Macrothink Institute™
International Journal of Accounting and Financial Reporting
ISSN 2162-3082
2025, Vol. 15, No. 1

The Volatility of Sugar and Ethanol Prices: A Tale of Two Markets Using Wavelet Analysis

Carine Gonçalves Távora

Master, São Paulo State University - UNESP

Department of Electrical and Electronics Engineering, Brazil

Rodolfo Vieira Nunes (Corresponding author)

Assistant Professor, Federal University of Juiz de Fora – UFJF

Institute of Applied Social Sciences, Brazil

E-mail: rodolfo.nunes@ufjf.br

Received: November 25, 2024 Accepted: December 30, 2024 Published: February 1, 2025

doi: 10.5296/ijafr.v15i1.22422 URL: https://doi.org/10.5296/ijafr.v15i1.22422

Abstract

This study ventures into the dynamic and interconnected realms of sugar and ethanol prices, unveiling their volatility patterns using the powerful tool of wavelet analysis. The first part of the study establishes a link between Brazil's sugar price surge and significant economic events, including the National Alcohol Program (Proálcool), the military dictatorship, and the implementation of the Real Plan. The second part zooms out to global factors, such as concerns about the greenhouse effect, flex-fuel engine technology, and recent challenges like droughts and COVID-19. The analysis uncovers distinct patterns in the volatility of sugar and ethanol prices. Factors like global supply and demand, climate-induced crop variations, and government policies influence sugar prices. In contrast, ethanol prices are more directly influenced by energy market dynamics, particularly crude oil prices, due to its role as a biofuel component. Furthermore, the study reveals time-frequency correlations between these two markets, shedding light on moments of synchronization and divergence. In this narrative of the two markets, wavelet analysis emerges as a powerful tool for deciphering past volatility and predicting future trends. It allows both estimating the degree of correlation and verifying the unfolding of these relationships over time. The findings of this study contribute as a bridge between theory and practice for decision-making, such as resource allocation and risk management in a constantly evolving economic scenario, highlighting the importance of analysis in this context.

Keywords: Correlation, Price dynamics, Agricultural commodities, Energy markets, Time-frequency analysis

1. Introduction

Most phenomena in the world are uncertain and full of risks. Nevertheless, the global landscape has intricated economic, financial, and socio-political systems that exhibit patterns and behaviors over time. Reliable tools can use historical data to predict future price movements, unveil hidden trends, anticipate potential outcomes, and develop strategies for managing price risk, which can mitigate the impact of volatility and inform decision-making.

Volatility, especially price volatility, is of enormous importance to everyone involved in the financial markets. Price variations can impact consumption patterns, corporate capital investment decisions, leverage decisions, and other business cycles and macroeconomic variables (Daly, 2008). Studying volatility is important because it can help investors, traders, and financial analysts make informed decisions.

Considering Brazil's commodities, sugar is one of the most important in this scenario. In Brazil, Sugar is produced by sugar cane, and sugarcane cultivation has a long history in the country, dating back to the colonial period. It has significant economic and social importance, providing employment and income for millions of people. Another fact that makes sugar cane important to Brazil is that it is used to produce ethanol. Since the mid-1970s, Brazil has provided a stimulus for ethanol production to stabilize gasoline prices and reduce its dependence on fossil fuels in the supply of motor vehicles. Therefore, Brazil started to manufacture vehicles powered by hydrous ethanol and added anhydrous ethanol to the gasoline used for vehicles. Initially, the mixture was 15% anhydrous ethanol, but it grew to 20% and then 27% (Carpio, 2019). In this way, Brazil is not only the country that is a leading global producer and net exporter, but it also possesses the world's largest fleet of ethanol-fuelled cars. According to the Food and Agriculture Organization of the United Nations, ethanol use is expected to rise roughly 18% by 2028, and Brazil stands as one of the countries that could supply this additional output (Palazzi, Meira and Klotzle, 2022). Besides that, Brazil is also the world's leading sugar exporter, accounting for approximately 40% of global exports (Carpio, 2019).

