Evolution of the impact of oil prices on electricity, natural gas, and coal prices:

causality and interaction

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Resumo

Exploramos o impacto dos preçoes do petróleo nos preços da electricidade, gás natural, e carvão, com um foco nos mercados Europeus. Usando como modelos, o Modelo de Vector de Correcção de Erro (VECM) e o Modelo Multivariado Generalizado Autoregressivo Condicionalmente Heterocedástico - Correlação Condicional Dinâmica (DCC-MGARCH), os nossos resultados provaram a intuição de que o preços do petróleo têm um impacto nos preços da electricidade, gás natural, e carvão. Enquanto que a maioria da literatura foca-se nas relações entre os preçoes do petróleo e gás natural, os nossos resultados mostram que uma relação forte também existe hoje entre os preços do petróleo e do carvão, em particular para contratos de futuros de mês seguinte de carvão. Finalmente, demos algumas luzes sobre os mercados de electricidade Ibéricos e descobrimos que os preçoes da electricidade ibérica são menos afectados pelos preços do petróleo, em comparação com os preços da electricidade Francesa e Alemã.

Palavras-chave: Mercados de Energia, Preços do Petróleo, Cointegração, VECM, DCC-MGARCH

Abstract

We explored the impact of oil prices on the electricity, natural gas, and coal prices, with a focus on European markets. Using as models, the Vector Error Correction Model (VECM) and the Dynamic Conditional Correlation - Multivariate Generalized Autoregressive Conditionally Heteroskedastic Model (DCC-MGARCH), our results proved the intuition that crude oil prices do indeed have an impact on the prices of electricity, natural gas, and coal. While most of the literature has been focused on the relationship between oil and natural gas prices, our results showed that today a strong relationship also exists between oil and coal prices, especially for coal month-ahead futures contracts. Finally, we shed some light on the electricity markets in Iberia and found that Iberian electricity prices seem to be less affected by oil prices, in comparison to the French and German electricity prices.

Keywords: Energy Markets, Oil Prices, Cointegration, VECM, DCC-MGARCH

Contents

Acknowledgements……………………………………………………………………………………..i
Abstract………………………………………………………………...…………………………….ii
Resumo………………………………………………………………………………..………………..iii
List of Tables ………………………………………………………………………………………. vi
List of Figures ……………………………………………………………………………………. . vii
Nomenclature . ………………………………………………………………………...…………. viii
1. Introduction ……………………………………………………………………..……………1
1.1. Motivation………………………………………………………………………………….……1
1.1 Background ……………………………………………………..……………………………. . 1
1.2. Objectives………………………………………………………………………………………1
1.3. Methodology……………………………………………………………………………………1
1.4. Thesis outline…………………………………………………………………………..………2
2. Oil, Natural Gas, Coal, and Electricity – General Overview…………….……….…………..3
2.1. Oil………………………………………………………………………….…….………………..3
2.1.1. Benchmarks…………………………………………………………………..…………3
2.1.2. Worldwide reserves, major producers and consumers, and global trade flow……..………..3
2.2. Natural Gas……………………………………………………………………………..……6
2.2.1. Worldwide reserves, major Producers and consumers, and global trade flow……………….6
2.2.2. Major natural gas traded hubs in Europe……………………………………..…………..…..8
2.2.3. Rationale for the impact of oil prices on natural gas prices…………………………………..10
2.3. Coal…………………………………………………………………………………...…..……10
2.3.1. Worldwide reserves, major producers and consumers, and global trade flow…………..…10
2.3.2. Coal indexes……………………………………………………………………………..…12
2.3.3. Relationship of coal with natural gas and oil……………………………………….……..13
2.4. Electricity………………………………………………………………..…………..……13
2.4.1. Energy mix in Iberia, France, and Germany……………………………..…………..……13
2.4.2. European interconnections…………………………………………………………..…16
2.4.3. Power exchanges…………………………………………………………………….….19
2.4.4. Rationale for the impact of oil prices on electricity prices……………………..…………….19
3. Literature Review…………………….………………………………………………….……21
3.1. Evidence of relationship between several energy commodities……………………………….21
3.2. Summary…………………………………………………………………..…………..……24
4. Analysis of the Impact of Brent Prices on Electricity, Natural Gas, and Coal Prices…....26
4.1. Model methodology…………………………………………………………………………..26
4.1.1. Introduction to time series…………………………………………………..………..……26
4.1.2. Stationarity tests……………………………………………………………………..…..……26
4.1.2.1. Augmented Dickey-Fuller (ADF) test………………………………………………..………26
4.1.2.2. Phillips-Perron (PP) test…………………………………………..………..……..………..26
4.1.3. Models for multivariate relations……………………………………………………...……..27

4.1.3.1. Vector Autoregression (VAR) model……………………………………………..………….27
4.1.3.2. Vector Error Correction Model (VECM)……………………………………………………28
4.1.3.3. Criteria to choose the number of lags (Akaike, Hannan-Quinn and Schwarz)……..……28
4.1.3.4. Trace test……………………………………………………………………….………..29
4.1.4. Jarque-Bera (JB) normality test…………………………………………….…..………29
4.1.5. Granger test for causality……………………………………………………….………30
4.1.6. MGARCH and the specific case of DCC-MGARCH…………………………..…….……..30
4.2. Results and analysis…………………………………………………………………….……31
4.2.1. Impact of oil prices on Year-ahead futures contracts……………………….…………..…32
4.2.1.1. Stationarity tests outputs: Augmented Dickey-Fuller and Phillips-Perron tests outputs.32
4.2.1.2. Vector Autoregressive (VAR) model and Vector Error Correction Model (VECM) outputs…………………………………………………………………………………...……….32
4.2.1.3. Granger test outputs……………………………………………………….……….……34
4.2.1.4. Impulse Response Functions (IRFs) outputs……………………………..……….…….34
4.2.1.5. DCC-MGARCH outputs……………………………………………...…………….36
4.2.2. Impact of oil prices on Month-ahead futures contracts……………………..……………40
4.2.2.1. Stationarity tests outputs: Augmented Dickey-Fuller and Phillips-Perron tests outputs.40
4.2.2.2. Vector Autoregressive (VAR) model and Vector Error Correction Model (VECM) outputs………………………………………………………………….…….….…………40
4.2.2.3. Granger test outputs……………………………………………………………..……42
4.2.2.4. Impulse Response Functions (IRFs) outputs…………………..…..……..………..….42
4.2.2.5. DCC-MGARCH outputs……………………..……………………….………..…..…………43
5. Conclusions………………..…………………………………………….………..…..…………….47
5.1. Achievements…………………………………………………….………..………..………47
Bibliography……………………………………………………………………………..…………..48
Appendix…………………………………………………….…...………………………………52

List of Tables

1: World's largest oil consumers in 2020…………………………………………..……………….4
2: Traded volumes in European traded gas hubs…………………………………………….…….9
3: Summary of the literature review……………………………………………………………...25
4: Stationarity test using the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) unit root test, both with drift: test statistics for both the original time series (on log scale) and the first differences of the time series (on log scale), when testing for stationarity. The null hypothesis is that the series has a unit root, i.e., it is non-stationary……………………………..…………….32
5: Akaike, Hannan and Quinn and Schwarz model selection criteria for the optimal lag order of the VAR with a constant and trend……………………………………………………….....…33
6: Trace test of cointegration, when the constant is within the cointegration space….….…….33
7: Granger test. The null hypothesis for the test is that lagged values of the price of Brent do not explain the variation in the lagged values of the prices of the other energy types, i.e., Brent's price changes do not Granger-cause the prices changes in the other energies………..…………34
8: DCC(1, 1) MGARCH estimates for Brent, API2, OMIP, EEX_FR. EEX_DE and TT…………...39
9: Stationarity test using the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) unit root test, both with drift: test statistics for both the original time series (on log scale) and the first differences of the time series (on log scale), when testing for stationarity. The null hypothesis is that the series has a unit root, i.e., it is non-stationary………………………………………….40
10: Akaike, Hannan and Quinn and Schwarz model selection criteria for the optimal lag order of the VAR with a constant and trend…………………………..…………………..…………41
11: Trace test of cointegration, when the constant is within the cointegration space……41
12: Granger test. The null hypothesis for the test is that lagged values of the price of Brent do not explain the variation in the lagged values of the prices of the other energy types, i.e., Brent's price changes do not Granger-cause the prices changes in the other energies………………12
13: DCC(1, 1) MGARCH estimates for Brent, API2, OMIP, EEX_FR. EEX_DE and TT……….46

List of Figures

1: Evolution of the world's major oil producers…………………………………………….…….4

2: World's largest exporters and importers of oil in 2019……………………………………..5

3: Growth of world's largest exporters and importers between 2011 and 2019……….…..5

4: Map of the world's oil net trade in 2019…………………………………………………6

5: World's largest importers and exporters of natural gas in 2016……………….…….….7

6: Natural gas trade movements in 2020……………..…………………………….……..8

7: Map of European traded gas hubs……………..………………………………..…………9

8: Evolution of the world's coal production by region between 2010 and 2020……..…11

9: Evolution of the world's coal consumption by region between 2010 and 2020..………11

10: Coal trade movements in 2016……………………..……………………………..………12

11: Evolution of the Portuguese energy mix between 2010 and 2019……………………..……14

12: Evolution of the Spanish energy mix between 2011 and 2019……………………..……..14

13: Evolution of the French energy mix between 2010 and 2019…………….………….……15

14: Evolution of the German energy mix between 2010 and 2019…………………....…………15

15: European power grid's cross border connections………..……..…………..…………….16

16: French-German and French-Spanish cross border grid connections……….…………..…..17

17: Portuguese-Spanish cross border grid connections…………………………….…………..……18

18: Evolution of the differential between production and consumption in France, Germany, Portugal, and Spain, between 2010 and 2019……………………….…………………….…..19

19: OLS CUSUM tests for the VAR(6) model with the logarithms of Brent, API2, OMIP, EEX_FR, EEX_DE and TTF………………………………………………..…………………..………34

20: Impulse Response Functions of the time series in log…………………………….…….…….36

21: Time-varying standard-deviations estimated with the DCC(1,1) MGARCH for Brent, API2, OMIP, EEX_FR. EEX_DE and TTF…………….……………………………………….……..37

22: Time-varying correlations estimated with the DCC(1,1) MGARCH between Brent and the other energy types (API2, OMIP, EEX_FR, EEX_DE, TTF)…………………………………….……..38

23: Impulse Response Functions of the time series in log………………..……………..………43

24: Time-varying standard-deviations estimated with the DCC(1,1) MGARCH for Brent, API2, OMIP, EEX_FR. EEX_DE and TTF……………………………………………………….…..44

25: Time-varying correlations estimated with the DCC(1,1) MGARCH between Brent and the other energy types (API2, OMIP, EEX_FR, EEX_DE, TTF)……………………..……………..………45

Nomenclature

ADF - Augmented Dickey-Fuller

AIC - Akaike

ARA - Amsterdam-Rotterdam-Antwerp

CIF - Cost, Insurance and Freight

CFR - Cost and freight

CIS - Commonwealth of Independent States

DCC - Dynamic Conditional Correlation

EEX - European Energy Exchange

EIA - U.S. Energy Information Administration

ENTSO-E - European Network of Transmission System Operators for Electricity

FOB - Free on Board

HQ - Hannan-Quinn

IEA - International Energy Agency

IRF - Impulse Response Functions

JB - Jarque-Bera

LNG - Liquefied natural gas

MGARCH - Multivariate Generalized Autoregressive Conditionally Heteroskedastic Model

MIBEL - Iberian Electricity Market

NAR - Net as Received

NBP - National Balancing Point

OLS-CUSUM - Ordinary Least Square Cumulative Sum

PP - Phillips-Perron

R/P ratio - Reserves to Production ratio

SC - Schwarz

TTF - Title Transfer Facility

VAR - Vector Autoregressive Model

VECM - Vector Error Correction Model

WTI - West Texas Intermediate

1. Introduction

1.1. Motivation

What is the relationship between oil prices and electricity, natural gas, and coal prices? Do oil prices have any impact on the prices of the other three commodities? If so, what kind of impact and can this impact change across time? These are the questions we intend to answer.

Energy commodities are leading actors in the economic and financial scene, influencing vital indicators such as inflation, industrial production, stock market returns, amongst others. Variations in the price of energy commodities can also change the flow of international trade and severely affect the economy of entire nations. With the energy security and the economy of their countries at stake, it is vital for national leaders and policy makers to find tools that help them anticipate energy prices. This topic is thus important for a large variety of actors.

The literature in this topic is very rich, especially in regards with the oil and natural gas prices relationship, but the constant changing nature of the markets makes most studies obsolete very quickly. We also found that studies focusing on Southwestern Europe are not very common, meaning that this is also an area to which our work could contribute.

1.2. Objectives

We will explore the impact of oil prices on the electricity, natural gas, and coal prices, with a focus on European markets. We intend to quantify such impact and search for any variations across time.

1.3. Methodology

We will first select the time period that we intend to study. A period from 28/12/2011 to 25/09/2021, nearly an entire decade, provides us with enough data points to explore long term trends and is recent enough for our work to be novel and relevant for today's actors such as traders and policy makers.

Each data point in our time series will correspond to a weekly average of all the traded prices in the aforementioned period, and all data will be retrieved from the Refinitiv Eikon (former Thomson Reuters Eikon) database.

Energy commodities are traded across several markets and using several benchmarks, so we will have to choose the appropriate benchmarks for each one of the commodities for our study.

For oil we will use the Brent benchmark, as it is the most commonly used benchmark in the world. For natural gas we will use the data related to the TTF trading hub, one of the most liquid hubs in Europe, and for coal we will base ourselves on the API2 index, the most relevant index for coal in Europe.

Regarding electricity prices, we decided to focus on Iberia (Portuguese and Spanish electricity prices are usually coupled and we find that studies focusing on this region are lacking, when comparing to other regions), and France and Germany (the two largest economies of the European Union and good representatives of countries with a low percentage of fossil fuels in their energy mix in the case of France, and the opposite in the case of Germany). Iberian electricity prices will come from OMIP (branch of

MIBEL responsible futures contracts), and French and German electricity prices will come from EEX (European Energy Exchange).

All prices, if the commodities are not already traded in Euros, will be converted to Euros.

We will then proceed to study the time series proper, using VECM and DCC-MGARCH models, and finally we will study the outputs obtained. For this study we will make use of the programming language R.

1.4. Thesis outline

This thesis is divided in five chapters.

The present chapter (chapter 1) introduces this thesis' motivation and objectives and also gives an outline of its structure and methodology followed.

Chapter 2 will present us with an overall review of oil, natural gas, coal, and electricity markets. It will also provide us with an historical analysis of the prices we are going to study.

In chapter 3 we will look at some important papers that dealt with questions relating to the relationship of the commodities we are going to study. An emphasis will be given to their conclusions and methodology studied.

Chapter 4 will start by presenting us with the statistical methods that we are going to use to study our time series. After this introduction to the relevant statistical methods, the results from their application to our problem are presented.

Chapter 5 will end this thesis by looking at its conclusions.

2. Oil, Natural Gas, Coal, and Electricity – General Overview

2.1. Oil

2.1.1. Benchmarks

Several kinds of crude oil exist in the world and the origin of oil impacts not only its characteristics, but also, the costs of production and transportation. Benchmarks therefore serve a very important role in oil markets, they are reference points for sellers and buyers of specific oil contracts, each contract then being tied to specific oil categories. Thus, they allow for price discovery in the market and provide liquidity.

The three main benchmarks today are (information retrieved from theice.com and eia.gov):

- **Brent:** About two-thirds of the entire crude contracts globally would refer to the Brent Blend. This makes it the most widely utilized marker of all time. Currently, Brent refers to the oil arising from up to four various fields, including Brent, Forties, Oseberg, Ekofisk, and Troll. Crude oil arising from these regions is usually lighter and sweeter, making them quite ideal for refining using diesel fuels, gasoline, and other highly demanded products. Since the supply is water-borne as it arises from North Sea, it is easier to transport to distant locations.
- **WTI:** West Texas Intermediate refers to the oil that has been extracted from the wells across the USA, that is then sent through pipelines to Cushing, Oklahoma. This fact implies that supplies are land-locked, which a massive setback in terms of costs and ease of transportation. The oil itself is exceptionally light and sweet, therefore making it ideal for refining gasoline. WTI keeps being a significant benchmark despite the challenges it faces, as it serves as a benchmark for North American crude oil.
- **Dubai:** The Middle Eastern crude oil has become significant in terms of oil referencing. This oil though, has a lower grade, unlike the WTI or Brent crude. Dubai oil appears as a basket product that has crude from three regions: Dubai, Oman, and Abu Dhabi. This product is quite more cumbersome with higher sulphur content. This places it under a sour category. Dubai/Oman have served as the critical reference area for Persian Gulf oil that is delivered throughout the Asian markets.

2.1.2. Worldwide reserves, major producers and consumers, and global trade flow

According to the data presented at the BP Statistical Review of World Energy (70th edition, 2021), the countries with the largest proven reserves are Venezuela and Saudi Arabia, with 17.5% and 17.2% of the word's reserves, respectively. In third place we find Canada, with 9.7% of the world's reserves. Overall, OPEC countries possess 70.2% of the world's proven reserves.

However, while in most regions the proven reserves have remained relatively stable, they have almost doubled in the USA in the last decade, due to the so called "shale revolution". This fact has allowed the USA to become the world's biggest producer of oil, having surpassed Russia and Saudi Arabia in 2018, according to data from EIA. As of 2020 the USA amounted to 15% of the world's total oil production, followed by Russia at 13% and Saudi Arabia at 12%.

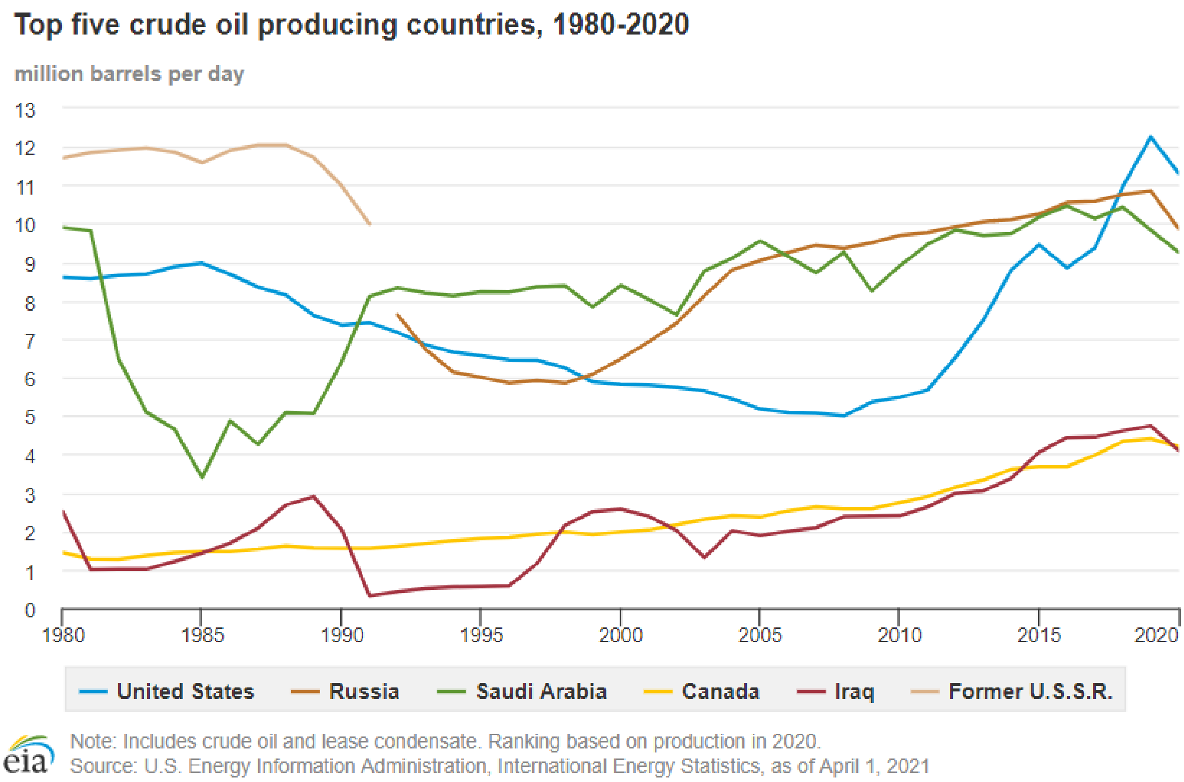


Figure 1: Evolution of the world's major oil producers (image retrieved from EIA)

However, despite this huge progress in terms of oil production, the USA remains a net importer of oil due to the fact that it is also, by far, the world's largest consumer, contributing to 21% of the word's consumption (also according to data from EIA), followed by China at 14%, and India at 5%.

Table 1: World's largest oil consumers in 2020 (data retrieved from EIA)

Country	Share of world total
United States	21%
China	14%
India	5%
Japan	4%
Russia	4%
Saudi Arabia	3%
Brazil	3%
South Korea	3%
Canada	3%
Germany	2%
Total top 10	60%

Saudi Arabia remains the world largest exporter of crude oil, followed by Russia. On the other hand, China is the world's largest importer, representing more than 20% of the world's total, followed by the USA.

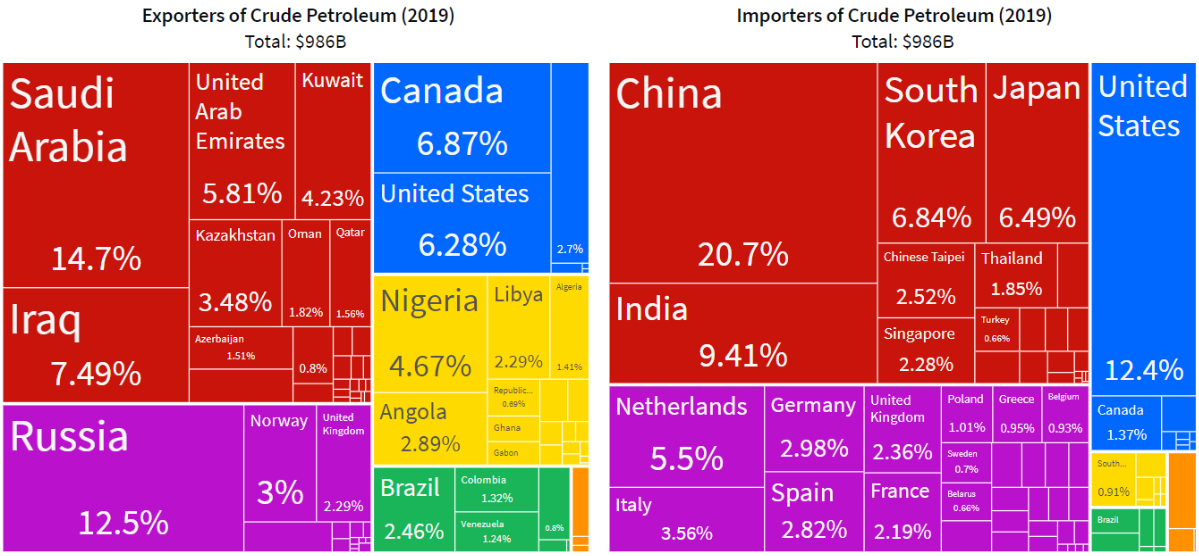


Figure 2: World's largest exporters and importers of oil in 2019 (image retrieved from oec.world)

However, when comparing to data from 2010, we notice a negative growth for some traditional exporters like Saudi Arabia and Russia and a tremendous increase in the value of USA exports. We also noticed a decline in USA imports and a continued growth of Chinese imports.

