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Price transmission among biofuels and related commodities

Bachelor's thesis

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Declaration of Authorship

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Peter Kravec

Abstract

This thesis investigates the price transmission among ethanol and its feedstock on the Brazilian and US market. The price transmission among biodiesel and its feedstock on the European and US market was also analyzed. The prices of commodities related to the biofuels are examined under the Johansen co-integration test followed by the Vector Error Correction Model over the period between 2003-2020. The period was further divided into 4 periods, that capture the development of world food prices. Together we had 858 weekly observations mostly captured on Friday. In most cases, our result indicates a co-movement, the strength of which changes over periods. The price transmission was not confirmed among US ethanol and related commodities.

JEL Classification	Q14, Q42, Q54,
Keywords	Biofuels, Biodiesel, Ethanol, Food, Feed, Price Transmission
Title	Price transmission among biofuels and related commodities
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Abstrakt

Táto práca skúma prenos cien medzi cenami etanolu a cenami jeho surovín na Brazílskom a Americkom trhu. Takisto sme analyzovali aj cenový prenos medzi cenami bionafty a jej surovinamin na Európskom a Americkom trhu. Ceny komodít sú skúmané medzi 2003 - 2020. Spomínané obdobie bolo ďalej rozdelené do 4 období, ktoré zachytávajú vývoj svetových cien potravín. Spolu sme mali 858 týždenných pozorovaní. Náš výsledok vo väčšine prípadov naznačuje spoločný pohyb, ktorého sila sa v priebehu času mení. Iba v prípade Amerického ethanolu a jemu príbuzným komoditám sa cenový prenos nepotvrdil.

Klasifikace JEL	Q14, Q42, Q54,
Klíčová slova	Biopalivá, Etanol, Bionafta, Jedlo, Krmivá
Název práce	Price transmission among biofuels and related commodities
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Acronyms

OLS Ordinary Least Squares

VECM Vector Error Correction Model

ECM Error Correction Model or Equilibrium Correction Model

ADF Augmented Dickey Fuller

AIC Akaike Information Criterion

IRA Impulse Response Analysis

SIC Schwarz info criterion

iLUC indirect land-use change

LCA Life Cycle Assessment

WHO World Health Organization

Bachelor’s Thesis Proposal

Author	Peter Kravec
Supervisor	prof. Ing. Karel Janda, M.A., Dr., Ph.D.
Proposed topic	Price transmission among biofuels and related commodities

Research question and motivation The topic of biofuels became more interesting and important after the oil crisis of the 1970s as a possible replacement for fossil liquid fuels. At present biofuels is important environmental, economic and socio-political topic discussed worldwide as part of the discussion about climate and environmental changes and also of food and energy safety. Global production of biofuels experienced a rapid increase in last decades. The main drivers behind this growth are government policies which have been justified based on topic of food and energy safety as well as topic of climate changes. In this thesis I will be studying the relationships between biofuel and related commodities prices.

Some studies are already dedicated to this topic (Štěpán Chrz Karel Janda Ladislav Krištoufek, 2014. " Modeling Interconnections within Food, Biofuel, and Fossil Fuel Markets," Politická ekonomie, University of Economics, Prague, vol. 2014(1), pages 117-140.).

Methodology For the purpose of this thesis I will use dataset, which was used in (Filip, O. Janda, K. Kristoufek, L. Zilberman, D.: Dynamics and evolution of the role of biofuels in global commodity and financial markets, Nature Energy 1:16169) along with the newest data. I will use standard econometrics techniques like: Single Equation Models; Single Variables;Time-Series Models; Dynamic Quantile Regressions

Expected Contribution Given the very dynamic development of the economics of biofuels sub-field, the bachelor thesis will contribute to the frontiers of knowledge on biofuels price transmission by providing quantitative econometric estimations of biofuels price transmission based on the most recent detailed data. The bachelor thesis will also provide the most up-to-date detailed review of biofuels price transmission literature and the relevant descriptive statistics of the biofuels production, consumption on global and regional scales. The bachelor thesis will also provide qualitative expert predictions of expected near future development in the area of biofuels with a focus on price transmission among biofuels and relevant commodities.

Outline

1. Introduction
2. Literature Review
3. Data introduction
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Štěpán Chrz Karel Janda Ladislav Krištoufek, 2014. " Modeling Interconnections within Food, Biofuel, and Fossil Fuel Markets," Politická ekonomie, University of Economics, Prague, vol. 2014(1), pages 117-140.

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Author	Supervisor

Chapter 1

Introduction

In the world of ecologically sustainable development, we cannot underestimate the role of biofuels. The topic of biofuels and their usage, as a possible replacement of fossil fuels in transportation, became more relevant after oil export embargo, which led to the oil crisis in the 1970s. During the following decades, the popularity of biofuels had a growing tendency due to rising interest of the general public in environmental and climate issues. Biofuels were not only considered as "greener" solutions but also could possibly help in the reduction of the country's dependence on crude oil imports.

Relatively fast growth in the biofuels industry was fueled, primary by wide government-backed support, especially by subsidies, tax exemptions, blending mandates and targets. Statista (2019) estimated the size of the biofuels market worldwide in 2024 to more than 150 billion U.S. dollars, compared to 2019 when the market size was around 136 billion dollars. According to USDA ERS US Bioenergy Statistic, since 2012 the production of biofuels in the U.S. has grown steadily, rising from 53.3 billion litres in 2012 to almost 65 billion litres in 2016. With more than 60 billion litres of produced ethanol in 2017, according to U.S. EIA the United States of America, may be considered as the world leader in producing ethanol. The US ethanol is mostly obtained from corn and soybeans. Almost 40% of the whole corn production in the U.S. is used for ethanol production according to USDA ERS. The Brazilian ethanol industry is the second biggest one, producing more than 26 billion litres according to RFA. The main difference between U.S. and Brazil's ethanol is that Brazil ethanol is predominantly made from sugarcane. Altogether U.S. and Brazil produce more than 84% of the total worldwide ethanol production.

From a market perspective, we can denote EU as the biggest producer of bio-diesel followed by the U.S. and by South American countries such as Brazil and Argentina. One can also observe the development of the worldwide overall production of biofuels. The European Commission has committed itself, as part of its environmental responsibility, to ensuring that 10% of transport fuel from each EU country is acquired from renewable sources, for example through biofuels. Last but not least, suppliers are required to reduce the GHG of the EU's fuel mix by 6% by 2020 compared to 2010[1]. In U.S the ethanol is mostly used in blends such as low-level E10 (10% ethanol 90% gasoline) or as flex-fuel E85 containing (51% to 83%). The truth is that ethanol's blend performance is not as good as gasoline, for instance, Blend with 83% ethanol share has about 27% less energy per gallon than gasoline, but it is important to say that engines in gasoline vehicles are primarily optimized for gasoline. If the engines would be optimized to run on the ethanol blends, we may expect that the engine efficiency would be increased[2].

The question of the price transmission between biofuels and related commodities became economically interesting immediately after the boom in biofuels in 2005. The topic became even more interesting and important for policy-makers during, or shortly.. after, the food crisis. To illustrate the importance of a relatively stable food price, De Hoyos & Medvedev (2011) (the World Bank report) argued that the food crisis pushed approximately 155 million people into the moderate or extreme poverty, mostly in less developed countries in the East and South Asia and also in Sub-Saharan Africa. Additional problems occurred in the food-importing countries, such as political instability and internal conflicts. Nevertheless, the topic of food versus fuel is not a question of just the last decade, even before the enlargement of producing biofuels, multiple papers related to the co-movement prices of food and fuels commodities were published. Especially Pindyck & Rotemberg (1990) estimated the degree of co-movement among prices of cocoa, copper, cotton, crude oil, gold, lumber and wheat. Besides, the topic was introduced to the economic literature by Barnard (1983). The results of numerous researches on the topic are quite various, what is shown from a strong relationship between fuel and food price to the price neutrality between them. For a better understanding of such a complex environment of research questions and used methods and, of course, corresponding results, we provide closer literature review in the Chapter 2. At the same time, we will partially outline the issue of climate change in rela-

[1] https://ec.europa.eu/energy/topics/renewable-energy/biofuels/overview$_en$

[2] https://afdc.energy.gov/fuels/ethanol$_benefits.html$

tion to biofuels. The rest of the bachelor's thesis is structured as follows: In Chapter 3 we introduce our dataset. The qualitative and quantitative analysis will also be provided in this chapter. The Chapter 4 gives further information about the used methodology. The simplest possible explanation of the used statistical concepts will be present. The Chapter 5 provides the results of our analysis, followed up by the conclusion in the **??**, in which we will summarize our findings.

Chapter 2

Literature review

In this chapter, we intend to provide a brief review of the recent literature focusing on the price transmission between (bio)fuels and food commodities. There has been a broad spectrum of research questions as well as used methodologies to investigate the interconnection of the system. The most recent, moreover well organised, summary of the researches, which cover the topic is provided by Janda & Krištoufek (2019). We have also drawn from the summary article provided by Serra & Zilberman (2013).
In general, and a little simplified, there are two main trends of interests. Before the biofuel boom, it was more common to investigate the price transmission between fuel and food commodities in a more general way, what means that in those research papers had not been paid attention to biofuels. We are particularly interested in the latter and the one in which biofuels participate in the system.

First of all, we will provide a review of that researches in which biofuel data were not used. Very first who have introduced food vs fuel problematic to the economic literature was Barnard (1983). The author questioned the economical viability of the gasohol program and outlined the program as potentially very disruptive for the domestic (U.S.) and global food sector.
Yu *et al.* (2006) were investigating the long-run interdependence between crude oil prices and four traded edible oils prices sunflower, soybean, rapeseed and palm oils. Their data consists of 378 weekly observations from the first week of January 1999 to the fourth week of March 2006. They have used data on the edge of the biofuels boom and at the same time, the research was done before the world food crisis in 2007/2008. Authors used the method of co-integration and concluded, that the influence of crude oil prices on the edible oil prices is

not significant over the studied period. Zhang & Reed (2008) obtained a similar result on the Chinese market, where authors were investigating the effects of the world crude oil price on feed grain prices and pork prices using vector ARMA model. The authors have not detected any significant influence of crude oil price to grain prices or pork prices in China.
One of the instructive researches engaging the topic came from Esmaeili & Shokoohi (2011) in which authors were interested in the co-movement of food prices and the macroeconomic indexes, especially the oil price. Authors examined the monthly food prices of eggs, meat, milk, oil-seeds, sugar, rice and wheat. Regarding the macroeconomic variables, authors were studying crude oil prices, consumer price indexes, food production indexes and GDP around the world. Authors took the data from the period between 1961-2005. Using principal component analysis (PCA) and VAR model authors obtained the conclusion that *"food production index has the greatest direct influence on the macroeconomic index and that the oil price index has a unidirectional influence on the food production index."* (Esmaeili & Shokoohi (2011) p.1024) Consequently, the crude oil price has an indirect effect on food prices and world GDP as well.