This intriguing market observation highlights a fundamental connection. Both sugar and ethanol originate from the same source: sugarcane. When the industry prioritizes ethanol production, its sugar output is consequently diminished. While some flexibility exists in adjusting the sugar-to-ethanol ratio, these commodities compete for the same industrial resources and plant capacity. Research has consistently demonstrated the inherent advantages of flexible plants over those exclusively dedicated to either ethanol or sugar production. Flexible plants can adapt to market dynamics, allowing them to capitalize on favourable prices for ethanol and sugar. Consequently, such adaptable facilities can maintain prolonged operational periods, consistently optimizing their revenue under varying market conditions. (Pantoja, Samanez, Castro and Aiube, 2016).

While both sugar and ethanol are derived from sugarcane and have some level of correlation due to their shared agricultural origins, their price dynamics are primarily driven by distinct market forces. Sugar prices are closely tied to factors such as global supply and demand for sugar, weather conditions affecting sugarcane crops, government policies (like subsidies and tariffs), and consumer preferences. The price of sugar is indeed related to the sugar market itself. It is influenced by factors like changes in sugar production, export/import regulations, and the consumption of sugar in various industries, including the food and beverage sector. On the other hand, ethanol prices are more directly linked to the energy market, particularly the price of crude oil. Ethanol is often blended with gasoline, and the demand for biofuels influences its price, government mandates on ethanol content in gasoline, and fluctuations in oil prices. Ethanol prices tend to follow changes in oil prices rather closely, as they are both used as fuel. While these two commodities are not typically seen as moving in perfect alignment, their correlations can vary over time and may share intricate interdependencies within global markets.

To address and help in the studies of the sugar and ethanol price volatility, the use of the Wavelet Transform to investigate price dynamics is timely. A wavelet is a mathematical function used in signal processing and analysis. The wavelet technique decomposes the return series into timescale components and represents the variability and structure of the stochastic processes on a scale-by-scale basis. The wavelet function is small and can be manipulated (stretched or squeezed over time) to extract the frequency components from a complex signal (Bouri Lucey, Saeed and Vo, 2021). In other words, wavelets can be used to decompose a signal into different frequency components, and by decomposing a signal into its constituent wavelets, analysts can identify patterns and trends at different frequencies and scales. Although wavelets have been more popular in signal and image processing, meteorology, and physics fields, such analysis can also provide fruitful insights into several economic phenomena (Rua and Nunes, 2009). In finance, wavelet analysis can analyze volatility through financial time series data, identify patterns and trends that may be useful for predicting future price movements, and develop trading strategies, risk management plans, and investment portfolios.

In this context, the objective is to understand the volatility of sugar prices and their relation to ethanol prices, which is crucial for effective policymaking and optimal risk management strategies. Furthermore, inefficient risk-sharing mechanisms during periods of considerable price volatility may distort input allocation, curb agricultural investment, and slow productivity growth (Palazzi, Meira and Klotzle, 2022). This could have severe implications for consumers, farmers, and countries. Therefore, this work can contribute to the studies of the volatility of sugar prices and their relation to ethanol prices over decades by means of wavelet-based analysis.

The interdependence between sugar and ethanol markets represents a critical field of study from an academic and practical perspective. This work stands out for offering an innovative approach that fills gaps in the literature and directly contributes to formulating policies and business strategies. The methodological sophistication stems from the wavelet technique that complements traditional techniques and offers new perspectives on market dynamics. This research provides a solid foundation for understanding and managing volatility in these essential markets by exploring price dynamics across different time scales and historical contexts. The Findings of this study have direct implications for policy formulation and industrial strategies. They can guide the development of public policies that promote market stability and help optimize production strategies.

2. Theoretical Reference

2.1 Characteristics of Sugar and Ethanol Markets

The origin of sugarcane cultivation in Brazil dates to colonization (16th century). Over time, sugarcane production and the manufacture of sugar and its derivatives gained international importance, guaranteeing Brazilian competitiveness in this field of activity. Due to the international economic situation resulting from the oil crisis, the need arose to restructure the country's energy matrix, which made it possible to organize several economic activities to strengthen ethanol production in Brazil (Shikida and Bacha, 1999).