Overall, China has the world's most negative net trade balance, while Russia and Saudi Arabia present the highest net trade balances.

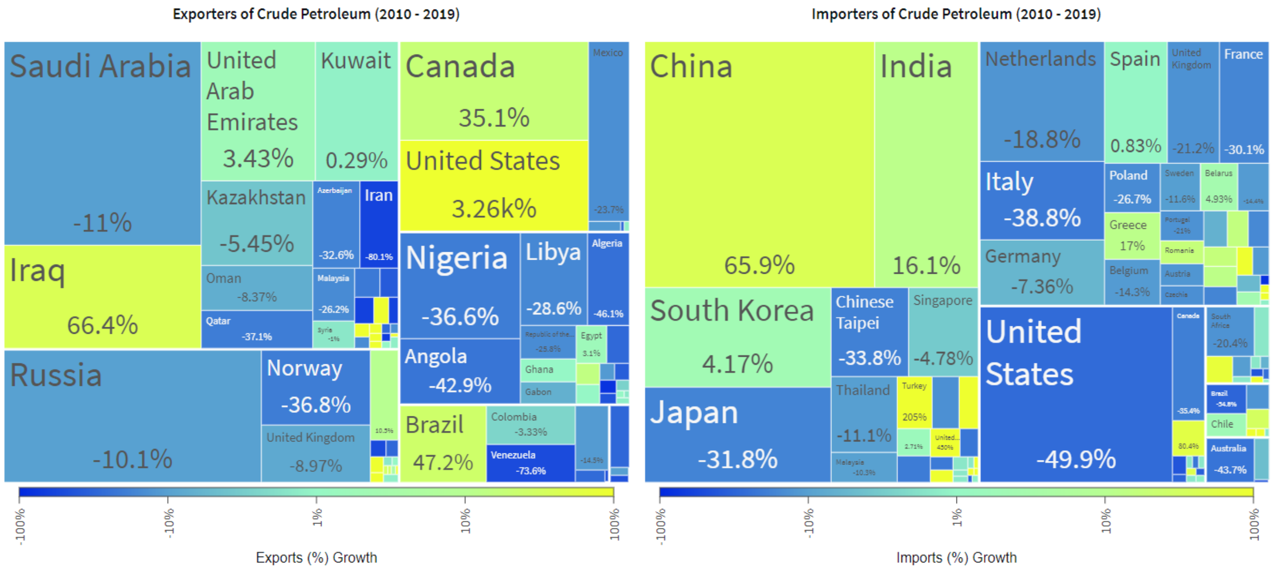


Figure 3: Growth of world's largest exporters and importers between 2011 and 2019 (image retrieved from oec.world)

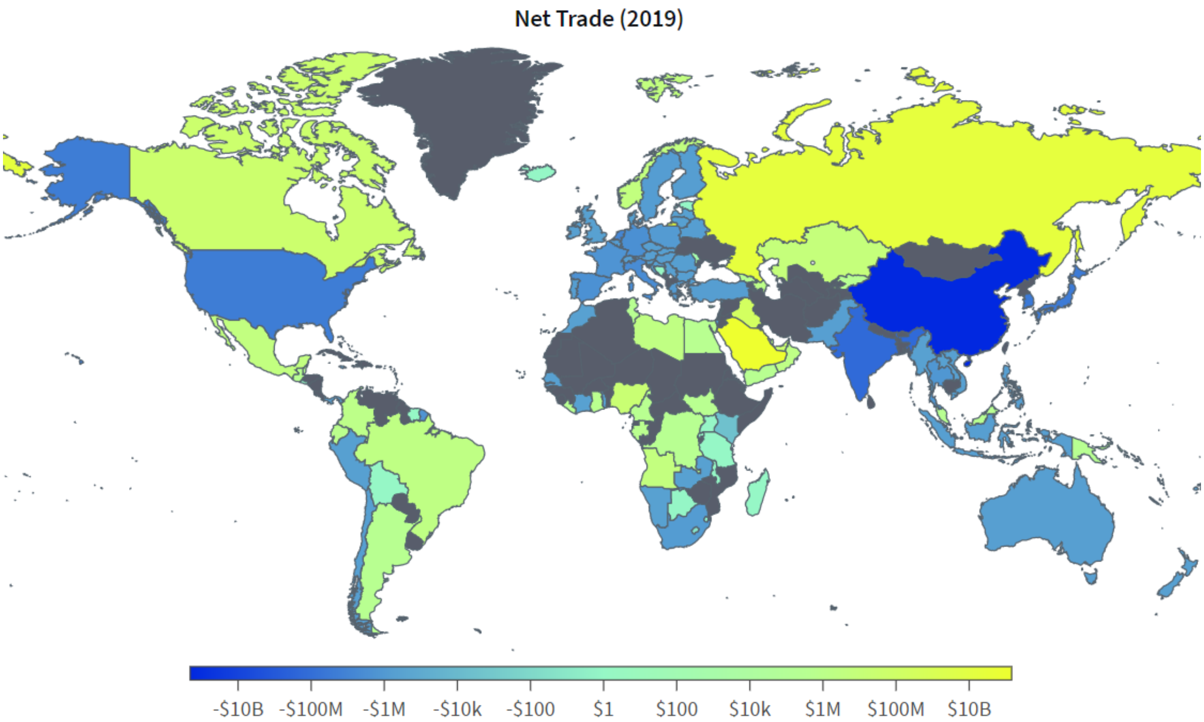


Figure 4: Map of the world's oil net trade in 2019 (image retrieved from oec.world)

2.2. Natural Gas

2.2.1. Worldwide reserves, major Producers and consumers, and global trade flow

According to the data presented at the BP Statistical Review of World Energy (70th edition, 2021), three countries alone account for more than half of the world's proven reserves. Russia possesses the biggest proven reserves in the world, with a share of 19.9% of the world's total, followed by Iran with 17.1% and Qatar with 13.1%.

However, in terms of production, the USA dominate, providing 23.7% of the world's total natural gas production. Russia follows in second place, with a share of 16.5% of the world's production. Iran and Qatar on the other hand have high R/P ratios and only account for 6.5% and 4.4% of the world's natural gas production, respectively.

The USA are also the main driver behind the world's natural gas consumption, accounting for 21.8% of the world's total. In second and third place we find Russia and China, with shares of 10.8% and 8.6%, respectively. European Union countries' consumption accounts for 9.9% of the world's total.

Natural gas transportation can be divided between transport by pipelines and liquefied natural gas (LNG). The last decade has seen a rise in LNG trade and, also according to the data presented at the BP Statistical Review of World Energy (70th edition, 2021), by the end of 2020 it accounted for 39% of the world's total trade movements (rising from 32% just four years before). Much of this increase in LNG is driven by demand from East Asia.

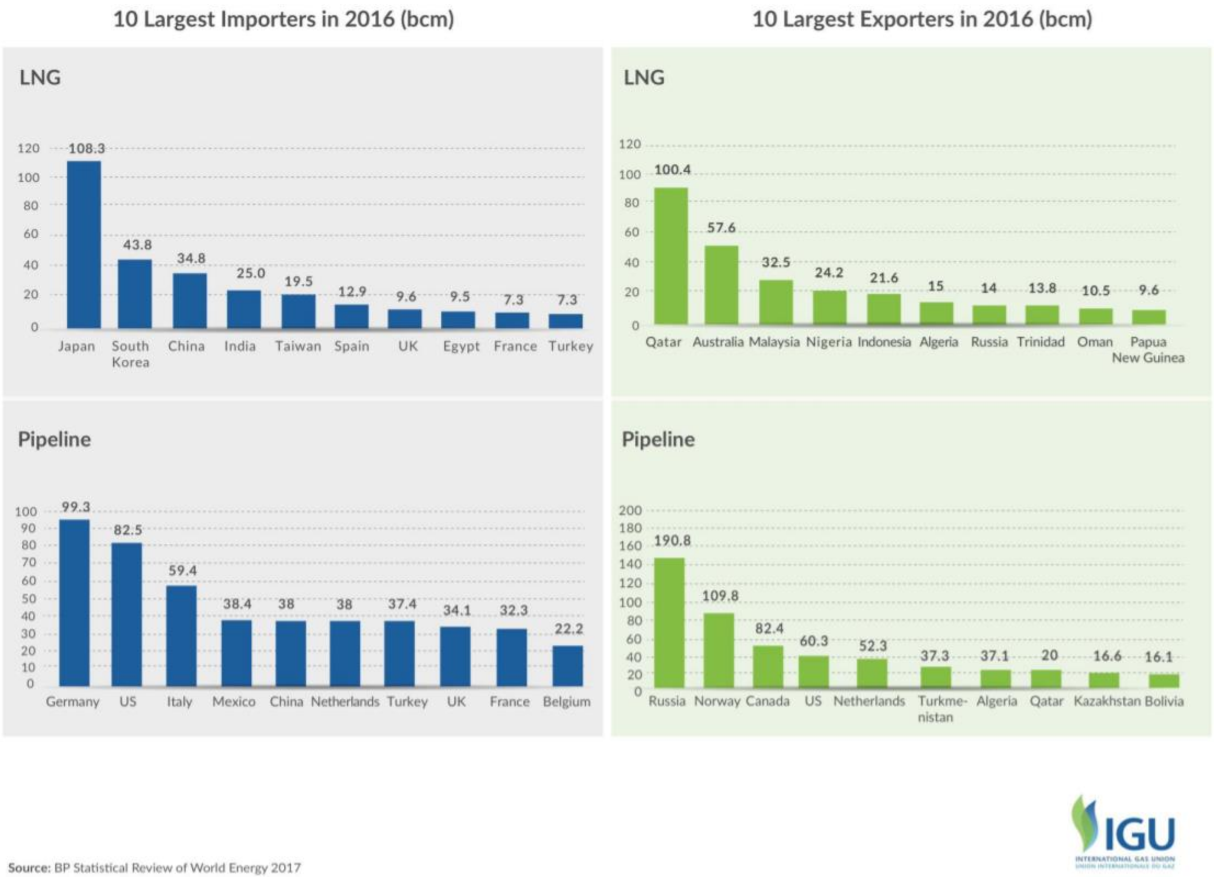


Figure 5: World's largest importers and exporters of natural gas in 2016 (image retrieved from igu.org)

We find major differences in terms of exporters and importers when accounting for this division. For natural gas transported through pipelines, the world's major exporters are Russia and Norway, while the major importers are Germany and the USA. Considering LNG, the largest exporters are Australia and Qatar, and the world's largest importers are Japan, South Korea, and China (that has nearly tripled its LNG imports in the last five years).

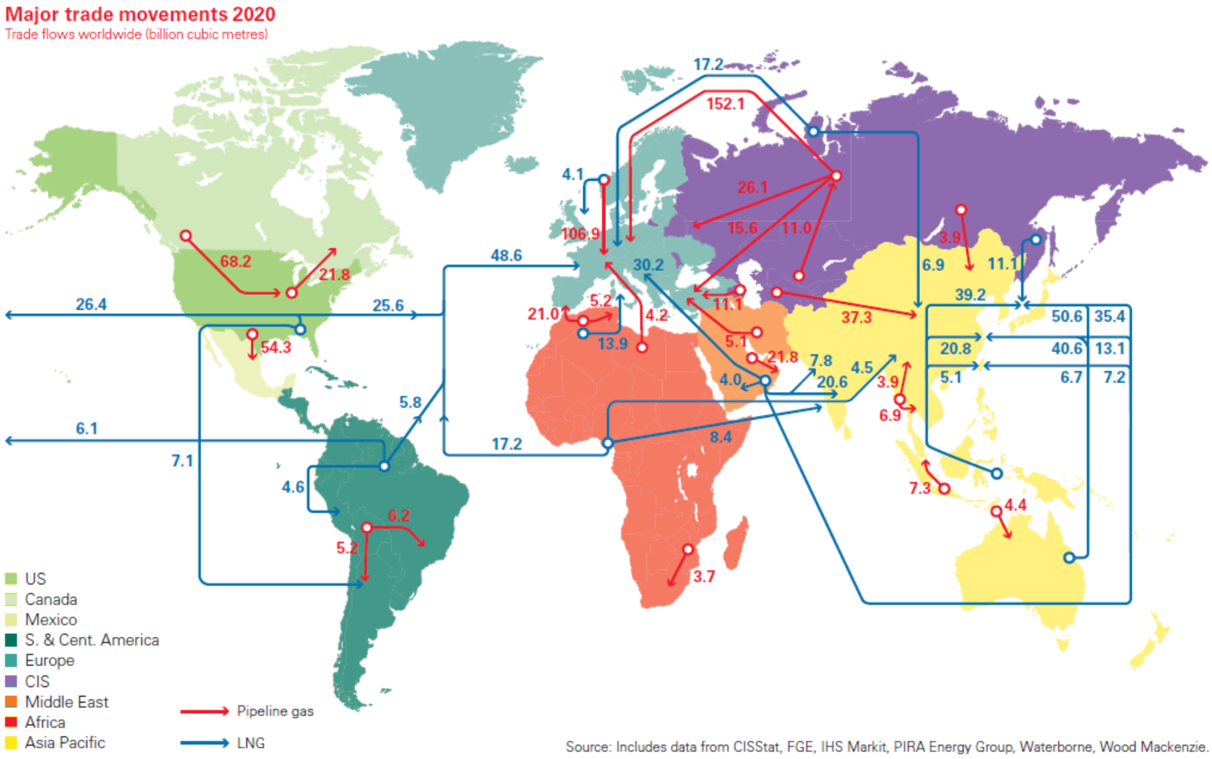


Figure 6: Natural gas trade movements in 2020 (image retrieved from BP Statistical Review of World Energy (70th edition, 2021))

Most LNG supplied to East Asia comes from Australia, which has resulted in an increase of its exports. As of 2020, Australia is now the world's largest exporter of LNG, having surpassed Qatar (21.8% vs 21.7% of the world's share, respectively).

However, according to data from Enerdata Global Energy Statistical Yearbook 2021, there was a decline of 7.6% of LNG imports in the European Union in 2020, with a variation of -16% in France and -6% in Spain, as the surge in renewable generation reduced gas-fired power generation. Nevertheless, European imports of LNG are still much higher than they were in 2018, as 2019 saw a huge increase in European LNG imports from the USA and Russia (BP Statistical Review of World Energy (70th edition, 2021)).

2.2.2. Major natural gas traded hubs in Europe

Natural gas traded hubs tend to be located at the major points of connection of natural gas infrastructure, that is, pipelines and LNG terminals. The most mature European gas hubs are (information retrieved from the Oxford Institute for Energy Studies):

- **TTF (Netherlands):** The Title Transfer Facility (TTF) is by far the largest natural gas traded hub in Europe. Over the past decade TTF has risen to become not only a major European benchmark, but also a global benchmark. TTF contracts are priced in euros/MWh.
- **NBP (UK):** National Balancing Point (NBP) is the major traded hub in the UK and was also Europe's first actively traded gas hub. While it is still one of the major hubs in Europe, it was once the major European hub, but was passed by TTF in 2016. NBP contracts are priced in pence/therm.

Other relevant European natural gas hubs include Zeebrugge (ZEE) in Belgium, a hub that like the NBP has declined in the last years and TRF, created in 2018 as a consolidation of French hubs. The Iberian gas hubs are the PVB and MIBGAS. Recently there are also plans to merge the German hubs, GPL and NCG, creating the third largest European natural gas hub.

Figure 7: Map of European traded gas hubs (image retrieved from the Oxford Institute for Energy Studies)

Table 2: Traded volumes in European traded gas hubs (data from the Oxford Institute for Energy Studies)

2020	TOTAL TRADED VOLUMES* (TWh)						
HUB	2008	2011	2018	Δ% =>	2019	Δ% =>	2020
TTF	560	6295	28220	+43	40390	+16	46690
NBP	10620	18000	15105	-17	12480	-19	10060
NCG	EST.215	880	1760	+25	2205	-11	1965
PSV	160	185	1060	+36	1440	+1	1455
GPL	EST.145	310	1150	+20	1375	-2	1350
VTP	CEGH 165	CEGH 170	650	+34	870	+16	1010
TRF	PEG N 185	PEG N 430	780	+24	970	-8	890
ZEE	500	870	460	-17	380	-38	235
ZTP	n/a	n/a	150	+27	190	+24	235
PVB	n/a	n/a	100	+30	130	+12	145
VOB	n/a	n/a	80	+19	95	⇔	95

*rounded to nearest 5TWh; not the same data sources in all years.

2.2.3. Rationale for the impact of oil prices on natural gas prices

Up until the shale revolution, the idea that oil and natural gas prices moved together was well accepted. A major reason for this was that the exploration of their reserves has always linked to each other. In fact, natural gas is many times a by-product of drilling for oil. Amongst the types of wells that produce natural gas, associated wells serve mainly to extract oil, with the natural gas that is extracted as well being a secondary resource, and even in non-associated wells, that serve mainly to explore natural gas, some oil is sometimes extracted.

Given that many wells can produce both oil and natural gas, it’s natural that their prices tend to a balance. For example, if the price of natural gas rose significantly, the owners of an associated well would have an incentive to switch some of their production from oil to natural gas.

However, the shale revolution has had an impact on this conventional wisdom, with oil and natural gas prices moving away from each other in the beginning of the last decade.

Many academic publications have dealt with these problems, how to quantify the relationship between oil prices and natural gas prices? What was the impact of the shale revolution? And what can we expect in the future? In this work we hope we can help answer some of those answers.

2.3. Coal

2.3.1. Worldwide reserves, major producers and consumers, and global trade flow

The world’s largest reserves are located in the USA, which accounts for 23.2% of the world’s total according to the BP Statistical Review of World Energy (70th edition, 2021). The USA reserves are followed by the Russian and Australian reserves, that respectively amount to 15.1% and 14.0% of the world’s total. Chinese and Indian coal reserves, not long ago also amongst the largest in the world, have fallen to 13.3% and 10.3% of the world’s total in 2020, respectively. Chinese coal reserves, in particular, have only a R/P ratio of 37, while for example the R/P ratio of Russian reserves is 407.

Between 2000 and 2010, there was a huge increase in both the global production and the global consumption of coal, driven mainly by China. However, according to data from the Enerdata Global Energy Statistical Yearbook 2021, in the last decade, both the production and the consumption of coal have globally remained more or less stable. This relative stability is mostly due to a decrease in both production and consumption in North America and Europe, mostly notable in the last three years, in part due to environmental concerns. On the other hand, this reduction has been balanced by China taking an even larger share of the world’s production and consumption of coal. Today, China accounts for more than half of both the world’s coal production and the world’s coal consumption.

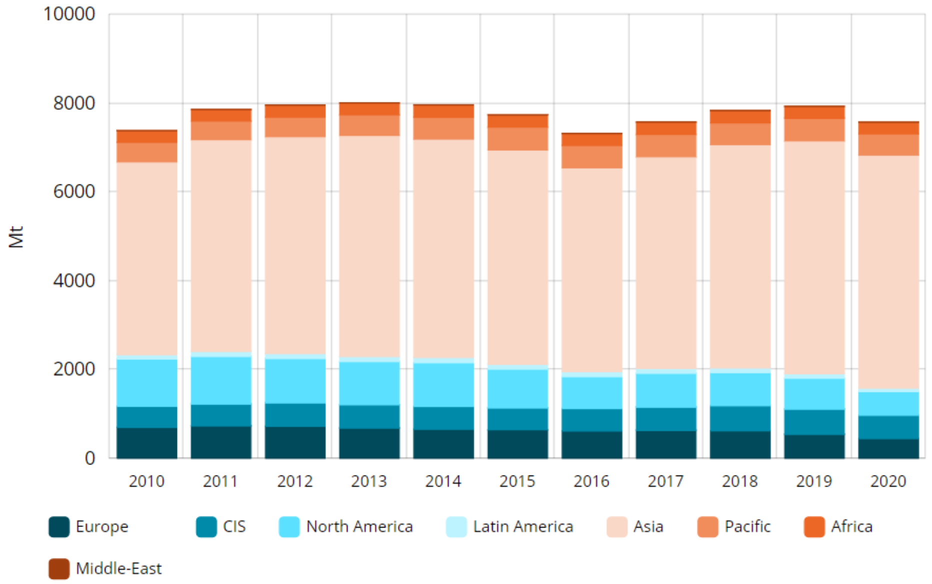


Figure 8: Evolution of the world's coal production by region between 2010 and 2020 (image retrieved from yearbook.enerdata.net)

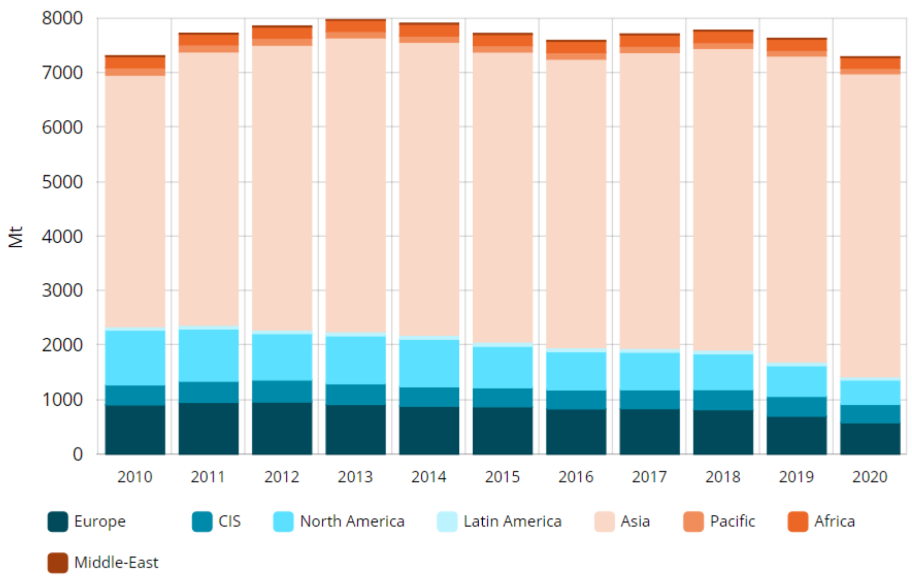


Figure 9: Evolution of the world's coal consumption by region between 2010 and 2020 (image retrieved from yearbook.enerdata.net)

In terms of imports and exports, China, despite being the world's largest producer, is the world's largest importer, having a share of 20.8% of the world's total. Other significant importers of coal are Japan, India, and South Korea, all with shares between 10% and 15%. Europe (excluding CIS countries) accounts for 12.3% of the world's total. The world's main exporters are Australia and Indonesia, together the account for more than half of the world's exports. (Data retrieved from BP Statistical Review of World Energy (70th edition, 2021))

