explore the causal relationships between the employed energy price series, by considering the conditional quantile functions given by Equations (4.7) and (4.8) — using the longest available span of data.[5] For our empirical analysis we consider in total eight large quantile intervals for the above conditional quantile functions, similar to Ding *et al.* (2014). More precisely, we examine three large quantile intervals, namely [0.05, 0.95], [0.05, 0.5], and [0.5, 0.95], and five small quantile intervals, namely [0.05, 0.2], [0.2, 0.4], [0.4, 0.6], [0.6, 0.8], and [0.8, 0.95]. Table 4.2 reports the sup-Wald test statistics and the selected lag truncation order.

Panel (a) of Table 4.2 reports the tests results for non-causality from crude oil price to diesel, gasoline, heating, and natural gas prices. For the quantile interval [0.05, 0.95]

[5]This applies to the price series of diesel, gasoline, heating, and natural gas, which starting being available in January 1997.

Table 4.2: The sup-Wald tests of non-causality in different quantile ranges.

$\tau \in$	[0.05,0.95]	[0.05,0.5]	[0.5,0.95]	[0.05,0.2]	[0.2,0.4]	[0.4,0.6]	[0.6,0.8]	[0.8,0.95]
(a). Crude oil price → energy prices								
Diesel	73.78***	73.78***	5.56	73.78***	45.89***	11.32***	9.58***	2.77
	(2)	(2)	(1)	(2)	(2)	(1)	(2)	(1)
Gasoline	52.22***	52.22***	26.64***	52.65***	4.83	0.83	0.12	26.64***
	(4)	(4)	(4)	(4)	(1)	(1)	(1)	(4)
Heating	68.52***	68.52***	5.61	68.52***	19.56***	2.19	0.53	20.37***
	(7)	(7)	(1)	(7)	(2)	(1)	(1)	(4)
Natural gas	40.45***	17.94***	12.25**	18.16**	2.08	2.14	9.01*	24.74***
	(4)	(4)	(2)	(4)	(1)	(1)	(2)	(6)
(b). Energy prices → crude oil price								
Diesel	6.10	2.32	7.20*	2.32	1.10	1.03	1.24	7.20*
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Gasoline	3.43	3.43	1.91	3.47	1.35	1.96	1.78	1.84
	(1)	(1)	(1)	(1)	(1)	(1)	(1)	(1)
Heating	5.13	5.13	16.67**	33.63***	19.53***	3.60	12.21*	16.67**
	(1)	(1)	(4)	(6)	(4)	(1)	(4)	(4)
Natural gas	5.25	1.79	5.25	8.87	1.62	1.79	0.89	5.25
	(1)	(1)	(1)	(4)	(1)	(1)	(1)	(1)

Notes: Sample Period, monthly observations, 1997:01-2017:12. Each interval in the square brackets is the quantile interval on which the null hypothesis of Granger non-causality, as per Equation (4.7) and (4.8), holds. The sup-Wald test statistics and the selected lag orders (in parentheses) are reported.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

crude oil price Granger-causes all the energy prices at the 1% significance level, while the quantile sub-intervals indicate significant causality deriving from the lower and upper levels of quantiles, for three out of the four relationships. For instance, there is no Granger causality over the quantile levels, [0.2, 0.4], [0.4, 0.6], and [0.6, 0.8], for gasoline and natural gas prices. Similarly, for the case of heating, the middle quantile intervals [0.4, 0.6] and [0.6, 0.8] do not show any causality arising from the crude oil price changes. To put it differently, there is causality from crude oil to gasoline, heating, and natural gas prices arising only over the low or high quantile intervals. Hence, crude oil does not improve the predictions of these energy products, beyond predictions that are based on their own past price development alone, when the latter fluctuate around their median. For the case of diesel there is causality from crude oil price changes over all the quantile intervals, except for the upper interval of [0.8, 0.95].