This rearrangement involves, in addition to the plants and distilleries, the automobile industries, capital goods industries, organizations, research centers, the State, and consumers (Shikida, 2010). Throughout the 20th and 21st centuries, the Brazilian government instituted numerous measures to encourage sugarcane cultivation: first experiments with vehicles powered by ethanol, the maximum mixture of 5% ethanol with gasoline, the National Sugar and Alcohol (regulate and establish standards), the National Alcohol Program - Proálcool (promote large-scale production), setting the official mixing ratio of anhydrous ethanol with gasoline between 20 and 25%; flex-fuel cars and the reduction to zero of the Contribution for Intervention in the Economic Domain - CIDE (tax on fuels), together and in their moment, these public policies harmonized the leverage of production in the sugar and alcohol sector (Sant'anna, Shanoyan, Bergtold, Caldas and Granco, 2016).

In this productive scenario, the Southeast Region concentrates more than 64% of the sugar and alcohol sector's production. São Paulo is responsible for around 83% of regional production and more than 53% of national production. In this context, it has become the largest producer in the Brazilian sugar and alcohol industry (UNICA, 2023). It is essential to highlight that sugarcane fields, plants, and distilleries are considered components of the sugar and alcohol sector, that is, agroindustries.

This market has high relevance to Brazil, and it impacts the global economy since Brazil is the world's largest sugarcane producer and contributed to approximately 38.6% of the world's total production in 2019 (Zheng, dos Santos Luciano, Dong and Yuan, 2021), shown at Figure 1.

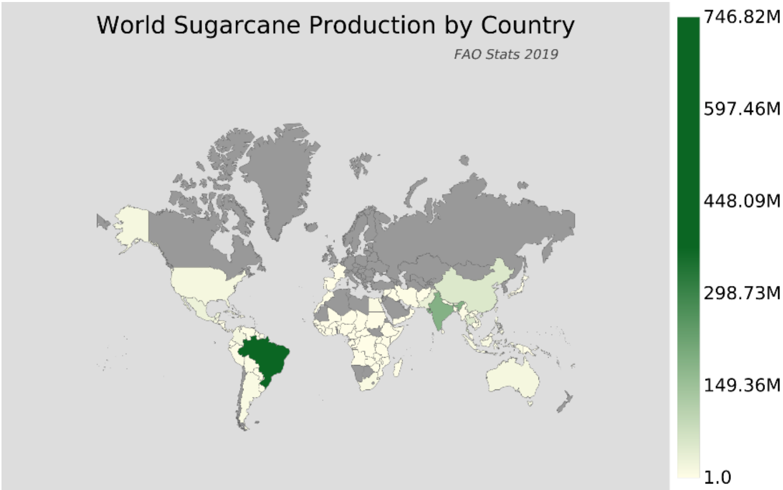

Figure 1. World Sugarcane Production by Country (2019)

Source: Atlas Big (2020).

The sugarcane production in 2019 was 639.0 million tonnes, which was 2.3% higher than the previous year; the national sugar production was 29.2 million tonnes, while the production of ethanol was 35,156 billion liters, 69.8% of which corresponded to hydrous ethanol, consumed purely as fuel, and the remaining 30.2% was consumed mixed with gasoline in the form of anhydrous ethanol. Considering the internal energy offer 2019, the sugarcane products (bagasse and ethanol) reached 18.00% of the total energy offer (Palacios-Bereche *et al.*, 2022).

In 2021, crop and livestock production accounted for 8 percent of Brazil’s Gross Domestic Product (GDP). The University of São Paulo’s Center for Advanced Studies on Applied Economics estimated that when activities such as processing and distribution are included, Brazil's agriculture and food sector accounts for 29 percent of the country's GDP, valued at $1.8 trillion in 2021. Brazil's latest agricultural census shows that agriculture employs 15.1 million people in rural establishments, equivalent to 15 percent of the labor force. The value of Brazil's agricultural exports in 2021 reached $125 billion, led by soybeans and soybean meal, sugar, beef, poultry, corn, cotton, pork, coffee, and citrus (Valdes, 2022), as shown in Figure 2.