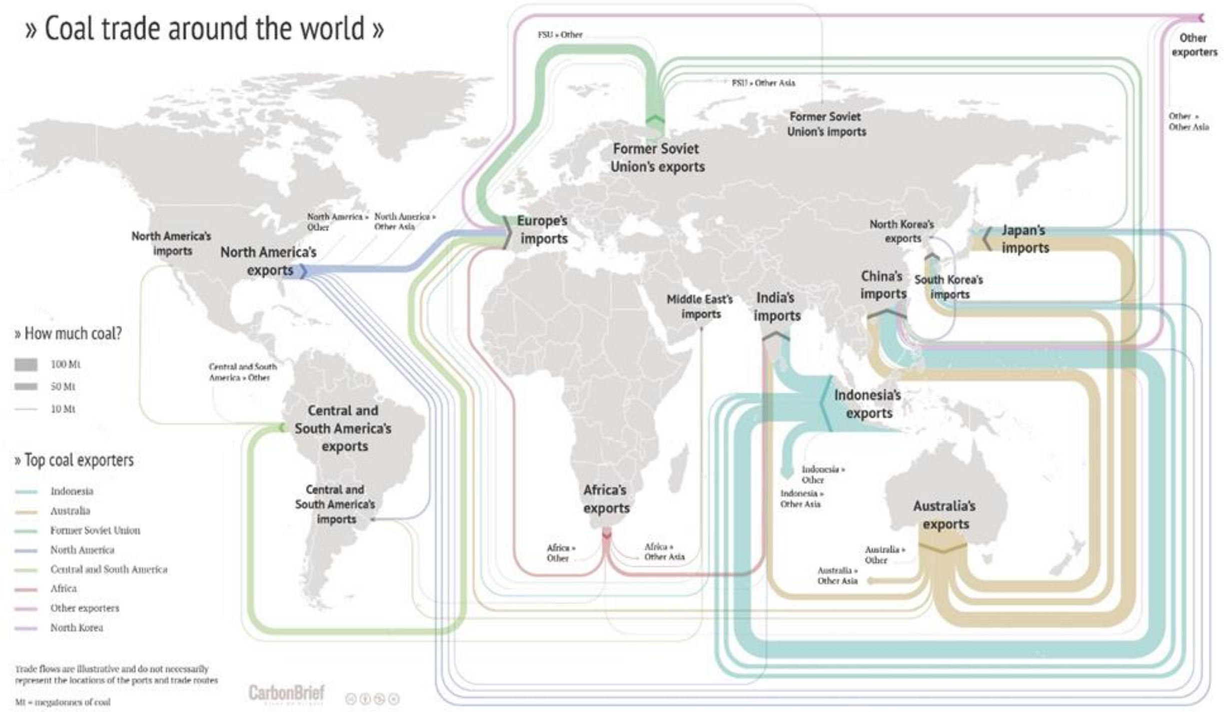


Figure 10: Coal trade movements in 2016 (image retrieved from carbonbrief.org)

2.3.2. Coal indexes

Coal price indexes are used as reference prices in physical supply and derivative contracts, for mark-to-market purposes, and as an indication of value for risk management. The most relevant ones include (information retrieved from argusmedia.com and ihsmarkit.com):

- **API 2:** The API 2 price assessment is the standard reference point for the price of coal imported to north-western Europe and is calculated as an average of the Argus CIF ARA assessment price and the IHS McCloskey NW Europe Steam Coal marker. Together with the API 4, the settlement basis for more than 90% of the world's derivative contracts.
- **API 4:** The API 4 is the reference price for coal exported from the Richards Bay terminal in South Africa. Its value is the result of the average of the Argus FOB Richards Bay price assessment and HIS McCloskey FOB Richards Bay marker. The API 4 is also the most liquid and transparent FOB price of coal globally and, as mentioned before, more than 90% of the world's derivative contracts are settled against the API 2 and the API 4.
- **API 5:** The API 5 price assessment is used for coal supply contracts in Australian and Chinese markets. It references a lower-heat product in comparison to the API 4 and the API 2. It is calculated as an average of the McCloskey and Argus assessment prices for FOB Newcastle (Australia) 5500 kcal/kg NAR coal. The API 5 benchmark refers to a high-ash coal and the lower-heat 5500 kcal/kg specification is a common thermal coal type that is replacing 6000 kcal/kg one for some thermal power generators in Asia-Pacific.
- **API 6:** Like the API 5, the API 6 refers to coal exported from Australia and is an average of the McCloskey and Argus assessment prices for FOB Newcastle 6000 kcal/kg NAR coal.

- **API 8:** The API 8 price assessment is the benchmark price reference for the import market in southern China. It is calculated as an average of the Argus CFR south China 5500 kcal/kg NAR coal price assessment and the IHS McCloskey/Xinhua Infolink south China CFR marker.
- **API 12:** The API 12 price index is used to assess mid-quality coal delivered into India's eastern region from South Africa, Australia, Indonesia as well as other producers, and reflects a 5500 kcal/kg NAR coal basis.

Given that our work will focus on European markets, all the coal price data that we will use will refer to the API 2.

2.3.3. Relationship of coal with natural gas and oil

Wholesale electricity prices are dependent on the utilization of coal and natural gas for generating electric power and these two commodities are generally substitutes. Traditionally, coal has been the cheaper fuel but, since the shale revolution the price of natural gas has proven to be very competitive against the price of coal in the USA, leading to a decrease in coal consumption. The European context is of course different and there isn’t an abundance of cheap natural gas, but the political pressure and the recent rise in the price of CO2 allowances can make the use of coal less viable in comparison to the use of natural gas.

On the other hand, a break on the supply chain of one of these commodities can drive up the demand for the other, given that they are substitutes, leading to a price increase in in this second commodity. Therefore, we must assume that it’s not only the prices of coal and natural gas that influence each other, but their availability also has an impact on the market forces that drive each other’s prices.

If coal and natural gas are substitutes and their prices are connected, and if, as we discussed on previously, oil prices have an impact on natural gas prices, then it follows that oil prices must also impact coal prices. The literature on this question is much poorer than the one relating natural gas and oil prices, and our work can also have a contribute here.

2.4. Electricity

2.4.1. Energy mix in Iberia, France, and Germany

The countries where we are going to focus our work present different paradigms in terms of the energy mix used to generate electricity.

Starting with Portugal, the country is characterized by a large presence of hydroelectric power, compared to other countries. While this brings some energetic independence, it also leads to some seasonality, with the summer moths being less productive. Portugal has also expanded its capabilities in terms of wind power generation over the last decades, which represents most of its non-hydro renewables’ production. Most of Portugal’s electricity derived from fossil fuels comes from natural gas but coal is also significant.

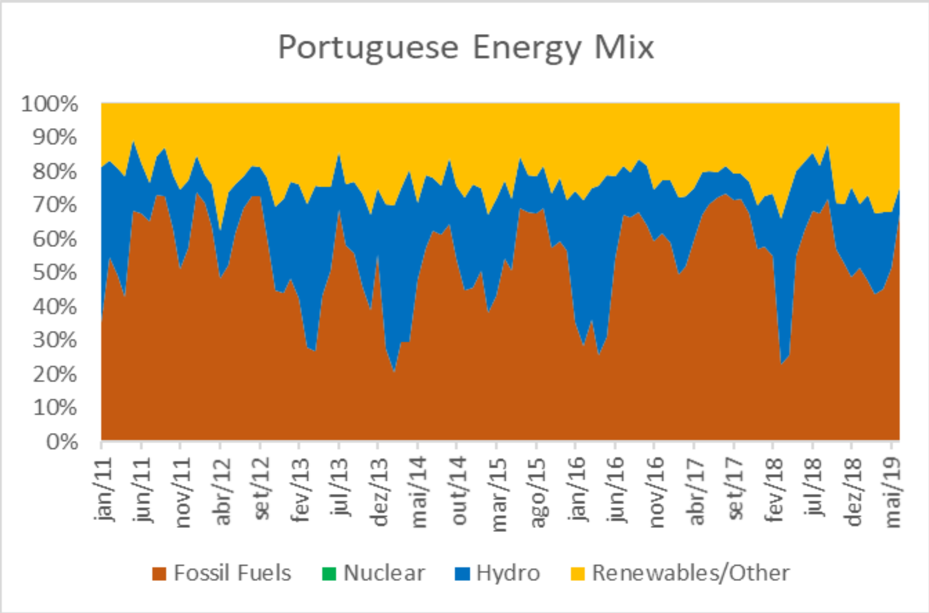


Figure 11: Evolution of the Portuguese energy mix between 2010 and 2019 (data retrieved from IEA)

Spain presents a very neutral energetic mix for electricity generation, without any source of energy dominating. Most its renewables come from wind power, but solar power is also present. While its share of electricity originating in fossil fuels has remained somewhat stable over the last decade, the percentage originating from coal has decreased in favour of natural gas.

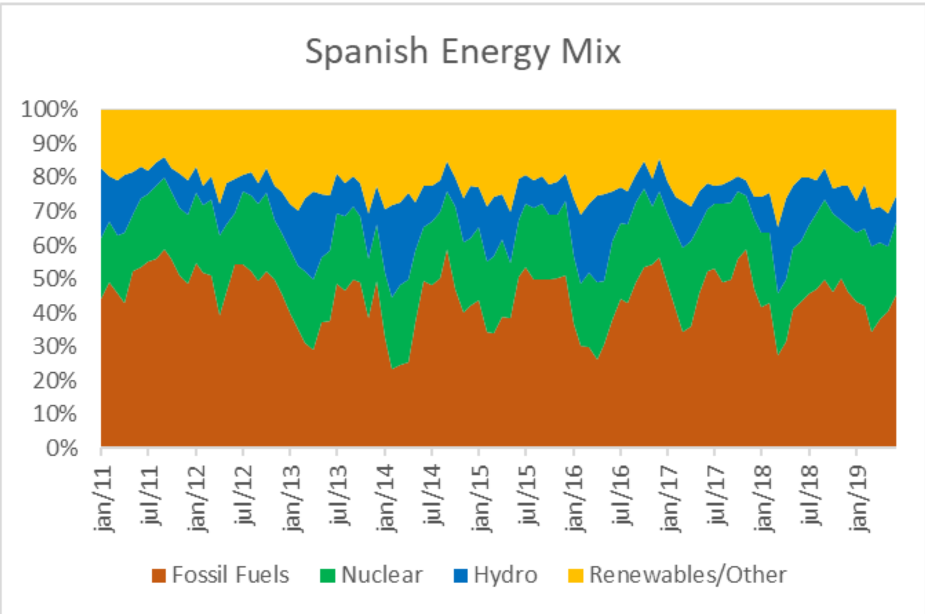


Figure 12: Evolution of the Spanish energy mix between 2011 and 2019 (data retrieved from IEA)

France represents the paradigm of a country that gets most of its energy from nuclear power, being the country with the biggest share of electricity derived from nuclear power in the world. As we can see, this makes the French energetic profile very stable and with low seasonality. We do notice however a continuous increase in the share of renewables over the last decade, an increase driven mainly by wind power generation. France serves an important role in the European electrical power grid, with its nuclear power providing a stable base for energy generation and low electricity prices.

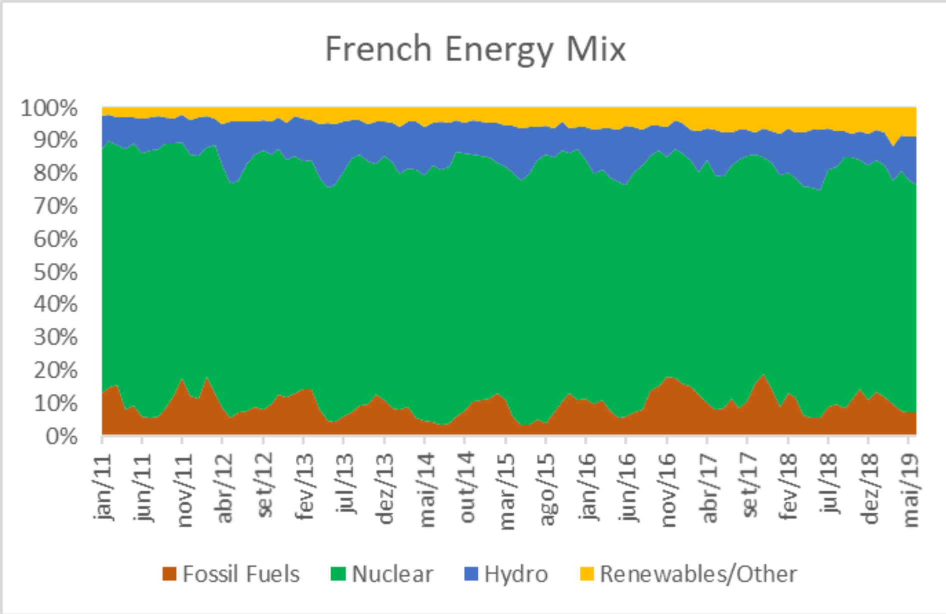


Figure 13: Evolution of the French energy mix between 2010 and 2019 (data retrieved from IEA)

While the decision to abandon nuclear power in Germany led to an increase in the production of electrical power with fossil fuel's origins, namely coal, the last decade has seen a very significant increase in its share of power production of renewable origin, and a continuous decline of the share of electricity originating from fossil fuels, especially coal. The German case is particularly interesting as its combination of wind and solar power allows for a lower level of seasonality than expected, with solar power providing energy during the summer and wind during the winter. The German experiment seems to be a positive one, as this has helped lower the price of electricity, as we will see further ahead, and the trend is for Germany to become an exporter of electricity.

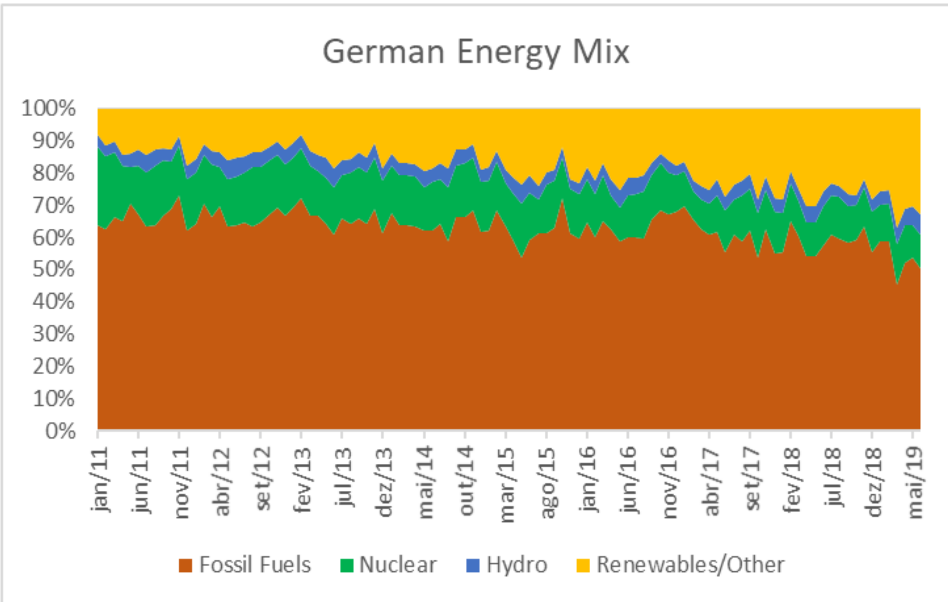


Figure 14: Evolution of the German energy mix between 2010 and 2019 (data retrieved from IEA)

2.4.2. European interconnections

Currently most of the European countries' power grid is interconnected with each other, as the political goal is to have more stable and liquid electricity markets. However, not all borders are equally interconnected, as we will see.

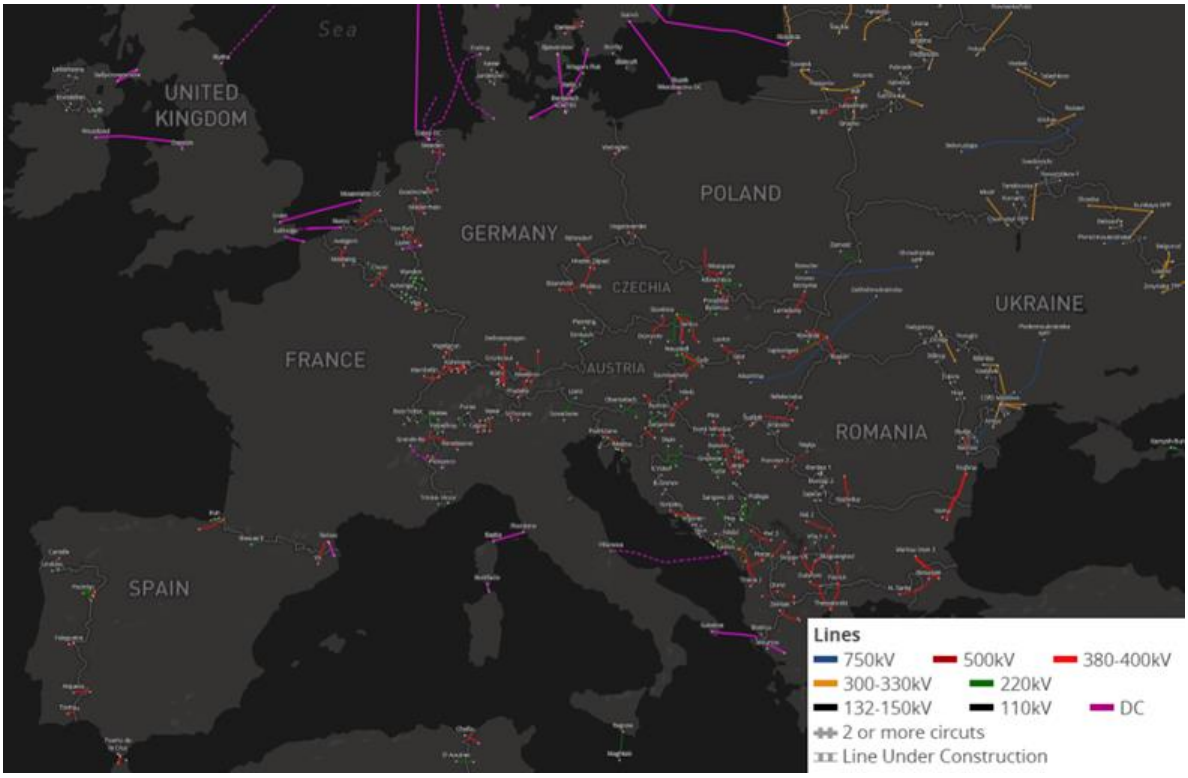


Figure 15: European power grid's cross border connections (image retrieved from ENTSO-E)

France's eastern border and Germany's western border are very well connected, not only with each other but also with their other neighbours. The connection between France and Spain on the other hand is somewhat limited, considering the scale of both markets, and, for example, according to data from RTE, France's power trade with Italy, Switzerland, and especially Germany-Belgium, during a typical period, is higher than with Spain.

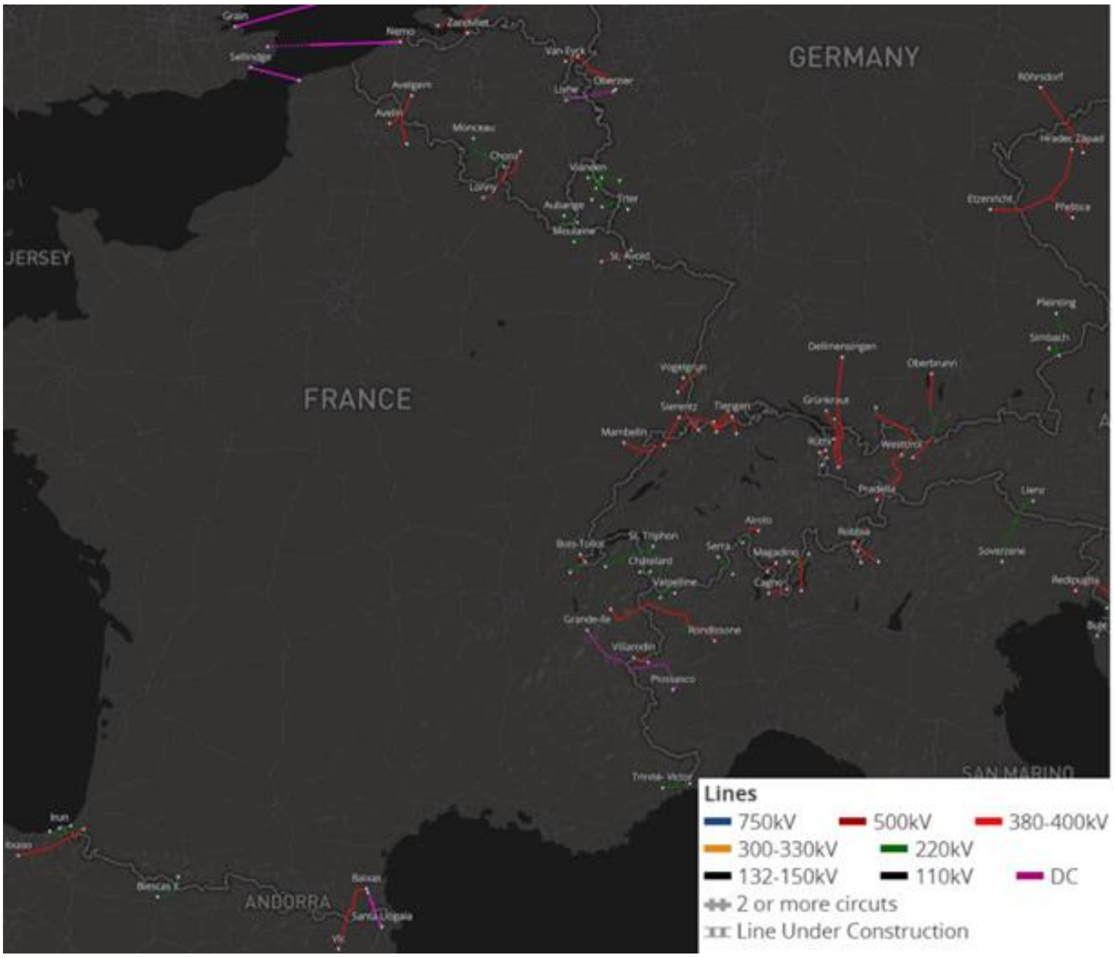


Figure 16: French-German and French-Spanish cross border grid connections (image retrieved from ENTSO-E)

The connection between Portugal and Spain, on the other hand, is enough to satisfy the necessities of these markets. Looking at data from OMIP and OMIE, we can see that the Portuguese and Spanish prices are almost always coupled, i.e., the connection between both countries is large enough that their respective prices can meet at an equilibrium point.

For this reason, while in our model we will only make use of Spanish power prices, we can consider that our study covers the entire geography of Iberia. In fact, given that Portuguese and Spanish prices are so tied together, when studying one of these countries power maker, we can never discount the presence of the other.

