



The impact of renewable energy on
the price linkage between crude oil
and agricultural commodities:
comparing Biofuel-Related and Non-
Biofuel-Related commodities

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ABSTRACT

This thesis explores how renewable energy usage affects the price linkage between crude oil and agricultural commodities, analyzing and comparing biofuel-related and non-biofuel-related commodities. Using monthly data from 1990 to 2020, the study employs complex regressions, causality tests and cointegration analysis to analyze changes over time, particularly before and after 2005 - a turning point marked by the expansion of biofuel policies and consequent production. The results show that biofuel-related commodities, such as Maize, Soybeans, and Wheat, experienced significant changes in their price dynamics with crude oil after 2005. Maize, as a key input for ethanol production, had a historical strong linkage with oil prices driven by production costs, however, post-2005, this linkage weakened as biofuel demand became the dominant driver of maize prices, reducing dependence on oil. Soybeans, widely used for biodiesel, saw a strengthening price linkage with oil after 2005 as a result of the growing integration of biodiesel into energy markets. Wheat, less tied to biofuel production, showed a moderately strengthening linkage post-2005, though its price dynamics remained relatively more stable compared to Maize and Soybeans. Non-biofuel-related commodities, such as Cocoa, Coffee, and Sugar, showed weaker and less linear relationships with oil prices, influenced primarily by regional renewable energy usage, situational production costs and local environmental policies. For Sugar, the dynamics varied significantly by region, with opposite results between the USA and the European Union.

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Keywords: renewable energy, oil, agricultural commodities, biofuel, ethanol, biodiesel

SUMÁRIO

Esta dissertação explora como o uso de energias renováveis afeta a relação de preço entre o petróleo e os principais produtos agrícolas, analisando produtos relacionados e não relacionados com a produção de biocombustíveis. Utilizando dados mensais de 1990 a 2020, o estudo aplica regressões complexas, testes de causalidade e análises de cointegração com o intuito de analisar mudanças ao longo do tempo, especialmente antes e depois de 2005, um ponto de viragem na indústria agrícola marcado pela expansão dos biocombustíveis. Os resultados mostram que produtos agrícolas relacionados com biocombustíveis verificaram mudanças significativas nas suas dinâmicas de preço com o petróleo após 2005. O milho, um elemento chave na produção de etanol, historicamente apresentava uma forte ligação com o petróleo devido aos custos de produção. Após 2005, essa ligação enfraqueceu com a procura por biocombustíveis a tornar-se o principal determinante dos preços do milho. A soja, amplamente utilizada na produção de biodiesel, apresentou um fortalecimento da ligação com o petróleo após 2005, reflexo da crescente integração do biodiesel nos mercados energéticos. O trigo, menos vinculado à produção de biocombustíveis, apresentou um fortalecimento moderado dessa ligação após 2005, embora as suas dinâmicas de preço tenham permanecido relativamente mais estáveis em comparação ao milho e à soja. Produtos agrícolas não relacionados com a produção de biocombustíveis, como o cacau, café e açúcar, mostraram relações mais fracas e menos lineares com os preços do petróleo, influenciadas principalmente pelo fator regional do uso de energia renovável, custos de produção situacionais e pelas políticas ambientais locais.

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Palavras-Chave : energia renovável, petróleo, produtos agrícola, biocombústivel, etanol, biodiesel

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INTRODUCTION

The relationship between energy markets and agricultural commodities is a topic of growing importance, especially with the world becoming more environmentally-conscious and transitioning towards renewable energy. My thesis explores how renewable energy usage influences the price linkage between crude oil and agricultural commodities. By focusing on both biofuel-related and non-biofuel-related commodities, my research aims to provide a broad and nuanced understanding of how renewable energy adoption is reshaping traditional price dynamics in these interconnected markets in different regions.

The motivation for this study arises from a gap in the current literature. While many studies have examined the historical relationship between oil and agricultural commodities, most focus on direct cost drivers like transportation or fertilizer expenses. For instance, Hanson et al. (1993) and Baffes (2007) highlighted how rising oil prices increase agricultural production costs, leading to price spillovers. Later research, such as Nazlioglu (2011), expanded this understanding by uncovering nonlinearities in the oil-commodity price relationship. Despite all these studies, the role of renewable energy—particularly its potential to moderate or amplify these linkages—remains underexplored. This thesis addresses this gap by incorporating renewable energy usage as a key variable and examining its impact over both the short and long term.

By employing a comprehensive methodological approach that includes time-varying regressions, cointegration tests, and dynamic models, this thesis captures both short-term fluctuations and long-term trends in these relationships. A particularly innovative aspect of the analysis is the division of the study period into two distinct eras: before and after the rise of biofuels in the mid-2000s. This detailed approach highlights how renewable energy adoption has impacted the role of biofuel-related commodities in energy markets, while also shedding light on the varying impacts of renewable energy on non-biofuel commodities.

The study's findings make important contributions to this area. For biofuel-related commodities such as maize, soybeans, and wheat, the results reveal significant changes in their price linkage with oil, driven by the rise of biofuels as a major energy source. For example, maize, a key input for ethanol production, has increasingly decoupled from oil prices over time, with renewable energy policies and an increasing demand for biofuels shifting its price dynamics. In contrast, soybeans, widely used for biodiesel, show a strengthening price linkage with oil in recent years, reflecting their growing integration into energy markets. Wheat, which plays a

smaller role in biofuel production, displays a more stable but still evolving relationship with crude oil.

For non-biofuel-related commodities, the results are less consistent and vary depending on regional and macroeconomic factors. These commodities, which are not directly tied to renewable energy production, display a non-linear relationship with oil prices that is shaped by local energy policies, market structures, and broader economic conditions. The findings suggest that renewable energy usage can influence these linkages, but its effects are not uniform and often depend on the specific context of each market.

LITERATURE REVIEW

1. Historical Price Relationship between Oil and Agricultural Commodities

The historical relationship between oil and agricultural commodity prices is complex, influenced by various direct and indirect sources. Initially, this relationship was explored on the basis of a cost-driven theory, in which rising oil prices led to increased costs for fertilizers, pesticides, and transportation, thus raising agricultural production costs. Early studies by Hanson et al. (1993) using a Computable General Equilibrium model noted the disproportionate and irregular impact of oil price shocks on the agricultural sector compared to other sectors, underlining agriculture's dependency on energy inputs. Baffes (2007) later reinforced these findings, showing that changes in crude oil prices significantly influence a range of agricultural commodities, with the magnitude of the effect varying across different commodity types.

Recent literature has sought to understand this relationship through linear and nonlinear causality models. For example, studies by Nazlioglu (2011) using nonlinear causality testing found persistent, unidirectional causality from the oil prices to commodities prices like Corn and Soybeans, even though linear models did not detect this relationship. These nonlinearities, deemed as a consequence of the time-varying nature of the volatility of agricultural commodity prices by Myers (1994), may result from factors like inventory holding behaviors, asymmetry in storage and carry costs, and the economic conditions surrounding supply and demand as for Ahti (2009), Deaton and Laroque (1995), and Rapsomanikis et al. (2003). Campiche et al. (2007) further explored these dynamics using cointegration techniques and reported a significant relationship between crude oil and certain agricultural commodity prices (Corn and Soybeans) during the biofuel-driven price boom of 2006-2007, a period marked by increased biofuel production that heightened oil-agricultural linkages, whereas there is proof of no

cointegration between such variables during the 2003-2005 period. Ciaian and Kancs (2011) corroborates this phenomenon by analyzing for an extended sample period.

The global food crisis experienced during the first decade of the 21st century underscored the interdependence of oil and agricultural prices. Researchers such as Mitchell (2008), Abbott et al. (2008), Radetzki (2006), Hamilton (2009), Kilian (2009) and Wolf (2008) argue that the crisis was driven by a mix of high oil prices, increased biofuel demand, and the increasing demand of highly growing economies which led to significant comovements between oil and food prices, rather than price spillovers from oil to agricultural commodity markets. Studies by Zhang et al. (2010) and Gilbert (2010) found that speculative activities further exacerbated the price surges, with oil prices and macroeconomic factors such as GDP growth and exchange rates indirectly driving agricultural markets through investor behavior and policy changes. Plus, the first aforementioned also states that there is a clear shift regarding the producers' motivation: now they need to decide whether to produce for oil or for people, which in the end comes down to the profitability of the choices. This crisis renewed academic interest in understanding the conditions under which oil prices drive agricultural markets and spurred further studies using both linear and nonlinear models to capture this nuanced dynamic.

In the years following the food crisis, studies employing structural and dynamic models such as the ones done by Wang et al. (2014) and Umar et al. (2021) have shown that price linkages tend to vary across different economic cycles and are particularly sensitive during periods of volatility. These models suggest that during periods of economic stability, agricultural prices are less sensitive to oil price changes, whereas during periods of instability agricultural commodities are more sensitive to oil shocks, supporting findings by Kristoufek et al. (2012) which show that the oil-agricultural linkages intensified post-crisis.

2. Impact of Oil Volatility on Agricultural Commodity Volatility

The transmission of oil price volatility to agricultural markets has gained significant attention, particularly as financialization has increased the integration of energy and agricultural markets. Volatility spillovers have been observed during times of crisis, where shocks (of every kind) in oil prices amplify price fluctuations in agricultural commodities. Du et al. (2011) found that volatility spillovers from oil to Corn and to Wheat became more pronounced as these commodities became essential inputs for biofuel production, thereby increasing their exposure to the oil market dynamics. On top of this, this study also highlighted how speculative activity

in energy markets significantly impacts agricultural commodity prices, reflecting an increasing interdependence mainly due to biofuel demand.

Additional papers, such as those by Kilian (2009) and Y. Wang et al. (2014), emphasize that oil price volatility impacts agricultural commodity prices differently depending on the origin of the shock (demand-driven or supply-driven). Kilian's decomposition of oil price shocks into demand, supply, and oil-specific shocks using SVAR frameworks found that demand shocks have the most substantial impact on agricultural commodity prices; Y. Wang, following the same methodology but distinguishing between pre- and post-food crisis (2006-2008), supported the same conclusion by obtaining significant results for demand shocks under both periods of analysis and non-significant results for supply shocks pre- and post-crisis and for oil-specific shocks pre-crisis. Similarly, Umar et al. (2021) found that volatility connectedness increases during economic crises, with risk shocks from oil markets having a more intense impact on agricultural commodities than demand- or supply-driven shocks. This differentiation among results underscores that volatility transmission is not uniform and is often amplified by exogenous economic shocks.