On the other hand, several papers have examined the effect of crude oil energy prices on the prices of agricultural commodities. Baffes (2007) examined the effect of crude oil prices on the prices of 35 internationally traded primary commodities, noting not only agricultural commodities were included for the 1960-2005 period. The author used the OLS method on annual data and found out that agricultural price index increases by 1.8 % in response to the 10 % increase in crude oil prices.
Targeting mainly to agricultural commodities, Nicola *et al.* (2016) provided comprehensive analysis, using MV-GARCH model of the extent of co-movement among the prices of 11 major energy, agricultural, and food commodities by using monthly data between 1970 and 2013. They concluded: Firstly, the authors found out that the price returns of energy and agricultural commodities are highly correlated. Secondly, the overall level of co-movement has been increasing during the last studied period, noting that authors had been using data covering the period up to 2013. The increase in the level of co-movement was mainly driven by energy and those agricultural commodities, which are taking an important part of the biofuel-related network.
TThe notable paper came from Lucotte (2016), who divides the 1990-2015 period into sub-periods. The first one is between January 1990 and December

2006 and the second one is a "post-boom" period, January 2007 - May 2015. Using the correlations of VAR forecast errors at different horizons the author reveals strong positive co-movements between crude oil and food prices during the commodity boom after 2007. In the first sub-period, they did not observe any statistically significant co-movements between crude oil prices and food prices.

Pal and Mitra have already dedicated few studies to the topic. We will mention just three of them. In those set of papers, authors used two dataset and different modelling approaches across the studies, chronologically in 2016 authors had been using quantile autoregressive distributed lag model, in 2017 they had been using TY – Toda and Yamamoto causality in combination with wavelet analysis and in 2018 authors used detrended cross-correlation analysis. Regarding empirical analysis Pal & Mitra (2016) used monthly time series from January 2004 to June 2014, evidence from the USA. Considering the modelling approach authors built on Jr *et al.* (2013) and also used quantile autoregressive distributed lag model to examine the relationship between diesel price and soybean price. Authors showed that in the upper quantiles soybean price fluctuations react robustly to diesel price fluctuations and in the long run soybean and diesel prices do not move uniformly.

Pal & Mitra (2017) used monthly data between January 1990 and February 2016. Using Johansen cointegration test authors confirmed the statistically significant correlation between crude oil prices and food prices. Using wavelet method authors also observed that in the short-run food prices co-move with crude oil prices, furthermore revealed that food prices, in the short-run, are led by crude oil prices. The result of Toda–Yamamoto causality affirmed co-movement of crude oil price and the world food price index in the long run.

In their following research Pal & Mitra (2018) decided to divide data into four sub-periods: January 1990 to October 1999, November 1999 to February 2005, March 2005 to September 2010, and October 2010 to July 2016. If we focus more precisely on these periods, we will find out that the distribution of periods enabled authors to compare fuel–food co-movement across pre-crisis, during the food crisis, and post-crisis periods. Authors employed detrended cross-correlation analysis and according to the analysis concluded that world food price index and crude oil co-move.

In the next few paragraphs, we will look at the price transmission regarding biofuels more closely. In price transmission among biofuels, literature is very likely to meet U.S. agricultural commodities, consequently U.S. ethanol. Despite this, we will try to provide an overview of the researches where not only U.S. ethanol is included, but also along with some others biofuels or non-U.S. commodities or financial assets.

Vacha *et al.* (2013) showed the differences between EU and U.S. biofuels markets, employing wavelet analysis over non-crisis period authors found out that the ethanol is correlated with corn and biodiesel is correlated with German diesel. Authors also pointed out that during the crisis ethanol were led by the corn price and biodiesel led by German diesel. Price dependence among biofuels, crude oil and agricultural commodities has been confirmed by several studies, among the most recent studies with similar methodological approach belong to Kristoufek *et al.* (2016) and Filip *et al.* (2016). Authors partially agree with Vacha *et al.* (2013) and pointed out that ethanol's productions factors prices leading only the price of ethanol i.e. ethanol price have no significant effect on feedstock prices. On the other hand, they found just moderate connection between European biodiesel and biodiesel's production factors. Kristoufek *et al.* (2014) involved leading biofuel markets to their research. Using VAR authors figured out, that ethanol price is linked to the corn price, sugarcane is also linked to the U.S. gasoline and biodiesel is not only linked to the soybeans but also the German diesel. Furthermore, they revealed, that during the food crisis of 2007/2008 all of the significant pairs experienced an increase in the mutual price responsiveness.

One of the most recent studies was introduced by Al-Maadid *et al.* (2017). Authors built the paper on the daily data, obtained from the Bloomberg, for crude oil and ethanol and six food commodity prices (cacao, coffee, corn, soybeans, sugar and wheat) covering January 2003 - June 2015, altogether they obtained 2253 observations, furthermore, they used the S&P 500 stock market index to proxy the U.S. business cycle. The used framework is able to analyse shifts resulting from four crucial events: the 2006 food crisis, the Brent oil bubble, the introduction of the Renewable Fuel Standard policy and the 2008 global financial crisis. Results suggest the presence of significant linkages between food and both oil and ethanol prices. Additionally, the food crisis in 2006 and the financial crisis in 2008 had the most significant impact on the dynamic interactions between energy (crude oil, ethanol) and food prices. On the other side, Myers *et al.* (2014) argued that there were not any indications of co-integration between crude oil, ethanol, corn and soybean prices in the long-run. In the following subsection, more attention will be paid to the papers in which VAR, VECM, (ARDL) or co-integration have been used as we will use these methods in the thesis.

Allen *et al.* (2018) examined ten years of daily spot and futures prices for wheat, corn, sugar ethanol, and oil prices in the period from July 2006 to July 2015. Markov-switching VECM and Impulse Response Analysis (IRA) used on pairs of cointegrated series, obtained by Engle-Granger test reveals, that there are significant interconnections in these markets, but the linkages differ depending on, whether they are in low or high volatility regimes. Al-mulali & Solarin (2016) published an interesting analysis of the influence of biofuel energy consumption on Brazil's economic growth. The dataset covers the period from 1980 to 2012 and the results of VECM and ARDL revealed structural breaks in the early 1980s (Latin American debt crisis) and at the beginning of the millennium. Al-mulali & Solarin (2016) also revealed that economic growth, biofuel energy consumption, capital, urbanization, and globalization are co-integrated. Research showed, as expected, short-term and also long-term positive relationships between biofuel energy consumption, capital, urbanization, globalization and economic growth. Zou (2018) provided further insight and by using VECM, examined the relationship between U.S. oil prices, carbon emissions and U.S. GDP between 1983 and 2013. The results confirm the precondition, that carbon emissions change as oil prices fluctuate in the short and also in the long run. On the other hand, according to the paper, there is no connection between GDP fluctuation and the growth of carbon emissions. Results also suggest only the gentle impact of oil price on GDP and carbon emissions in the long-run. Focusing on the Spanish market, Hassouneh *et al.* (2012) reveal price transmission between food and energy prices. Weekly biodiesel, sunflower and crude oil prices between November 2006 and October 2010 confirm the existence of a long-run equilibrium relationship among the included commodities. The comparison of adjustment coefficients for bio-diesel revealed the difference in speed of adjustment relative to the price of bio-diesel. When the price was relatively low the speed of adjustment was faster than in the case of the higher price. The results also suggest that energy prices in the short-run also affect sunflower oil prices.

More internationally focused research was recently published by Capitani *et al.* (2018). Authors aimed to study not only the Brazilian market but also the U.S. one. They estimated the structural vector autoregressive model with error correction along with employing methodological frameworks of co-integration and causality testing. They included international oil prices along with ethanol sugar and corn prices in Brazil and also in the U.S. One of their outcomes suggests that ethanol price on the domestic market is influenced by international oil prices, what supports the idea of the significant impact of fuel markets to the ethanol price over markets, especially taking into account the substitution effects of ethanol by fossil fuel. Authors also pointed out, that on Brazilian market sugar prices also have significant causality effect on ethanol prices. Considering U.S. market, authors stated that ethanol prices influence corn price, but they did not prove corn prices causality effect on ethanol prices. Last but not least, authors found a causality effect of Brazilian ethanol on U.S. ethanol prices, demonstrating the relevant influence of the traditional Brazilian production to the biggest producer in the world, USA. Using the same methodology Fernandez-Perez *et al.* (2016) using daily prices of the crude oil, ethanol, corn, soybean, and wheat from the United States covering June 2006 - 22 January 2016, authors claimed that crude oil has a unidirectional contemporaneous impact on the agricultural commodities, also pointed out U.S. ethanol production factors corn and soybean have a unidirectional contemporaneous impact on ethanol prices.

Dutta (2018) was primarily focused on the Brazilian ethanol industry. The author studied interrelation between ethanol, crude oil and sugar prices. He applied the autoregressive distributed lag model on 668 weekly observations in the period from May 2003 to December 2016. Obtained result of ARDL bound test suggests that crude oil and sugar prices lead ethanol prices in the long-run on the Brazilian market. The author also noticed the positive impact of sugar prices on ethanol prices and not vice versa i.e. raising sugar prices would cause raising ethanol prices as well. Bentivoglio *et al.* (2016) explored the impact of Brazilian ethanol prices on sugar and gasoline prices. Employing vector error correction model (VECM) and Granger causality tests, obtained result favours the idea that ethanol prices growth with an increase in both gasoline and sugar prices in long-run. They also revealed that sugar and gasoline prices affect ethanol prices in the short-run.

2.1 Climate changes

In the recent decades, the scientific community has been diligently discussing and studying the greenhouse effect. The accumulation of carbon dioxide (CO2) and the other greenhouse gases is leading to global warming and other significant climate change. Research on climate change agrees that there is a significant human impact on rapid climate change in the 21st century (Church *et al.* (2013)). Biofuels are still seen as a greener solution to the possible exchange of fossil fuels in transportation, but economic studies on biofuels pay little or no attention to the environmental impact of biofuels in terms of sustainable development.
In the next few paragraphs, we will focus on research that takes into account all polluting factors during the production process, such as the production of feedstocks, the conversion of feedstocks into biofuels, the transport of biofuels and feedstocks and finally the combustion of biofuels in vehicles. These sub-processes have a direct impact on the emissions produced. We will also pay attention to the associated problem of biofuels, in particular Land Use Change. The method, for determining the environmental impact of a product throughout its whole life cycle, is called Life Cycle Assessment (LCA).

When it comes to environmental sustainability, the issue of the (environmental) benefits of biofuels deserve the place among wider discussion of policymakers. As mankind continues to grow, it will be more difficult to meet its needs. Röös *et al.* (2017) expect the world's population to increase to 9-11 billion by 2050. Agricultural production should not lag and should reflect the demand for the food, biofuels and feed. Ray *et al.* (2013) argue that the world food production needs to increase by 60-100 % to meet estimated food demand by 2050. We should not forget about the deteriorating impact of climate change on the soil fertility (for example extreme heat, drought, floods, etc.). St. Clair & Lynch (2010), despite the difficulties in prediction of the impact of climate change, suppose a negative impact of climate change on the soil fertility consequently on crop mineral nutrition. As a result, they expect food insecurity to increase, especially in developing countries.
According to the European Environment Agency[1], expects climate change to have a significant impact on soil fertility. However, the extent of the impact is still uncertain, mainly due to the complexity of the system, and is still subject of research.