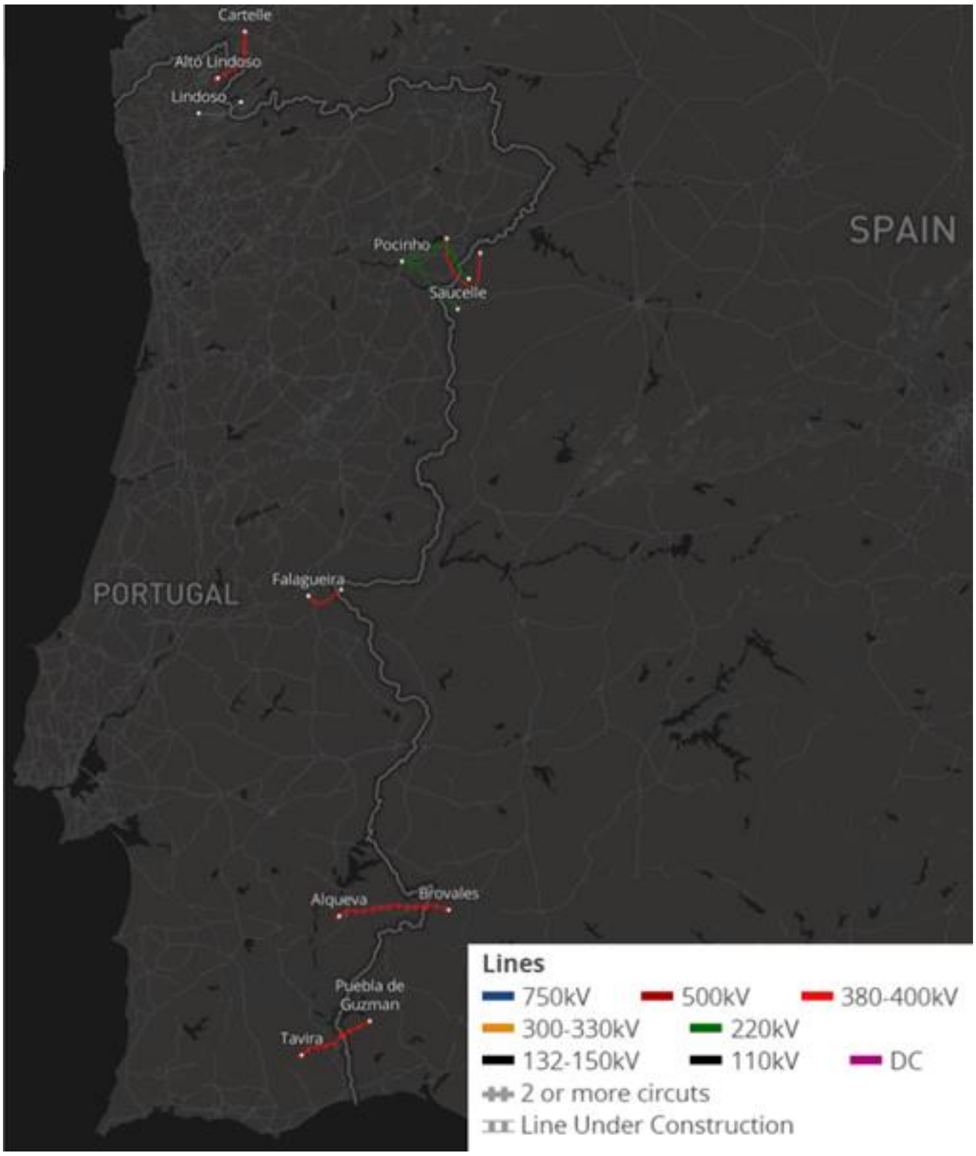


Figure 17: Portuguese-Spanish cross border grid connections (image retrieved from ENTSO-E)

An interesting fact is that during the first half of the last decade, Portugal had a lower (and usually negative) production-consumption difference when compared to Spain, but this situation seems to have inverted around the middle of the last decade. Another trend that we can see, is that the production-consumption difference in Germany has been slowly, but steadily, rising. As for France, only in some winters does the country momentarily needs to consume more electricity than it produces.

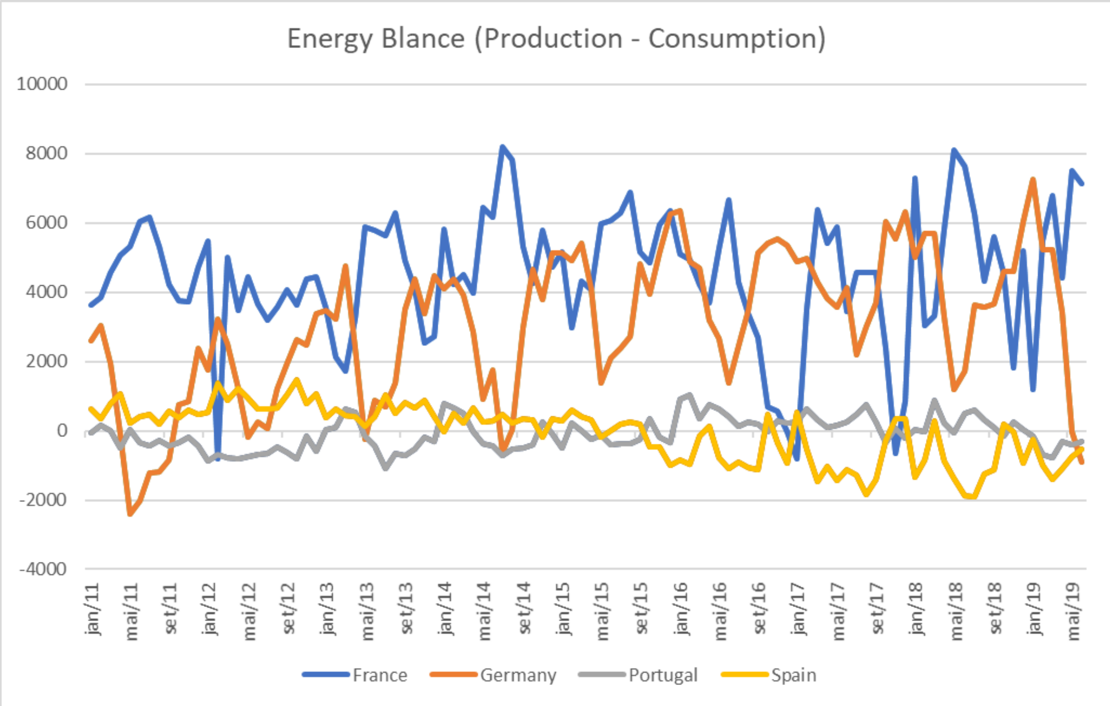


Figure 18: Evolution of the differential between production and consumption in France, Germany, Portugal, and Spain, between 2010 and 2019 (data retrieved from IEA)

2.4.3. Power exchanges

Electricity markets are less international than the ones of the previous commodities we discussed, so for our work we will have to focus only on the electrical power exchanges relevant for the geographies we are going to study. The exchanges in question are the OMIP and the EEX (information retrieved from omip.pt and eex.com)

- **OMIP:** OMIP together with OMIE are the operators of MIBEL (Iberian Electricity Market). MIBEL was established with the goal of creating a single Iberian electricity market, promoting Iberian electricity reference prices, and efficiency and liquidity on the Iberian market. MIBEL is structured in a way that OMIP, based in Portugal, is the single operator for futures and forward contracts, while OMIE, based in Spain, is the single operator for the spot market.
- **EEX:** Based in Germany, the European Energy Exchange (EEX) is a major exchange for energy derivatives that is currently present in most European markets but is particularly significant in Central Europe. Power prices from EEX will be the base for our study of French and German electricity prices. Spot markets are covered by a subsidiary of EEX, EPEX Spot.

2.4.4. Rationale for the impact of oil prices on electricity prices

We discussed before the rationale for the impact of oil prices on natural gas and coal prices. Given that much of the electricity produced in Germany, and to a lesser extent in Portugal and Spain, derives from coal and natural gas, logic follows that if oil prices indeed influence natural gas and coal prices, then this effect should “spill” into the electricity prices in those countries.

In the case of France, while its own electricity is mostly derived from nuclear power, with little fossil fuels in the mix, this is by no means a guarantee that the country's electricity is protected from effects from variations in oil prices. As we have seen, France is very interconnected to its Eastern neighbours, namely Germany, and if oil influences German electricity prices, then by extension it also has an effect on French prices.

We do, however, expect to find a weaker relationship between oil and French electricity prices than with, for example, German electricity prices.

3. Literature Review

3.1. Evidence of relationship between several energy commodities

Emery and Liu (2002) noted that a mutual practice by power businesses to use natural gas as peripheral fuel for making peak power is a principal justification. The results conclude that crude oil prices do not affect electricity prices because WTI futures influence the global crude market as unlike Henry hub prices are determined by demand and supply situation.

Mohammadi (2009) researched short and long dynamics between electricity and coal, natural gas, and crude oil. The author uses a dataset from 1960-2007 to test co-integration. Using the VECM and ECM models, the author analysed the data set for coal, electricity, and natural gas prices. From the data, the author found a significant long-term interaction between power and coal values, but there was no correlation between electricity prices with oil prices or natural gas prices. As such, conclusions are never alternate despite generating unequal changes in power prices towards balance, which produces short-term coal and natural gas price causality to power prices. The author affirms that while fuel rates do not profoundly affect US power prices, procedures linked to the coal sector can expressively impact electricity rates. Notably, different environmental laws can create a cumulative consequence on the coal prices as well as electricity generation.

Bencivenga et al. (2010) investigated an association of crude oil, natural gas, and electricity prices. Using a co-integration approach, the authors assert that the association of these energy commodities could have various inferences for estimating derivative products and risk management. The study analysed the short and long-run links among day-to-day price information from Brent crude oil, NBP natural gas and EEX electricity. The authors used the Engle-Granger co-integration framework and found that the energy commodity markets integrate.

Hassan (2011) noted that while the focus of price volatility has been studied for US markets, integration of these commodities has not been studied for the European market, and as such, the authors focus on the European market to identify integration with data collected between 2001 and 2007. Results from the short-run relation did not avail valuable acumens on the association among these energy elements, as stated later by Frydenberg et al. (2014). However, the long-run relationship showed that significative coefficients are found for power and gas. The authors acknowledge that in areas without deregulation, oil prices were leading factors for electricity and gas prices.

Asche et al. (2012) objective was to test the hypothesis that the shale revolution created a sharp divergence between oil and natural gas prices. The authors used data from the European gas market from 1996 to 2010 to conduct ADF and KPSS tests. The authors also performed The Johansen test based on a Vector Error Correction Model (VECM) to assess co-integration indications. Ultimately, the study found a long-term equilibrium between oil and gas prices.

Joëts et al. (2012) study is significative because it evaluated the association among oil, natural gas, coal, and electricity forwards. The authors utilized data from 2005 to 2010 from European forward prices. The authors use the panel dynamic OLS (DOLS) procedure, the Error Correction Model (ECM), and the

PSTR model. The authors' research found that the forward price series are co-integrated. To be more precise, the study revealed a definite link between oil, gas, and coal forward prices, but there is a lack of interaction among oil and electricity owing to the substitution effect.

Ramberg and Parsons (2012) assert that on the interaction between oil and natural gas, the link is not always a correlative one because there has been evidence that both commodities “decouple” due to the intensified volatility. The study confirms that there is an impact of oil on gas prices, even after the shale revolution.

Mishra (2013) used three methodologies to evaluate energy source prices and volatility empirically. Specifically, the author used Granger's causality to recognize the associations among natural gas, crude oil, propane, and heating oil. As well, the author used Johansen’s maximum likelihood technique to scrutinize the long-term equilibrium. The author then examined price volatility using the ARCH Model. From the research, the author found relationships among all pairs of commodities except for Henry Hub Natural gas and WTI crude oil values. The data used for this research covered a period between 1997 and 2012. The research contradicted the research that a long-run equilibrium association existed between natural gas and crude oil.

Nakajima et al. (2013) tested the causal interaction among general power prices with initial energy estimates. Notably, the study used the Granger causality among crude oil and power, as well as natural gas values. Adopting a cross-correlation function method, the authors found causality invariance and mean. The study found that an assessment with gas prices causes electricity prices. However, there was no causality among variables under the variance test. The authors used the LA-VAR and the CCF methods to test the Granger Causality. The study used data from the 2005 to 2009 period from Entergy, Henry Hub, and WTI natural logarithms. From the study results, there was a 1% significance level between electricity prices with natural gas means. It appears that Gas power plants are essential in the supply capability for topmost demand, so fuel prices impact wholesale power prices.

Frydenberg et al. (2014) conducted a study to find if there is a long-term link between electricity prices with oil, natural gas as well as coal. The study focused on the United Kingdom (UK), Germany, and Nordic nations. The research hypothesized that because these energy sources derive electricity production, it is likely that in the long run, these prices of these commodities will correlate. Thus, the objective of the research was to find a co-integration association of electricity prices and related energy commodities as well as finding error correction models for energy prices. The significance of this research is that it assesses co-integration from futures markets perspectives and not the spot market. The authors used data from 2006 to 2012. To test for co-integration, the authors used the well-established augmented Dickey-Fuller test (ADF). The results from their research show that the ADF tests reveal a non-stationary on 1% confidence level. A Johansen Trace test to show co-integration reveals an interaction of binary items, including oil and coal prices. However, the ADF outcomes are more conclusive than the Johansen trace test. The authors found co-integration between imminent power estimates in Europe as well as substitute energy bases that could include coal and gas. It is critical to consider that lack of integration could be due to short periods analysed and because contracts consist of short periods. The authors suggest that stronger co-integration would exist if the contracts were as they would reflect supply and demand conditions.

Madaleno et al. (2015) study the European markets to analyse both long term interactions and short term interactions between oil, natural gas, and coal on one side, and electric power on the other. From the results, the authors show a robust long-term interaction among power and fuel values in the commerce segment. The tests reveal that there is a dependency across countries and that power and fuel estimates integrate. However, their oil and coal values display different effects over power prices in residential and the industry segment. Since the industry component encompasses futures, unlike household prices, that may explain why the industries' power estimates are less sensible to fuel values in the short-term. The research primarily used the Dickey-Fuller (ADF) tests to evaluate the relationship and LLC test to highlight the stationary of the energy commodities.

Caporin et al. (2017) noted that the shale revolution has caused various changes in the gas marketplace. As such, the authors found a long-term interaction of oil and natural gas values between 1997 and 2013. Using the VECM, the authors found a significant effect on oil and gas interaction.

Ji et al. (2018) showed that a steady coexistent causal movement from oil to natural gas existed between 1999 and 2017. It appears that when some other factors are put into consideration, a long-standing symmetry association amongst oil and natural gas exists. The study by Ji et al. notes that because the USA exists in a liberalized price market, more factors must be considered. The authors use the VAR/ECM model to assess a lasting co-integration relationship and DAG to assess the causality of factors in the oil sector. The study outcomes show a significant relationship between crude oil prices with natural gas in consideration with other factors such as hurricanes, storage changes, as well as the seasonality impact on natural gas estimates, and this aspect was documented from Brown and Yucel's (2008) study that the weather and natural gas portfolios are critical drivers of natural gas prices. However, Geng et al. (2016) assert that the volatility in natural gas prices has lessened. The researchers noted that the production of shale gas in the United States had created an oversupply of shale gas as well as supply and demand inequities.

Perifanis et al. (2018) studied time-varying prices and volatility transmission between 1990 to 2019 in the US. The authors use crude oil futures daily NYMEX closing prices. The authors noted that due to the unconventional methods that lead to natural gas increase, markets are decoupled, further enhancing commodity independence. Perifanis et al. used the Momentum Threshold Autoregressive (MTAR) co-integration approach to establish assess if crude oil and natural gas prices will have a certain irregularity. For illustration, increases in oil prices create rapid alterations to natural gas prices as opposed to a price reduction. When one percent change in price is injected in the market, it leads to a positive long-term influence of gas price (about 0.01% or 0.02%). To test volatility transmission, the authors used the Dynamic Conditional Covariance (DCC) - Generalized Autoregressive Conditional Heteroscedasticity (GARCH) procedure.

Caporin et al. (2019) showed evidence of long-term interaction between WTI with Brent values. The study used data from 2000 to 2017 to assess co-integration despite the rise of shale production in 2011.

The econometric tests included the the Dickey Fuller (ADF), the Phillips-Perron test, and the VCM to assess interaction and volatility levels of both WTI and Brent prices. The study indicates that the lack of co-integration could be due to the unpredictability prompted by shale revolution and due to various issues that WTI faced, including transportation as well as refining difficulties. The authors further noted that due to the shale revolution, there had been a widening of the WTI-Brent price level, since 2014. As a result, there is an emerging different long-run interaction between the two elements.

De Salles et al. (2019) also examined the link between global natural gas and oil values. The study performed a Dickey-Fuller (DF) and the autoregressive distributed lag (ARDL) model to analyse data from two crucial global benchmarks for gas, the HH and NBP. For crude oil data, the author analysed data from Brent and WTI. According to this research, most of the studies to assess relationships among energy elements have been conducted using the Engle-Granger co-integration test and mainly in the United States context. The study showed that oil revenues affect variations in natural gas return values. The outcomes were constant with the extensive theory that oil values affect the natural gas price. The study illustrates and conforms to Hartley et al. (2014) in asserting the long term interaction between natural gas and crude oil. In a different study by Leykam et al. (2008) on the cointegration of spot price data, the Engle-Granger and Johansen cointegration tests showed a direct long-run significant interaction between both energy elements.

3.2. Summary

This chapter aimed to assess the extent to which various dynamics impact oil, natural gas, coal, and electricity markets. We saw that the commodities market can change drastically very quickly, and studies in this topic can quickly become obsolete. This is why there is a need from researcher to continue exploring these topics with ever more recent data. This is also why our present work can contribute to this field.

We can also conclude that because every study is divergent and includes distinctive features to assess, the level of cointegration has been different, but for the most part, there has been long term interactions between energy prices.

The following table presents a short resume of some the papers that we found most interesting in terms of methodology. While we will not follow every methodology presented here, we will take inspiration on these papers to select the methods that we are going to use. Some of these methods, like the commonly used Vector Error Correction Model (VECM), are going to be explained in detail in the next chapter.

Table 3: Summary of the literature review

Authors	Countries	Period	Method	Conclusions
Perifanis & Dagoumas (2018)	United States	1997 to 2016	1: Momentum Threshold Autoregressive (MTAR) co-integration approach 2: Dynamic Conditional Covariance (DCC)-Generalized Autoregressive Conditional Heteroscedasticity (GARCH) methodology.	The authors' research concludes that there is any evidence of a decoupling market exists among oil and gas comprehensive market between 97 and 2016. Using gas and oil price variables, the authors find positive asymmetry, which means that an upsurge in oil values causes surges in natural gas.
Frydenberg, Onochie, Westgaard, Midtsund, N., & Ueland (2014)	United Kingdom (UK), Germany and Nordic nations	2006 to 2012	1: Dickey-Fuller test (ADF). 2: A Johansen Trace test 3: Error correction vectors for a VECM model	The results from their research show that the ADF tests reveal a non-stationary on a one percent confidence level. A Johansen Trace test to show co-integration reveals the long-run interaction of oil and coal. However, results from the ADF are more conclusive than the Johansen trace test.
Ji, Q., Zhang, H. Y., & Geng, J. B. (2018).	United States	1999 to 2017	1: VAR/ECM model 2: DAG theory	A longstanding equilibrium connection between crude oil and natural gas price yields considering supplementary dynamics.
Bencivenga, C., Sargenti, G., & D'Ecclesia, R. L. (2010)	Europe	2001 to 2007	1: Engle-Granger 2: Johansen method ---- vector error correction model (VECM)	Gas and oil encompass diverse dynamics from natural gas as natural gas follows crude oil in the long-term. Hence, oil, gas, and power values interact. However, the research found one trend in the energy market, oil which means that it affects electricity and gas dynamics.
Mohammadi, H. (2009)	United States	1960-2007	1: VECM and 2: ECM models	There was a noteworthy long-term interaction between power and coal values, but there was no correlation between electricity prices with oil prices or natural gas prices. As such, findings never change regardless of creating unequal alterations in electricity values towards balance, which creates short-term causality of coal and natural gas prices to power estimates.
Mishra, A. K. (2013)	United States	1997 to 2012	1: Granger's causality 2: Johansen's maximum likelihood procedure 3: ARCH Model.	There existed relationships among all pairs of commodities except for Henry Hub Natural gas and WTI crude oil price. Research contradicted current research already indicated here that a long-term symmetry association existing among price, return as well as volatility level of natural gas with oil.
Caporin, M., & Fontini, F. (2017)	United States	1997 to 2013	1: VECM and 2: A Johansen Trace test 3: Perron (1997) unit root test	There was a probable long-term influence of gas magnitudes on prices. In recent years there has been instability in the stationarity of the quantities of gas due to the intensification of the shale revolution. There is an impact t of oil on gas prices, especially after shale gas evolution.
Nakajima, T., & Hamori, S. (2013)	United States	2005 to 2009	1: LA-VAR and 2: CCF 3: (Granger Causality)	There was a 1% significance level between electricity prices with natural gas means. It appears that Gas power plants are essential in the supply capability for topmost demand, so fuel prices impact wholesale power prices.
Madaleno, M., Moutinho, V., & Mota, J. (2015)	22 European countries	1992 to 2013	1: Dickey-Fuller (ADF) 2: LLC test 3: ECM model	There is a robust long-term interaction between power and fuel prices in the commerce segment. There is a stronger short and long-term interaction between electricity and fuel prices in the residential segment.
De Salles, A. A., & Campanati, A. B. M. (2019)	Global Perspective	2007 to 2016,	1: Dickey-Fuller (DF) 2: The autoregressive distributed lag (ARDL)	The outcomes were unswerving with the extensive theory of the link between crude oil values with natural gas prices. There is a long-term interaction between natural gas and crude oil prices.
Ferkingstad, E., Løland, A., & Wilhelmsen, M. (2011)	Spain	2002-2005	1: VAR method 2: CECM 3: Granger causality test.	Information illustrating this relationship bases reason for the interaction with the fact when crude oil becomes scarce, the price of fuel increases. Most importantly, gas and fuel prices correlate with crude oil because both rely on raw materials.
Caporin, M., Fontini, F., & Talebbeydokhti, E. (2019)	United States	2000 to 2017	1: Dickey Fuller (ADF), 2: The Peron test 3: VCM	There is a long-term interaction between WTI and Brent prices. The study indicates a lack of co-integration due to the unpredictability prompted by the shale revolution and various issues WTI faces, including transportation as well as refining difficulties.
Joëts, M., & Mignon, V. (2012)	Europe	2005 to 2010	1: OLS (DOLS) 2: Error-correction model 3: (ECM) 4: PSTR model.	There is a co-integration between all the energy commodities with forwards apart from electricity and oil prices due to the substitution effect among the two elements in the long-term
Chevallier, J. (2012)	Europe	1996 to 2010	1: ADF 2: DCC-MGARCH	The study found a long-term symmetry among oil and gas values. The econometric investigation of the gas and oil price interaction over time demonstrates that considerable short-term alterations ascend amongst the two.