Beyond crisis periods, other research highlights that the method of analysis can significantly influence findings on volatility spillovers. For example, regarding early stages of the relationship analysis, Babula and Somwaru (1992) discovered that oil shocks directly impact prices of agricultural chemicals and fertilizers, which in turn increase production costs for agriculture. Saghaian (2010) and Cha and Bae (2011), using Vector Error Correction Models (VECM) and Vector Autoregression (VAR) models, respectively, proved causality and concluded that volatility from oil prices indeed spills over to agricultural markets, particularly for Corn, Soybeans, and Wheat. In addition to this direct correspondence, Esmaeili and Shokoohi (2011) point out the inherent indirect effect of oil prices on food prices as a result of the former's impact on the Food Production Index. The findings align with those of Natanelov et al. (2011), who noted that financialization in commodities markets through index investments and speculation further enhances the volatility spillovers between oil and agricultural commodities, creating a feedback loop where fluctuations in one market impact the other.

Studies utilizing GARCH and Stochastic Volatility (SV) models, like those of Engle (2002) and Taylor (1994), are the two main used in the literature and have been instrumental in capturing the complexity of volatility spillovers. This methodological diversity provides robustness and ultimately reveals that agricultural commodities are increasingly subject to the volatility

characteristics of the oil market, with volatility effects being more pronounced for biofuel-related crops like Corn and Soybeans.

3. Impact of Biofuel/Renewable energy Production on the Oil-Agriculture Price Linkage

The introduction of biofuels has drastically redefined the relationship between oil and agricultural commodities by creating a direct demand link between the two. Biofuels such as ethanol (derived from Corn and Wheat) and biodiesel (derived from Soybeans) have led to a phenomenon where agricultural commodities are increasingly affected by oil prices, as demand for these commodities evolves accordingly with oil prices. Baffes (2013) pointed out that the "food versus fuel" debate highlights this linkage, with high oil prices incentivizing biofuel production, which in turn leads to increases on food prices due to the channeling of food crops towards energy production.

Saghaian (2010) and Serra et al. (2013) conducted empirical studies to analyze the price adjustments between oil and biofuel-linked crops and found that agricultural commodities prices not only adjust more rapidly to oil price increases when biofuel demand is high as well as suffer more intensive spillovers, suggesting a structural shift in price dynamics related to biofuel policies and incentives. These policies, prominent in the U.S. and EU, have encouraged biofuel production and led to increased sensitivity of agricultural prices to oil markets.

Wang et al. (2014) also emphasize the role of biofuels in enhancing price transmission, as rising oil prices push up biofuel demand, creating a demand-driven effect on agricultural commodity prices. Their research illustrates that biofuel-related crops, due to their dual-purpose role in food and energy, have a stronger linkage with oil prices than any other agricultural commodities.

Moreover, international policy developments have accentuated this relationship. Chen et al. (2010) model shows that each percentage increase in oil prices can significantly increase the prices of biofuel-linked crops, which then can be further amplified by policies supporting renewable energy production and carbon reduction. These biofuel policies promote a price dependency between oil and agricultural commodities, with Corn and Soybeans particularly impacted as they form the primary inputs for ethanol and biodiesel production.

In sum, biofuel production has not only created a direct price linkage but also introduced a new level of interdependence between oil and agricultural markets. This cyclical dependency between food and fuel is expected to deepen as the world becomes more environmentally-aware and biofuel policies continue to expand, making agricultural markets more and more vulnerable

to fluctuations in oil prices. Consequently, the impact of renewable energy on price transmission will remain a significant area of research, shaping future analyses of oil-agricultural commodity relationships.

DATA

For this study I obtained monthly commodity price data from the World Bank Group website¹ from 1990 to 2020 for 6 different agricultural commodities: Cocoa, Coffee (Arabica), Sugar (European Union versus United States of America), Maize (corn), Soybeans and Wheat (US HRW). I selected these not only because they are the most well-known and traded but also because I wanted to compare the impact of renewable energy usage on two different types of agricultural commodities: the ones that are not used on the production of biofuel or other alternative energy sources, which are the first three aforementioned, and the ones that are used for that purpose on top of being used in the food industry, which are the latter three.

I used the same database to obtain price data regarding crude oil. On this study I mainly used WTI oil data solely because it was the best approximate for oil price given the regions I was studying for the majority of commodities, however, I also used Brent oil in order to make the comparison between EU and the US regarding Sugar. The descriptive statistics regarding this data are presented in Table 1. Moreover, Figures 1 to 3 show how the prices of oil and the agricultural commodities under analysis evolved over time.

	Involved in Renewable fuels (\$/mt)			Not involved in Renewable fuels (\$/kg)				Crude oil (\$/bbl)	
	Soybeans	Maize	Wheat (US HRW)	Sugar EU	Sugar US	Cocoa	Coffee (Arabica)	Brent	WTI
Mean	341.1	148.7	192.5	0.5	0.5	1.9	2.9	49.0	47.5
Std. Dev	117.7	59.1	68.1	0.1	0.1	0.7	1.1	32.5	28.9
Max.	684.0	333.1	439.7	0.8	0.9	3.5	6.6	133.9	133.9
Min.	183.0	75.3	102.2	0.3	0.4	0.9	1.2	9.8	11.3
Skewness	0.8	1.3	1.0	-0.2	1.9	0.4	0.7	0.8	0.7
Kurtosis	-0.4	1.1	0.4	-1.3	3.5	-0.9	0.6	-0.5	-0.5
Jarque-Bera	210.6	157.9	169.4	282.7	224.9	253.6	126.0	232.3	226.2

Table 1 - Descriptive statistics of all agricultural commodities and crude oil under scope

¹ <https://www.worldbank.org/en/research/commodity-markets>

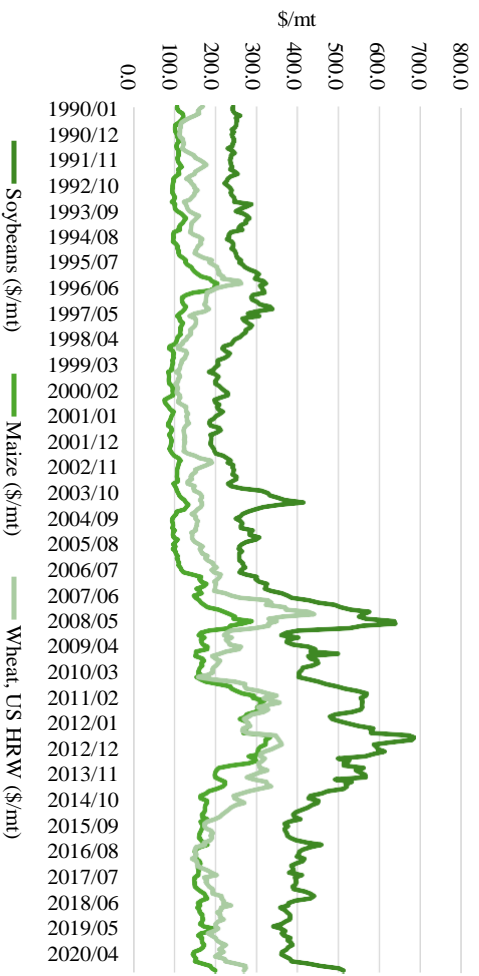


Figure 1 - Price of biofuel-related commodities between 1990 and 2020

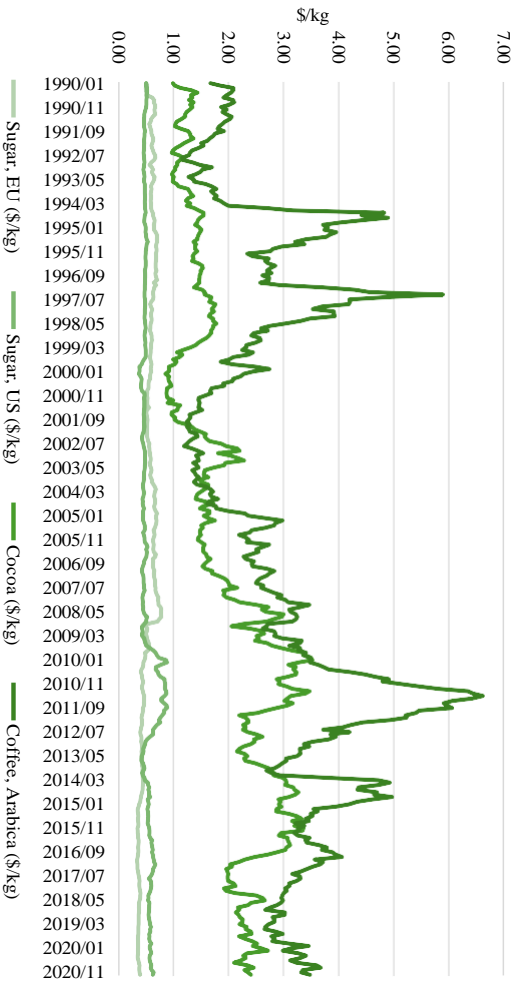


Figure 2 - Price of non-biofuel-related commodities between 1990 and 2020

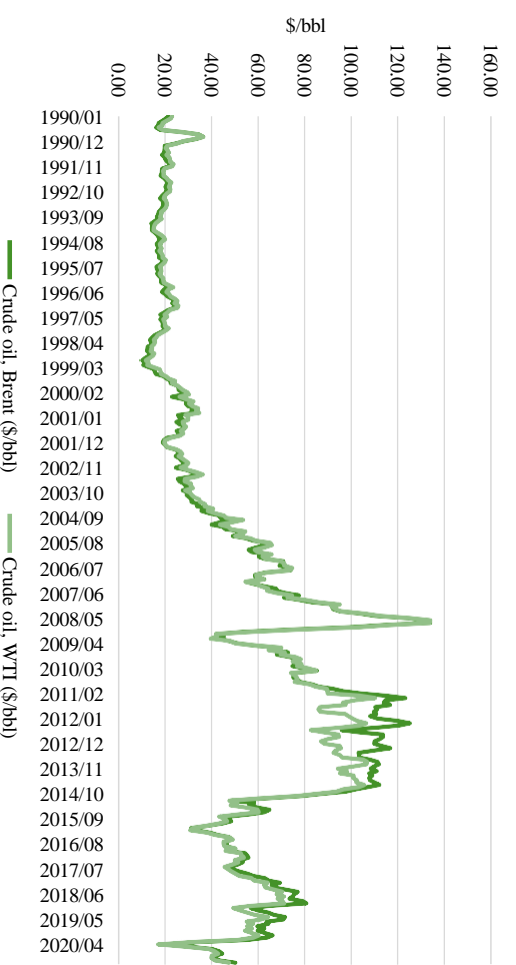


Figure 3 - Price of crude oil between 1990 and 2020

When it comes to the metric for renewable energy, I opted to use the renewable energy consumption as a percentage of the total final energy consumption of a country or region. Such data was also retrieved from the World Bank Group website but only on an annual basis from 1990 to 2020, and its evolution regarding every country and region studied is show in Figure 4.