[1]https://www.eea.europa.eu/themes/soil/climate

To sum it up, it is very difficult to accurately predict the impact of climate change, due to various socio-economic development scenarios. Thus, it is difficult to predict the impact on soil fertility and agricultural production. On the other hand, an increase in demand for food and, consequently, for agricultural land can be expected. Undoubtedly we have to reckon with increasing agricultural production. Increased agricultural production can come from two distinct processes either extensification (the expansion of agricultural land onto previously uncultivated land) or intensification (increased production from the land without an increase in acreage).

Direct and indirect land-use change[2] is closely linked to the previous paragraph and at the same time to the issue of biofuels themselves. Direct land-use change is caused by supporting the cultivation of feedstocks specifically for biofuels production. Secondly, the indirect land-use change (iLUC) occurs when the market for the agricultural land is not in the equilibrium (demanded side is not met) then land such as forest, pasture is cultivated to meet the demand for the agricultural land. Quantify the indirect land use change attributable to the biofuels is often almost impossible, due to the interconnection of the world agricultural markets. There exists many methods used for forecasting the changes in land use, including empirical observations, surveys and dynamic models. These methods are quite extensive to describe, so lets skip them for the moment. It is possible to find a good overview of the frequently used methods in the Koomen & Stillwell (2007).
In general, it seems that every model used for the description of these changes has some weaknesses and limitations that need to be considered before drawing conclusions from their results. For instance, Kløverpris et al. (2013) argue that GTAO-BIO model does not capture the dynamic changes such as demography, technology, climate, or where agricultural land is expanding or decreasing over time. Despite Laurance (2008) argues, that shifting from soy to maize as biofuels feedstock in the U.S. may help the deforestation of the Amazon in the Brazil. Arima *et al.* (2011) also support the issue of iLUC in the Amazonian forest. Authors argue that in particular, a 10% reduction in soybeans cultivated in old pastures would reduce deforestation by up to 40% in heavily forested districts of the Brazilian Amazon. Besides, they observe a voluntary moratorium signed by soybean farmers has not been working and therefore has not stop deforestation. Overmars *et al.* (2011) argue that, given the historical iLUC emissions related to the EU biofuels, they can shift the balance towards conventional fos-

[2]https://farm-energy.extension.org/what-is-direct-land-use-or-direct-land-use-change/

sil fuels. However, they observed some of the uncertainties in their approach. Fargione *et al.* (2008) did not focus only on ethanol produced from maize and suggest that land use change in Brazil, Southeast Asia and the United States creates a "carbon debt" by releasing 17 to 420 times more carbon dioxide than biofuels obtained from the fields would safe by the displacement of fossil fuels. Authors also suggest that biofuels made from waste biomass or biomass grown on degraded and abandoned agricultural lands provides immediate and sustained solution. Another study suggesting that biofuels are not as green as was expected, because of land-use change was conducted by Searchinger *et al.* (2008). Authors argue that significant papers, which are in favour of reducing greenhouse gases via substituting biofuels for the fossil fuels have not counted with the carbon emissions related to the land-use change effect. Authors estimated emissions from land-use change by a worldwide agricultural model. They found that corn-based ethanol almost doubled greenhouse gas emissions in 30 years and increased greenhouse gases for 167 years, as opposed to assumed 20% savings in greenhouse gas production. They also argue that cultivation of switchgrass as biofuels feedstock grown on U.S. corn lands increase the GHG by 50%.

Smeets *et al.* (2014) focused on effectiveness of biofuel policies in reducing GHG emissions. They argue, that the rebound effect of the blend mandates in the EU in 2020 at 10% level will not save as many emissions as was initially assumed. They also argue that GHC may even arise as a consequence of the blending mandates. Results bring considerably uncertainty to the effectiveness of biofuel policies. EPA & Venugopal (2018) pointed out that agricultural extensification (Cropland expansion) and natural habitat loss including deforestation have been documented internationally during the employment of Renewable Fuel Standard (RFS) program. The report claim that it is likely that biofuel production has contributed to the mentioned land-use change, on the other hand also claim that there remains significant uncertainty about the amount and type of land-use changes that can be attributed to U.S. biofuels production and consumption, respectively.

Focusing more on LCA. Luo *et al.* (2009) were interested in LCA and life cycle costing (LCC), respectively of Brazilian bioethanol made from sugarcane. Authors presented the result of two cases. First one, called base case, says that ethanol production from sugarcane and electricity generation from bagasse. The second one, the future one discuss the ethanol production from both sugarcane and bagasse and electricity generation from wastes. Considering the year of publication, we will conclude the result of the second one case i.e. the future case. Their findings suggest a decrease in levels of Abiotic depletion (ADP) and Greenhouse gases emissions by 87% and 24%, respectively, through replacing gasoline by ethanol fuels. On the other side, photochemical oxidation (POCP) emissions will remain unchanged due to reduction of produced emission from natural gas production and crude oil exploitation balanced with the enhancement of emission produced by ethanol storage, bagasse treatment, fermentation and electricity co-generation. Authors were also examined the LCC and figured out that costs of 1 km driving are lower in the case of E10 and E85, respectively than in gasoline case. It sounds very well in favour of fuels blended with ethanol but only the production cost had been taken into account. The real market price is influenced by many other factors such as taxes, subsidies etc. The methodology does not count with land-use change. Reporting mainly first generation of biofuels Menichetti & Otto (2009) bring quite informative summary of the topic of Life Cycle Assessment of the biofuels.

Hypothetically, biomass-cellulosic ethanol is possible to reduce the greenhouse gas emissions up to 86% according to U.S. Department of Energy[3]. According to the recalculations of Biofuels Association of Australia[4], one litre of cellulosic ethanol possibly reduces the emissions of CO2 by over 90.9%. Following the same recalculations, 2.33kg of CO2 is emitted for every consumed litre of gasoline (acquired by US EPA). Assuming this, every litre of cellulosic ethanol will possibly save 2.11kg of CO2.

To conclude, the impact of climate change to futher development whether biofuels or society is still a bit mysterious and is still under the research, so take a clear position to the problematic is almost impossible. On the other hand, we can observe that, more and more attention is being paid to alternative non-fossil solution such as the electromobility or engines powered by the hydrogen.

[3]https://www.energy.gov/sites/prod/files/edg/media/BiofuelsMythVFact.pdf
[4]https://chemistryaustralia.org.au/DownFile.Aspx?fileid=1320

Chapter 3

Data

For the purpose of this thesis we have chosen a wide range of commodities and assets inspired by Filip *et al.* (2016), because we believe that choosing the appropriate dataset is crucial for delivering precise and significant results regardless of the used methods. Dataset from which we draw, contains 38 price time-series from different sources every one of these time-series carries an information about price development of specific item or commodity over time. In this chapter we provide a brief description of employed assets and commodities. Noting, that statistical properties such as Mean, Median, Skew and Kurtosis of employed datased may reader found in Appendix A.1

3.1 Dataset overview

We have employed wide range of commodities and assets to the dataset and we have also divided them into various categories such as Biofuels, ethanol feedstock, biodiesel feedstock, fossil fuels. We will look at them more precisely in the following subsections. We analyze (price) time series which were collected on weekly basis in period between 11/2003 and 4/2020 altogether we have 858 observations. Most of the data were collected on Friday, in the case of absence Friday's data, we used the data from the first previous available business day.

3.2 Examined subperiods

As the data have covered the period since 11/2003, the market has undergone through numerous significant structural changes and some significant fluctuations, notably during the great food crisis in 2007 - 2008 and in 2010 - 2012.

Further the great recession in 2009, last but least data also cover the start of Covid-19 period. To ensure the integrity of the results we divided the dataset into sub-periods in manner as Filip *et al.* (2016) along with related papers, introduced. In the relevant-chosen subsections, we will try to describe conditions and circumstances on the market relating to a specified period.
The Food Price Index[1] published by Food and Agricultural Organization of the United Nations is measure of the monthly change in international prices of a basket of food commodities.

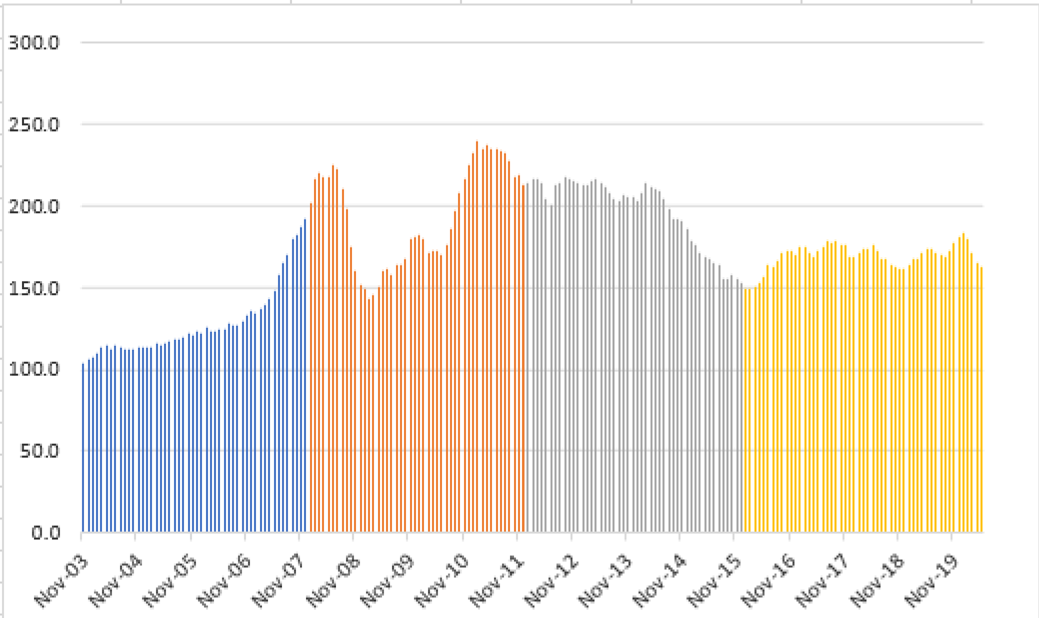

Figure 3.1: Food Price Index in 2002-2004 prices

The 3.1 shows the FPI in respect to the following Sub-periods:

1. Sub-period 1: 21.11.2003 - 28.12.2007, 215 observations
2. Sub-period 2: 4.1.2008 - 30.12.2011, 209 observations
3. Sub-period 3: 6.1.2012 - 25.12.2015, 208 observations
4. Sub-period 4: 1.1.2016 - 24.4.2020, 226 observations

[1] http://www.fao.org/worldfoodsituation/foodpricesindex/en/

3.2.1 Sub-period 1:

From the point of our interest, nothing significant had happened on the markets, till the 2007, when the World food price crisis started.

3.2.2 Sub-period 2: The World food price crisis

As the title suggests, this sub-period will reflect the world food price crisis. The crisis had been caused mainly by drought in developing countries, where the grain was produced, but also by rising oil prices[2]. According to the World resource institute and A.T.Kearney (2008)[3] prices increased dramatically between 2006 and 2008. The prices for rice rose by 217%, wheat by 136%, maize by 125%, and soybeans by 107%. The crisis resulted in the deepening of food insecurity and consequently to the political and economic instability. The crisis also fueled the discussion about biofuels and theirs influence on the food prices. Last but not least this sub-period also covers the second escalation of the world food prices after the short lull during 2009.Perez[4] stated, that high food prices along with climate change were one of the triggers of Arab Springs. The period after 2009 was also marked by great recession on the financial markets around the globe.