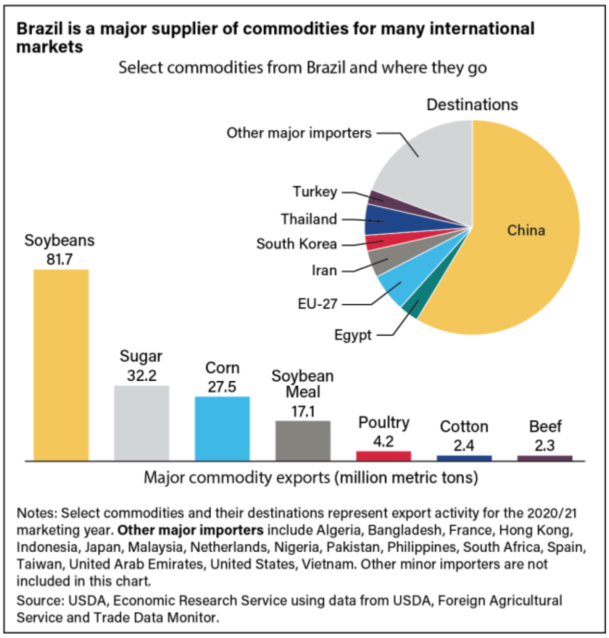

Figure 2. Brazil is a major supplier of commodities for many international markets

Source: Valdes (2022).

Brazil holds a prominent position as a significant global sugar exporter. Between 2010 and 2014, Brazil was responsible for 26% of world sugar production, compared to 16.3% in 2000-2004. Furthermore, between 2010 and 2014, Brazil was responsible for around 58% of world sugar exports raw, while it was responsible for 23% of the world's total refined sugar exports (FAO, 2015). Even though sugar is a commodity, it is still one of the most protected products; countries seek to protect producers by implementing protectionist policies, such as tariff barriers, minimum price levels, and agricultural subsidies (Amrouk and Heckelei, 2021).

However, its significance extends beyond the international market, with ethanol playing a vital role in its internal economy. Sugarcane is also used as a raw material to produce ethanol. However, the interaction between sugar and ethanol is most evident in Brazil, with both products competing for the same essential input (Amrouk and Heckelei, 2021). According to Sant'anna *et al.* (2016), the USA and Brazil are the largest producers of ethanol, and in 2014, ethanol consumption in the countries was 13.47 billion gallons and 6.76 billion gallons, respectively, while ethanol production was 14.34 billion gallons and 7.56 billion gallons.

This shows that ethanol production in Brazil is mainly destined for the domestic market, as ethanol competes with gasoline as a fuel in the transport sector. This is a government practice that involves fiscal policies and various subsidy programs that support the subsector Brazilian biofuel sector (Rezende and Richardson, 2015; Amrouk and Heckelei, 2021).

When examining fuel consumption patterns within Brazil, particular attention is paid to the Otto cycle, which pertains to the demand for combustion engine fuels. In 2022, Brazilian otto cycle fuel consumption reached a substantial 54 billion litters, marking the second-highest consumption level on record. Notably, 42% of this total was attributed to ethanol, as illustrated in Figure 3.