4. Analysis of the Impact of Brent Prices on Electricity, Natural Gas, and Coal Prices

4.1. Model methodology

4.1.1. Introduction to time series

A time series is a series of data points indexed in time order (usually at equal time intervals), i.e., it is a sequence of discrete-time data. Time series data can exhibit a variety of patterns, therefore it is often useful to split it into components, each representing an underlying pattern. This is usually done by decomposing the time series into three components: trend, seasonality, and noise. The trend component represents the long-term patterns of the time series. A trend exists when there is a persistent increasing or decreasing direction in the data. The seasonality component represents repeated periodic patterns. The noise component represents the residuals (or remainder) of the time series after the other components have been removed.

4.1.2. Stationarity tests

4.1.2.1. Augmented Dickey-Fuller (ADF) test

The stationarity test (aka: unit root test) proposed by Dickey and Fuller (1979), the Augmented Dickey-Fuller (ADF), accommodates some forms of serial correlation, being used for larger and more complicated set of time series models, especially when compared to the Dickey-Fuller test. The ADF is represented as follows:

$$y_t = a + \gamma^t + \sum_{i=1}^{p} \beta_i y_{t-1} + \varepsilon_t \qquad (1)$$

where y_t is the variable, ε_t is the white noise component and a, γ, and β are constant parameters.

Nonetheless, if there is one-unit root, then the process is unit root non-stationary, resulting in the following representation:

$$\Delta y_t = \mu + \gamma^t + a y_{t-1} + \sum_{i=1}^{\rho} \beta_i \Delta y_{t-i} + \varepsilon_t \qquad (2)$$

where Δ is the difference operator ($\Delta y_t = y_t - y_{t-1}$), μ is a constant parameter.

Still, each one of these two versions of the test has its own critical value, directly depending on the size of the sample. In both cases the null hypothesis refers to the existence of a unit root ($\gamma = 0$) (Dickey and Fuller, 1979).

4.1.2.2. Phillips-Perron (PP) test

Phillips and Perron (PP) proposed an alternative stationarity test as way to address the problem of serial correlation. Essentially, this test estimates the non-augmented Dickey-Fuller (DF) test equation, modifying the t-ratio of the a coefficient so that the serial correlation does not affect the asymptotic distribution of the test statistic. The PP test is represented as follows:

$$\tilde{t}_a = t_a \left(y_0 / f_0^{1/2} - \frac{T(f_0 - \gamma_0)(se(\tilde{a}))}{2 f_0^{1/2} s} \right) \qquad (3)$$

Where $\tilde{a}$ refers to the estimate, t_a to the t-ratio of a, if $(\tilde{a})$ to the coefficient standard error, s to the standard error of the test regression, and f_0 to the estimator of the residual spectrum at the zero frequency (Phillips and Perron, 1988).

4.1.3. Models for multivariate relations

When modelling the interrelationships between variables, notably oil, gas, electricity, and coal, one can choose among a variety of possible empirical estimation strategies. The time series may be studied independently as univariate time series, each characterized by its own mean and autocovariance function (Alberola et al., 2008; Oberndorfer, 2009). However, when choosing a univariate approach, one fails to take into account the possible dependence between the time series, which is often of great importance to understand the observed values of the time series and its dynamics and evolution through time.

This is why here it was decided to estimate a vector of oil, natural gas, electricity and coal prices whose conditional covariance matrix evolves through time. First, we will present a VAR, then a VECM and, lastly, for complementary, a DDC-MGARCH model.

4.1.3.1. Vector Autoregression (VAR) model

The VAR model allows for simultaneous influence among the different variables and the existence of multiple linear independent cointegration vectors, the multivariate model is more general and allows for rich dynamics.

The general representation of a VAR model consists of a set of K endogenous variables $z_t = (z_{k_t}, \dots, z_{k_t})$ for $k = 1, \dots, K$, i.e., these variables depend linearly on their k previous values, as well as on the current value of the deterministic components:

$$z_t = \mu + \sum_{\tau=1}^{k} A_\tau z_{t-\tau} + \gamma D_t + \varepsilon_t \quad (4)$$

where z_t represents the vector of n jointly determined (endogenous) variables, μ is a constant vector, the A_τ matrices contain the coefficients associated to each $z_{t-\tau}$ vector, D_t represents the vector of deterministic variables (e.g. constant, trend, seasonal dummy variable, pulse, or shift dummy variable), and γ represents the vector of coefficient associated to each of the deterministic components. ε_t represents an unobservable error term, e.g., a random variable vector with normal distribution (Sims, 1980; Hamilton, 1994).

In this model, all variables must have the same order of integration. If all variables are stationary, $I(0)$, we have the standard case of a VAR model. If all variables are non-stationary, $I(d)$, $d > 1$, we have two choices. Either, and if the variables are not cointegrated, one differentiates the variables d times in order to obtain a VAR, or, if the variables are cointegrated, one may use a VECM.

4.1.3.2. Vector Error Correction Model (VECM)

Consider only the case where the variables z_t are $I(1)$, i.e., they must be differenced one time in order to achieve stationarity. Accordingly, the set of $I(1)$ variables is cointegrated when there is a $I(0)$ linear combination of them.

The VECM form is used to explicitly describe the co-integration relations between the variables, and it can be derived from the VAR:

$$\Delta z_t = \mu + \Pi z_{t-1} \sum_{\tau=1}^{k-1} \Gamma_\tau \Delta z_{\tau-t} + \gamma D_t + \varepsilon_t \quad (5)$$

where Δ is the difference operator ($\Delta z_t = z_t - z_{t-1}$), and Γ_τ is a coefficient matrix relating changes in z_t for lagged τ periods to current changes in z_t (short-run parameters). The Π matrix is called an error correction term, which compensates for the long-run information lost through differencing (Juselius, 2006).

If the VAR process has unit roots, the Π matrix is singular. Then Π can be decomposed in two matrices, α and β, as $\Pi = \alpha\beta'$, where α represents the convergence speed of the different variables at equilibrium, also known as the loading matrix, and β represents the long-run relationship coefficient matrix, also known as cointegration space or co-integration matrix. (Note that the α and β matrices are not unique.) Rewriting equation (5), we get

$$\Delta z_t = \mu + \alpha\beta' z_{t-1} \sum_{\tau=1}^{k-1} \Gamma_\tau \Delta z_{\tau-t} + \gamma D_t + \varepsilon_t \quad (6)$$

Comparing (4) and (5) we get

$$\Pi = \alpha\beta' = -\mathrm{I} + \sum_{\tau=1}^{k} A_\tau \quad (7)$$

and

$$\Gamma_\tau = -\sum_{i=\tau+1}^{k} A_\tau \quad (8)$$

The matrices α and β have dimensions $n \times r$, where r is the number of cointegration relations. There is cointegration in the case where $r \leq (n-1)$.

4.1.3.3. Criteria to choose the number of lags (Akaike, Hannan-Quinn and Schwarz)

If $L_n(k)$ is the likelihood of a model with k parameters based on a sample of size n, and let k_0 be the correct number of parameters. Suppose that for $k > k_0$ the model with k parameters is nested in the model with k_0 parameters, so that $L_n(k_0)$ is obtained by setting $k - k_0$ parameters in the larger model to constants. The Akaike (AIC), Hannan-Quinn (HQ), and Schwarz (SC) information criteria for selecting the number of parameters are, respectively:

$$\text{AIC: } c_n(k) = -2.\,ln\big(L_n(k)\big)/n + 2k/n \quad (9)$$

$$\text{HQ: } c_n(k) = -2.\,ln\big(L_n(k)\big)/n + 2k.\,ln\big(ln(n)\big)/n \quad (10)$$

$$\text{SC: } c_n(k) = -2.\,ln\big(L_n(k)\big)/n + k.\,ln(n)/n \quad (11)$$

i.e., k_0 can be estimated by

$$\hat{k} = argmin_k c_n(k) \quad (12)$$

For the specific case of a Gaussian VAR(p) model,

$$Y_t = a_0 + \sum_{j=1}^{p} A_j Y_{t-j} + U_t,\ U_t \sim i.i.d.N_m[0,\Sigma] \quad (13)$$

where $Y_t \in \mathbb{R}^m$ is observed for the $t = 1 - p, \ldots, n$, then $k = m + m^2.p$ and

$$ln(L_n(k)) = -\frac{1}{2}n.m - \frac{1}{2}n.ln[det(\hat{\Sigma}_p)] \quad (14)$$

where $\hat{\Sigma}_p$ is the maximum likelihood estimator of the error variance Σ. Then we may use these criteria to determine the order p of the VAR:

$$\hat{p} = argmin_p c_n^{VAR}(p) \quad (15)$$

where

$$\text{AIC: } c_n^{VAR}(p) = ln\left(det(\hat{\Sigma}_p)\right) + 2(m + m^2.p)/n \quad (16)$$

$$\text{HQ: } c_n^{VAR}(p) = ln\left(det(\hat{\Sigma}_p)\right) + 2(m + m^2.p)ln(ln(n))/n \quad (17)$$

$$\text{SC: } c_n^{VAR}(p) = ln\left(det(\hat{\Sigma}_p)\right) + 2(m + m^2.p)ln(n)/n \quad (18)$$

4.1.3.4. Trace test

The most usual cointegration test, according to Harris and Sollis (2003), is the Johansen trace test (Johansen, 1991), given by:

$$\lambda_{trace} = -T\sum_{i=r+1}^{n} Ln(1-\lambda_i),\ r = 1, \ldots, n-1 \quad (19)$$

It consists of estimating the eigenvalues (λ) associated with each hypothesis for the cointegration vectors, i.e. $r = 0, \ldots, r = n - 1$. In order to prove cointegration, it is necessary to prove that there is at least one λ_i, with $i = 1, \ldots, n - 1$, that is significantly non-zero. That is, the null hypothesis is

$$H_0: \lambda_i = 0, \text{ with } i = r + 1, \ldots, n \quad (20)$$

The test is sequential, beginning for the hypothesis of the trace test being zero and increasing r whenever it is rejected, i.e., $r = 0$ versus $r > 0$, then $r = 1$ versus $r > 1$ etc. If one of the tests does not reject the null hypothesis, the test stops, and one can conclude that there are as many cointegration vectors as the number of rejections of the null hypothesis that occurred in the test.

4.1.4. Jarque-Bera (JB) normality test

The Jarque-Bera (JB) normality test estimates that if both the skewness and the kurtosis of the data are different from the theoretical normal distribution, being represented as it follows:

$$JB = \frac{n}{6}\left(S^2 + \frac{1}{4}(k-3)^2\right) \quad (21)$$

Where the S refers to the sample skewness, the n to the sample size, and the k to the sample kurtosis. Overall, if the observed value is bigger than the critical value, the null hypothesis from which the sample is drawn, namely from a normally distributed population, can actually be rejected. Nevertheless, considering that the JB test assesses if the sample is close to the normal distribution by the datasets skewness and kurtosis. One of its main weaknesses relate to the fact that it can break down if the dataset has outliers, not being very useful in such cases (Jarque and Bera, 1980, 1987; Öztunan et al., 2006).

4.1.5. Granger test for causality

Granger (1969) causality helps to identify interdependence relations among variables, thus being useful in determining the benefits of including certain variables in the model. That is, if some past values of a variable have explanatory power of current ones.

In the framework of a bivariate VAR process, a variable z_2 is said to be Granger-causal for another z_1, if at least one $\alpha_{12,\tau}$ in

$$\begin{bmatrix} z_{1,t} \\ z_{2,t} \end{bmatrix} = \sum_{\tau=1}^{p} \begin{bmatrix} \alpha_{11,\tau} & \alpha_{12,\tau} \\ \alpha_{21,\tau} & \alpha_{22,\tau} \end{bmatrix} \begin{bmatrix} z_{1,t-\tau} \\ z_{2,t-\tau} \end{bmatrix} + \gamma D_t + \varepsilon_t \qquad (22)$$

is non zero, where $\tau = 1, \dots, p$. Here, $\alpha_{ij,\tau}$ and γ are constants coefficients and D_t is deterministic regressor, i.e. trend, seasonality dummies.

Likewise, for a bivariate VECM process, z_2 is said to Granger-cause z_1 if both $\alpha_1\beta_2$ and at least one $\gamma_{12,\tau}$ in

$$\begin{bmatrix} \Delta z_{1,t} \\ \Delta z_{2,t} \end{bmatrix} = \begin{bmatrix} \alpha_1\beta_1 & \alpha_1\beta_2 \\ \alpha_2\beta_1 & \alpha_2\beta_2 \end{bmatrix} + \sum_{\tau=1}^{p-1} \begin{bmatrix} \gamma_{11,\tau} & \gamma_{12,\tau} \\ \gamma_{21,\tau} & \gamma_{22,\tau} \end{bmatrix} \begin{bmatrix} \Delta z_{1,t-\tau} \\ \Delta z_{2,t-\tau} \end{bmatrix} + \gamma D_t + \varepsilon_t \qquad (23)$$

are non zero, where $\tau = 1, \dots, p-1$.

4.1.6. MGARCH and the specific case of DCC-MGARCH

Consider k time series of return innovations $\{X_{i,t}, i = 1, \dots, k\}$. Stacking these innovations into a vector $\boldsymbol{X}_t$, we define $\sigma_{ii,t} = var(X_{i,t}|\zeta_{t-1})$ and $\sigma_{ij,t} = cov(X_{i,t}, X_{j,t}|\zeta_{t-1})$. We note that $\sum_t \sigma_{ij,t}$ is the conditional variance-covariance matrix of all the time-series.

The main difficulty encountered with MGARCH modelling lies in finding a suitable system that describes the dynamics of Σ_t parsimoniously. Besides, the multiple GARCH equation needs to satisfy the positive definiteness of Σ_t, which is a numerically difficult problem. Finally, the number of parameters to be estimated increases very rapidly as the dimension of the time-series increases, which can take a very long time during the numerical implementation. To address these questions, we detail below three parametric formulations for the structure of the conditional covariance matrices.

Chevallier (2011) has studied the relationship between energy and emissions markets using VAR and a few variants of the GARCH models, from which the Dynamic Conditional Correlation MGARCH approach showed the most satisfactory fit to the properties of these types of data and analysis. Hence, in this paper we will also estimate a DCC-MGARCH model.

The DCC-MGARCH model attempts at making the conditional correlation time-varying, which is considered a preferable approach to deal with the possibly overly restrictive assumption of constant conditional correlations (Engle, 2002).

Hence, we introduce the following dynamic matrix process:

$$Q_t = (1 - a - b)S + a\epsilon_1 {\epsilon'}_{t-1} + bQ_{t-1} \quad (24)$$

with a and b, respectively, are positive and non-negative scalar parameters such that $a + b < 1$, S the unconditional correlation matrix of the standardized errors ϵ_t, and Q_0 is positive definite. To produce valid correlation matrices, Q_t needs to be re-scaled as follows:

$$P_t = (I \odot Q_t)^{-1/2} Q_t (I \odot Q_t)^{-1/2} \quad (25)$$

Having detailed the VAR, VECM and DCC-MGARCH models and the testing tools on which our empirical study is based, we now present the results and respective interpretation in the next section.

4.2. Results and analysis

In this section we will apply the methods of the previous section to the study of the impact of oil prices on electricity, natural gas, and coal prices.

Before we proceed, we must first select our data. As mentioned in previous sections, the focus of this work is on Western Europe, in particular, Iberia, France, and Germany.

Therefore, in terms of electricity prices, our time series will use data from OMIP electricity futures contracts (for the Iberian market), EEX French electricity futures contracts (for the French market), and EEX German electricity futures contracts (for the German market).

For natural gas prices, we base ourselves on TTF natural gas futures contracts, and for coal we will base ourselves on coal futures contracts indexed to API 2.

We chose to work with futures contracts instead of spot prices as we believe that spot prices are more sensible to other short term external and exogenous factors that can influence supply and demand, such as extreme weather spikes, unexpected pluviosity, amongst others.

However, our oil prices will correspond to Brent spot prices, because here we want to see higher volatility, and our interest is to see how long term agents in commodities markets interpret sudden events in oil prices.

To explore more nuances, we will also divide this section in two parts. In the first, we will study the impact of Brent spot prices on Year-ahead contracts relating to the other commodities. In the second part, we will then repeat the same study for Brent spot prices influencing Month-ahead contracts.

Also, we should take notice, we named our time series according to the following code, relating to a correspondent commodity:

- **Brent:** Brent crude oil spot prices, in €/bbl

- **API2:** Coal futures contracts indexed to API 2, in €/t
- **TTF:** TTF natural gas futures contracts, in €/MWh
- **EEX_FR:** EEX French electricity futures contracts, in €/MWh
- **EEX_DE:** EEX German electricity futures contracts, in €/MWh
- **OMIP:** OMIP Spanish electricity futures contracts, in €/MWh

The period covered will be from 28/11/2011 to 25/09/2021, and all data refers to baseload values when applicable. The data also refers to daily closing prices, and afterwards a weekly average was made, as it is common in the literature, in order to avoid an excess of data points in our time series.

4.2.1. Impact of oil prices on Year-ahead futures contracts

4.2.1.1. Stationarity tests outputs: Augmented Dickey-Fuller and Phillips-Perron tests outputs

From Table 4 below, one can observe strong statistical evidence that all series are integrated of order 1, ($I(1)$), except OMIP. When taking the usually applied 5% level of statistical significance, for OMIP, in the ADF test, we cannot reject the null hypothesis that the series is $I(1)$, while in the PP test, there is statistical evidence of the series being $I(0)$.

Despite the inconsistency in the test outcomes for OMIP, we assume all the series to have the same order of integration, $I(1)$, and we utilise a VECM, instead of a VAR in first-differences, to estimate the impulse response function. We can only do this, of course, after checking and concluding for the existence of cointegration between the series.

Table 4: Stationarity test using the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) unit root test, both with drift: test statistics for both the original time series (on log scale) and the first differences of the time series (on log scale), when testing for stationarity. The null hypothesis is that the series has a unit root, i.e., it is non-stationary

	Augmented Dickey-Fuller (ADF)		**Phillips-Perron (PP)**	
Series in log	Original data	First differences	Original data	First differences
Brent	-2.3142	-8.5103***	-2.2877	-15.6273***
API2	-2.0099	-12.9771***	-1.9575	-17.5198***
OMIP	-2.6551*	-4.8755***	-3.1219**	-7.7471***
EEX_FR	-2.3116	-9.4927***	-2.3819	-9.6023***
EEX_DE	-1.6315	-7.4731***	-1.7418	-10.6465***
TTF	-1.967	-7.0632***	-1.8295	-14.6997***

*** Significant at 1%
** Significant at 5%
* Significant at 10%

4.2.1.2. Vector Autoregressive (VAR) model and Vector Error Correction Model (VECM) outputs

Following what was recommended by Lütkepohl and Krätzig (2004), we firstly tested the order of integration of the time series.

Second, for the estimation of the VAR and the VECM, the respective optimal lag orders were chosen based on the Akaike, Hannan and Quinn and Schwarz criteria. VAR models were estimated up to the

26th lag and based of the mentioned criteria, a VAR(6) is the one that minimizes the selection criteria, notably Akaike, as can be seen in Table 5 below.

Table 5: Akaike, Hannan and Quinn and Schwarz model selection criteria for the optimal lag order of the VAR with a constant and trend

	Lag order				
Model selection criterion	1	2	3	4	5
Akaike (AIC)	-4.712787e+01	-4.738937e+01	-4.738606e+01	-4.738883e+01	-4.752700e+01
Hannan and Quinn (HQ)	-4.694513e+01	-4.708480e+01	-4.695967e+01	-4.684062e+01	-4.685696e+01
Schwarz (SC)	-4.666273e+01	-4.661414e+01	-4.630075e+01	-4.599343e+01	-4.582151e+01
	6	7	8	9	10
Akaike (AIC)	-4.754390e+01	-4.746666e+01	-4.740213e+01	-4.740469e+01	-4.735619e+01
Hannan and Quinn (HQ)	-4.675203e+01	-4.655297e+01	-4.636662e+01	-4.624735e+01	-4.607702e+01
Schwarz (SC)	-4.552832e+01	-4.514099e+01	-4.476637e+01	-4.445884e+01	-4.410025e+01
	11	12	13	14	15
Akaike (AIC)	-4.729374e+01	-4.725686e+01	-4.721614e+01	-4.721103e+01	-4.717593e+01
Hannan and Quinn (HQ)	-4.589275e+01	-4.573404e+01	-4.557149e+01	-4.544456e+01	-4.528763e+01
Schwarz (SC)	-4.372771e+01	-4.338074e+01	-4.302993e+01	-4.271473e+01	-4.236954e+01
	16	17	18	19	20
Akaike (AIC)	-4.714259e+01	-4.711404e+01	-4.705854e+01	-4.699905e+01	-4.694800e+01
Hannan and Quinn (HQ)	-4.513247e+01	-4.498210e+01	-4.480476e+01	-4.462346e+01	-4.445058e+01
Schwarz (SC)	-4.202612e+01	-4.168748e+01	-4.132188e+01	-4.095231e+01	-4.059117e+01
	21	22	23	24	25
Akaike (AIC)	-4.690702e+01	-4.689459e+01	-4.687869e+01	-4.686031e+01	-4.684001e+01
Hannan and Quinn (HQ)	-4.428777e+01	-4.415352e+01	-4.401579e+01	-4.387558e+01	-4.373346e+01
Schwarz (SC)	-4.024009e+01	-3.991758e+01	-3.959159e+01	-3.926311e+01	-3.893273e+01
	26				
Akaike (AIC)	-4.677490e+01				
Hannan and Quinn (HQ)	-4.354653e+01				
Schwarz (SC)	-3.855753e+01				

After, the Trace test (rank test) was run, indicating that there is, at least, one vector of cointegration between the time series, i.e., there is strong statistical evidence in favour of cointegration between the series. This means that the prices of Brent, natural gas, electricity and coal, despite shocks in the markets, always converge to a mean difference in the long run that is somewhat constant.

Table 6: Trace test of cointegration, when the constant is within the cointegration space

Rank	**Trace test**	**Critical values**		
(r)	**statistic**	10%	5%	1%
r ≤ 5	1.60	7.52	9.24	12.97
r ≤ 4	6.98	17.85	19.96	24.60
r ≤ 3	17.74	32.00	34.91	41.07
r ≤ 2	35.66	49.65	53.12	60.16
r ≤ 1	69.38	71.86	76.07	84.45
r ≤ 0	113.28	97.18	102.14	111.01

In addition, the OLS CUSUM tests were performed to check the existence of any break in the time series so that this information could be included in the VECM as a deterministic component. Moreover, the identification of a break in the series is very relevant as, if not controlled for, this could compromise the unit root tests, i.e., lead to erroneous conclusions.