3.2.3 Sub-period 3

After an unprecedented period of price growth, a steady decline can be observed until 2015. After that, prices were relatively stable. During these periods, we witnessed significant economic growth, despite geopolitical conditions.

3.2.4 Sub-period 4, COVID-19 appeared

Despite the start of the period was in 2016, the important events happened by the end. Until the end, the index was relatively stable, with slight fluctuations. Larger fluctuations came at the end of the period

The world has been dealing with the virus COVID-19 since December 2019, when the first outbreak was observed in Wuhan, China. Since then, there have

[2]https://www.nytimes.com/2008/04/10/opinion/10thu1.html

[3]https://pdf.wri.org/rattling$_supply_chains.pdf$

[4]https://www.scientificamerican.com/article/climate-change-and-rising-food-prices-heightened-arab-spring/

been more than 16 million confirmed cases and more than 644,000 deaths, making it a global pandemic. We have chosen the start of this period according to the declaration, dated to 30-01-2020, of World Health Organization (WHO) in which marked the outbreak, as a Public Health Emergency of International Concern.
The onset of the virus has been accompanied by a sharp decline in financial markets, as one of the consequences of measures to prevent the spread of the virus. Nowadays we witness an unprecedented help to the economies of the EU member states, from the side of EU via grants and loans. These "rescue packages" should help Member States to rebuild regional economies and implement structural reforms. One of the areas targeted by the aid is environmental sustainability, which may lead to a departure from the original biofuels program at EU level. Electromobility or hydrogen energy has been identified as a promising.

3.3 Groups of the assets and commodities

As we have employed many commodities and assets we have grouped them into following groups:

3.3.1 Biofuels

- **US and Brazil Ethanol**

As we have already mentioned above the geo-location of 2 of the biggest biofuels markets are in the United States of America and in Brazil and these markets are quite different. We are trying to provide the complex view to the biofuels problematic, so we have combined several biofuels data streams. United States of America, the biggest producer of ethanol, is presenented by New York Harbor Price Ethanol index from the database Bloomberg Datastream. New York Harbor Price Ethanol index provides us the information about spot price of anhydrous ethanol for the US market in USD per gallon(3.79L).
Information about price of the anhydrous ethanol made by the second biggest producer is provided by Centro de Estudos Avancados em Economica Aplicada (CEPEA) quoted in USD/L.

- **Biodiesel**

Biodiesel is playing the main role in European's Union "green" program and stands for approximately 80% of the used biofuels in transportation. EU biodiesel is mostly made from rapeseed and we have obtained data from Thompson Reuters Eikon database. We have two time series for biodiesel first one gives us information about US market quoted in USD/tonne, the second, European, one is quoted in EUR/Tonne.

3.3.2 Biofuels feedstock

- **Ethanol Feedstock**

Production process of ethanol requires crops, which are a rich source of sugar, because first step of the process is that the feedstock is converted into the glucose, where sugar goes through fermentation and the ethyl alcohol is obtained, which is in the next step distilled and dehydrated.

Brazil have an unquestionable advantage in the production of ethanol from sugarcane, because the process of obtaining the glucose is easier for sugar cane or sugar beet than for starch crops such as grain, wheat or corn. This may be the reason why Brazil is the leading country in the share of ethanol usage on the domestic market, despite of the Brazilian economy.

On the other hand the United States of America is the biggest producer in the world, despite that US ethanol is predominantly made from the corn, it is caused by climate conditions in the U.S. and at the same time by the fact, that sugar cane has demanding growing conditions, i.e. the natural habitats of sugar based plants are not so extended in U.S. Differently corn has natural habitat in the extensive part of U.S. mainly in the states such as Iowa, Illinois, Nebraska or Minnesota[5].

Dataset contains three sugar related price indexes, the first one is related to the sugar cane and it was obtained from Intercontinental Exchange (ICE). Sugarcane price on Brazilian market is represented by CEPEA Crystal sugar price index. the last one for Sugar beet is represented by LIFFE Sugar beets price index and comes from Bloomberg Datastream database. Corn price is represented by Chicago Board of Trade (CBOT). Wheat took the second place on the rank of most used feedstock in bio-ethanol production in the U.S. and we obtained information about it's price again from Chicago Board of Trade.

[5]Source: USDA, NASS, Crop Production 2018 Summary, Feb.8, 2019 www.worldofcorn.com/

- **Biodiesel Feedstock**

Biodiesel is more common choice of biofuel on the European markets than on any other market in the world with market share over 75%. As we have already mentioned, EU is simultaneously the biggest producer of this commodity. The most common biodiesel feedstock is rapeseed oil with 43% share among others in 2018 according to EU Biofuels Annual report[6]. Palm oil is also used as biodiesel feedstock as well as the used cooking oil with almost 20% Rapeseed oil as biodiesel feedstock deserved its popularity by its natural habitat and simultaneously by fact, that from one hectare producers are able to gain more oil than from many other feedstock except palm oil. Rapeseed oil is popular in the EU mainly due to its freezing point what can be quite useful in colder period of the year and in colder regions. These reasons are causing that most of the EU biodiesel is made just from rapeseed oil.
Palm Oil mostly comes from Malaysia and Indonesia. The natural habitat of palm is not that friendly with European climate, but the consumption of palm oil based biodiesel have rising tendency in recent years according to EU Biofuels Annual report[7]. As we have noticed above from one Hectare of Palm we are able to gain the most oil than from any feedstock, which come as input to the production process of biodiesel. Despite of these facts palm oil has been recently criticized and some companies have already started to avoiding the palm oil in their products due to negative environmental impacts of palm oil's derivation.

3.3.3 Fossil fuels

Fossil fuels are an inseparable part of the fuel system. Biofuels represent an alternative for them. There is no doubt that crude oil and its derivatives are strongly connected to the biofuels. Firstly we employed sweet light crude oil. Sweet light crude oil contains small amounts of hydrogen sulfide and carbon dioxide. High-quality, low-sulfur crude oil is frequently used for processing into gasoline. We know two main benchmark prices for purchases of oil worldwide. First one is Brent Crude and it is used for crude oil, which is extracted from the North Sea. It is used to price two thirds of the world's traded crude oil. Second benchmark is marked as West Texas intermediate (WTI), also known

[6] apps.fas.usda.gov
[7] apps.fas.usda.gov

as Texas light sweet. WTI is extracted from the Midwest of US and from Gulf Coast. Alongside crude oil we have obtained prices of gasoline or diesel for every significant market in order to discern for local differences. To obtain these data we employed several data streams first of all EU prices were replaced by German prices and these were obtained through Thompson Reuters Datastream. To capture U.S. market we have used data from US Energy Information Administration (EIA). Last but not least, we covered the Brazilian market using data from The Brazilian National Agency of Petroleum, Natural Gas and Biofuels[8]. As there are different sources and currencies and metric system data were recalculated to the format USD/Gallon. In addition our dataset contains substitutes of gasoline and diesel. Natural gas is traded at NYMEX- New York Mercantile Exchange as Henry Hub Natural in US dollars per MMBTU. Heating oil was also employed and it is traded at NYMEX as well as natural gas.

3.3.4 Food

In previous subsections we have already introduced some agricultural commodities which directly binds to biofuels as their feedstock. As we are also interested in how biofuels influence the food market we will introduce in this subsection some others agricultural commodities, which are not used as biofuels feedstock. In the pattern of previous papers, which are related to our topic especially Filip *et al.* (2016), dataset contains rice, coffee, cocoa and oranges. In addition the feeder cattle and US cotton were added to the dataset.

Serra & Zilberman (2013) came with analysis where authors were interested in price links between biofuels and commodities with involvement of financial time series out of biofuels-related network. Their work suggests to employ some external factors which may possibly influence the network.

[8]Agencia Nacional do Petroleo, Gas Natural e Biocombustiveis data are available on www.anp.gov.br

Chapter 4

Methodology

In the previous chapter, we have introduced the data descriptions and summary properties of the dataset. This one is dedicated to the reasoning of used methodology and to the methodology itself. The basic statistical concepts related to the topic will also be described.

As we have already mentioned our goal is to study price transmission and interconnection of biofuels environment. To evaluate long-run price linkages, a wide portfolio of methodologies (models) is offered. Until the early 1970's numerous papers were investigating the co-movement of price series or time series in general, using Ordinary Least Squares (OLS) regression. Results of those estimations seemed as very significant explanation relationships among variables. Granger and Newbold were among the first who questioned those results and also usage of OLS without any adjustments, in general. After the concept of the non-stationarity had been considered in econometrics theory, taking first differences of each of non-stationary variables were commonly used. Regarding univariate modelling, this is a correct approach. If long-run multivariate relationships are the point of our interest differencing of I(1) variables will not bring desired results, because differencing removes long-run relations. Consequently, we will not have any evidence of whether variables have an equilibrium relationship Brooks (2008). To resolve the non-stationarity issue without losing long-term relations and without assuming that our system is stable as a whole, we will use method co-integration and we will estimate VECM as well. This brief introduction will be followed by a proper explanation of the statistical concepts which will be tested as well as the description of used tests and the model.

4.1 Unit root

Mathematically explained, presence of the unit root in a linear stochastic process means that the root of the process's characteristic equation equals 1. Denoted as I(1)
If the unit root is presented in the process, then the shocks will have a permanent effect on the process. In other words, if time series have a unit root, then the shock in the past will affect the present and the future value as well. Once possibly persisting trend is estimated and removed from the data, then there is still the possibility of the trending mean or variance, what plays in favour of the idea of non-stationarity, therefore other forms of the adjustment should be considered. When stationarity assumption does not hold, then we are not able to rely on the standard assumptions, and thus testing is not valid.
As a consequence of the presence of the unit root i.e. the consequence of non-stationarity Granger & Newbold (1974) introduced the concept known as "spurious regression". Signs of spurious regression consist of the high value of R^2 or adjusted R^2, a low value of the Durbin-Watson statistic and extremely strong positive autocorrelation in residuals. A high value of R^2 also suggests the statistical evidence of a linear relationship between variables, but in the fact the evidence is misleading, i.e. there is no economic or any other connection between variables.

4.1.1 Augmented Dickey Fuller test

Augmented Dickey Fuller (ADF) test is commonly used for testing the presence of the unit root in a stochastic process. The test is based on the same idea as Dickey & Fuller (1979) test but is augmented by p-lags of the dependent variable, i.e. allows an autoregressive model of order p. The test is applied to the following model:

$$\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \cdots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_t \tag{4.1}$$

$$\mathbf{H_0} : \gamma = 0 \tag{4.2}$$

where:

- α represents intercept, or constant term.
- β stands for time trend if present.

- $\Delta y = y_t - y_{t-1}$ or $\Delta y_p = y_t - y_{t-p}$ in general.
- $\delta_1 \cdots \delta_{p-1}$ represent coefficient on lag differences of y.
- ε_t represents error term.

The null hypothesis of ADF test suggests the presence of the unit root in the process, thus the process is non-stationary. Alternative hypothesis may be formulated as "process is stationary" or "process is trend-stationary", what depends on the chosen model, which we have used for the purpose of the test. The importance of taking Δy_t rests in the opportunity of regressing Δy_t against t and y_{t-1} et cetera. The idea of testing if $\gamma = 0$ is quite straightforward. If the process contains the unit root, lagged value of y_{t-1} would not provide any information in predicting of Δy_t, besides the one obtained in the Δy_{t-1}. In other words, there would not be any "force" which would guarantee a stable mean over time.