Panel (b) of Table 4.2 reports the sup-Wald test statistics for non-causality from diesel, gasoline, heating, and natural gas price to oil price. None of the test results for the quantile interval [0.05, 0.95] are significant at our significance levels. This might be partly a result of the fact that diesel, gasoline, and heating are refined petroleum products, and therefore cannot improve the prediction of future oil price development. However, by considering causal relationships in the context of quantiles, we find significant Granger causality from heating price to crude oil price for the quantile intervals [0.05, 0.2], [0.2, 0.4], and [0.8, 0.95]. This implies that, similar to most of the results of the panel (a), no causality arises around the conditional median, namely [0.4, 0.6], but only from the tail region of the conditional distribution. It is only between crude oil and heating price changes that we find statistically significant bi-directional causality. Combining the results from both panels of Table 4.2, we conclude that the investigated energy markets depend more on each other under extreme market conditions, and therefore consideration of these relationships during only normal market situations may lead to an inefficient risk management strategy, or unintended energy policy outcome.

4.4 Conclusion

The interaction between the crude oil price and other energy prices, also other than natural gas price which is mostly studied in the literature, is an important research topic yet to be fully addressed. This paper investigates the non-linear causal relationships between the crude oil price and a set of other energy prices, namely diesel, gasoline, heating, and natural gas prices for the United States. To the best of our knowledge, no study has used the quantile Granger non-causality methodology to model the relationships of these energy price series. Our results suggest significant causal relationships between the employed price series, especially in the tail quantiles, but also a bi-directional causal relationship between heating and crude oil prices, for which the classical Granger non-causality test suggests otherwise. Interdependence between energy prices on different locations of the conditional distribution renders risk hedging across fuels even more challenging when fuel prices are extreme volatile. Policy makers should also be cautious and limit the risk exposure by constructing well-diversified energy portfolios in different sectors, such as transportation, heating, agriculture, and particularly electricity, where natural gas accounted for the first time in 2017 more than 27% of total gross electricity production in OECD countries, substituting largely crude oil (IEA, 2017).

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4.5 Appendix

Table A4.1: Summary statistics

Series	Mean	Variance	Minimum	Maximum	Skewness	Kurtosis	Normality
Crude oil	53.968	957.025	9.810	129.030	0.476***	-0.995***	19.910***
Diesel	1.724	0.807	0.391	3.894	0.375**	-0.991***	16.218***
Gasoline	1.591	0.689	0.307	3.292	0.320**	-1.098***	16.955***
Heating	1.608	0.805	0.304	3.801	0.430***	-0.949**	17.212***
Natural gas	4.410	4.961	1.720	13.420	1.423***	2.375***	144.252***

Notes: Sample Period, monthly observations, 1997:01-2017:12. Asterisks indicate rejection of null hypothesis of skewness, kurtosis, and normality. The skewness and kurtosis statistics include a test of the null hypothesis that each is zero. The Jarque-Bera test is used to test for normality.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

Table A4.2: Contemporaneous correlations

Series	Crude oil	Diesel	Gasoline	Heating	Natural gas
Crude oil	1	0.762	0.808	0.816	0.235
Diesel	0.762	1	0.716	0.809	0.207
Gasoline	0.808	0.716	1	0.728	0.208
Heating	0.816	0.809	0.728	1	0.346
Natural gas	0.235	0.207	0.208	0.346	1
	$x^2(10) = 888.782$				

Note: Monthly data from 1997:01 to 2017:12.

Table A4.3: Unit roots and stationary tests

	Test			
Series	ADF	DF-GLS	KPSS	Decision
Crude oil	-9.529***	-8.291***	0.060	$I(0)$
Diesel	-13.630***	-13.634***	0.055	$I(0)$
Gasoline	-11.616***	-11.902***	0.045	$I(0)$
Heating	-12.733***	-6.408***	0.066	$I(0)$
Natural gas	-15.438***	-2.381	0.033	$I(0)$

Note: Sample Period, monthly observations, 1997:01-2017:12.
*** Denotes significance at the 1% significance level.
** Denotes significance at the 5% significance level.
* Denotes significance at the 10% significance level.