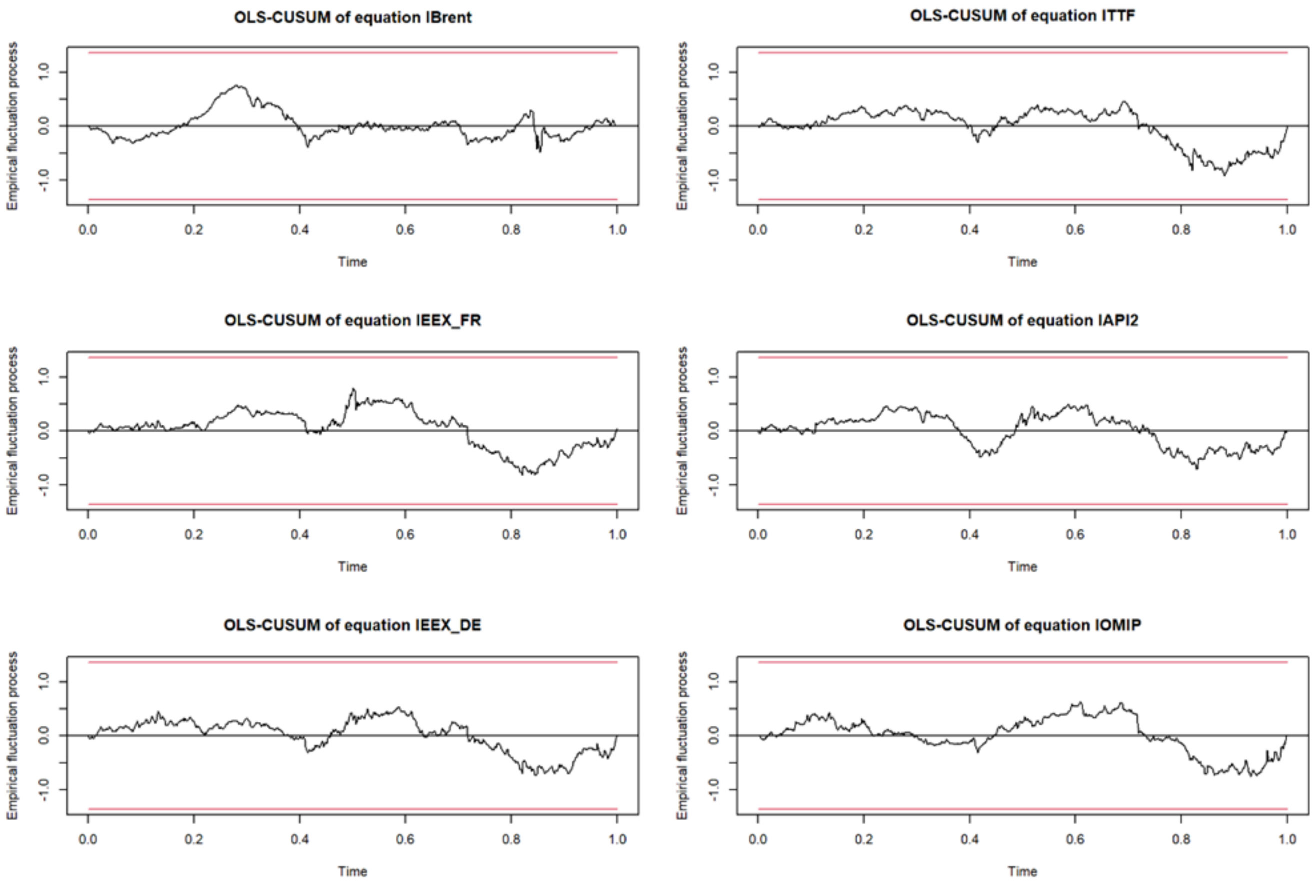


Figure 19: OLS CUSUM tests for the VAR(6) model with the logarithms of Brent, API2, OMIP, EEX_FR, EEX_DE and TTF

4.2.1.3. Granger test outputs

Table 7: Granger test. The null hypothesis for the test is that lagged values of the price of Brent do not explain the variation in the lagged values of the prices of the other energy types, i.e., Brent's price changes do not Granger-cause the prices changes in the other energies

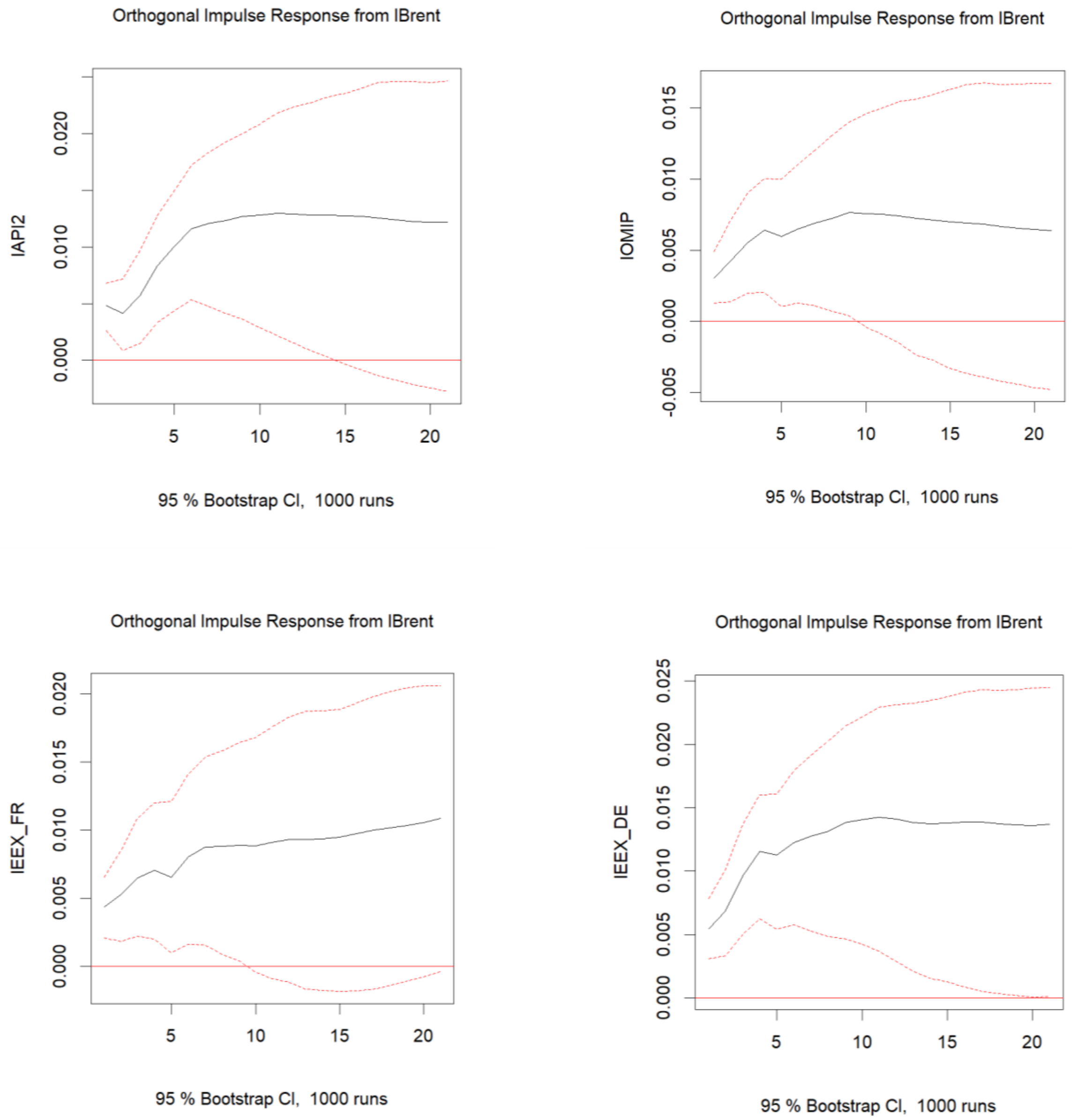
Test	Statistic
H0: "Brent does not Granger-cause API2"	0,9849
H0: "Brent does not Granger-cause OMIP"	0,9678
H0: "Brent does not Granger-cause EEX_FR"	0,7867
H0: "Brent does not Granger-cause EEX_DE"	1.5341**
H0: "Brent does not Granger-cause TTF"	1,1675

*** Significant at 1%
** Significant at 5%
* Significant at 10%

4.2.1.4. Impulse Response Functions (IRFs) outputs

In order to analyse dynamic effects of the model responding to certain shocks, further analysis is made through impulse response functions. So, after establishing that a causality relationship exists between the price of Brent and the remaining prices, one can now estimate what is the impact the variation in the price of Brent on the prices of the other energy types. The question we want to answer here is:

when the price of Brent varies by one standard deviation, how will the other commodities vary? This estimation is made using an impulse response function (IRF) (see Figure 20 below).



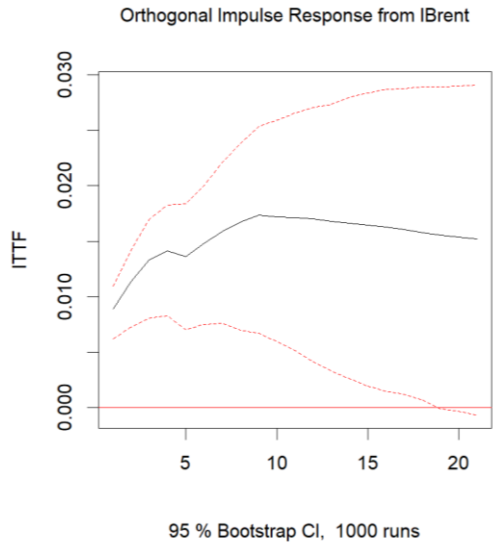
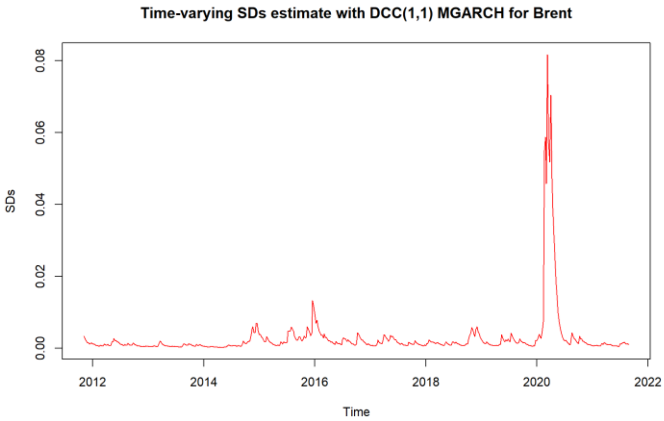


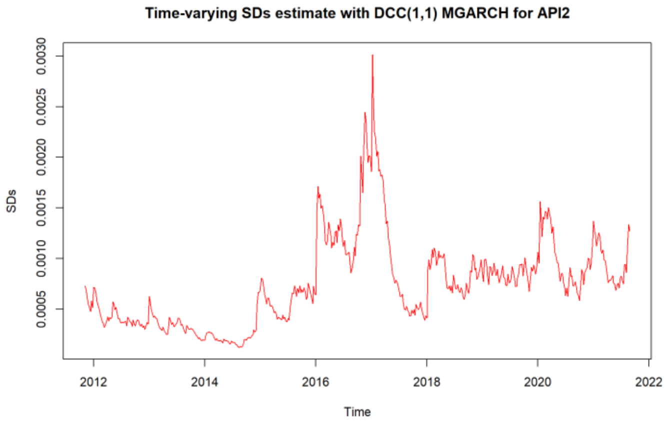
Figure 20: Impulse Response Functions of the time series in log

The figure above shows that, overall, a one standard deviation positive change in the price of Brent leads to a positive change (response) in the prices of the other energy types in the immediate periods.

4.2.1.5. DCC-MGARCH outputs

After observing the high volatility of the time series, as per the ACF of the squared residuals of the VECM (see appendix), we concluded there are indicia of a correlation through time between the series. Therefore, we used a DCC-MGARCH model to estimate the conditional variance of the series and the dynamic correlations with Brent along time. To do so, we made use of the series returns, i.e., of the first differences of their natural logarithm (see appendix).





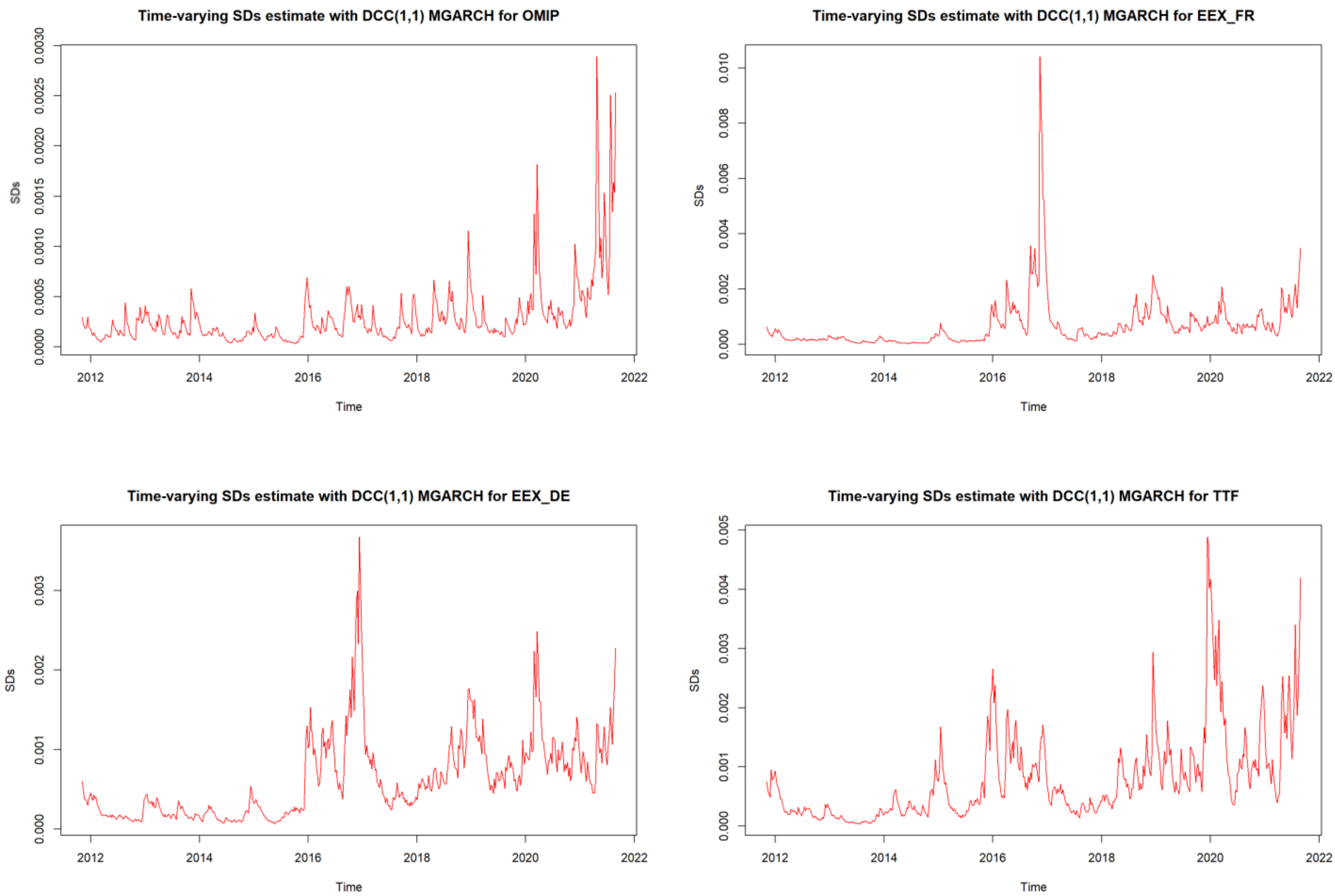


Figure 21: Time-varying standard-deviations estimated with the DCC(1,1) MGARCH for Brent, API2, OMIP, EEX_FR. EEX_DE and TTF

From the standard-deviations graphs (in Figure 21 above) we can see that there was an increase in the variance of oil prices in 2016 and even stronger increase in 2020, most likely due to the Covid-19 pandemic crises. Also, the prices of coal and French and German electricity showed big volatility at the end of 2016, and Iberian electricity prices have been oscillating a lot and show a growing trend from early 2020 onwards. Finally, natural gas prices show a continuous trend in terms of increase in volatility along the analysed period.

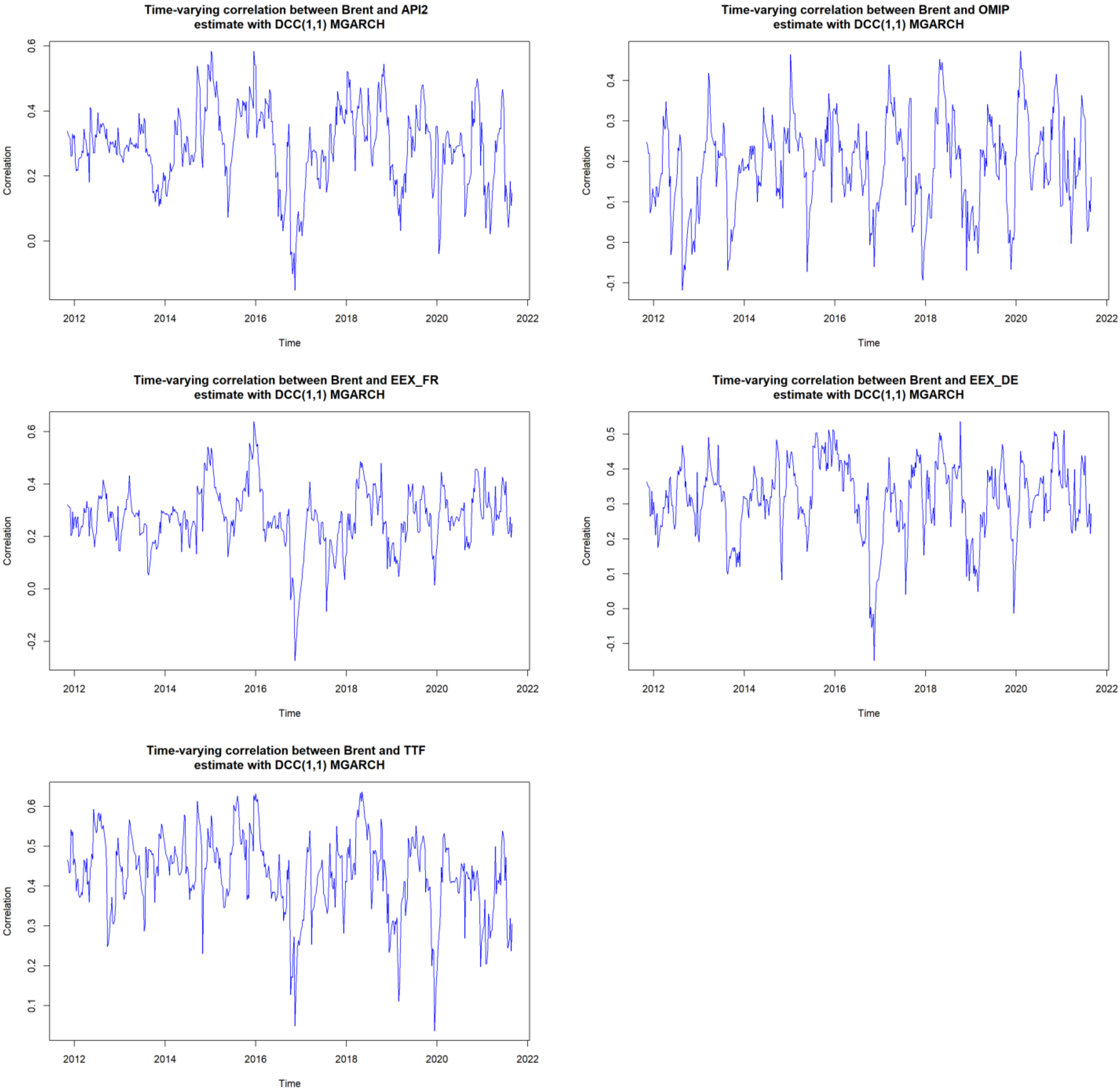


Figure 22: Time-varying correlations estimated with the DCC(1,1) MGARCH between Brent and the other energy types (API2, OMIP, EEX_FR, EEX_DE, TTF)

From Figure 22 above, one can observe that, overall, all series show a positive correlation with the price of Brent. Natural gas shows the strongest correlation through time, followed by coal, German electricity, French electricity and, lastly, Iberian electricity. This seems to follow our initial intuition that natural gas prices where the most affected by oil prices, while electricity prices only suffer indirect impacts.

It also follows out intuition that since Germany has the biggest percentage of power derived from fossil fuels, from the countries studied, that its electricity prices would be the most affected by variations in oil prices.

It is also possible to see, in the OMIP's graph that Iberian electricity prices present the greatest volatility in its correlation with Brent prices during the period under analysis. An explanation for this could be the high seasonality of the Portuguese and Spanish energy mix that we referred before.

Table 8: DCC(1, 1) MGARCH estimates for Brent, API2, OMIP, EEX_FR. EEX_DE and TT variables

Parameter	Estimate	Std. Error
GARCH parameters		
μ_{lBrent}	-0.001060 ***	0.000210
ω_{lBrent}	-0.359349 ***	0.119254
α_{lBrent}	-0.183938 ***	0.040626
β_{lBrent}	0.943852 ***	0.018671
γ_{lBrent}	0.320044 ***	0.079257
μ_{lAPI2}	-0.001307 ***	0.000342
ω_{lAPI2}	-0.103178 *	0.060550
α_{lAPI2}	-0.028817	0.035424
β_{lAPI2}	0.984524 ***	0.007503
γ_{lAPI2}	0.176035 **	0.082560
μ_{lOMIP}	-0.000167 ***	0.000012
ω_{lOMIP}	-0.718563	0.487063
α_{lOMIP}	0.046818	0.041556
β_{lOMIP}	0.911172 ***	0.057863
γ_{lOMIP}	0.435146 ***	0.133076
μ_{lEEX_FR}	0.000238 ***	0.000013
ω_{lEEX_FR}	-0.162333	0.173672
α_{lEEX_FR}	0.035552	0.031122
β_{lEEX_FR}	0.976160 ***	0.021472
γ_{lEEX_FR}	0.392749 ***	0.080956
μ_{lEEX_DE}	-0.000885	0.000796
ω_{lEEX_DE}	-0.140089	0.139575
α_{lEEX_DE}	-0.009599	0.028005
β_{lEEX_DE}	0.980179 ***	0.018177
γ_{lEEX_DE}	0.310623 ***	0.075398
μ_{lTTF}	-0.000226	0.000714
ω_{lTTF}	-0.135920	0.166154
α_{lTTF}	-0.012966	0.027273
β_{lTTF}	0.980479 ***	0.022041
γ_{lTTF}	0.389759 ***	0.127559
Correlation parameters		
α_1^*	0.071601 ***	0.013198
β_1^*	0.816786 ***	0.046149
Log-likelihood	8191.925	
ES p-value	24.87647	
ES X2 statistic	0.005585	

*** Significant at 1%
** Significant at 5%
* Significant at 10%

DCC-MGARCH coefficients are not easily interpretable. Nonetheless, we can see that DCC-MGARCH shows a good fit to the data, as most of the coefficients are statistically significant. This means we can examine the contemporaneous relationships between volatility and correlation on the prices of the energies, notably the price of oil and the prices of the other energy types. We can conclude that there is strong evidence of time-varying correlations amongst all the commodities studied.