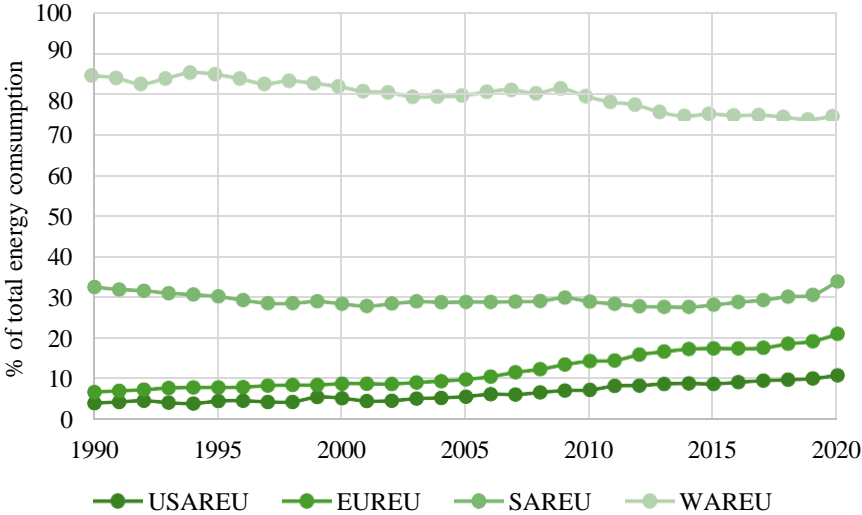


Figure 4 - Renewable energy usage levels of the regions under analysis from 1990 to 2020

The selection criteria for the countries’ renewable energy usage analyzed for every commodity was based on the quantity produced by country or region regarding 2022 obtained from the FAOSTAT website².

For Maize (corn), the United States of America was the country with the highest quantity produced with around 349 million tons, representing close to 30% of the world’s production. Regarding Cocoa, in order to better support my analysis, I decided to aggregate data by region rather than focusing on a single country. As a result, with four countries represented in the top six producers of Cocoa worldwide, West Africa was my choice with its top four producers (Côte d'Ivoire, Ghana, Cameroon and Nigeria, by order) accounting for almost 67% of the world's production (3.9 million tons). I apply the same thought process to Soybeans and Coffee: for the former, I select South America as the region of analysis, since Brazil, Argentina, Paraguay and Bolivia are all part of the top ten producers of 2022 (with Brazil as the biggest one) representing almost 50% of total production with more than 172 million tons; for the latter, I consider the same region (South America) as Brazil, Colombia and Peru are part of the seven

² <https://www.fao.org/faostat/en/#data/QCL>

biggest producers in the world (with Brazil topping the ranking once again) and hold close to 40% of the world's Coffee production with almost 4.2 million tons produced. When it comes to Wheat, the country under observation will be the United States of America solely because of a limitation in my data: the database of monthly data I use only has the price of American-produced Wheat; However, the USA is still the fourth biggest Wheat producer worldwide. For Sugar, the situation is quite different once again due to a limitation of the dataset: it provides data for the European Union and for the United States of America, which is useful for comparisons that will later be done, but it does not contribute to the ideology seen above as these two do not represent the main producers of Sugar worldwide, barely accounting for 10% of the world's production.

METHODOLOGY

With the aforementioned dataset, I employed a comprehensive and multi-faceted methodological approach in order to analyze the impact of renewable energy usage on the price linkage between oil and agricultural commodities. This approach integrates a range of econometric techniques such as OLS regression, fixed effects models to dynamic VAR analysis, Granger causality testing, cointegration analysis, and rolling window regressions, each chosen to capture different aspects of the complex relationship between energy and agricultural markets.

The study begins by importing and preparing the relevant data, which includes key variables such as the agricultural commodities' prices, oil prices whether it is WTIOil (West Texas Intermediate) or Brent, and a measure related to the renewable energy usage regarding the region under scope (REU). I also created an interaction term as the product of these last two variables. The interaction term captures the indirect effect of renewable energy on commodity prices through its modulation of the oil-commodity price linkage. In this case, an interaction term is essential because it allows for the combined influence of two variables to be analyzed, providing insights that single-variable effects cannot capture. Theoretically, these make sense when the relationship between the dependent variable and one independent variable depends on the level of another independent variable. In this study, renewable energy usage potentially alters how oil prices affect commodity prices, reflecting an interdependent dynamic, and so, an interaction term ensures that the model can account for these joint effects.

Firstly, an ordinary least squares (OLS) regression is conducted to provide a baseline understanding of the relationship between oil prices, commodity prices, and renewable energy.

This regression serves as a simple estimation tool, offering an initial assessment of how fluctuations in oil prices and REU might affect agricultural commodities.

I then add year fixed effects to my model to control potential biases caused by time-specific factors. This approach isolates the effects of variables such as WTIOil/BrentOil and REU on commodity prices by accounting for unobserved and exogenous temporal influences, including possible macroeconomic changes, policy shifts, or market-wide shocks.

In addition, I generate several time-varying interaction terms to allow the model to account for changing relationships in these market variables over time. These terms include the products of the “year” variable with WTIOil/BrentOil, REU of the region of analysis, and their interaction term. This time-varying regression is conducted because it differs from the OLS and fixed-year effects regressions in its ability to explicitly model how relationships between variables evolve over the time period of analysis: while OLS assumes that the relationship between variables is constant throughout the entire period and just captures the average effect of a variable across it, and fixed-year effects control for annual fluctuations by including dummy variables for each year, the time-varying regression is able to capture trends in how the relationship evolves, allowing for an estimate of whether and how the strength of these relationships progresses.

I then perform Vector autoregressions (VAR) to better understand the dynamic relationships between oil prices, renewable energy usage, and commodity prices. For this, I first need to find the optimal lag for each commodity. Unlike traditional regressions which focus on one-way relationships, VAR models treat all variables as interdependent and captures how each variable affects and is affected by itself and others over time. This is particularly beneficial for my study since it helps analyzing the feedback loops and time-lagged effects between variables.

To further explore the directionality of these interactions, Granger Causality Wald tests are conducted. These tests complement VAR by examining whether past values of one variable contain useful information for predicting future values of another variable, thereby offering evidence of causality. Establishing such causality is crucial for understanding whether changes in a certain variable drive changes in others, if the relationship is bidirectional, or if other dynamics are at play. Granger causality testing helps corroborating the findings observed with VAR by verifying possible trends and highlighting the drivers of movements.

Then, and after verifying the stationarity level of every variable and its optimal lag, I performed a Cointegration test that explores long-term relationships between oil prices, renewable energy

usage, and commodity prices. Differently from the aforementioned regressions that focus on short-term dynamics and immediate effects, cointegration analysis investigates whether these variables share a stable equilibrium relationship over the long run, despite occasional fluctuations over small periods of time. Thus, in search for consistency, cointegration tests results may differ from those of regressions because it operates on different timescales and assumptions. However, by integrating both approaches, I obtain complementary perspectives on how renewable energy usage shapes the oil-commodity price linkage across both short- and long-term horizons. It is important to note that even though the third regression performed (time-varying regression) accounts for the evolution of the relationship over time, it still differs from the cointegration test because it focuses on how the strength or direction of the relationship changes within the observed period, while the cointegration test identifies whether the variables are fundamentally tied together over extended periods despite short-term fluctuations (stable, long-term equilibrium).

Finally, to capture the changing nature of the coefficients over time, a rolling window regression is employed. This approach involves recalculating regression coefficients over a moving one-year window, allowing for the detection of temporal trends, structural breaks, and shifts in the relationship's intensity. I decided to work with a 12-month window because I am working with agricultural commodities, and such allows the regression to capture seasonal effects, like planting, harvesting, and market fluctuations driven by weather patterns, policy changes, or demand shifts. To have reasonable representations, I decided to winsorize the data by 5%.

RESULTS

To start my analysis, I will first look at commodities that are not related to the production of renewable energy/biofuel. Such commodities, which in this case are Cocoa, Coffee (Arabica), SugarUS and SugarEU, are then connected to oil and renewable energy mainly through production and transportation cost mechanisms.

Beginning with Cocoa, in the initial regression, the interaction term has a positive but statistically insignificant coefficient of 0.0005 (p-value = 0.119). When year fixed effects are introduced, the interaction term's coefficient increases to 0.0008 and approaches statistical significance (p-value = 0.086), implying that, once time-specific factors are accounted for, there is a more pronounced although very small moderate effect of renewable energy usage on the price linkage under analysis. In the third regression, which incorporates time-varying terms, the interaction term shifts and becomes highly significant and negative, with a coefficient of -

0.2726 (p-value < 0.001). This result shows that, as renewable energy usage declines (which is the case for West Africa), its ability to mitigate the influence of oil price fluctuations on Cocoa prices weakens, leading to a stronger and more adverse price linkage, essentially amplifying the sensitivity of Cocoa prices to oil prices. Plus, the significant coefficient for the time-varying interaction term (Time Interaction) further indicates that this combined effect strengthened over time, albeit very little.

When it comes to Coffee (Arabica), in the first regression, the interaction term has a coefficient of -0.0019 with a p-value of 0.236, indicating that it is not statistically significant. This suggests that, in this basic model, renewable energy usage does not meaningfully influence the price linkage between oil and Coffee. When year fixed effects are introduced, the interaction term remains insignificant, with a coefficient of -0.0014 and a p-value of 0.437. However, SAREU becomes statistically significant with a positive coefficient of 1.0160 (p-value < 0.001) revealing that renewable energy usage in South America independently and significantly influences Coffee market dynamics. As for the time-varying regression, the conclusion remains the same regarding the interaction term and is reinforced regarding the SAREU impact on Coffee prices. It supports the finding that SAREU does not significantly moderate the oil-Coffee price linkage but rather plays a significant role in directly shaping Coffee prices over time. However, the time-varying term for SAREU (Time SAREU) is statistically significant, with a coefficient of -0.0014 (p-value = 0.023) which indicates that the influence of renewable energy usage on Coffee prices diminishes slightly over time.

Now, analyzing Sugar prices in the European Union (SugarEU) and in the USA (SugarUSA), it is possible to reveal contrasting dynamics in how renewable energy usage influences these markets, mainly shaped by the regions' distinct renewable energy adoption patterns and market structures, particularly the larger and more mature renewable energy usage in the EU (EUREU) compared to the USA (USAREU), even though both regions verified a growing trend over time. It is also important to clarify that, in this study, Sugar is considered an agricultural commodity that is not related to renewable energy production due to the regions I am analyzing (USA and EU); if I was working with data regarding Sugar from South America, I would have had to include it in the category related to biofuel production.

In the first regression, the interaction term shows opposing effects: regarding the EU, it is negative and highly significant, indicating that increasing EUREU weakens the oil-Sugar price thus reducing the dependence of Sugar prices on oil prices, likely due to improved energy

efficiency and lower fossil fuel reliance in the EU's Sugar production systems; in contrast, for the USA, the interaction term is positive and significant, showing that increasing USAREU strengthens the oil-Sugar price linkage. At a first glance, these results seem to reflect the role of Sugar in biofuel production whether it was ethanol (moves in the opposite direction of crude oil prices) or biodiesel (moves alongside crude oil prices). However, that is not the case given that in both the US and the EU Sugar is mainly used for consumption. Additionally, EUREU has a negative and significant effect on Sugar prices, highlighting its role in reducing Sugar prices presumably by decreasing direct production costs, whereas USAREU and WTIOil in the USA show no significant independent effects.