4.1.2 Akaike Information Criterion

Before we run the ADF test it is crucial to choose the best fitting Auto-Regressive (AR) model for each time series. Once we know the model, which fits our data the best, then we are able to include as many lags to the model (4.1), as necessary to ensure no serial correlation in ε_t from equation 4.1.
In order to find the best fitting AR model we decided to use the Akaike Information Criterion (AIC), which was introduced by Akaike (1974). AIC uses a model's maximum log-likelihood estimation as a measure of fit. AIC consider not only under-fitting but also over-fitting. The idea of consideration over-fitting is following: AIC penalizes for including another variable to the model, but it is logical when we do so, the goodness of fit probably increases so it is all based on this trade-off.

4.2 Co-integration

According to Committee (2003) the concept of co-integration was introduced to the econometric theory by Granger (1981). Modelling of non-stationary, co-integrated (economic) time series was afterwards examined in "Granger representation theorem" by Granger & Weiss (1983). Committee (2003) also notes that co-integration has become a frequently used econometric tool for empirical analysis, where long-run relationships are present and affect present values, e.g.

current long-term interest rates are determined by expected short-term rates. Definition of Co-integration: An $(n \times 1)$ vector time series x_t consisting of I(1) series is said to be co-integrated if there exist a non-zero vector β such that a linear combination β'x_t is stationary i.e. I(0). Then the β is referred to the co-integrating vector. In other words, if a linear combination of a set of I(1) variables is I(0), then the variables are cointegrated.
In the case of two-time series, the idea of co-integration is straightforward. Suppose we have two time series x_t and y_t, which are integrated of order one I(1), both are non-stationary. If they are co-integrated, then we are able to find β such that $y_t - \beta x_t = \mu_t$ where μ_t is stationary. Thus we find a linear combination of non-stationary time series which is stationary. It is easily conceivable suppose we plot βx_t and y_t on the graph, the distance between βx_t and y_t remains approximately unchanged over time if they are co-integrated. Testing for co-integration is a crucial part of our estimate because the Vector Error Correction Model (VECM) provides well-grounded results only if I(1) variables are co-integrated.

4.2.1 Johansen co-integration test

Later development of the concept of the co-integration brings Johansen test, introduced by Johansen (1991). Compared with the Engle-Granger test, Johansen test is more applicable, because (it) is suitable for more than one relationship of co-integration. Johansen proposed the trace test and the maximal eigenvalue test. Both of them are based on Granger's error correction model (ECM) representation. VECM will be explained in more detail in the following section.
The test is applied to the model:

$$\Delta X_t = \alpha + \delta t + \Pi X_{t-1} + \Gamma_1 \Delta X_{t-1} + \cdots + \Gamma_{p-1} \Delta X_{t-p+1} + \varepsilon_t, \quad t = 1, \ldots, T \quad (4.3)$$

Where:

- μ represents intercept or constant term.
- δ stands for time trend if present.
- X_t is (n $\times$ 1) vector of studied variables.
- Π is the co-integration matrix.

- Γ is the matrix of coefficients on lagged differences of X. Number of lags used is the same as it was in ADF test. The number must be optimal because lag length in VECM can affect the results of the Johansen test.

- ε_t represents the white-nose error term. [1]

Π (co-integration matrix) is product of α (n $\times$ r) and β' (r $\times$ n) i.e.

$$\Pi = \alpha \times \beta' \tag{4.4}$$

Interpretation of α and β' will be provided in the following sections.
As we have mentioned, the test allows more than one co-integration vectors. The Johansen test is performed gradually for a rejection or not rejection of H_0 of the specific number of co-integrating vectors. The null hypothesis is then formulated as "there is no co-integrating vector". In case of rejection of the null hypothesis, the new H_0 "there is one co-integrating vector" would be tested. The process of testing will continue by induction until we do not reject H_0 or the H_0 will not be "there are n-1 co-integrating vectors.", where n is the number of variables. The number of co-integrating vectors, denoted as r, is then equal to the rank of Π. Therefore there are three possible outcomes of the test (Brooks (2008)):

- $Rank(\Pi) = 0$, there is no co-integration between variables nor long-run relationships. So differencing of I(1) series can proceed. The Vector Auto-Regressive (VAR) model or simple OLS is probably suitable for estimating such a system.

- $Rank(\Pi) = r$, where $0 < r < n$, r co-integrating relationships are presented in the system. Equation (4.4) holds and VECM can be estimated.

- $Rank(\Pi) = n$, where n equals to the number of variables in X_t from (4.3), if Π has full rank, it means that X_t is already I(0) thus stationary and different model is more suitable than VECM. Potentially, this case would not occur, because we would test the presence of the root unit in X_t in the first place.

[1] A time series is a white noise if mean equals to zero and with variance σ^2. From the nature of time series variables do not have to be i.i.d. Also, each value has a zero correlation with all other values between periods.

4.3 Vector Autoregression (VAR) Model

Sims (1980) critique of restrictions in macro-econometric models started a revolution in the economic usage of VAR models. Nowadays the role of VAR in macroeconomics modelling has been partially taken by DSGE models. Karlsson (2013) attributed the popularity of VAR to its relative simplicity, resilience, and ability to fit the data well. VAR models are still widely used for the qualitative analysis as well as are providing the robust forecasting tool. In general, VAR is multivariate extension of univariate autoregressive (AR) model. The model is capturing mutual relationships among individual time series across time periods represented by their lags and is given by following equation:

$$X_t = \alpha + \beta_1 X_{t-1} + \cdots + \beta_p X_{t-p} + \epsilon_t, \quad t = 1, \ldots, T \tag{4.5}$$

where:

- α represents intercept.
- X_t is (n $\times$ 1) vector of studied variables at the time of t.
- $\beta_1 \cdots \beta_p$ are the matrices of coefficients.
- μ_t represents white nose error term.

From (4.5) we are able to obtain (4.3) by not so straightforward derivation, that will not be provided. For further understanding please refer to Brooks (2008) or any other econometric book.

4.4 Vector Error Correction Model (VECM)

As we have outlined at the beginning of the chapter co-integration and VECM allow us to study long-run relations among I(1) variables. Consider two time series y_t and x_t both I(1). If we want to estimate relationship between them, transforming variables into Δy_t and Δx_t may seem appropriate. The truth is that such a transformation would make them I(0), thus stationary. But considering the case when $\Delta y_t = 0$ and $\Delta x_t = 0$, i.e. variables have already converged to long-run values and are no longer evolving in time. That is why such a model does not have a long-run solution. This idea is explained in more details in Brooks (2008).

An error correction model, or an equilibrium correction (ECM) model, seems more appropriate in the case. The logic of the model will be shown on the bi-variate case with one lag, the extension to multivariate (VECM) with an optional number of lags is straightforward and will bring us to (4.3). Suppose model:

$$\Delta y_t = \beta_0 + \beta_1 \Delta x_t + \beta_2 (y_{t-1} - \gamma x_{t-1}) + \mu_t \tag{4.6}$$

again we are assuming, that y_t and x_t are I(1) and furthermore are co-integrated. From (4.6) it follows that the model solve the problem by including first differences and lags of co-integrated variables. Noting that γ is coefficient of co-integration therefore $w_{t-1} = y_{t-1} - \gamma x_{t-1}$ will be I(0) thus OLS regression may be considered, because all of included regressors are now I(0) and long-run relations are preserved. Clearly β_1 correspond to short-run relation between Δy_t and Δx_t. Coefficient for error correction term β_2, describes the speed of returning to equilibrium. Brooks (2008) states the definition of β_2 as it measures the proportion of last period's equilibrium error that is corrected for. By including variables in the same way to (4.6) we will obtain the VECM (4.3). Now we have n variables what makes the interpretation of coefficients a little bit more complicated. $\Gamma_1 \cdots \Gamma_{p-1}$ from (4.3) refers to β_1 in bi-variate case (4.6). Interpretation of Π (4.3) is for our thesis crucial. The decomposition

$$\underset{n\times 1}{\Pi} = \underset{n\times r}{\alpha} \times \underset{r\times n}{\beta}\,' \text{ (4.4)}$$

where n is the number of variables and r is the number of co-integration vectors, will make it make it easier. $\alpha(n \times r)$ is the matrix of error correction coefficients and corresponds to β_2 in (4.6), while β' is the matrix of co-integration vectors contains just r co-integration vectors and corresponds to γ in (4.6). Noting that coefficients in α are also known as the 'adjustment parameters'. To sum up, since we know how Π looks like, the connection between cointegration and VECM is unequivocal. Cointegration tells us if variables of our interest are co-integrated and after normalization with respect to target variable e.g. price of crude oil, provides long-run equilibrium equation of the system. Based on the equilibrium VECM then studies the deviations. One of the undoubted advantages of using VECM is that it allows us to study both long-term and short-term relationships

As we are interested in biofuel environment as the whole system, VECM provides us a robust tool, because all of the variables are threaded as exogenous i.e. all of them have the same importance in the model.

To sum up, the process of choosing the appropriate model consists of the following. First of all, one should find out the order of integration of each time series. Now, we are on the threshold of branching, if all of the series are I(1), then one can proceed to Johansen co-integration test or any other chosen test for the co-integration. In the case of stationarity of each employed series, VAR can be estimated. The case when the series does not have the same order of integration left. After all, it is not a big trouble. Let's go back to the co-integration test, if the test shows the co-integration among the series, VECM is offered as a suitable choice to estimate such a system. If not, the differentiation of each series until, all of them would not be I(0) and afterwards, estimating VAR is a possible solution. The same procedure can be applied to the case when the series does not have the same order of the integration. Noting that differentiation causes the lost of long-run solutions for the model.

Chapter 5

Results

The following chapter is dedicated to the presentation of results of our empirical approach. The results will be listed according to the groups of the assets and commodities chronologically and accordingly to the Chapter 4. Unless otherwise stated, we use a significance level of 5%. Noting that we had checked the inverse root, consequently the stability of estimates, before we interpreted the result.

5.1 Unit root

As been already said, to test the presence of the unit root we primary used Augmented Dickey Fuller test. Of course, before the test was employed, we had been choosing the optimal number of lags AIC suggests to employ 2 lags in our series due to cross-checking we employed also Schwarz info criterion (SIC), obtaining same result, we conclude that we are employing 2 lags.

The results of ADF tests The related p-values[1] of the test can be found in appendix A.2. In the most of the assets and commodities we observed the presence of the unit root, but in some of the employed series namely in oranges price in P3 and U.S. Ethanol also in P3. Thus testing for co-integration can proceed for the suitable groups. We also performed the first differentiation of each time series in all period, the result of ADF on first differentiation series suggests according to our expectation and shows stationarity of such series. Noting we employed test for each of the listed sub-periods listed in 3.1.

[1]In statistical hypothesis testing, the p-value is the probability of obtaining test results, at least as, extreme as the results actually observed during the test, assuming that the null hypothesis is correct Dahiru (2008). Intuitively one might say, that p-value tell us how likely it is to get a result like this, assuming the validity of the null hypothesis

5.2 Johansen co-integration test / VECM

As mentioned in chapter 4, in order to obtain precise results we should include as many lags as AIC suggests, in our case we use 2 lags. We also assume that there is no time trend. Noting the numbers below the coefficients will represent related t-values.