Figure A4.1: Crude oil price and its logarithmic returns

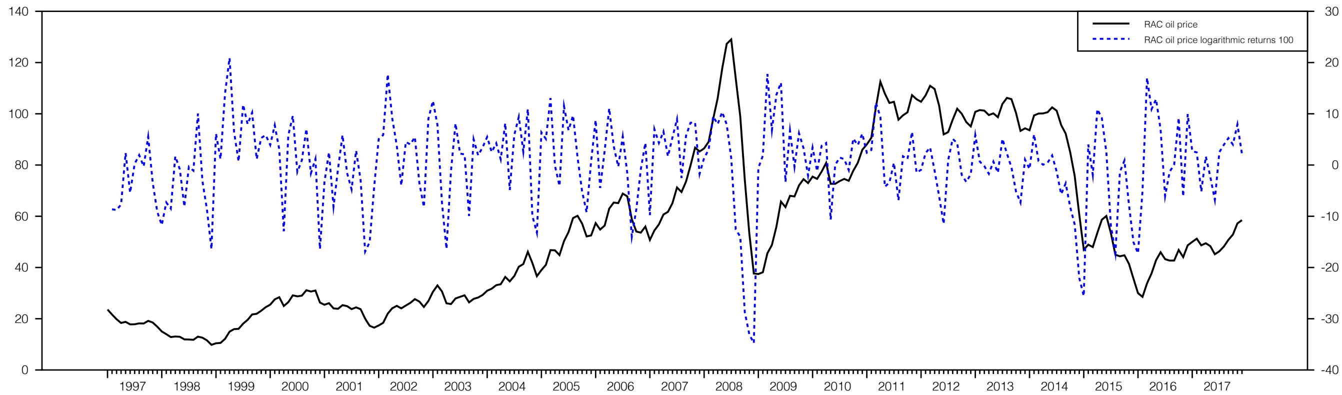

Figure A4.2: Diesel price and its logarithmic returns

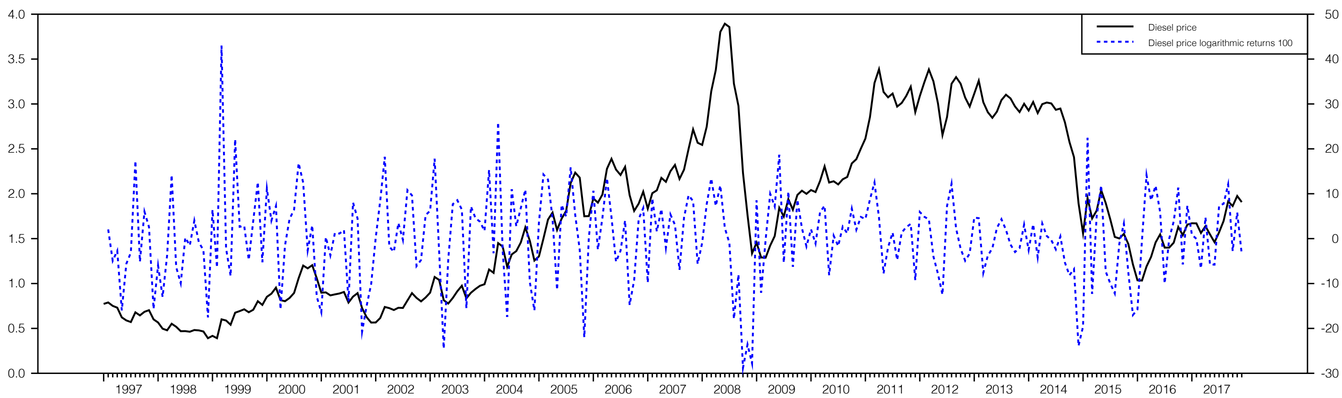

Figure A4.3: Gasoline price and its logarithmic returns