When year fixed effects are introduced in the second regression, the results for the EU remain consistent, with EUREU reducing Sugar prices and weakening the oil-Sugar price linkage. The interaction term for SugarEU remains negative and significant, reinforcing the idea that renewable energy adoption in the EU decouples Sugar prices from oil price fluctuations. BrentOil retains its significant and positive effect, confirming that oil prices still influence Sugar prices, albeit mitigated by renewable energy usage. On the other hand, for SugarUSA, the interaction term becomes insignificant, and USAREU and WTIOil remain statistically insignificant, which could suggest that year-specific exogenous factors overshadow the direct relationship between these variables in the USA, further highlighting the weaker influence of renewable energy on Sugar prices compared to the EU.

In the third regression, which includes time-varying interaction terms, the divergence between the EU and USA become even clearer. For the EU, the interaction term remains negative and significant, whereas the time-varying interaction term is also significant but positive, thus revealing that, over time, renewable energy increasingly weakens the oil-Sugar price linkage in the EU. Interestingly, EUREU becomes positive and significant in this model, suggesting that while renewable energy reduces production costs in the short term, its broader adoption over time could contribute to systemic/market changes that raise Sugar prices.

For the USA, the results contrast sharply. The interaction term becomes more strongly positive and significant, but the time-varying interaction term, even though very small, is negative and significant. This demonstrates that renewable energy in the USA strengthens the oil-Sugar price linkage, but such phenomenon has been losing its strength as time goes by. USAREU itself has a significant negative effect on Sugar prices, indicating that despite strengthening the linkage with oil, renewable energy adoption still reduces prices, exerting downward pressure on costs.

WTIOil, however, remains insignificant, which goes to show its limited direct influence on Sugar prices in the USA when time-varying dynamics are accounted for.

The difference in the interaction term between the EU and USA, despite both primarily using Sugar for consumption, can most likely be explained, among other things, by differences in energy policies, market structures, and renewable energy adoption. In the EU, higher and rapidly growing renewable energy usage (EUREU) weakens the oil-Sugar price linkage, likely due to improved energy efficiency and reduced reliance on fossil fuels in Sugar production. Additionally, EU agricultural subsidies and localized supply chains further separate Sugar prices from oil price fluctuations. Conversely, in the USA where renewable energy adoption (USAREU) is slower and on a smaller scale and biofuel policies play a larger role, the oil-Sugar price linkage is stronger. Such result could be a symptom of USA's greater dependence on oil for transportation and agricultural inputs, as well as spillover effects from biofuel production dynamics.

Moving to the Vector Autoregression (VAR) model, results for Cocoa reveal that the lagged values of Cocoa prices (L1 and L2) significantly influence current Cocoa prices, with coefficients of 1.1554 (p-value < 0.001) and -0.1946 (p-value < 0.001), respectively, highlighting strong price autocorrelation. However, the coefficients for WTIOil and WAREU in both lags are insignificant, which means that neither oil prices nor renewable energy usage independently drive Cocoa prices within this framework. On top of this, the Granger causality Wald tests back up such conclusions, as the results indicate that the price dynamics of Cocoa are largely self-driven, with no significant causal relationship detected between Cocoa, WTIOil, and WAREU.

The VAR results for Coffee (Arabica) show significant autocorrelation in Coffee prices, with L1 (coefficient = 1.1240, $p < 0.001$) positively influencing current prices and L3 (coefficient = -0.1107, $p = 0.032$) having a smaller negative effect, whereas WTIOil and SAREU are insignificant in the Coffee equation. Moreover, SAREU at L3 (coefficient = 3.1407, $p = 0.002$) significantly impacts WTIOil, suggesting renewable energy may indirectly influence oil price dynamics. Once again, the Granger causality Wald tests confirm these findings, showing no evidence that WTIOil or SAREU Granger-cause Coffee prices (p-values = 0.243 and 0.433, respectively), but rather that SAREU appears to Granger-cause WTIOil (p-value = 0.014).

The Vector Autoregression (VAR) analysis reveals, once again, differing dynamics between Sugar in the European Union (SugarEU) and Sugar in the USA (SugarUSA). For SugarEU, the

results demonstrate significant autocorrelation in Sugar prices with positive influence from the first lag (coefficient = 1.0892, $p < 0.001$) and a smaller, negative influence from the second lag (coefficient = -0.2308, $p = 0.003$). Brent oil prices at the first lag positively impact SugarEU prices (coefficient = 0.0006, $p = 0.007$), reflecting a linkage between energy prices and Sugar markets in Europe. Additionally, the Granger causality tests confirm a bidirectional relationship between SugarEU and Brent oil prices. As for SugarUSA, the VAR results also show strong autocorrelation, with the first lag having a positive influence on current Sugar prices (coefficient = 1.2954, $p < 0.001$) and the second lag exerting a negative influence (coefficient = -0.3311, $p < 0.001$). However, unlike SugarEU, neither WTIOil nor USAREU shows direct significant effects on SugarUSA prices in the VAR results. Moreover, the Granger causality tests indicate no significant causal relationships between SugarUSA, WTIOil, and USAREU, suggesting that Sugar prices in the USA may operate more independently of energy price dynamics than their European counterpart.

Overall, we can observe that Cocoa, Coffee (Arabica) and Sugar (USA and EU) prices are mainly self-driven with their own historical price movements significantly influencing current prices, rather than by external factors like oil prices, renewable energy usage, or other macroeconomic variables.

Lastly, the Johansen cointegration tests for Cocoa, Coffee (Arabica) and Sugar (USA and EU) reveal a statistically significant long-term relationship for all commodities.

In terms of Cocoa, WTIOil has a negative and significant coefficient (-0.7109, $p = 0.018$), indicating that higher oil prices are associated with lower Cocoa prices over time. Plus, renewable energy usage in West Africa (WAREU), which has been declining over time, also shows a significant negative impact on Cocoa prices (-0.4101, $p = 0.025$). These results could appear to be quite contradictory but could just be reflecting an indirect effect rather than a direct cost relationship, as we are not accounting for other macroeconomic effects, competitive pressures and market and political dynamics. On the other hand, the interaction term between WTIOil and WAREU is positive and significant (0.0082, $p = 0.027$), which indicates that renewable energy usage, despite its decline, plays a critical role in mitigating the adverse effects of oil price fluctuations on Cocoa prices. While a positive interaction term implies a stronger linkage, the ongoing reduction in WAREU decreases this effect, making the oil-Cocoa price linkage progressively weaker.

In the case of Coffee (Arabica), contrary to Cocoa, WTIOil has a positive and significant coefficient (0.8641, $p = 0.024$), indicating that higher oil prices lead to higher Coffee prices over time. As for renewable energy usage in South America (SAREU), which has remained relatively stable over time, it exhibits a counterintuitive positive and significant impact on Coffee prices (1.2310, $p = 0.024$), suggesting that the consistent level of renewable energy usage may help supporting market prices. However, the interaction term between WTIOil and SAREU is negative and significant (-0.0314, $p = 0.018$), evincing that renewable energy helps dampen the long-term impact of oil price increases on Coffee prices.

Regarding SugarEU, the cointegration test finds a significant positive interaction term (coefficient = 0.00065, $p = 0.001$). The fact that renewable energy usage levels in the EU strengthen the oil-Sugar price linkage over the long term weirdly suggests that oil price dynamics remain closely tied to Sugar prices as renewable energy expands in the region. BrentOil, on the other hand, report a negative significant coefficient whereas EUREU is insignificant.

When it comes to SugarUSA, the cointegration test presents a significantly negative interaction term (-0.0051, $p = 0.001$). This finding demonstrates that renewable energy usage in the U.S. weakens the oil-Sugar price linkage over the long term. As renewable energy adoption grows in the U.S., Sugar prices appear to decouple from oil price fluctuations, even though, on a long-term basis, increases in WTIOil and USAREU alone would positively contribute to an increase in SugarUSA.

The cointegration results partially align with the findings from the earlier regressions, offering a deeper understanding of the long-term dynamics at play. For Cocoa, both analysis emphasize the significant impact of declining renewable energy usage (WAREU) in West Africa. While the regressions showed that WAREU independently reduced Cocoa prices and moderated the impact of oil prices, the cointegration results reinforce this by highlighting WAREU's role in buffering the long-term adverse effects of WTIOil, despite its ongoing decline. In the case of Coffee, the stable level of renewable energy usage (SAREU) in South America emerges as a key factor in both analyses. The regressions demonstrated that SAREU positively influences Coffee prices and weakens the oil-Coffee price linkage, which is echoed in the cointegration results (significantly this time), where SAREU stabilizes the market though supporting higher prices. The results for SugarEU also highlight a drastic contrast between short-term and long-term dynamics. In regressions, the interaction term was consistently negative, suggesting a

weakening oil-Sugar price linkage. However, the cointegration test finds a surprisingly positive interaction term (albeit small), indicating that renewable energy actually strengthens this linkage over time. Given that this commodity is not primarily used for biofuel production, I could not find a reason as to why this shift occurs other than the fact that the first regressions focus on a short-term scenario whereas the cointegration test provides a long-term perspective. As for SugarUSA, the latter findings offer a contrasting view when compared to the regressions since these always present a positive interaction term (even though not always significant) and the cointegration test reports a negative one. Such discovery highlights once again the short-term vs long-term dichotomy by showing that, on a short-term basis, renewable energy usage increases the oil-Sugar price linkage but, on a longer time perspective, it ends up weakening it, most likely due to the fact that Sugar is not tied to biofuel production in the USA. Strangely enough, as I mentioned before, Sugar is also not tied to biofuel production in the European Union, but the results do not match USA's numbers, which is something I have to attribute to regional differences and non-identical market dynamics. Additionally, USAREU and WTIOil, which were variables that were rarely significant on the first regressions, gain heavy and positive significance on the cointegration test.

In all cases, these results highlight the nuanced and region-specific role of renewable energy in moderating the linkage between oil prices and agricultural commodities, with its regional trends - declining, stable, or increasing - shaping both short-term impacts and long-term dynamics.