5.2.1 Ethanol and its feedstock

Brazil

We began our analysis in the Brazilian market. We examined the level of co-integration at ethanol, sugar, sugar cane and gasoline prices. We decided to include sugar as possible replacement of the sugarcane usage. In other words, one may say that sugar is the substitute of sugarcane-ethanol on the Brazilian market.

Base period: 2003-2020

We obtained the equilibrium equation normalized with respect to Brazilian ethanol as following:

$$Ethanol_{Br} \underset{0.079}{-0.016 Gasoline_{Br}} \underset{7.83}{+3.865 Sugar} \underset{-9.072}{- 4.948 Sugarcane} \tag{5.1}$$

At first glance, the insignificance of the Brazilian gasoline coefficient can be surprisingly concluded. After the re-estimating of model with omitting of the gasoline we obtained the equilibrium equation:

$$Ethanol_{Br} \underset{7.77}{+ 3.592 Sugar} \underset{-9.15}{- 4.656 Sugarcane} \tag{5.2}$$

In order to interpret 5.2, we must conclude the significance of all coefficients, the price transmission among the Brazilian ethanol and sugarcane is according to expectation, 4.656 % of increase in sugarcane price will influence the price of ethanol by 1 %. On the other hand, we may observe the positive coefficient in sugar, what may be interpreted as when the price of the sugar is decreasing, than the price of ethanol will increase. One possible explanation occurs, the surplus on the sugar market push the price downwards and the demand for ethanol is still increasing, thus price of the ethanol is increasing.

Commodity	Adjustment coefficients	Standard error
Br_ethanol	-0.012	0.003
Sugar	-0.021	0.0025
Sugarcane	0.000292	0.004

Table 5.1: Adjustment coefficients related to the 5.2

The error correction terms or Adjustment coefficients provided in Table 5.1 refer to speed of the adjustment to the equilibrium, when the shock occurs. Since, we use weekly data, the adjustment speed refers to this fact and it is relatively slow. The interpretation of the coefficients are following: Ethanol$_{Br}$ adjusts 1.2% from the disequilibrium over in the period, after the shock. Since we use weekly data, it corresponds to adjustment speed in a week, after the shock occurs.

The sugarcane adjustment coefficient is nearly to zero and positive, what is caused by the fact, that prices of the sugarcane are not influenced by other employed commodities. Along with the fact, that equilibrium exists it may suggest that prices of the employed commodities follow the trend of the sugarcane prices. Together with all the facts mentioned so far, the adjustment coefficient of sugar is bigger than coefficient of Ethanol, mainly caused by the fact that ethanol is not only made from sugarcane, what sugar is, so sugar will be more prone to shock in sugarcane price than ethanol.

Brazil, pre-crisis period 2003-2007

For Sub-period 1 we obtained the equilibrium equation normalized with respect to Brazilian ethanol as follows:

$$Ethanol_{Br} \underset{-6.306}{-8.072} Gasoline_{Br} \underset{7.083}{+4.406} Sugar \underset{-9.072}{-\ 4.137} Sugarcane \tag{5.3}$$

Unlike the base period, the Brazilian gasoline prices are now significant and have huge impact on the ethanol prices. The remaining coefficients correspond to the base period, despite the coefficient of sugar still brings some question and is a bit mysterious, but possibly it may be still interpreted as was in the base period.

Commodity	Adjustment coefficients	Standard error
Br_ethanol	-0.018	0.007
Sugar	-0.039	0.005
Sugarcane	-0.006	0.008
Br_Gasoline	0.003	0.001

Table 5.2: Adjustment coefficients related to the 5.3 in the sub-period 1

By significance of the Brazilian gasoline, we may observe the replacement of the dominant role in the system. We may confirm now, that prices are lead by gasoline according to Table 5.2. In other words, we may meaningfully conclude that gasoline is not influenced by employed commodities and the others are.

Brazil, crisis period 2008-2011

In the sub-period, marked by World food price crisis along with recession on the markets we have to again conclude the insignificance of the Brazilian Gasoline. For the second sub-period the equilibrium equation normalized with respect to Brazilian ethanol looks like:

$$Ethanol_{Br} \underset{-0.04351}{-0.156 Gasoline_B} \underset{4.62079}{+3.556 Sugar} - \underset{-5.145}{4.585 Sugarcane} \tag{5.4}$$

The insignificance of gasoline is mainly caused by its high standard error. The price of gasoline has risen sharply in the mid of 2011 so hypothetically we can say that the shock in the gasoline price caused the high standard error and consequently caused the insignificance.

After the gasoline omitting from the system we obtained:

$$Ethanol_{Br} + \underset{4.582}{2.904 Sugar} - \underset{-5.41852}{3.882 Sugarcane} \tag{5.5}$$

Commodity	Adjustment coefficients	Standard error
Br_ethanol	-0.024	0.008
Sugar	-0.032	0.006
Sugarcane	-0.012	0.012

Table 5.3: Adjustment coefficients related to the 5.5 in the sub-period 2

Brazil, post-crisis period 2012-2015

Since the sugar seems as spurious for this period, we have omitted it from the equation, the gasoline coefficient was insignificant so it was also omitted, therefore our equation comprise as follows:

$$Ethanol_{Br} - 0.821 \underset{-5.703}{Sugarcane} \tag{5.6}$$

Commodity	Adjustment coefficients	Standard error
Br_ethanol	-0.066	0.019
Sugarcane	-0.022	0.031

Table 5.4: Adjustment coefficients related to the 5.6 in the sub-period 3

The obtained Co-integration vector is quite good reflection of the importance of the sugar cane to the Brazilian ethanol. We can observe relatively strong co-movement between ethanol and sugarcane. The result suggest strong interconnection between the commodities.

Brazil, period 4 2016-2020

Johansen Co-integration Test did not confirm any co-integration vector at 5% level of the significance thus, in this period there is no long-run relationship among employed commodities.

The reason for such result may lay in the stability of the system in the period. Covid-19 violated this condition, but the period in our dataset concerned by the virus is not long enough, so once the data will be available the selection of the suitable period may bring different results.

USA market

By trying and failing method, we discarded: Cattle, Rice, Oranges, Cocoa, WTI. The mentioned series had small to none influence on US ethanol. After several rounds of elimination The US ethanol/gasoline, Corn and wheat left. Firstly we have to point out that ADF test suggests stationarity in the base period as well as in the post-crisis period 3, so in those periods we are not able to perform VECM, thus exploring the system from long-run relations perspective. We are able capture the short-run effect by VAR or ARDL, but we are trying to capture the long-run relations. More sophisticated modelling approaches, such as Wavelet analysis, are suitable to capture the significant long-run relationships in these periods. Furthermore in the pre-crisis period the result of the test is on the edge of the stationarity, so the acquired co-integration vector may not reflect the reality and the interpretation should consider this fact. Reminding the result of the ADF test can be found in the Appendix A.2.

USA, Pre-crisis period 2003-2007

As we indicated, there is no observable co-integration vector at 5% level of significance in this period. The result does not have to meet with reality due to limitation of the chosen empirical approach. Before drawing a general conclusion from the result, a more advanced empirical approach needs to be considered instead of VECM.

USA, crisis period 2008-2011

Johansen Co-integration Test does not suggest any Co-integration vector at 5% level of the significance thus, in this period there is no long-run relationship among employed commodities. We tried several combinations of The US ethanol/gasoline, corn and wheat. The Johansen test does not suggest any significant co-integration vector. We could choose the wrong commodities to justify the result, but intuition told us that corn, as the main feedstock for US ethanol, belongs to the system, just as US gasoline can be considered as a feedstock because ethanol is mixed at a certain level to gasoline. The wrong choice of period boundaries together with a limitation of empirical approach could also lead to the result obtained.

USA, period 4 2016-2020

Since in the previous periods we have not discovered any significant proof of price transmissions, now we found the evidence of price co-movement between us gasoline prices and corn.

$$Gasoline_{US} - 4.4\underset{-3.649}{Corn} \tag{5.7}$$

The result could be interpreted as by the increase of 1% in gasoline price the price of the corn will rise by 4,4%. After the increase in gasoline price the transportation cost would arise as well, what is converted to the price of the corn.

Commodity	Adjustment coefficients	Standard error
US_Gasoline	-0.0001	0.033
Corn	0.029	0.008

Table 5.5: Adjustment coefficients related to the 5.7

5.2.2 Biodiesel and its feedstock across the markets

EU Market

Firstly we employed prices of the US Biodiesel, US Diesel, Sunflower-seed, Rapeseed, Palm oil, Natural gas, Heating oil, Soybeans and Cotton after several rounds of estimating and reviewing this system, we decided to omit the Natural gas, Heating oil and Cotton. The omitted variables were chosen due to little to no effect on the dependent variable, and we also found that in most cases these price transfers were negligible. Since cotton is utilized primarily in the textile industry, natural gas and heating oil are not widely utilized in transportation in the Europe.

$$Biodie_{EU} \underset{-3.529}{-0.021} Die_{GE} \underset{-7.13}{-0.977} Rapes. \underset{-4.215}{-0.327} PalmO \underset{4.232}{+0.214} Sunflow. \underset{6.6768}{+0.467} Soy \tag{5.8}$$

Compared to the result of US market in the same period we may see the difference in the significance of the soybean coefficient, what is actually pretty spurious in the context of the EU and US Biodiesel's feedstocks. We would expect insignificance of soybean in the EU rather than in the US market. The spuriousness of the soybean coefficient is power by its negativity, since it is major feedstock in US and it is on the second place, as regards cultivation for biofuels, in the Europe, we excepted that the relationship will be positive and significant, at least in the US. We also confirmed the strong price transmissions among the Biodiesel and rapeseed. The co-movement is relatively low among the Eu biodiesel and German diesel but still significant. The influence of the palm oil is basically the same as on the US Market.
Last but not least we may observe a bit mysterious negative relation between the EU biodiesel and sunflower seed.

Commodity	Adjustment coefficients	Standard error
EU_Biodiesel	-0.054	0.012
PalmOil	0.019	0.016
Sunflowerseed	-0.049	0.016
GE_Diesel	-0.007	0.018
Rapeseed	-0.025	0.017

Table 5.6: Adjustment coefficients related to the 5.8

Europe, pre-crisis period (2003-2007)

In this period, the usage of palm oil was relatively unknown and consequently was not used as much as nowadays, besides the environmental impact. The lower usage rate caused the insignificance of palm oil in estimating similar equation to the 5.8. The sunflower seed was also insignificant in this period. After the omitting insignificant series, we have system consist of EU Biodiesel, German diesel, rapeseed and soybean:

$$Biodie_{EU} - \underset{-3.115}{0.024 Die_{GE}} - \underset{-6.135}{0.903 Rapes.} + \underset{2.172}{0.023 Soy} \tag{5.9}$$

The price transmission among the EU biodiesel and soybean is smaller than in the base period and it is on the edge of significance. It may be caused mainly due to early period in European biofuels history, when the share of rapeseed based biodiesel was probably higher than nowadays. Already at the start of the European biofuel era, we had been observing the negative price transmission among the commodities. The coefficient of German diesel as well as rapeseed, are comparable to the coefficients in the base period.