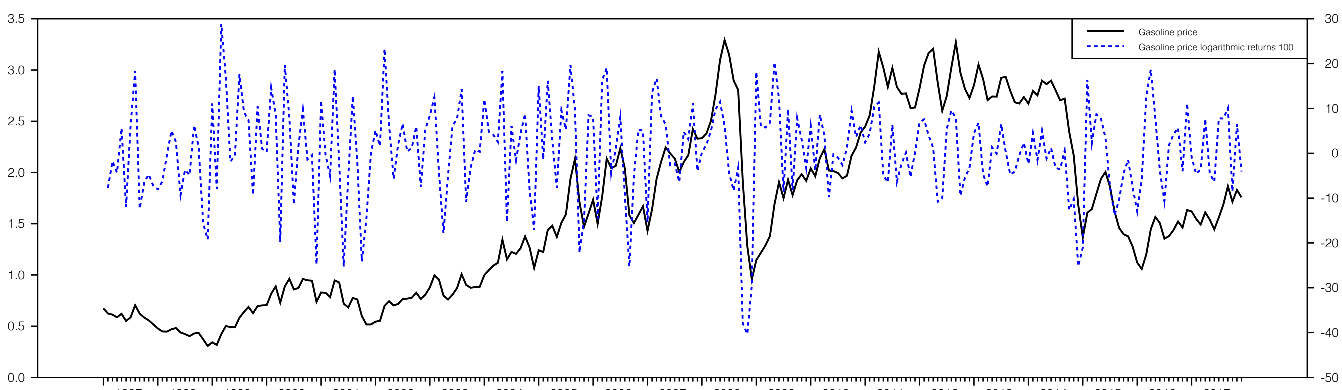

Figure A4.4: Heating price and its logarithmic returns

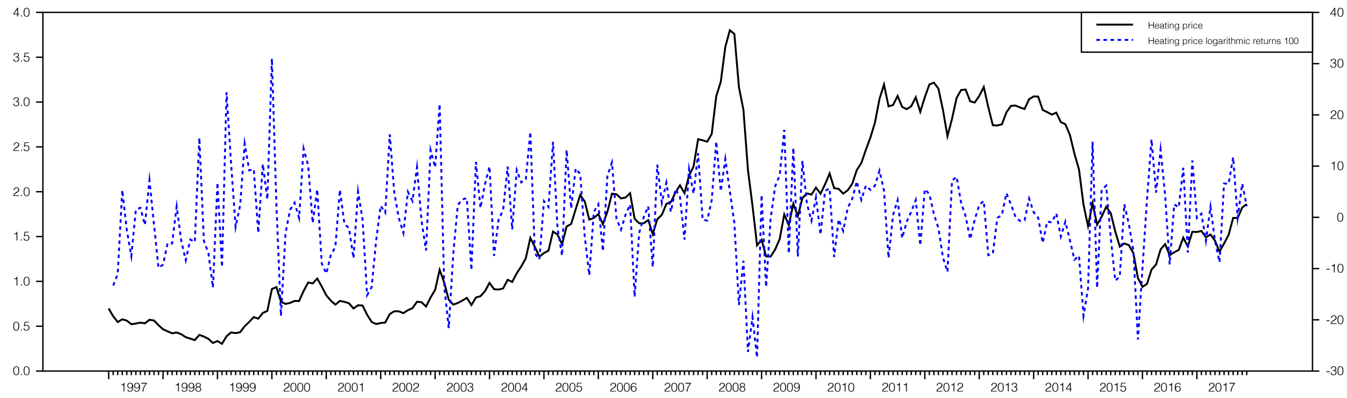

Figure A4.5: Natural gas price and its logarithmic returns