	Involved in Renewable fuels (\$/mt)			Not Involved in Renewable fuels (\$/kg)			
	Soybeans	Maize	Wheat (US HRW)	Sugar EU	Sugar USA	Cocoa	Coffee (Arabica)
Crude oil	12.21***	(1.32)***	0.54	0.01***	(0.00)	(0.03)	0.76
Region REU	18.31***	(9.66)***	(5.52)**	(0.01)***	0.01	(0.10)***	0.04
Crude oil (Year-fixed)	2.08	(0.22)	2.54***	0.01***	0.00	(0.05)	0.05
Region REU (Year-fixed)	95.94***	5.83**	18.59***	(0.01)***	0.00	(0.13)***	1.02***
Crude oil (Time-varying)	(143.55)	6.79	73.90	0.28**	(0.02)	16.61***	8.40
Region REU (Time-varying)	12.88	(2208.99)***	(1570.84)**	2.71***	(4.60)***	0.62	3.00**
Time Crude Oil	0.08	(0.01)	(0.04)	(0.00)**	0.00	(0.01)***	(0.00)
Time Region REU	0.01	1.09***	0.77**	(0.00)***	0.00***	(0.00)	(0.00)**
Crude Oil (Cointegration)	(6.63)	5.14***	1.56	(0.01)***	0.03***	(0.71)**	0.86**
Region REU (Cointegration)	(16.34)	39.40***	26.16***	(0.01)	0.22***	(0.41)**	1.23**

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 2 - Coefficients of all commodities under scope from the regressions and the Johansen cointegration test

	Involved in Renewable fuels (\$/mt)			Not Involved in Renewable fuels (\$/kg)			
	Soybeans	Maize	Wheat (US HRW)	Sugar EU	Sugar USA	Cocoa	Coffee (Arabica)
Interaction (OLS)	(0.2971)***	0.3772***	0.1858***	(0.0003)***	0.0003**	0.0005	(0.0019)
Interaction (Year-fixed)	0.0022	0.0405	(0.2062)*	(0.0003)***	0.0001	0.0008*	(0.0015)
Interaction (Time-varying)	(2.5152)	102.9863***	54.8529***	(0.0774)***	0.1894***	(0.2726)***	(0.4242)
Time Interaction	0.001	(0.0505)***	(0.0269)***	0.0000***	(0.0001)***	0.0001***	(0.0002)
Interaction (Cointegration)	0.062	(0.9879)***	(0.5719)***	0.0007***	(0.0051)***	0.0082**	(0.0314)**

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3 - Interaction terms of all commodities from regressions and Johansen cointegration test

I now turn my analysis to agricultural commodities that are key in the production of biofuels and other agricultural-related renewable energy sources to explore how renewable energy usage impacts the oil-commodity price linkage for this specific type. I will now have to account not only for the impact renewable energy usage has on the production of these commodities, but also for the impact these commodities have on the production of renewable energy.

Starting with Soybeans, in the first regression, the interaction term is negative and significant (coefficient = -0.2971, $p = 0.004$), which is a sign that renewable energy usage in South America weakens the oil-Soybeans price linkage. Consequently, this means that the higher the renewable energy usage, the less Soybeans are affected by oil price fluctuations. In addition, both WTIOil and SAREU exhibit a positive and significant impact (coefficient = 12.2147, $p < 0.001$ and coefficient = 18.3106, $p < 0.001$, respectively) on the price of Soybeans, suggesting that increases in both lead to an increase in the price of the agricultural commodity under scope. The former is quite expected since an increase in oil prices innately leads to an increase in production and transportation costs and also leads to an increase in demand of biodiesel which in turn increases the demand and consequently the price of soybeans; however, the latter is a bit more counter-intuitive mainly because of the coefficient of the interaction term but, as I mentioned before, renewable energy usage may actually not lead to a reduction in costs but rather to an additional value as a result of sustainability premiums. With the inclusion of year fixed effects, the interaction term actually becomes insignificant (coefficient = -0.0022, $p = 0.988$), showing that the moderating effect of renewable energy usage on the oil-Soybeans price linkage is less evident when accounting for year-specific factors, such as macroeconomic conditions or energy policies. SAREU remains positive and highly significant (coefficient = 95.9419, $p < 0.001$), with an even larger magnitude compared to the first regression, whereas

WTIOil becomes insignificant (coefficient = 2.0811, $p = 0.633$), suggesting that oil prices' influence on Soybeans prices is less consistent when temporal dynamics are considered.

Looking at the time-varying regression, the interaction term remains negative and insignificant (coefficient = -2.5152, $p = 0.877$). Such results demonstrate that there is no statistically meaningful influence of renewable energy on moderating the oil-Soybeans price linkage when time effects are accounted for, which ends up aligning with the relatively stable levels of South American renewable energy usage over time, indicating that its moderating effect does not change significantly in the long term. On top of this, the time-varying interaction term (Time interaction) is insignificant (coefficient = 0.001, $p = 0.902$), showing no significant change in the moderating role of renewable energy over time.

Overall, the regressions for Soybeans highlight that renewable energy usage in South America initially appears to weaken the oil-Soybeans price linkage. Although these effects become less pronounced and statistically insignificant when temporal factors are accounted for, SAREU's relatively stable levels over time most likely explain this result, as its role in moderating the oil-Soybeans price relationship remains consistent but not dynamic. Disregarding this and knowing its importance in biodiesel production, a direct substitute of oil, I would have expected the oil-Soybeans price linkage to actually strengthen over time.

Maize, like Soybeans, is a critical input for biofuel production, but rather for ethanol. Looking now for the results obtained regarding such commodity we can see that, in the first regression, the interaction term is positive and highly significant (coefficient = 0.3772, $p < 0.001$). This indicates that the growing American renewable energy usage strengthens the oil-Maize price linkage, and so, as USAREU increases, the impact of oil price changes on Maize prices becomes more pronounced. Since Maize is used for ethanol production and considering that ethanol is not a direct substitute of oil like biodiesel is, such result was not expected. USAREU itself has a negative and significant coefficient (coefficient = -9.6619, $p < 0.001$), suggesting that higher renewable energy usage is associated with lower Maize prices, probably due to a cost reduction effect of renewable energy in Maize production. WTIOil has a negative and significant coefficient (coefficient = -1.3178, $p < 0.001$), which is unexpected and may be a result of exogenous market dynamics.

In the second regression, after controlling for year fixed effects, USAREU becomes positive and significant (coefficient = 5.8304, $p = 0.037$). This shift makes sense and could imply that, when accounting for temporal dynamics like biofuel policies that impact Maize or ethanol

production or global market conditions, higher renewable energy usage correlates with higher Maize prices, given that an increasing ethanol production leads to a growing Maize demand. Meanwhile, WTIOil and the interaction term become insignificant, hinting that there could be some year-specific factors like agricultural subsidies, trade policies, or other economic conditions that overshadow not only the impact of renewable energy usage on the oil-Maize price relationship but also the relationship itself.

The results obtained in the third regression when accounting for time-varying effects and its evolutionary behavior are mostly consistent with the ones obtained in the first regression given that I could observe a positive and highly significant interaction term (coefficient = 102.9863, $p < 0.001$) and a negative and significant USAREU coefficient (coefficient = -2208.993, $p < 0.001$). Regardless, the time-varying interaction term is negative and significant (coefficient = -0.0505, $p = 0.010$), indicating that the strengthening effect of USAREU on the oil-Maize price linkage slightly decreases over time, which faintly supports the increasing role of renewable energy in shaping the Maize market as biofuel policies and investments in renewable energy infrastructure expand over time.

All in all, these regressions for Maize reveal that renewable energy usage (USAREU) plays a dual role in this situation: on top of directly lowering Maize prices through what I believe to be cost-saving efficiencies, it simultaneously amplifies the oil-Maize price linkage, even though counterintuitively. Nevertheless, this cost-demand dynamic in which Maize is seen both as the final product as well as a mean to an end becomes less pronounced over time.

For Wheat, in the first regression, the interaction term (WTIOil * USAREU) is positive and significant (coefficient = 0.1858, p -value = 0.001), suggesting that renewable energy usage amplifies the impact of oil prices on Wheat prices. However, USAREU itself has a significant negative coefficient (coefficient = -5.5197, p -value = 0.026), indicating that higher renewable energy usage reduces Wheat prices, likely by cutting logistics costs.

When year fixed effects are added in the second regression, the interaction term becomes negative and marginally significant (coefficient = -0.2062, p -value = 0.072). This shift implies that renewable energy usage might moderate the oil-Wheat price linkage when time-specific factors are accounted for. Interestingly, USAREU's coefficient becomes positive and strongly significant (coefficient = 18.5921, p -value < 0.001), suggesting that renewable energy usage supports higher Wheat prices in this model, potentially reflecting broader energy-related market dynamics or stabilization effects.

Such disparity of results is clarified on the third regression model that presents an interaction term that is highly significant and positive (coefficient = 54.8529, p-value < 0.001), indicating that renewable energy usage strongly amplifies the oil-Wheat price linkage over time. However, the time-varying interaction term (Time interaction) is negative and significant (coefficient = -0.0269, p-value = 0.006), suggesting that this amplification diminishes slightly as time progresses, most likely due to adjustments regarding market dynamics or renewable energy policies. Notably, USAREU itself becomes strongly negative (coefficient = -1570.844, p-value = 0.012), reflecting its direct cost-reducing impact on Wheat prices when isolated from time dynamics and interaction effects.

Moving into the autocorrelation and causality testes, the VAR results for Soybeans indicate strong price autocorrelation, with L1 positively (1.1381, $p < 0.001$) and L2 negatively (-0.1774, $p = 0.001$) affecting current prices. WTIOil does not directly influence Soybeans prices, but Granger causality tests show that WTIOil Granger-causes Soybeans prices ($p = 0.009$), suggesting an indirect effect. SAREU shows significant autocorrelation, with L1 (0.9973, $p < 0.001$) reflecting stable renewable energy trends, but it neither directly impacts nor Granger-causes Soybeans prices. Overall, Soybeans prices are shaped by their own lags and indirectly by oil price dynamics, while SAREU plays a limited role.

Concerning Maize, VAR tests reveal significant price autocorrelation, with L1 positively influencing prices (1.2039, $p < 0.001$) and L2 having a negative effect (-0.2483, $p < 0.001$). Maize prices at L1 significantly affect WTIOil (0.0526, $p = 0.019$), while WTIOil exhibits strong autocorrelation in its own lags (L1: 1.3427, $p < 0.001$; L2: -0.3869, $p < 0.001$). However, USAREU does not significantly impact Maize or WTIOil in this model. Granger causality tests confirm that Maize prices Granger-causes WTIOil ($p = 0.022$), indicating oil price dynamics are related to Maize markets, likely through shared production inputs or biofuel linkages. Overall, Maize prices are primarily influenced by their own history and related to oil prices, while USAREU shows no direct role in short-term price dynamics.

Regarding Wheat (US), the VAR results show significant autocorrelation in Wheat prices, with L1 (coefficient = 1.1857, $p < 0.001$) positively influencing current prices and L2 (coefficient = -0.2596, $p < 0.001$) negatively contributing, while neither WTIOil nor USAREU have a significant direct impact on Wheat prices across the lags. Interestingly, as for the causality tests, Wheat prices significantly Granger-cause WTIOil ($\chi^2 = 13.306$, $p = 0.001$), suggesting that

movements in Wheat prices may influence oil price dynamics, while USAREU does not appear to have a direct or causal effect on Wheat prices or WTIOil.