4.2.2. Impact of oil prices on Month-ahead futures contracts

4.2.2.1. Stationarity tests outputs: Augmented Dickey-Fuller and Phillips-Perron tests outputs

Like in the previous study, relating to Year-ahead futures contracts, we observe statistical evidence that all series are integrated of order 1, $(I(1))$. We assume all the series to have the same order of integration, $I(1)$, and we utilise a VECM, instead of a VAR in first-differences, to estimate the impulse response function.

Table 9: Stationarity test using the Augmented Dickey-Fuller (ADF) and the Phillips–Perron (PP) unit root test, both with drift: test statistics for both the original time series (on log scale) and the first differences of the time series (on log scale), when testing for stationarity. The null hypothesis is that the series has a unit root, i.e., it is non-stationary

	Augmented Dickey-Fuller (ADF)		**Phillips-Perron (PP)**	
Series in log	Original data	First differences	Original data	First differences
Brent	-2.3814	-18.1574***	-2.5144	-25.6446***
API2	-1.1919	-15.0908***	-4.0893***	-
OMIP	-1.0627	-7.9993***	-1.2741	-19.5163***
EEX_FR	-3.0965**	-	-3.0911**	-
EEX_DE	-1.4405	-13.3193***	-1.3453	-18.8024***
TTF	-1.5159	-4.4282 ***	-1.2441	-20.7521***

*** Significant at 1%
** Significant at 5%
* Significant at 10%

4.2.2.2. Vector Autoregressive (VAR) model and Vector Error Correction Model (VECM) outputs

Like before, the VAR models were estimated up to the 26th lag and based of the Akaike, Hannan and Quinn, and Schwarz criteria. Here a VAR(5) is the one that minimizes the selection criteria (again we give priority to the Akaike criteria), as can be seen in the table below.

Table 10: Akaike, Hannan and Quinn and Schwarz model selection criteria for the optimal lag order of the VAR with a constant and trend

Model selection criterion	Lag order 1	2	3	4	5
Akaike (AIC)	-3.323031e+01	-3.330378e+01	-3.331335e+01	-3.332437e+01	-3.348453e+01
Hannan and Quinn (HQ)	-3.302760e+01	-3.297945e+01	-3.286739e+01	-3.275679e+01	-3.279533e+01
Schwarz (SC)	-3.271430e+01	-3.247817e+01	-3.217813e+01	-3.187955e+01	-3.173010e+01
	6	7	8	9	10
Akaike (AIC)	-3.343026e+01	-3.338015e+01	-3.332273e+01	-3.330366e+01	-3.331332e+01
Hannan and Quinn (HQ)	-3.261943e+01	-3.244769e+01	-3.226865e+01	-3.212796e+01	-3.201599e+01
Schwarz (SC)	-3.136623e+01	-3.100651e+01	-3.063949e+01	-3.031081e+01	-3.001087e+01
	11	12	13	14	15
Akaike (AIC)	-3.327724e+01	-3.320018e+01	-3.315352e+01	-3.314892e+01	-3.312124e+01
Hannan and Quinn (HQ)	-3.185828e+01	-3.165961e+01	-3.149132e+01	-3.136510e+01	-3.121579e+01
Schwarz (SC)	-2.966518e+01	-2.927852e+01	-2.892226e+01	-2.860805e+01	-2.827077e+01
	16	17	18	19	20
Akaike (AIC)	-3.305804e+01	-3.304074e+01	-3.300924e+01	-3.294971e+01	-3.295379e+01
Hannan and Quinn (HQ)	-3.103097e+01	-3.089204e+01	-3.073891e+01	-3.055776e+01	-3.044022e+01
Schwarz (SC)	-2.789796e+01	-2.757105e+01	-2.722995e+01	-2.686081e+01	-2.655529e+01
	21	22	23	24	25
Akaike (AIC)	-3.288966e+01	-3.285133e+01	-3.284707e+01	-3.279878e+01	-3.278886e+01
Hannan and Quinn (HQ)	-3.025446e+01	-3.009451e+01	-2.996863e+01	-2.979871e+01	-2.966717e+01
Schwarz (SC)	-2.618155e+01	-2.583363e+01	-2.551976e+01	-2.516186e+01	-2.484234e+01
	26				
Akaike (AIC)	-3.278051e+01				
Hannan and Quinn (HQ)	-2.953719e+01				
Schwarz (SC)	-2.452439e+01				

Like in the previous case, the Trace test (rank test) was run, indicating that there is, at least, one vector of cointegration between the time series. This means that the prices of these commodities, despite shocks in the markets, always converge to a mean difference in the long run that is somewhat constant.

Table 11: Trace test of cointegration, when the constant is within the cointegration space

Rank (r)	Trace test statistic	Critical values 10%	5%	1%
r ≤ 5	0.94	7.52	9.24	12.97
r ≤ 4	8.23	17.85	19.96	24.60
r ≤ 3	17.68	32.00	34.91	41.07
r ≤ 2	33.46	49.65	53.12	60.16
r ≤ 1	74.02	71.86	76.07	84.45
r ≤ 0	141.17	97.18	102.14	111.01

Like before, OLS CUSUM tests were also performed to check the existence of any break in the time series so that this information could be included in the VECM as a deterministic component.

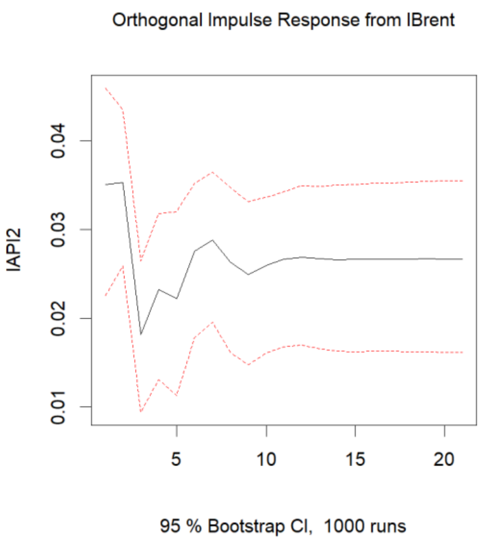
4.2.2.3. Granger test outputs

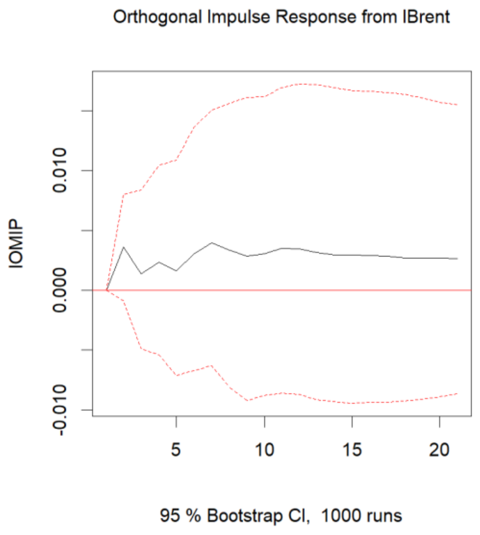
Table 12: Granger test. The null hypothesis for the test is that lagged values of the price of Brent do not explain the variation in the lagged values of the prices of the other energy types, i.e., Brent's price changes do not Granger-cause the prices changes in the other energies

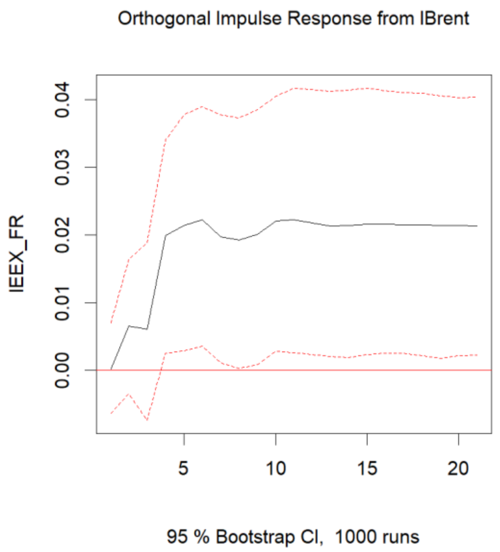
Test	Statistic
H0: "Brent does not Granger-cause API2"	1.7284 **
H0: "Brent does not Granger-cause OMIP"	1.8396 ***
H0: "Brent does not Granger-cause EEX_FR"	1.3147
H0: "Brent does not Granger-cause EEX_DE"	1.2058
H0: "Brent does not Granger-cause TTF"	1.1059

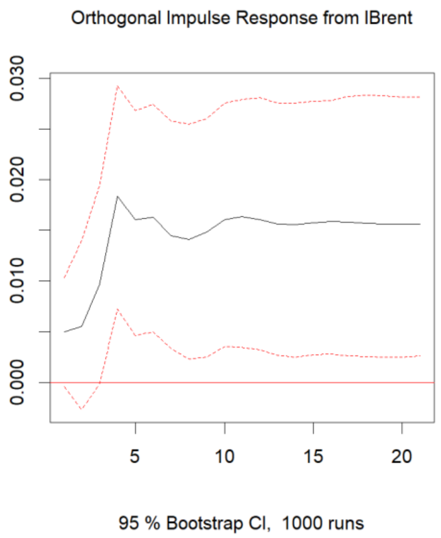
*** Significant at 1%
** Significant at 5%
* Significant at 10%

4.2.2.4. Impulse Response Functions (IRFs) outputs









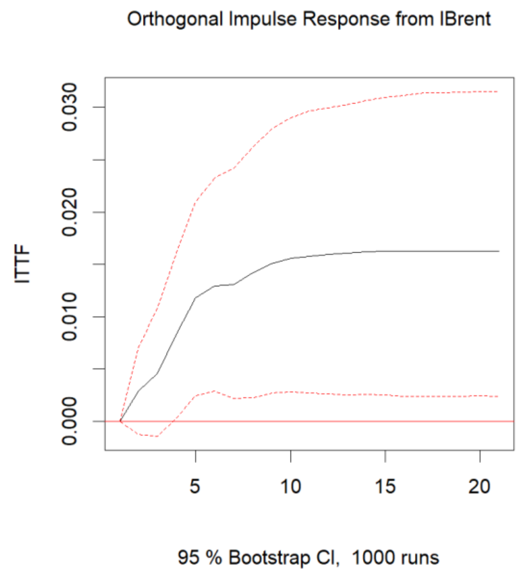


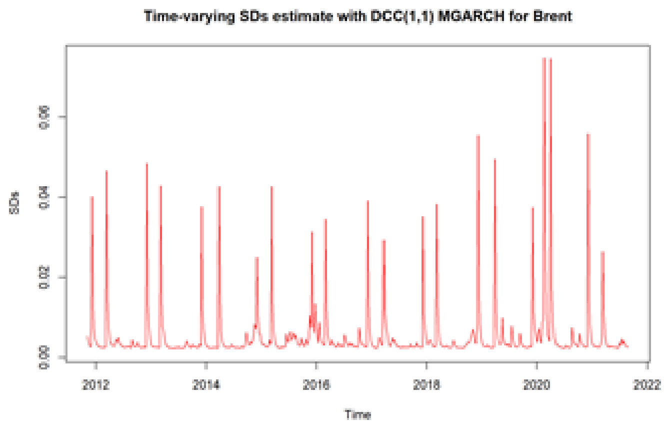
Figure 23: Impulse Response Functions of the time series in log

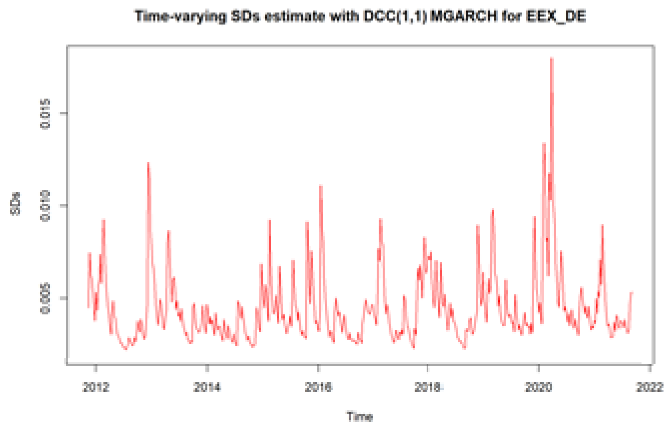
We can see that, overall, a one standard deviation positive change in the price of Brent leads to a positive change (response) in the prices of the other energy types in the immediate periods, like it was the case in the previous section.

However, it is interesting to notice that while IRF values for natural gas remain similar, coal month-ahead contracts show much higher values when comparing to year-ahead contracts. We also notice a bigger response on French and German power, possibly because an increase in coal prices leads to an increase in German electricity prices, and by contagium, French electricity prices.

4.2.2.5. DCC-MGARCH outputs

Again, following the same method as before, we used a DCC MGARCH model to estimate the conditional variance of the series and the dynamic correlations with Brent along time.





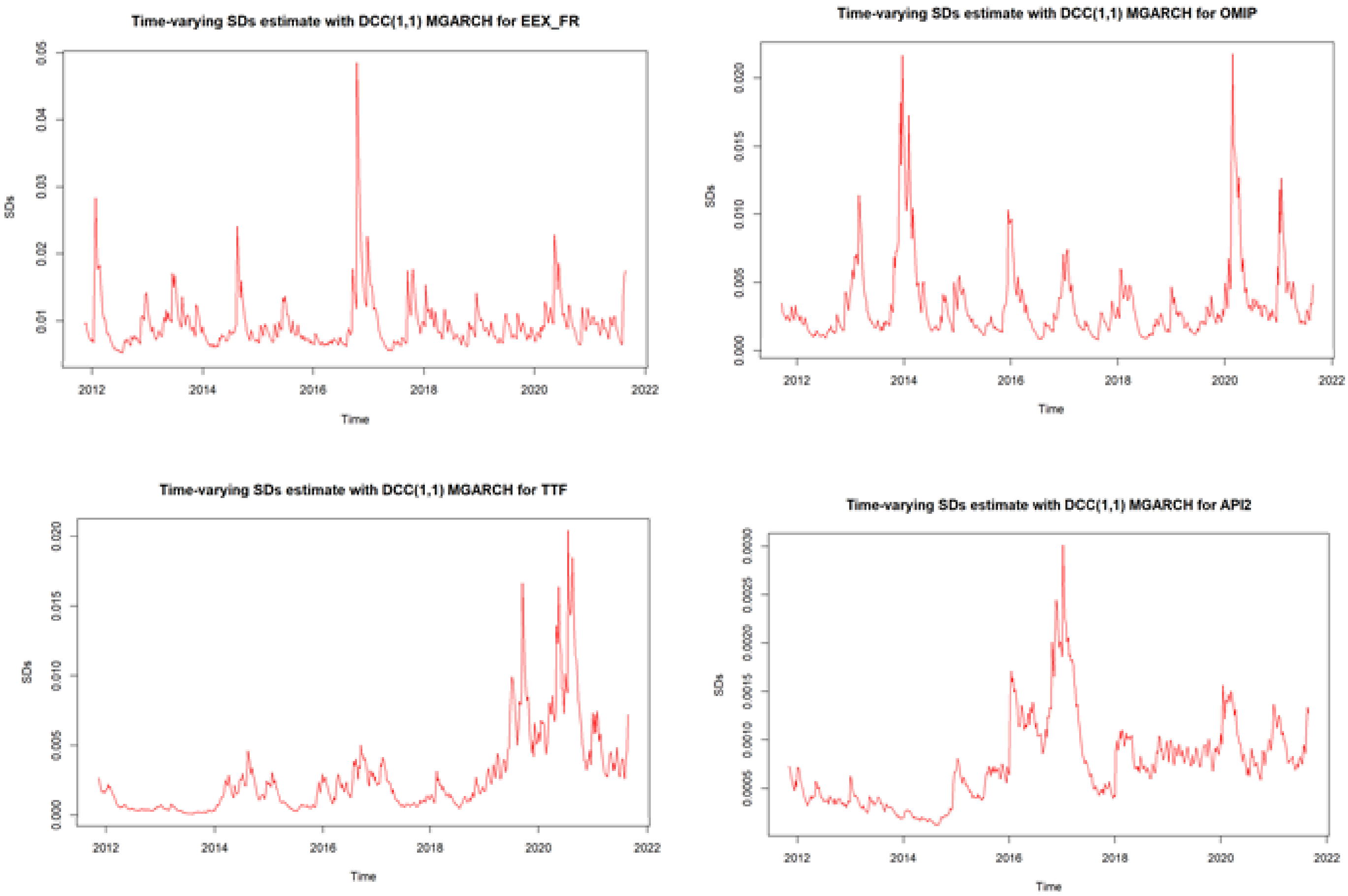


Figure 24: Time-varying standard-deviations estimated with the DCC(1,1) MGARCH for Brent, API2, OMIP, EEX_FR. EEX_DE and TTF

From the standard-deviations graphs (in Figure 24 above) we can see that the volatility of natural gas month-ahead contracts has been increasing since 2016. The spikes of volatility in Brent are probably just noise.

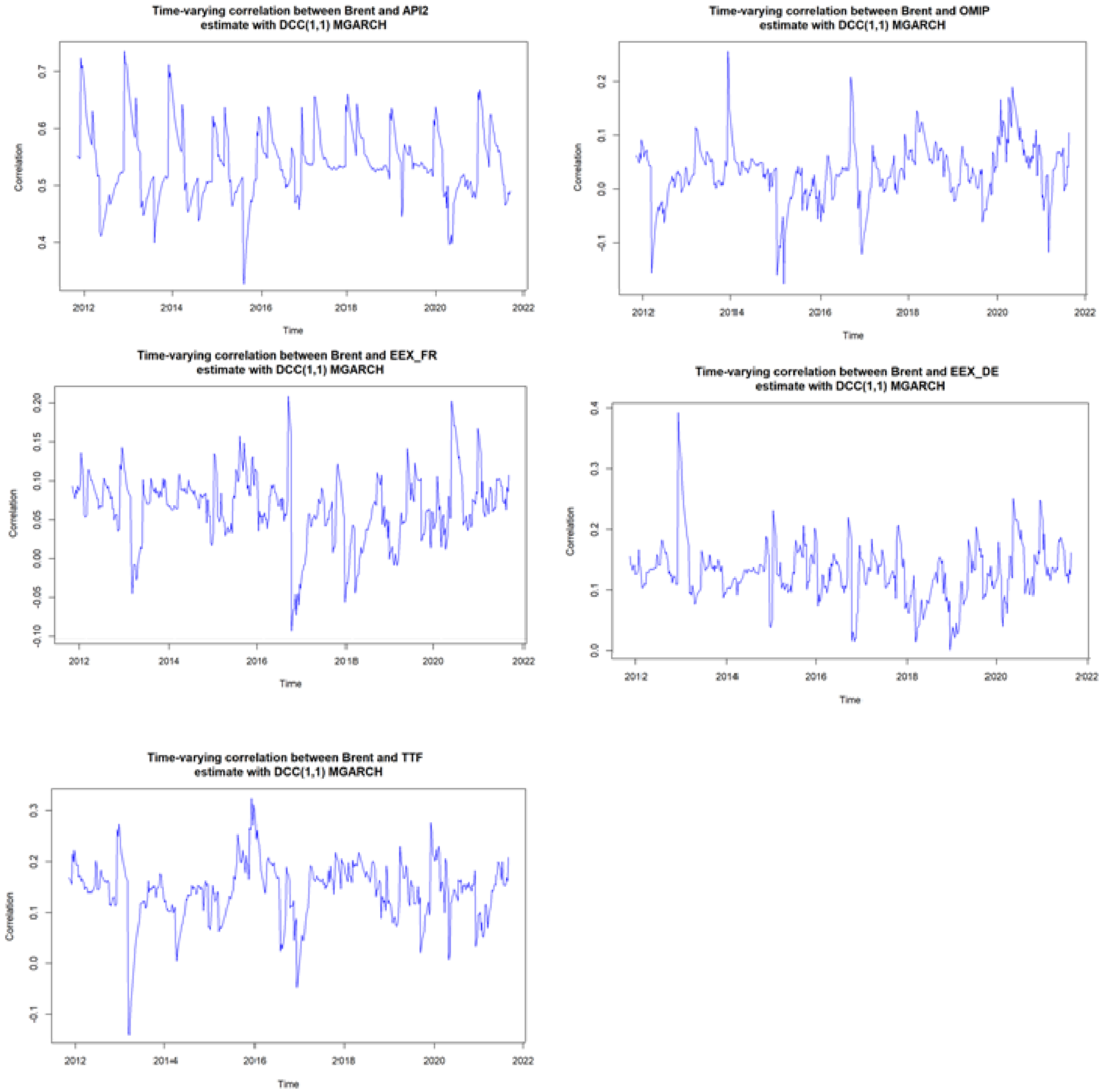


Figure 25: Time-varying correlations estimated with the DCC(1,1) MGARCH between Brent and the other energy types (API2, OMIP, EEX_FR, EEX_DE, TTF)

Looking at Figure 25, one can observe that, overall, all series show a positive correlation with the price of crude oil, like it was the case for year-ahead contracts. One interesting conclusion is that the impact of oil on coal seems to be bigger for month-ahead contracts, while we observe the opposite for natural gas and electricity.

This high value for the time-varying correlation between crude oil and coal is coherent with the results that we already observed on the study of IRFs.

We also see that most time-varying correlations are relatively stable across time, but this value became very low for the relationship between oil and French electricity around 2014, but has since been slowly rising.

Table 13: DCC(1, 1) MGARCH estimates for Brent, API2, OMIP, EEX_FR. EEX_DE and TT

Parameter	Estimate	Std. Error
GARCH parameters		
μ_{lBrent}	-0.007392 ***	0.001742
ω_{lBrent}	-2.314957 ***	0.375741
α_{lBrent}	-0.310903 ***	0.115348
β_{lBrent}	0.566723 ***	0.074019
γ_{lBrent}	0.415607	0.265547
μ_{lAPI2}	-0.004625 ***	0.001389
ω_{lAPI2}	-2.156368 ***	0.074853
α_{lAPI2}	-0.531762 ***	0.027734
β_{lAPI2}	0.559320 ***	0.004030
γ_{lAPI2}	-0.125803 **	0.053601
μ_{lOMIP}	-0.000215	0.002160
ω_{lOMIP}	-0.380491 ***	0.143682
α_{lOMIP}	-0.112806 ***	0.037596
β_{lOMIP}	0.929264 ***	0.024024
γ_{lOMIP}	0.325704 ***	0.083060
μ_{lEEX_FR}	0.004513	0.004447
ω_{lEEX_FR}	-0.626820 ***	0.201439
α_{lEEX_FR}	0.069546	0.072474
β_{lEEX_FR}	0.860470 ***	0.040891
γ_{lEEX_FR}	0.176411 **	0.087026
μ_{lEEX_DE}	0.003069	0.002961
ω_{lEEX_DE}	-1.009107	0.867067
α_{lEEX_DE}	-0.121976	0.078639
β_{lEEX_DE}	0.811551 ***	0.160128
γ_{lEEX_DE}	0.255339 **	0.119239
μ_{lTTF}	0.000202 ***	0.000039
ω_{lTTF}	-0.068137	0.075846
α_{lTTF}	-0.037665 *	0.021141
β_{lTTF}	0.987398 ***	0.011464
γ_{lTTF}	0.332951 ***	0.063684
Correlation parameters		
α_1^*	0.030652 ***	0.008292
β_1^*	0.844389 ***	0.053700
Log-likelihood	4519.022	
ES p-value	4.044688e-05	
ES X2 statistic	0.002334908	

*** Significant at 1%
** Significant at 5%
* Significant at 10%

We confirm the positive impact of oil prices on coal and natural gas prices, as well as the electricity prices in France, Germany, and Spain.