Commodity	Adjustment coefficients	Standard error
EU_Biodiesel	-0.104	0.003
Rapeseed	-0.024	0.026
Soybean	-0.138	0.046
GE_Diesel	0.077	0.003

Table 5.7: Adjustment coefficients related to the 5.9

Pre-crisis period is accompanied with expected transmission among Eu biodiesel and rapeseed or German diesel, the expected insignificance of palm oil was confirmed. We may see that EU biodiesel, as well as soybeen was relatively unstable, comparing to the base period. This instability can be attributed to the relative beginnings of the European biofuel program.

Europe, crisis period (2008-2011)

During the crisis period, except the German Diesel, we are able to observe the wilt of the co-integration relationships in comparison to the base period.

German diesel strength the co-movement, the equilibrium equation is then given as:

$$Biodie_{EU} \underset{-3.959}{-0.16 Die_{GE}} \underset{-6.041}{-0.449 Rapes.} \underset{-2.090}{-0.091 PalmO} \underset{-2.873}{-0.129 Sunflow.} \underset{2.11}{-0.113 Soy} \tag{5.10}$$

In addition to weaker relationships, we may also observe the turn of soybean and sunflower seed coefficient, to the positive relationship. Now the price-transmission is as we originally assumed. As we have already indicated, an increase in the price of soybeans or sunflowers will result in an increase in biodiesel in the EU.

As the period also covers the financial recession, the reasons for this change may vary. In our opinion, one of the possible explanation of the change would consist of a sharp increasing of agricultural commodities, the enhancement of the prices result in the unavailability to ensure the cheap feedstock. As was noticed, this period was accompanied by several droughts in regions, where the important agricultural commodities are cultivated. These shortages on the food market might be possibly replaced by biofuels feedstock, what consequently might cause the shortages on the biofuels feedstock's market.

Commodity	Adjustment coefficients	Standard error
GE_Biodiesel	-0.260	0.068
Rapeseed	-0.035	0.085
Soybean	0.078	0.140
GE_Diesel	-0.120	0.011
Sunflower seed	0.087	0.094
Palm oil	-0.131	0.115

Table 5.8: Adjustment coefficients related to the 5.10

We unsurprisingly conclude that the adjustment coefficients for the German diesel as well as for the diesel were increased and therefore the mentioned commodities, were more prone to shocks. It was a generally turbulent period, so no wonder that German diesel was unstable, since the biodiesel is blended with the diesel, which also unstable due to movement of financial markets.

Europe, post-crisis period (2012-2015)

Johansen Co-integration Test did not exhibit any Co-integration vector at 5% level of the significance thus, in this period there is no long-run relationship among employed commodities. Instead we edited all series to be I(0), thus stationary and after that we performed the VAR to reveal at least short-term transmission. Due to relative complexity of such a estimation, we will not describe the obtained VAR, but can be found in Appendix A.1

Europe, period (2016-2020)

Following the pattern from post-crisis period the Johansen Co-integration Test did not exhibit any Co-integration vector at 5% level of the significance.

USA Market

We started at same line as we had started on the EU market, but logically we used US Biodiesel and US diesel instead of EU oil products. We may conclude basically the same regarding to the omitting of cotton, heating oil and natural gas but in respect to the US.
The final composition of employed variables was made accordingly to the significance of the used variables in individual periods.

In the base period (2003-2020) we obtain following equilibrium equation:

$$Biodie_{US} \underset{-1.795}{-0.018Die_{US}} \underset{-5.23}{-1.153Rapes.} \underset{-3.215}{-0.418PalmO} \underset{8.010}{+0.679Sunflow.} \underset{0.294}{+0.679Soy} \tag{5.11}$$

Despite of the intuition, we may observe the insignificance of the soybean coefficient as well as the insignificance of US-Diesel. Since the soybean oil is the most used feedstock of US-Biodiesel according to the U.S. EIA[2], it was expected that soybean will have the significant influence on the Biodiesel price, but the opposite is true. So between years 2003 and 2020 we must conclude that, we do not observe significant influence of soybean prices to US Biodiesel prices.

After the re-estimation, noting soybean was not included, we acquired following equilibrium equation normalized with respect to US Biodiesel:

$$Biodie_{US} \underset{-2.449}{-0.215Die_{US}} \underset{-5.630}{-1.073Rapes.} \underset{-3.215}{-0.362PalmO} \underset{8.179}{+0.637Sunflow.} \tag{5.12}$$

Commodity	Adjustment coefficients	Standard error
US_Biodiesel	-0.015	0.009
PalmOil	0.042	0.012
Sunflowerseed	-0.032	0.012
US_Diesel	-0.013	0.004
Rapeseed	0.004	0.009

Table 5.9: Adjustment coefficients related to the 5.12

Equilibrium equation 5.12 along with Table 5.9 suggest that in the period between 2003 and 2020, there exists significant co-movements among the US Biodiesel and its feedstocks, on the other hand we refuted the possible transmission between soybean and the BioDiesel in the period. The reason of such

[2] https://www.eia.gov/biofuels/biodiesel/production/

behaviour may consist in the interconnection of biofuel market. As it is known, the BioDiesel's production is predominantly located in the EU, where the soybean is not as much cultivated as rapeseed, which came out from the analysis as significant with positive effect on the biodiesel price. Along with the Table 5.9 it may suggests interconnection among EU and US Biodiesel market. But this conclusion is just hypothetical and should be further investigated.

Except the sunflower seed, the coefficients behave accordingly to our expectations the very strong relationship is presented among rapeseed and biodiesel, since the rapeseed is main feedstock for EU market the economic insight is pretty straightforward here. Rapeseed is followed by palm oil as regards the strength of the co-movement. The weakest, but still significant relationship is from the US Biodiesel side.

Last but not least, we should not forget on the coefficient of sunflower seed, because it is the only one that is negative, which in fact means that with the rising price of sunflower seed it is possible to observe a falling price of the US biodiesel. Since we may observe same phenomenon in the EU market in comparable period, we decided to perform the Pairwise Granger Causality Tests. The test result indicates the absence of a causal relationship between sunflower seed and biodiesel in with the corresponding p value of 0.8616. But confirm the causality effect of the US Biodiesel prices on the sunflower seed's prices. But it does not answer the movements on the market, by pairwise causality test we only excluded the strictly correlation relationship. It should be further researched.

USA, pre-crisis period (2003-2007)

In this period we obtained Co-integration vector:

$$Biodie_{US} - \underset{-2.705}{0.336} Die_{US} - \underset{-4.250}{1.3797} Rapes. - \underset{-2.34}{0.642} PalmO + \underset{2.676}{0.596} Sunflow. + \underset{2.848}{0.676} Soy \tag{5.13}$$

During the pre-crisis period we may conclude the stronger interconnection between US biodiesel and rapeseed than in others examined periods. Possibly it may suggest the strong price transmission among biodiesel across markets, since the rapeseed is dominant feedstock in EU Biodiesel. To investigate the interconnection, we employed the Johansen Co-integration test on US biodiesel, German diesel and rapeseed, we must conclude that the Johansen test, refused the presence of the Co-integration vector, but the test statistics is on the edge of acceptance/rejection of the null hypothesis. We can also state that, the connection between the US diesel and US biodiesel is stronger than the connection between comparable tuple on the European market.

Commodity	Adjustment coefficients	Standard error
US_Biodiesel	-0.051	0.025
Rapeseed	-0.029	0.040
Soybean	-0.160	0.040
US_Diesel	0.046	0.020
Sunflower seed	0.095	0.035
Palm oil	-0.336	0.22

Table 5.10: Adjustment coefficients related to the 5.13

USA, crisis period (2008-2011)

During the crisis period, we can conclude that prices of Biodiesel were mainly co-integrated with rapeseed and palm oil, respectively. As these commodities are not used in the food or feed markets, this may indicate that the remaining quantities of conventional biodiesel's feedstocks have been utilized in the food and feed market and alternatives have been used more frequently during the crisis. Please note that this explanation is only a suggestion and should be carefully examined.

$$Biodie_{US} - \underset{-2.574}{0.4914Rapeseed} - \underset{-3.635}{0.654PalmO} \tag{5.14}$$

Commodity	Adjustment coefficients	Standard error
US_Biodiesel	-0.049	0.019
Palm oil	0.039	0.029
Rapeseed	-0.019	0.022

Table 5.11: Adjustment coefficients related to the 5.14

USA, post-crisis period (2012-2015)

In the post-crisis we do not discover any significant equilibrium equation, after all we did not discover any on the European market. We observed a co-integration vector among rapeseed and soybean but the co-integration coefficient was found as insignificant.

USA, period (2016-2020)

Johansen Co-integration Test did not exhibit any Co-integration vector at 5% level of the significance thus, in this period there is no long-run relationship among employed commodities.

Chapter 6

Conclusion

In this thesis, we divided the period between 2003 and 2020 to the four subperiods. In these periods we were able to observe a wide range of conclusions from the significant price transmissions to the non-existence of co-movement among variables. Besides the econometric estimation, we briefly review the price transmission literature, along with ecological issues of biofuels. Based on the acquired knowledge about the ecological issue of biofuels, we ask ourselves the questions about the real benefit of biofuels. We do not propose any extreme solution, because the environment and climate change is a very extensive topic. We rather encourage research on the topic of ecological and economical sustainability of biofuels.

Last but not least, we provided an overview of the used empirical methods, which provides a strong foundation of the price transmission empirical approaches, we were trying to bring to the reader a straightforward procedure that could easily be reproduced

To review the thesis in the same manner as we interpreted results in Chapter 5. We began our analysis with detection of the price transmission among Brazilian ethanol and its feedstock along with the sugar. Except for the pre-crisis period (2003-2007), the insignificance of the Brazilian gasoline was concluded in all periods. We also found the strong connection between sugarcane and Br ethanol. The interconnection between ethanol and sugarcane slowly decreased over the periods. In the last period, no price transmission was observed.

Regarding the US Market, we did not capture any significant price transmission among the US ethanol and maize, US gasoline and wheat.

Secondly, we were looking at the price transmission among the biodiesel and its feedstock on the EU and US market. To sum up the conclusions regarding the European market, we proved the existence of interconnection among Eu Biodiesel and its feedstock between 2003-2020. The interconnection exists also between 2003 - 2007 and in world food price crisis period (2008-2011). In the post-crisis period and followed sub-period, we failed to prove the existence of co-integration among employed variables. The non-existence of relationships might be caused by the stability of the market. We also may suggest that stability of biofuel-food market since 2012, might be caused by the boom of European biodiesel main feedstock-rapeseed, which is not so frequently used as feedstock or feed as maize does.

Regarding the US market, we proved the existence of interconnection among US biodiesel's feedstock in period 2003-2020, what turned out as mysterious is the negative relationship of soybean and sunflower, respectively. We observed stronger interconnection between biodiesel and diesel in the EU market. The mentioned co-movement was even stronger during the pre-crisis period. On the other hand, we must conclude the relatively strong price transmission among the US biodiesel and Rapeseed namely in the pre-crisis period, but also in the base period and the crisis period. In the last two periods, we did not reveal any significant evidence of co-integration among variables.