Considering now the Johansen cointegration test, results for Soybeans indicate no significant long-term interaction term (coefficient = 0.0620, $p = 0.910$), which means that it is not possible to say that renewable energy usage levels in South America strengthen or weaken the oil-Soybeans price linkage over time. Neither of the variables under analysis present significant results and so, notwithstanding the fact that these are bound by a long-term relationship, individually, WTIOil, SAREU, and their interaction do not have statistically significant impacts on Soybeans in the long term.

The cointegration test for Maize reveals a significant and negative interaction term (-0.9879 , $p < 0.001$), indicating that, in the long run, renewable energy usage in the U.S. weakens the oil-Maize price linkage. This weakening relationship highlights the separation of Maize prices from oil prices in all likelihood due to the use of Maize in ethanol production; however, WTIOil and USAREU still present highly significant and positive coefficients (5.1356 and 39.4039, respectively).

For Wheat, the cointegration test shows a markedly different pattern given that WTIOil has a positive but insignificant coefficient (1.5614, $p = 0.293$), and, in contrast, USAREU has a strong positive and significant coefficient (26.1584, $p = 0.006$), indicating that higher renewable energy usage is associated with higher Wheat prices over time. Nevertheless, the interaction term between WTIOil and USAREU is negative and significant (-0.5719 , $p = 0.005$), showing that increasing renewable energy usage in the USA reduces the sensitivity of Wheat prices to oil price changes, diminishing the literature-backed price linkage.

When comparing cointegration results with previous regressions, several differences and alignments emerge. For Soybeans, the cointegration test aligns well with regression findings, with both showing that the interaction term is insignificant, reflecting a weak or nonexistent relationship between oil, renewable energy, and Soybeans prices.

For Maize, however, the results differ significantly. While the regressions showed a heavily positive interaction term, suggesting a strengthening oil-Maize price linkage, the cointegration test reveals a negative interaction, indicating a weakening linkage over time. This discrepancy implies that the immediate short-term effects observed in the regressions may dissipate as markets and society in general adapt to renewable energy changes, with the long-term trend

leaning towards reduced oil dependence in the Maize market. It is important to note that the latter makes more sense given the context in which Maize is used in biofuel production (ethanol).

As for Wheat, the discrepancy in results occur most likely due to the short-term vs long-term dynamics of both models. The high positive interaction term in the time-varying regression reflects strong short-term sensitivity between oil and Wheat prices as renewable energy usage increases. In contrast, the smaller, negative interaction term in the cointegration test captures the stabilizing effects of renewable energy over time.

Overall, these comparisons underscore once more the importance of examining both short-term and long-term perspectives. While regressions highlight immediate price linkages, cointegration tests reveal underlying, enduring trends shaped by renewable energy adoption and regional market structures. These discrepancies observed accentuate the importance of context when analyzing renewable energy's role in agricultural commodity markets, emphasizing how the perspective under analysis can yield opposite conclusions.

Finally, I dived deep into biofuel-related commodities and decided to do another cointegration test, but now comparing two smaller periods of the main sample. Coincidentally, I divide the sample in half because the year 2005 represents a pivotal turning point in the global biofuel industry due to the convergence of key policy initiatives, economic drivers, and technological advancements that fundamentally reshaped biofuel's market. Central to this transformation was the introduction of the Renewable Fuel Standard (RFS) under the U.S. Energy Policy Act of 2005.³ This policy mandated the blending of renewable fuels, such as ethanol and biodiesel, into transportation fuels, starting with a target of 4 billion gallons in 2006 and increasing to 7.5 billion gallons by 2012. By providing substantial government support, the RFS incentivized investments in biofuel infrastructure and production, firmly integrating biofuels into energy markets. Globally, other regions followed similar trajectories. In the European Union, the implementation of the Biofuels Directive gained momentum, and Brazil's ethanol industry expanded significantly, supported by government policies. These policy shifts were partially driven by the rapid rise in crude oil prices in the early 2000s, which averaged \$50–60 per barrel in 2005, making biofuels an economically attractive alternative to fossil fuels.

³ <https://cen.acs.org/articles/84/i30/Biofuels-Reality-Check.html?utm>

These developments established new linkages between energy and agricultural markets, and so, as a result, 2005 serves as a natural demarcation point for the biofuel industry's expansion, marking the transition from a pre-biofuel era to one characterized by substantial integration of biofuels into global energy systems. This shift provides a clear justification for analyzing biofuel-related commodities in two distinct periods: 1990–2005 (pre-expansion) and 2006–2020 (post-expansion), allowing for a more precise examination of how renewable energy developments altered oil-commodity price dynamics.

Lastly, it is important to note that I decided to conduct only a Johansen cointegration test because I believe this approach is more suitable than a time-varying regression for isolating and understanding the structural changes in the oil-commodity price linkage due to the aforementioned long-term contribution to the study. Plus, I also chose it over other cointegration tests such as Autoregressive distributed lag (ARDL) models because, unlike the latter that focuses on a single relationship, Johansen's method handles multiple cointegrating vectors and captures how variables adjust to maintain equilibrium over time, which is crucial in a system with various interdependent variables like oil prices, renewable energy usage, and commodity prices.

Looking at the results, on the first term (1990–2005), the interaction coefficient for Maize is significantly positive (19.08), suggesting that renewable energy usage (USAREU) strengthened the price linkage between Maize and WTIOil, which makes sense because, during this period, Maize was primarily influenced by traditional agricultural markets, and its price had a closer dependence on energy markets driven by oil. Now, on the second term (2006–2020), it is clear that, with the rise of renewable energy production, Maize prices became increasingly driven by renewable energy demand and less by oil price movements (negative interaction coefficient of 20.03). Essentially, as Maize started to be used for ethanol production, its price dynamics decoupled from oil and became more aligned with alternative energy factors.

For Soybeans, the interaction term is significantly negative (-81.78) in the first term (1990–2005), indicating that renewable energy usage weakened the price linkage between Soybeans and WTIOil. This is not consistent with the results obtained for Maize, even though Soybeans was also primarily an agricultural commodity during this period, with minimal ties to energy markets. In the second term (2006–2020), the interaction term becomes significantly positive (9.60), with this shift reflecting Soybeans' growing role as a biofuel input, particularly for

biodiesel. As biofuel demand increased during this period, the oil-Soybeans price linkage strengthened due to Soybeans becoming a closer direct substitute for oil in energy markets.

The difference in movements between Maize and Soybeans is explained by the fact that, even though both ethanol and biodiesel are tied to WTIOil due to their roles as substitutes for petroleum-based fuels, biodiesel tends to have a stronger and more direct relationship because it competes with diesel, which is more closely linked to WTIOil. Diesel's stronger connection to WTIOil arises from its broader industrial and commercial use and the absence of significant substitutes (other than biodiesel), whereas ethanol's connection to WTIOil is less direct and more often influenced by a mix of oil market dynamics, government policies and agricultural factors.

Regarding Wheat, the interaction term is significantly positive in both periods but decreases over time (63.57 in the first term vs. 1.51 in the second term). Although the effect has diminished, these coefficients show that renewable energy usage consistently strengthened the oil-Wheat price linkage. Such findings make sense given the position of Wheat in the renewable energy panorama: despite being used for ethanol production, which helps separating the commodity from crude oil price movements, it is not as commonly used as Maize, for example, and so it is still linked to WTIOil, just not as much as before. Overall, the majority of these results corroborate and build on previous findings, providing a more profound explanation of these agricultural commodities co-movements with oil prices.

	Pre-Biofuel expansion (1990-2005)			Post-Biofuel expansion (2006-2020)		
	Soybeans	Maize	Wheat (US HRW)	Soybeans	Maize	Wheat (US HRW)
WTIOil	2368.01***	(112.5056)***	(375.2445)***	(262.3015)***	175.7701***	(16.6071)***
REU	1804.125***	(268.2803)**	(905.7811)**	(454.7539)***	1287.934***	(111.5847)***
Interaction	(81.7783)***	19.0803***	63.5694***	9.6023***	(20.0310)***	1.5137***

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4 - Johansen Cointegration tests on both biofuel eras

INVESTOR AWARENESS

The findings of this thesis, particularly from the two-period cointegration tests, offer valuable insights for investors who seek to perform trades on the evolving relationships between renewable energy, oil prices, and agricultural commodities. By understanding how the oil-commodity price linkage changes over time and in response to the evolution of renewable

energy usage, investors can make more informed decisions about commodities, energy markets, and even renewable energy assets. The aforementioned insights allow investors to tailor their strategies to capitalize on changing market dynamics. For example, during periods of rising oil prices, it could be wiser for traders to invest in Soybeans or biodiesel-linked assets that may yield better returns due to their strengthened linkage. Conversely, during periods of renewable energy expansion or biofuel policy shifts, Maize and ethanol-related markets may offer exciting opportunities as they are more influenced by renewable energy demand than by traditional oil markets. Also, Wheat, which is more stable and less influenced by energy markets when compared to Maize and Soybeans, could be used by investors as a safer, less volatile commodity investment in portfolios focused on agricultural markets. Thus, understanding these dynamics may be crucial for diversifying portfolios across commodities and energy markets, balancing high-volatility assets like Soybeans with more stable commodities like Wheat.

FINAL REMARKS

This thesis investigates the impact of renewable energy usage on the oil-agricultural commodity price linkage, inspired and building on existing literature by analyzing both biofuel-related and non-biofuel-related commodities. By comparing findings across two distinct periods (1990–2005 and 2006–2020), it also provides a better understanding of how renewable energy development, particularly the rise of biofuel production, has influenced these relationships over time.

For commodities unrelated to biofuel, such as Cocoa, Coffee, and Sugar, the findings reveal no consistent trends in the oil-commodity price linkage. If we look at previous studies, such as Baffes (2007), it highlights the dependence of agricultural commodities on oil prices through cost-driven mechanisms like transportation and production inputs. On my thesis, I was able to support these findings in certain cases, such as Cocoa's stronger oil-price linkage during periods of declining renewable energy usage, while also being able to identify variations influenced by regional or commodity-specific factors. For instance, Coffee, despite stable renewable energy levels in South America, shows limited connection to oil prices, suggesting that its market dynamics remain largely self-driven. Sugar presents contrasting regional outcomes: renewable energy adoption in the EU weakens the oil-sugar price linkage on short-term basis but strengthen when looking on a longer perspective, whereas it was possible to observe the exact opposite results and evolution in the USA. For biofuel-related commodities like Maize, Soybeans, and Wheat, clear trends emerge, underscoring the transformative effect of biofuel

production. Consistent with studies such as Campiche et al. (2007), Ciaian and Kancs (2011), and Baffes (2013), Maize shows a significant decoupling from oil prices in the second period as biofuel demand becomes the dominant driver of its price dynamics. This aligns with the aforementioned studies which basically emphasize how biofuel production introduces structural changes to commodity price dynamics, particularly for feedstock crops. Conversely, Soybeans exhibit a strengthening oil-price linkage in the second period, driven by their growing use in biodiesel production, supporting Saghaian's (2010) findings on the role of policy incentives and consequent increase in demand. Wheat, on the other hand, less involved in biofuel production, shows a less clear long-term trend, even though still reflecting its partial decoupling from oil markets while remaining more stable in its price dynamics.