As we expected, the time-varying correlation between oil and natural gas is the strongest, followed by coal. We notice however a slight decrease on the time-varying correlation values between oil and natural gas from 2009 and an increased volatility of these values.

We also find that the electricity prices in Spain seem to be less sensitive to oil process than the electricity prices in France and Germany.

5. Conclusions

5.1. Achievements

Our results prove the intuition that crude oil prices do indeed have an impact on the prices of electricity, natural gas, and coal. While most of the literature has been focused on the relationship between oil prices and natural gas prices, our results show that today a stronger relationship is that between oil prices and coal prices.

Given that our study covers most of the last decade, it also has shed light on the question of "have oil prices and natural gas prices decoupled?". While it is possible that a stronger relationship existed in the past, our results show that oil prices still have an impact on natural gas prices, and that this impact has remained more or less stable over the past ten years.

Finally, our work showed some light on the electricity markets in Iberia, an area that we thought hadn't been explored enough in the literature. An interesting result is that Iberian electricity prices seem to be less affected by oil prices than the French and German cases.

5.2. Future work

Our work focused on studying the impact of Brent spot prices on the futures contracts of the other commodities. Further work to be done, includes testing the impact of crude oil futures on other futures, as well as studying the impact of both Brent spot prices and Brent futures on the spot prices of the other commodities.

While our results show a relation between oil prices and the other commodities, we could still explore further these relationships by using this very same model to test for the impact of natural gas prices or the impact of coal prices on the other commodities.

Furthermore, we could expand our analysis for other geographies and markets.

And finally, we had to limit our number of variables to use in the DCC-MGARCH model, as with more variables this model would become to heavy to use. So, some interesting future work would be to test the impact of oil prices on each of the other commodities, one by one, and each accompanied by other variables that could have an extra influence, such as extreme weather events, exchange rates of major currencies, among others.

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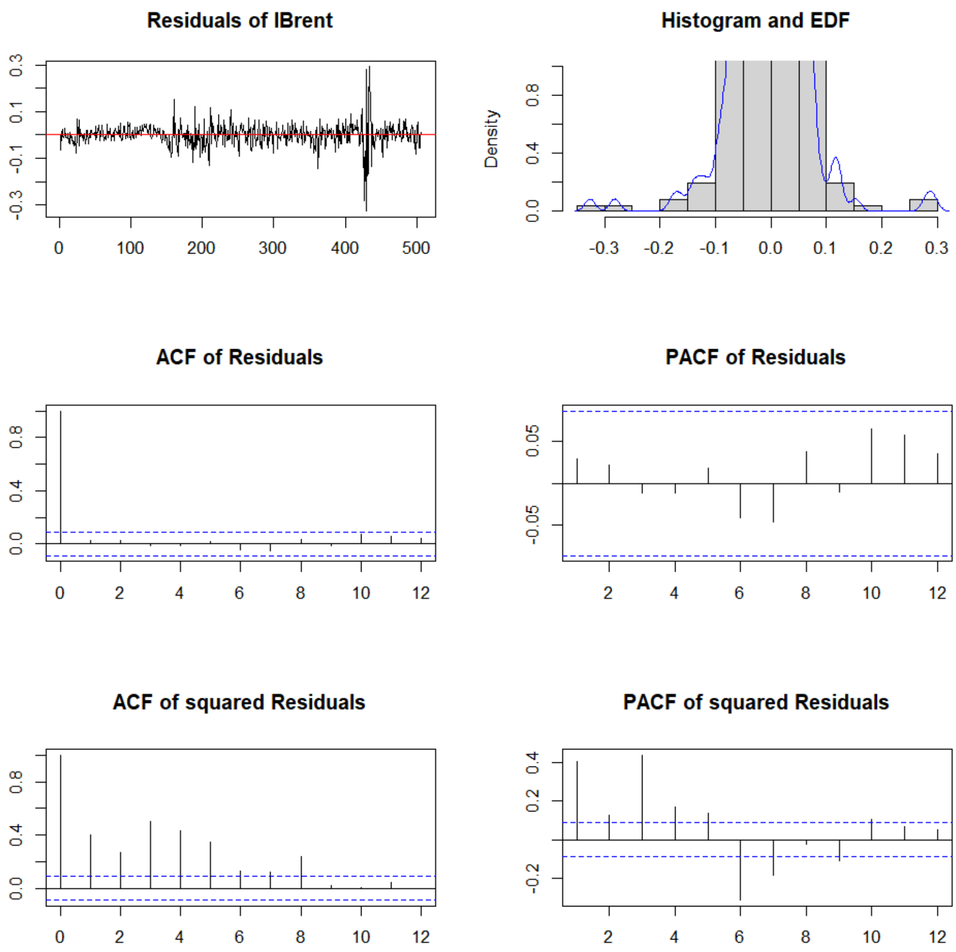
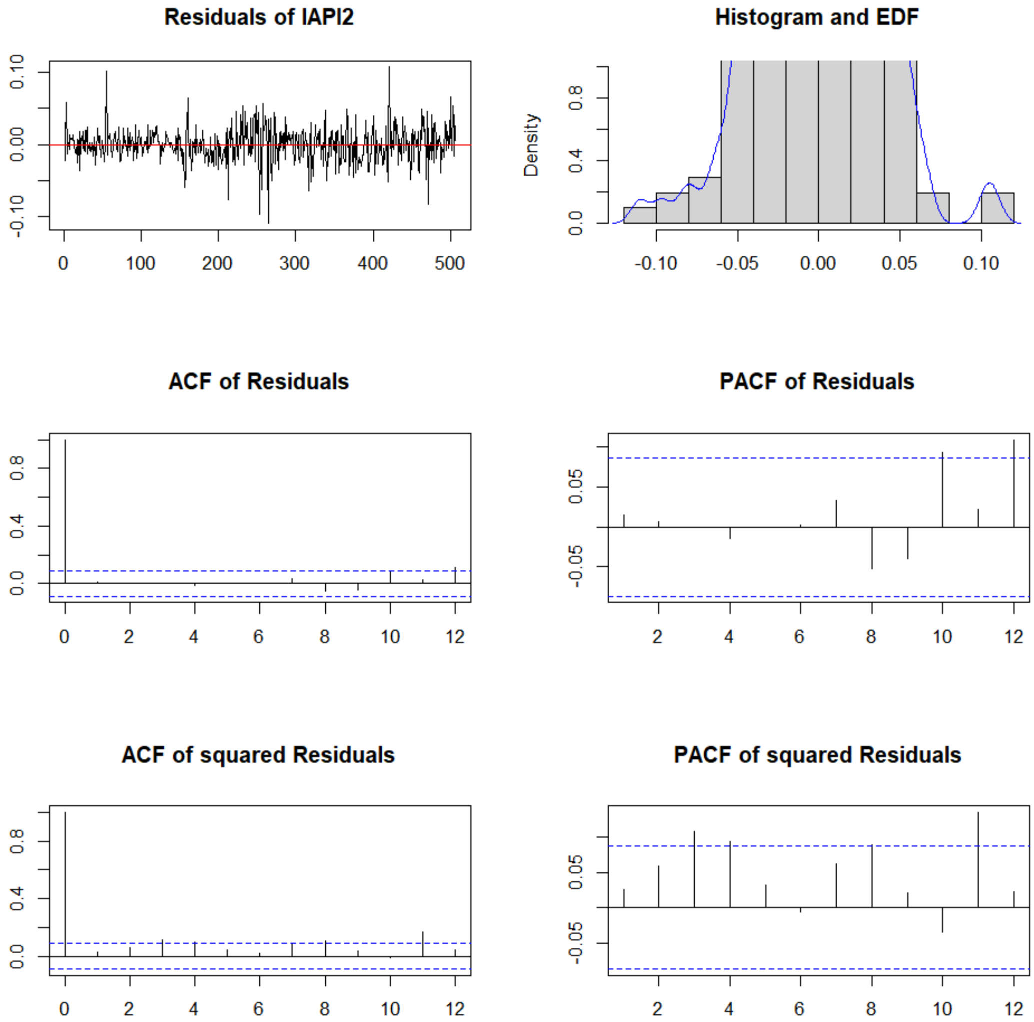
Appendix: Analysis of autocorrelation in the residuals (VECM)

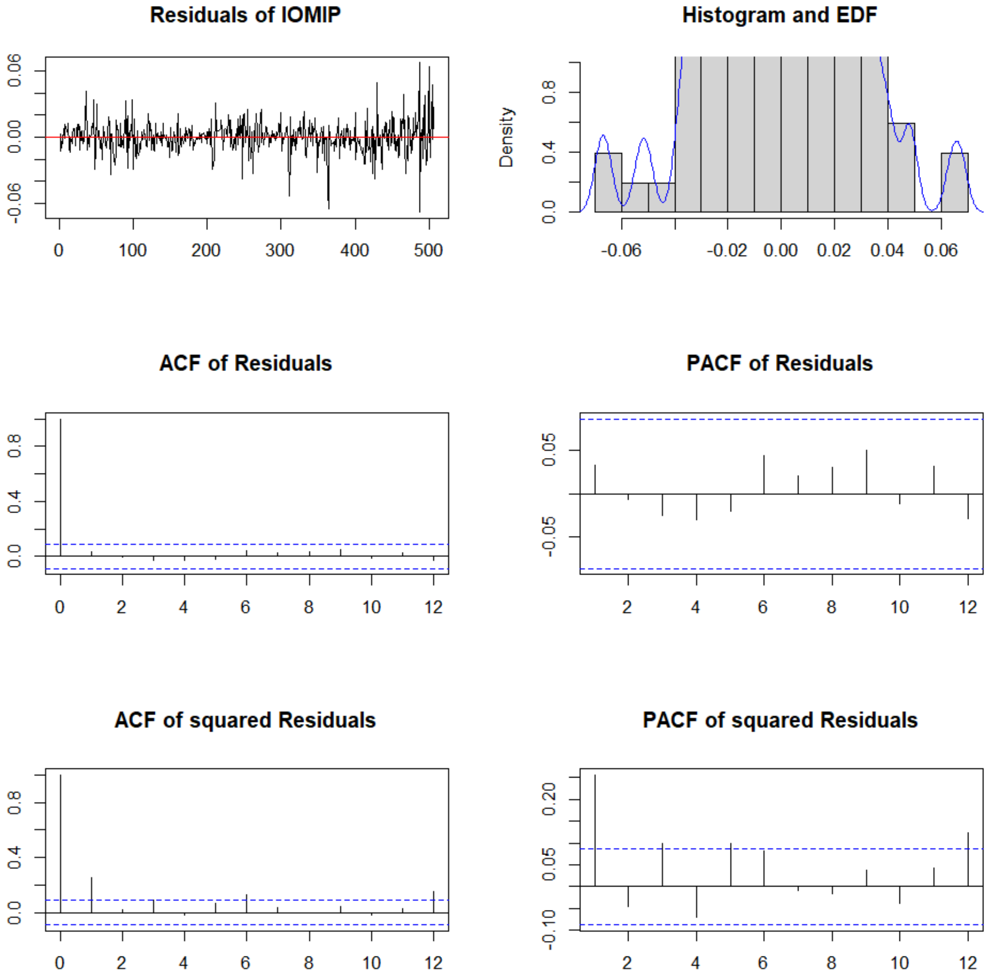
Brent

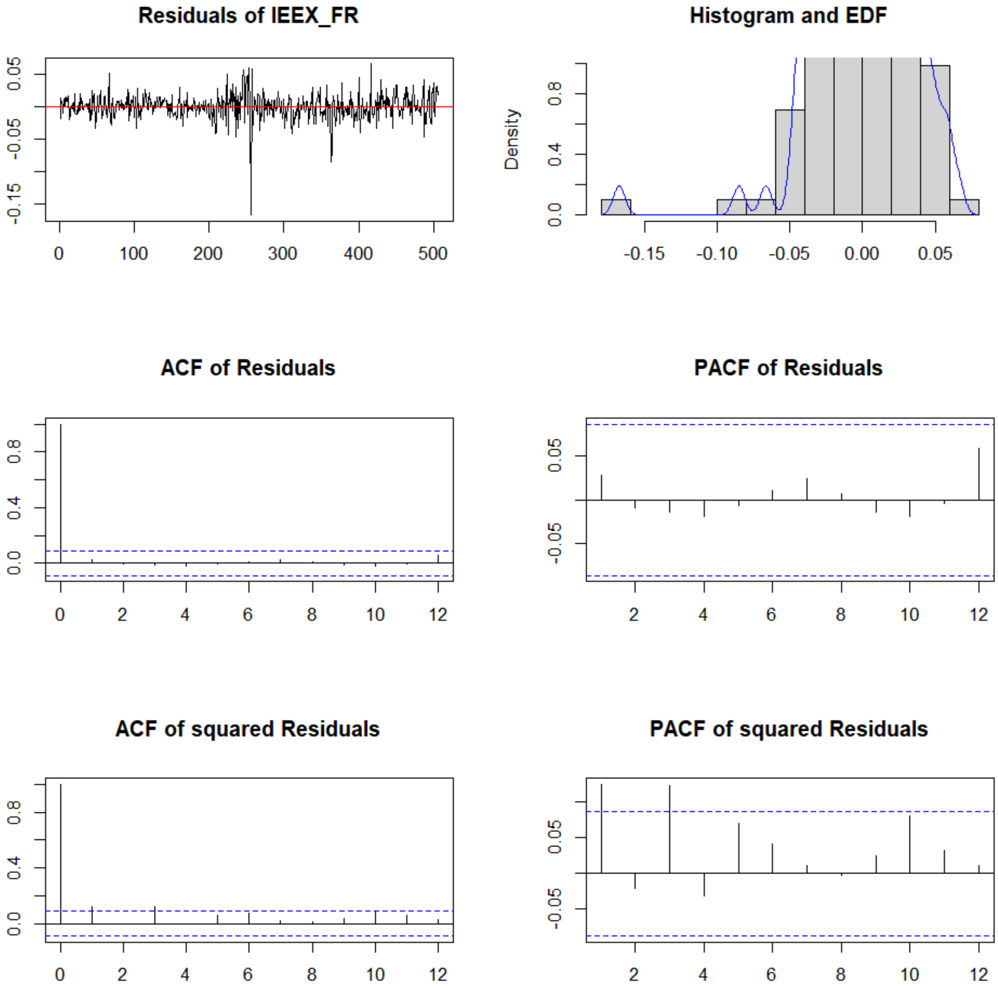


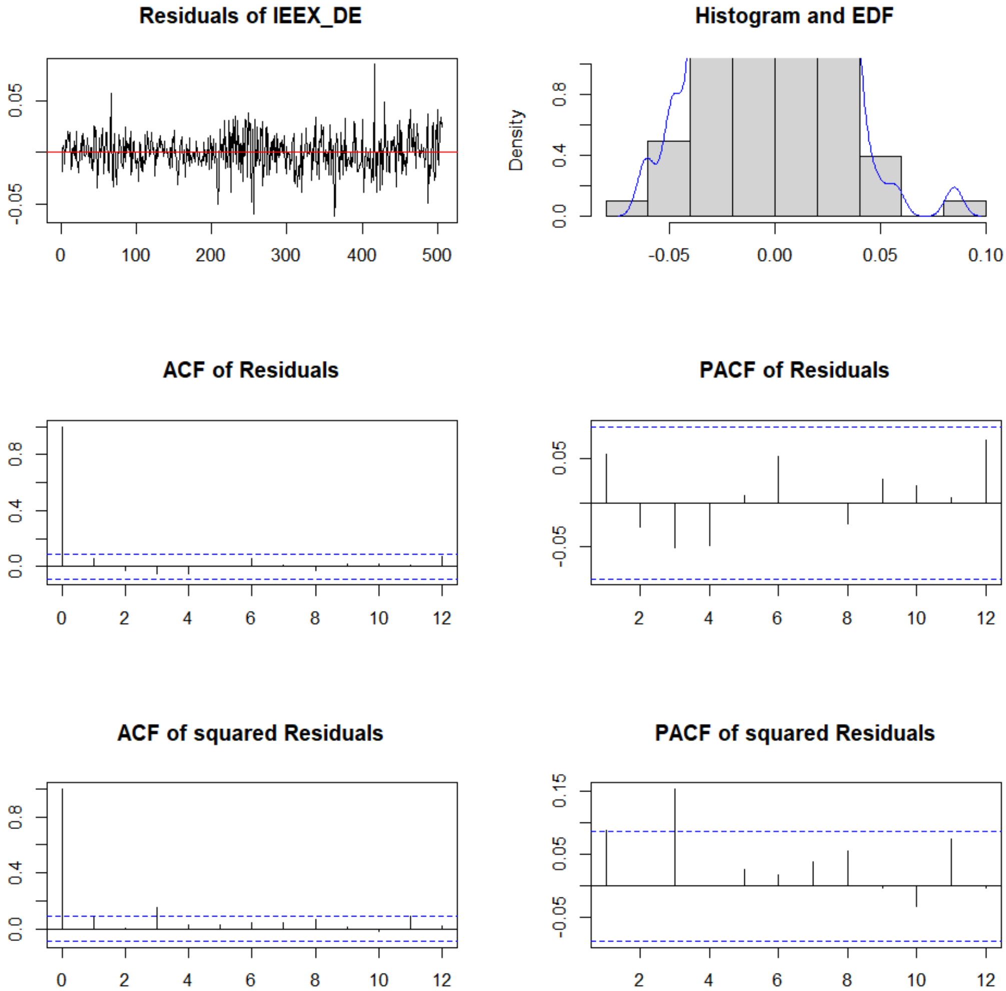
API2

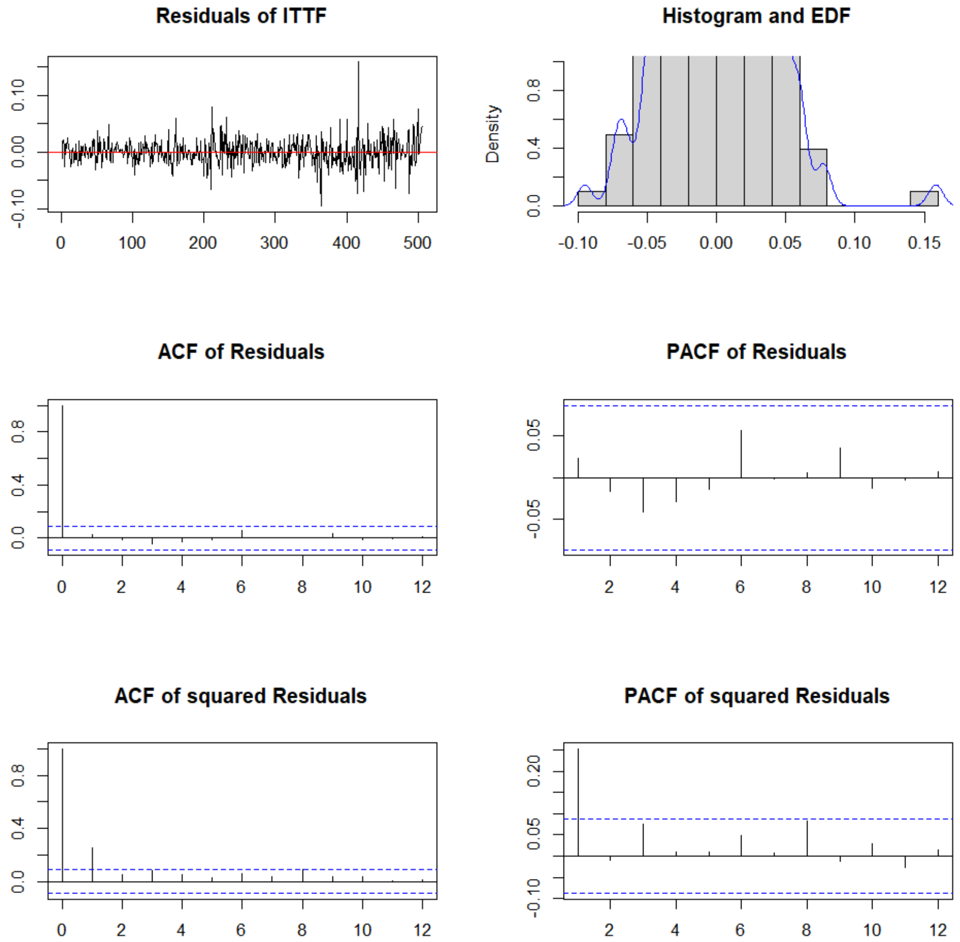


Residuals of IAPI2
Histogram and EDF
Density
ACF of Residuals
PACF of Residuals
ACF of squared Residuals
PACF of squared Residuals


Residuals of IOMIP
Histogram and EDF
Density
ACF of Residuals
PACF of Residuals
ACF of squared Residuals
PACF of squared Residuals


Residuals of IEEX_FR
0.05
-0.05
-0.15
0
100
200
300
400
500
Histogram and EDF
Density
0.0
0.4
0.8
-0.15
-0.10
-0.05
0.00
0.05
ACF of Residuals
0.0
0.4
0.8
0
2
4
6
8
10
12
PACF of Residuals
0.05
-0.05
2
4
6
8
10
12
ACF of squared Residuals
0.0
0.4
0.8
0
2
4
6
8
10
12
PACF of squared Residuals
0.05
-0.05
2
4
6
8
10
12


Residuals of IEEX_DE
0.05
-0.05
0
100
200
300
400
500
Histogram and EDF
Density
0.0
0.4
0.8
-0.05
0.00
0.05
0.10
ACF of Residuals
0.0
0.4
0.8
0
2
4
6
8
10
12
PACF of Residuals
0.05
-0.05
2
4
6
8
10
12
ACF of squared Residuals
0.0
0.4
0.8
0
2
4
6
8
10
12
PACF of squared Residuals
0.15
0.05
-0.05
2
4
6
8
10
12


Residuals of ITTF
Histogram and EDF
Density
ACF of Residuals
PACF of Residuals
ACF of squared Residuals
PACF of squared Residuals