We must add, regarding the used empirical approach, that there exist more sophisticated approaches, which, along with good workmanship would bring more significant results from which it is possible to bounce to the more answering conclusions. Such methods are Wavelet analysis or any clustering methods, which are experiencing a boom nowadays. From the market perspective, the examination of the Covid-19 period might be interesting.

Finally at the end, nowadays a climate change is a really serious issue with which we must deal in the following years because later it could be late, if we waste another opportunity to slow down the changes. We believe that the research of ecological and economical sustainability of biofuels will continue and bring significant results because with an increase in the population the fill mankind's needs will be harder year to year.

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Appendix A

Title of Appendix A

	DPALMOIL	DRAPESEED	DSOY	DGEDIESEL	EU_BIODIE...	DSUNFL
DPALMOIL(-1)	0.044383	0.111314	0.127729	0.019883	0.078435	0.065106
	(0.07761)	(0.06143)	(0.08273)	(0.06644)	(0.04420)	(0.07567)
	[0.57190]	[1.81201]	[1.54386]	[0.29927]	[1.77465]	[0.86037]
DPALMOIL(-2)	-0.005767	0.071899	0.002867	0.072791	0.002563	-0.084956
	(0.07531)	(0.05961)	(0.08028)	(0.06447)	(0.04289)	(0.07343)
	[-0.07658]	[1.20610]	[0.03571]	[1.12905]	[0.05976]	[-1.15695]
DRAPESEED(-1)	0.013941	-0.063509	0.221101	0.098561	0.039853	0.149707
	(0.11590)	(0.09174)	(0.12355)	(0.09922)	(0.06600)	(0.11301)
	[0.12029]	[-0.69227]	[1.78952]	[0.99338]	[0.60380]	[1.32476]
DRAPESEED(-2)	0.163406	0.003827	0.195487	-0.086124	0.011727	0.063632
	(0.10433)	(0.08259)	(0.11123)	(0.08932)	(0.05942)	(0.10173)
	[1.56621]	[0.04634]	[1.75758]	[-0.96424]	[0.19736]	[0.62549]
DSOY(-1)	0.012423	-0.104807	-0.171182	-0.015413	-0.020692	-0.078941
	(0.07577)	(0.05998)	(0.08078)	(0.06487)	(0.04315)	(0.07388)
	[0.16395]	[-1.74739]	[-2.11916]	[-0.23761]	[-0.47950]	[-1.06846]
DSOY(-2)	0.040704	0.019421	0.044942	0.068114	-0.033238	0.072613
	(0.07601)	(0.06017)	(0.08104)	(0.06508)	(0.04329)	(0.07412)
	[0.53548]	[0.32277]	[0.55459]	[1.04669]	[-0.76780]	[0.97967]
DGEDIESEL(-1)	-0.092563	0.080448	0.022662	0.058571	0.025050	0.045226
	(0.08407)	(0.06655)	(0.08962)	(0.07197)	(0.04788)	(0.08197)
	[-1.10107]	[1.20891]	[0.25286]	[0.81383]	[0.52323]	[0.55172]
DGEDIESEL(-2)	0.043424	-0.037464	0.002090	0.003623	-0.009670	-0.066365
	(0.08299)	(0.06569)	(0.08847)	(0.07104)	(0.04726)	(0.08092)
	[0.52326]	[-0.57031]	[0.02363]	[0.05100]	[-0.20460]	[-0.82014]
EU_BIODIESEL(-1)	-0.010816	0.016924	-0.012390	0.004543	0.970904	0.173904
	(0.15637)	(0.12378)	(0.16670)	(0.13386)	(0.08905)	(0.15247)
	[-0.06917]	[0.13673]	[-0.07433]	[0.03394]	[10.9027]	[1.14059]
EU_BIODIESEL(-2)	-0.011047	-0.017024	0.052446	0.006349	0.017878	-0.166520
	(0.15555)	(0.12313)	(0.16583)	(0.13317)	(0.08859)	(0.15167)
	[-0.07102]	[-0.13825]	[0.31627]	[0.04768]	[0.20181]	[-1.09788]
DSUNFL(-1)	-0.108233	-0.048492	-0.060232	-0.023031	-0.109180	-0.070223
	(0.07453)	(0.05900)	(0.07946)	(0.06381)	(0.04245)	(0.07268)
	[-1.45213]	[-0.82190]	[-0.75803]	[-0.36095]	[-2.57210]	[-0.96625]
DSUNFL(-2)	-0.002390	-0.037427	0.046472	0.056107	0.016658	-0.028532
	(0.07494)	(0.05932)	(0.07989)	(0.06415)	(0.04268)	(0.07307)
	[-0.03190]	[-0.63095]	[0.58172]	[0.87459]	[0.39032]	[-0.39048]
C	0.147625	0.000338	-0.273617	-0.076762	0.075652	-0.047443
	(0.12680)	(0.10038)	(0.13518)	(0.10856)	(0.07222)	(0.12364)

Figure A.1: Results of VAR, European market for Biodiesel in post crisis period

Table A.1: Descriptive statistics of employed dataset

	Mean	Median	Std. Dev.	Skewness	Kurtosis
BOVESPA	56658.64	56100.81	20171.38	0.490783	3.484411
BR_DIESEL	2.393073	2.12	0.646522	0.622842	2.208276
BR_ETHANOL	0.509665	0.499	0.161577	1.401609	11.2169
BR_GASOLINE	3.016795	2.74	0.719564	0.877267	2.564305
BR_SUGAR	20.96545	19.415	8.459488	1.02167	3.765888
BRENT_CRUDE	73.77414	68.085	26.09345	0.410876	2.148665
BRL_USD	2.594427	2.30515	0.80381	0.731972	2.649756
CATTLE	134.2482	132.5	33.50111	1.085482	3.960969
COCOA	2372.545	2391	580.6318	-0.162775	1.937715
COFFEE	134.9277	124.75	42.8298	1.382654	5.118976
CORN	412.8115	374.125	146.4922	0.891706	3.138496
COTTON	0.721808	0.6805	0.244019	2.690289	13.1104
DATE	734538.5	734538.5	1734.793	1.25E-16	1.799997
DAX	8086.406	7403.02	2856.695	0.293321	1.822083
DOW_JONES	15277.01	13127.98	5464.995	0.881193	2.665953
EU_BIODIESEL	863.3483	845.1	147.1835	0.259145	2.1166
FED_FUNDS	1.410944	0.525	1.652626	1.192099	3.181701
FTSE_100	6065.537	6100.06	951.914	-0.278508	2.310925
GE_DIESEL	2.097622	2.033372	0.485098	0.124121	2.355935
GE_GASOLINE	1.954678	1.918598	0.452682	0.085565	2.517858
HEATING_OIL	2.090539	1.9588	0.670295	0.401035	2.354564
LIBOR	1.731028	1.12819	1.673029	1.04296	2.856345
NATURAL_GAS	4.660812	3.915	2.381115	1.422511	5.097112
ORANGES	132.1931	135.2	35.37655	-0.009369	2.597428
PALM_OIL	2374.754	2378	592.3984	0.147625	2.589097
RAPESEED	351.3042	363.625	78.4243	-0.125803	2.316466
RICE	12.11467	11.95	2.95783	0.381958	3.275027
S_P_500	1703.749	1437.015	624.6121	0.764893	2.448937
SOYBEANS	1014.492	973.125	277.7414	0.296527	2.497157
SUGAR_BEETS	428.3197	397.55	135.5766	0.709155	3.040746
SUGAR_CANE	15.39174	14.355	5.596021	0.862465	3.473308
SUNFLOWERSEED	4254.394	4595	1411.6	-0.205178	2.302378
US_BIODIESEL	1054.901	981.875	215.469	0.957968	2.886151
US_DIESEL	3.016859	2.935	0.700274	0.127272	2.327961
US_ETHANOL	199.1946	177.5	53.17828	1.172329	5.621856
US_GASOLINE	3.081319	3.065	0.604961	-0.067801	2.31824
USD_EUR	1.264471	1.2689	0.122236	0.270766	2.428514
WHEAT	543.5924	510.75	159.6077	0.789203	3.345147
WTI	69.3752	64.85	22.91692	0.444218	2.554607

	Period_1	Period_2	Period_3	Period_4	P_1-P_4
BOVESPA	0.7811	0.7706	0.2064	0.4095	0.2589
BR_DIESEL	0.957	0.3024	0.2197	0.7167	0.6099
BR_ETHANOL	0.3014	0.0286	0.2912	0.2472	0.1083
BR_GASOLINE	0.9407	0.2461	0.9181	0.8459	0.5981
BR_SUGAR	0.9465	0.2014	0.1989	0.3605	0.6824
BRENT_CRUDE	0.41	0.8568	0.6966	0.9966	0.383
BRL_USD	0.3721	0.7863	0.9607	0.9842	0.9944
CATTLE	0.5769	0.8164	0.9828	0.4335	0.8901
COCOA	0.2359	0.2247	0.151	0.4245	0.4237
COFFEE	0.1917	0.584	0.3277	0.0669	0.3943
CORN	0.9469	0.7416	0.4414	0.733	0.5857
COTTON	0.3859	0.8459	0.3099	0.8255	0.4799
DAX	0.3648	0.5089	0.1573	0.4701	0.1506
DOW_JONES	0.4596	0.6358	0.3067	0.2975	0.3865
EU_BIODIESEL	0.9999	0.7122	0.8488	0.6768	0.4173
FED_FUNDS	0.9999	0.0007	0.9897	0.9999	0.9106
FTSE_100	0.0683	0.4397	0.5387	0.5599	0.1486
GE_DIESEL	0.3402	0.8784	0.1537	0.9323	0.4949
GE_GASOLINE	0.5191	0.5279	0.89	0.9508	0.3429
HEATING_OIL	0.6239	0.8773	0.8257	0.9999	0.7543
LIBOR	0.9999	0.4159	0.9999	0.9999	0.8245
NATURAL_GAS	0.2172	0.6207	0.89	0.2529	0.0138
ORANGES	0.9593	0.1706	0.0445	0.2396	0.1972
PALM_OIL	0.9885	0.5765	0.3577	0.1726	0.318
RAPESEED	0.9962	0.7544	0.6055	0.2363	0.5323
RICE	0.9384	0.3996	0.5238	0.9538	0.433
S_P_500	0.1339	0.6292	0.4869	0.0177	0.4855
SOYBEANS	0.9885	0.4944	0.0413	0.5445	0.5528
SUGAR_BEETS	0.9404	0.4562	0.2089	0.4962	0.5758
SUGAR_CANE	0.9037	0.5899	0.1478	0.4111	0.3487
SUNFLOWERSEED	0.8164	0.8436	0.8519	0.6417	0.2855
US_BIODIESEL	0.9998	0.7349	0.0551	0.3045	0.687
US_DIESEL	0.0815	0.8331	0.8315	0.9967	0.3394
US_ETHANOL	0.0594	0.6489	0.0039	0.3395	0.0005
US_GASOLINE	0.1001	0.4702	0.25	0.8958	0.0949
USD_EUR	0.914	0.4084	0.851	0.5471	0.2412
WHEAT	0.938	0.4795	0.1	0.1503	0.3078
WTI	0.5695	0.8345	0.8465	0.6338	0.566

Table A.2: Related p-values of ADF test across the specific periods