Thus, these results suggest distinct trajectories for commodities based on their relationship to biofuel production. For non-biofuel-related commodities, the oil-price linkage appears increasingly dependent on regional renewable energy usage and cost mechanisms rather than consistent global trends. For biofuel-related commodities, the findings highlight how the expansion of biofuel production has redefined their relationship with oil, either strengthening or weakening their price linkage depending on their specific role in energy markets.

LIMITATIONS

This thesis faced several limitations that could impact the depth and applicability of the findings. To start, one significant constraint was the reliance on monthly data since more detailed weekly or daily data was not available. Furthermore, the chosen metric for renewable energy usage—its percentage share of total energy consumption—was based on an assumption that may not fully represent the broader complexities of renewable energy adoption and its relationship with other energy markets. Plus, its accuracy can be slightly questionable as it can be quite complicated to measure.

Moreover, the geographical scope of the thesis, which focused on regions such as West Africa, South America, the USA, and the EU, means that the findings may not fully reflect global market dynamics. This regional emphasis could impact the usefulness of the results when applied on a larger scale. Another limitation was the exclusion of key external factors such as geopolitical risks, currency exchange volatility, global trade flows, and specific trade policies from the models, which could affect the robustness of the findings and would most likely explain or alter some of the dynamics observed.

Regarding the methodology, I would like to note that Granger causality tests have limitations when it comes to understanding directionality, especially in dynamic markets affected by external shocks. Even though these can show temporal relationships, it cannot prove true causation, which means that the results might oversimplify the complex ways the variables interact.

Lastly, the results primarily establish associations between renewable energy usage and oil-commodity price linkages, without providing conclusive evidence of causality. These limitations highlight the need for caution in interpreting the findings and suggest possibilities for future research to address these gaps.

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APPENDIX

	Vector Autoregression		
	Soybeans	WTIOil	SAREU
Soybeans L1	1.14***	0.02*	(0.00)
Soybeans L2	(0.18)***	(0.01)	0.00
WTIOil L1	0.36	1.33***	(0.00)
WTIOil L2	(0.23)	(0.39)***	0.00
SAREU L1	(1.13)	(0.72)	1.00***
SAREU L2	2.34	0.53	(0.00)

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5 - Vector Autoregression results for Soybeans

	Vector Autoregression		
	Maize	WTIOil	USAREU
Maize L1	1.20***	0.53**	0.00
Maize L2	(0.25)***	(0.04)*	(0.00)
WTIOil L1	0.02	1.34***	(0.00)
WTIOil L2	0.02	(0.39)***	0.00
USAREU L1	3.73	(2.05)	0.98***
USAREU L2	(3.43)	2.20	0.02

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6 - Vector Autoregression results for Maize

	Vector Autoregression		
	Wheat	WTIOil	USAREU
Wheat L1	1.19***	0.03*	0.00
Wheat L2	(0.26)***	(0.01)	(0.00)
WTIOil L1	0.25	1.34***	(0.00)
WTIOil L2	(0.13)	(0.41)***	0.00
USAREU L1	5.73	(2.04)	0.97***
USAREU L2	(5.45)	2.22	0.03

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7 - Vector Autoregression results for Wheat

	Vector Autoregression		
	Sugar EU	Brent Oil	EUREU
Sugar EU L1	1.09***	33.43**	0.76
Sugar EU L2	(0.23)***	(2.96)	(0.12)
Sugar EU L3	0.08	(24.83)	(2.54)***
Sugar EU L4	0.00	(5.09)	2.00***
Brent Oil L1	0.00***	1.35***	(0.00)
Brent Oil L2	(0.00)	(0.41)***	(0.00)
Brent Oil L3	(0.00)*	(0.07)	(0.00)
Brent Oil L4	0.00	0.11**	0.00
EUREU L1	(0.00)	(0.46)	0.93***
EUREU L2	0.01	(0.48)	0.02
EUREU L3	(0.00)	1.67	(0.00)
EUREU L4	(0.00)	(0.67)	0.06

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8 - Vector Autoregression results for Sugar EU

	Vector Autoregression		
	Sugar USA	WTIOil	USAREU
Sugar USA L1	1.30***	11.03	(0.01)
Sugar USA L2	(0.33)***	(9.57)	0.11
WTIOil L1	0.00	1.37***	(0.00)
WTIOil L2	(0.00)	(0.40)***	0.00
USAREU L1	0.01	(1.75)	0.98***
USAREU L2	(0.01)	1.93	0.02

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 9 - Vector Autoregression results for Sugar USA

	Vector Autoregression		
	Cocoa	WTIOil	WAREU
Cocoa L1	1.16***	(0.08)	0.05
Cocoa L2	(0.19)***	0.35	(0.09)
WTIOil L1	0.00	1.37***	(0.00)
WTIOil L2	0.00	(0.40)***	0.00
WAREU L1	(0.00)	(0.19)	0.97***
WAREU L2	0.00	0.14	0.02

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 10 - Vector Autoregression results for Cocoa

	Vector Autoregression		
	Coffee	WTIOil	SAREU
Coffee L1	1.12***	(0.03)	0.03
Coffee L2	(0.05)	0.74	0.02
Coffee L3	(0.11)**	(0.55)	(0.05)
WTIOil L1	0.00	1.36***	(0.00)
WTIOil L2	0.00	(0.39)***	(0.00)
WTIOil L3	(0.00)	0.00	0.00
SAREU L1	(0.07)	(0.65)	1.00***
SAREU L2	0.11	(2.51)*	0.00
SAREU L3	(0.03)	3.14***	(0.01)

*, **, *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 11 - Vector Autoregression results for Coffee

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
Soybeans	WTIOil	4.8426	2	0.089
Soybeans	SAREU	2.0403	2	0.361
Soybeans	ALL	5.7025	4	0.222
WTIOil	Soybeans	9.461	2	0.009
WTIOil	SAREU	1.6902	2	0.430
WTIOil	ALL	10.24	4	0.037
SAREU	Soybeans	.17577	2	0.916
SAREU	WTIOil	.1944	2	0.907
SAREU	ALL	.47625	4	0.976

Table 12 - Soybeans' Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
Maize	WTIOil	2.4072	2	0.300
Maize	USAREU	1.7681	2	0.413
Maize	ALL	5.3673	4	0.252
WTIOil	Maize	7.6124	2	0.022
WTIOil	USAREU	2.5697	2	0.277
WTIOil	ALL	10.914	4	0.028
USAREU	Maize	.21926	2	0.896
USAREU	WTIOil	.07636	2	0.963
USAREU	ALL	.48261	4	0.975

Table 13 - Maize's Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
WheatUSA	WTIOil	7.5145	2	0.023
WheatUSA	USAREU	1.5705	2	0.456
WheatUSA	ALL	11.149	4	0.025
WTIOil	WheatUSA	13.306	2	0.001
WTIOil	USAREU	3.195	2	0.202
WTIOil	ALL	16.658	4	0.002
USAREU	WheatUSA	2.4439	2	0.295
USAREU	WTIOil	.15409	2	0.926
USAREU	ALL	2.7088	4	0.608

Table 14 - Wheat's Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
SugarEU	BrentOil	18.666	4	0.001
SugarEU	EUREU	5.8747	4	0.209
SugarEU	ALL	34.048	8	0.000
BrentOil	SugarEU	11.729	4	0.019
BrentOil	EUREU	1.2842	4	0.864
BrentOil	ALL	13.501	8	0.096
EUREU	SugarEU	16.444	4	0.002
EUREU	BrentOil	4.7071	4	0.319
EUREU	ALL	25.196	8	0.001

Table 15 - Sugar EU's Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
SugarUSA	WTIOil	.45844	2	0.795
SugarUSA	USAREU	2.3688	2	0.306
SugarUSA	ALL	3.3654	4	0.499
WTIOil	SugarUSA	1.1224	2	0.571
WTIOil	USAREU	2.6221	2	0.270
WTIOil	ALL	4.3677	4	0.359
USAREU	SugarUSA	1.4442	2	0.486
USAREU	WTIOil	.09413	2	0.954
USAREU	ALL	1.7084	4	0.789

Table 16 - Sugar USA's Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
Cocoa	WTIOil	3.6172	2	0.164
Cocoa	WAREU	.64509	2	0.724
Cocoa	ALL	5.0247	4	0.285
WTIOil	Cocoa	.29464	2	0.863
WTIOil	WAREU	.32037	2	0.852
WTIOil	ALL	1.1389	4	0.888
WAREU	Cocoa	1.7526	2	0.416
WAREU	WTIOil	1.5121	2	0.470
WAREU	ALL	5.4079	4	0.248

Table 17 - Cocoa's Granger causality Wald tests results

Granger causality Wald tests

Equation	Excluded	chi2	df	Prob > chi2
CoffeeArabica	WTIOi1	4.1812	3	0.243
CoffeeArabica	SAREU	2.7417	3	0.433
CoffeeArabica	ALL	6.551	6	0.364
WTIOi1	CoffeeArabica	.96006	3	0.811
WTIOi1	SAREU	10.668	3	0.014
WTIOi1	ALL	11.937	6	0.063
SAREU	CoffeeArabica	1.5667	3	0.667
SAREU	WTIOi1	2.1989	3	0.532
SAREU	ALL	3.4114	6	0.756

Table 18 - Coffee's Granger causality Wald tests results

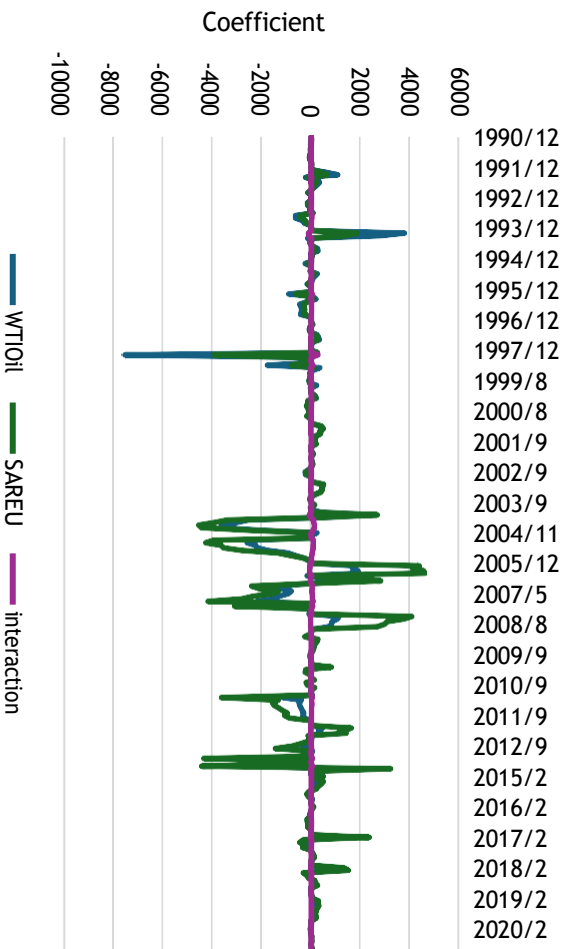


Figure 5 - Soybeans' rolling window regression coefficients

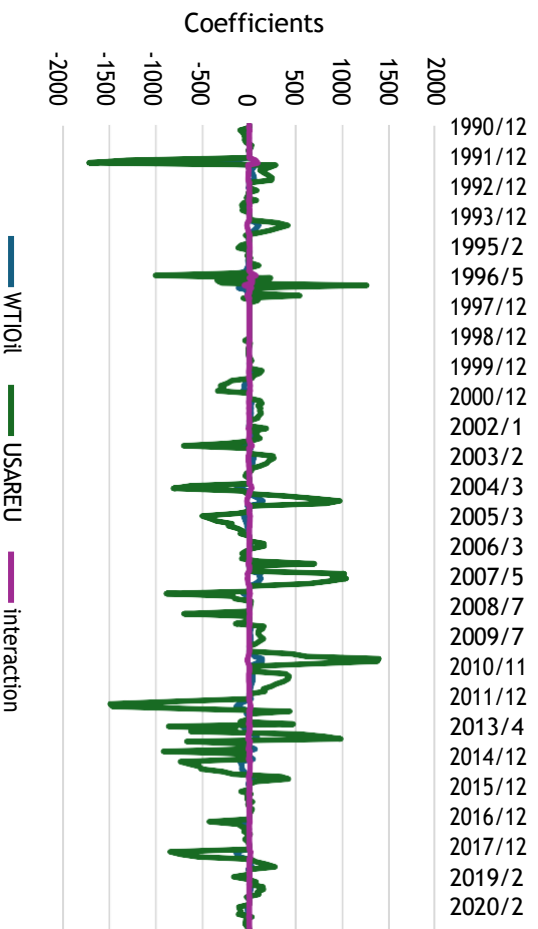


Figure 6 - Maize's rolling window regression coefficients

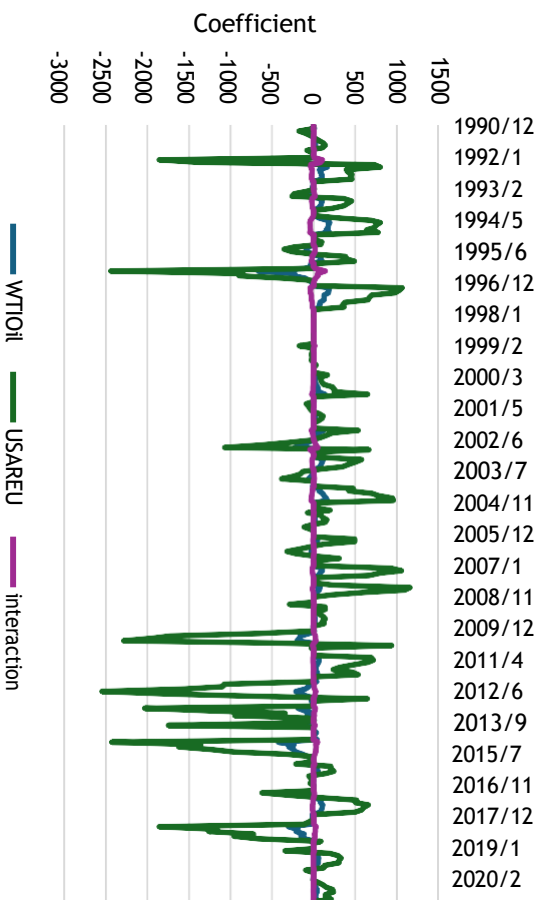


Figure 7 - Wheat's rolling window regression coefficients

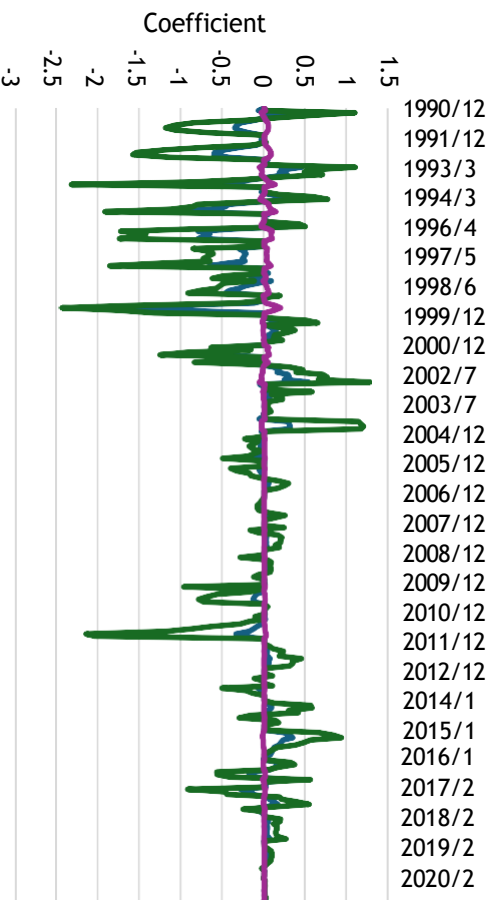


Figure 8 - Sugar EU's rolling window regression coefficients

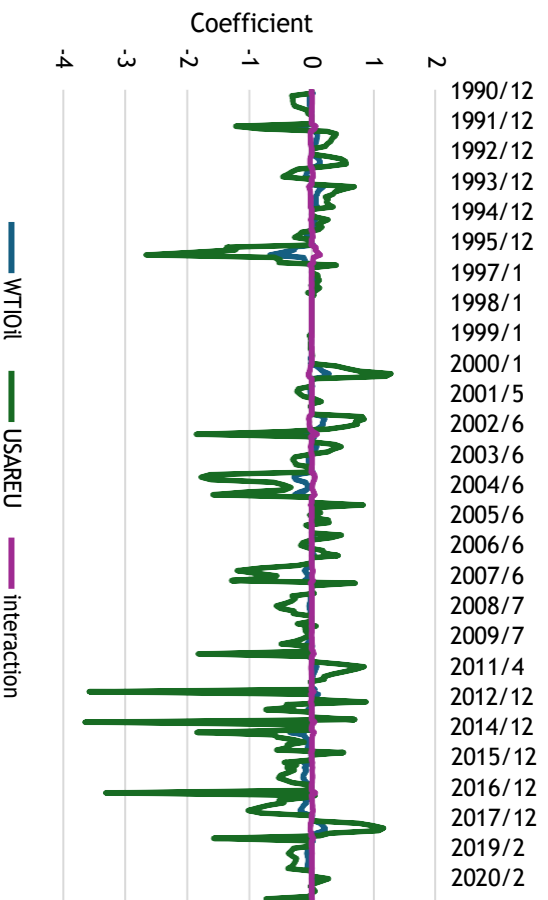


Figure 9 - Sugar USA's rolling window regression coefficients

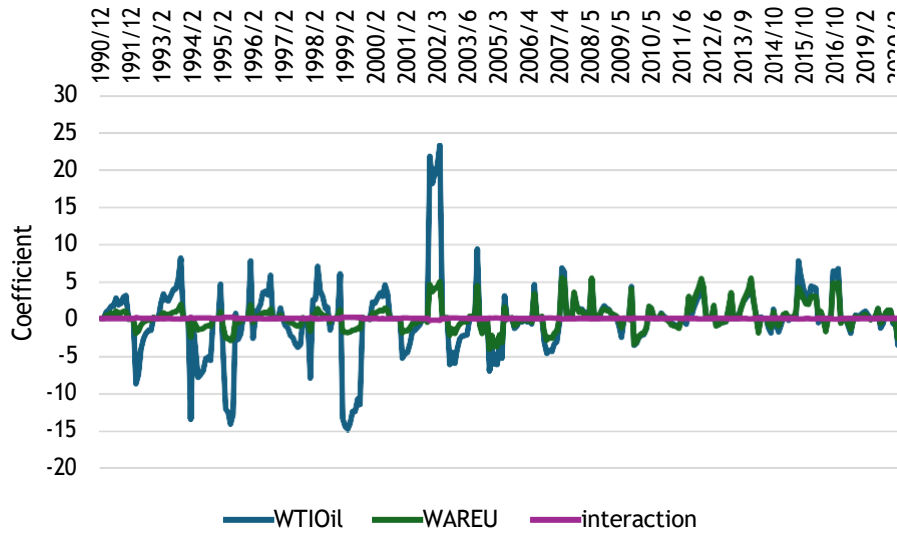


Figure 10 - Cocoa's rolling window regression coefficients

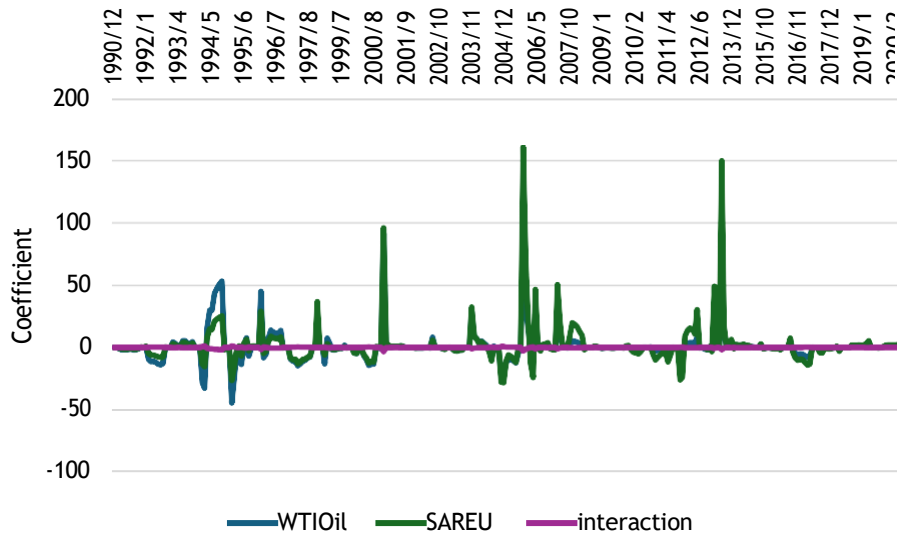


Figure 11 - Coffee's rolling window regression coefficients

Note: These rolling window regression graphs were computed solely for curiosity purposes. It was done on 12-month windows on the basis of normal regressions (OLS) and winsorized by 5% to better understand the results. My main goal with this test was to check how the coefficients of the main variables under scope would develop over time: which was the more volatile and how it compared between commodities and regions.