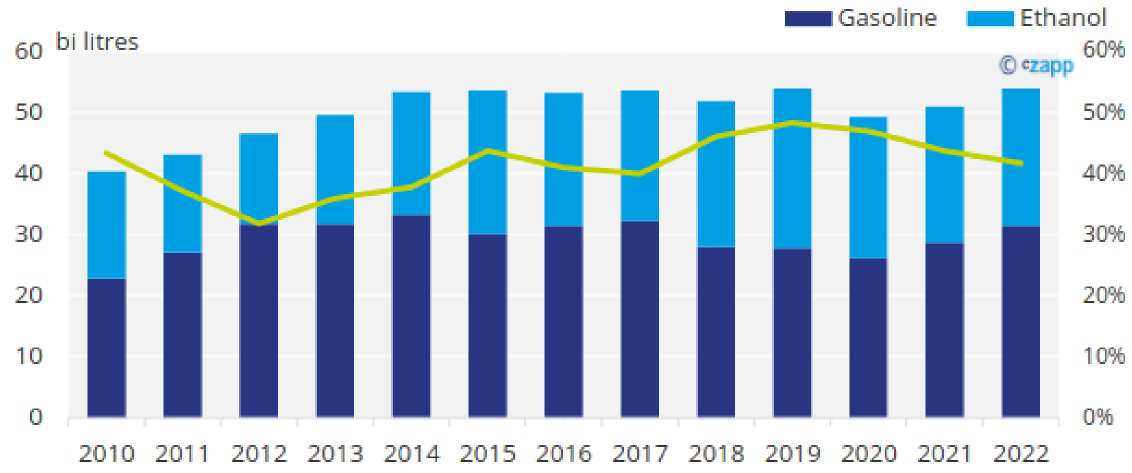

Figure 3. The importance of ethanol in the Brazilian fuel matrix (Otto Cycle)

Source: Czapp (2023).

It is undoubtedly essential to recognize the significance of sugarcane to the Brazilian economy and its impact on the global market. Sugar mills in Brazil have the infrastructure to produce both products, and the relative return on prices determines which will be produced. Most of the studies reviewed focus on the dynamics of one market or the other, rarely exploring in an integrated manner how sugar and ethanol production interact in terms of resource utilization and response to market conditions. As Brazil is the leader in global sugar production, the relative profitability between sugar and ethanol directly impacts Brazil's sugar export supply and, consequently, the product's international prices (Haley, 2015). In this industry, there is a tricky choice to make whether to focus on making ethanol for local use or producing sugar for international sales. Mills' flexibility to adjust the production mix between sugar and ethanol is frequently mentioned but little explored in depth. It is a complex decision involving analyzing sugar and ethanol prices during harvest. Plus, the ability to adapt the production plan as needed is crucial. What makes it even more challenging is that the prices of these two products do not sometimes move in sync as one might expect.

This paper investigates the price dynamics of sugar and ethanol simultaneously, revealing how competition for resources impacts the volatility of both markets. The approach allows us to identify patterns of correlation and divergence over time, offering unique insights into the relationship between the two products.

2.2 Volatility Models: GARCH (p,q) Model

Historical volatility is a straightforward approach to estimating volatility. This method consists of determining the variance/standard deviation of returns over a period, which then serves as the estimated volatility of the forthcoming periods. However, this method does not consider that volatility can be affected by recent events and can have more impact than older ones. A historical approach could lead to an artificial level of volatility that can lead to an erroneous market expectation (Costa, 2017). In this way, over the past two decades, empirical investigations have shown that volatility in financial time series exhibits highly persistent clustering phenomena. Consequently, numerous models have been proposed to describe the evolution of volatility. As a result, the literature has expanded considerably, with various specifications of auto-regressive models. In an autoregressive model, the value of a variable at a particular time is modeled as a linear combination of its past values and a random error term. The order of an autoregressive model specifies the number of past values used to predict the current value.

Until the early 1980s, numerous models of prediction based on autoregression were put forward. In two landmark papers by Engle (1982) and Bollerslev (1986), the ARCH and GARCH models have been proposed, and they are the most successful and popular models for predicting volatility. Their incredible popularity stems from their ability to capture, with a very flexible structure, some of the typical stylized facts of financial time series, such as volatility clustering, which is the tendency for volatility periods of similar magnitude to cluster. Usually, GARCH models can consider the time-varying volatility phenomenon over a long period and provide excellent in-sample estimates (Sadik, Date and Mitra, 2019).

The Autoregressive Conditional Heteroscedasticity (ARCH) model by Engle (1982) and its generalization, GARCH (Generalized Autoregressive Conditional Heteroscedasticity) by Bollerslev (1986), are the primary and widely used methodologies in modeling and forecasting volatility of financial time series. The standard GARCH (p, q) model expresses the variance at the time, t as (Miaha & Rahman, 2016):

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \, \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \, \sigma_{t-j}^2$$

σ_t^2 is the conditional variance, ε_t the residual returns, defined as $\varepsilon_t = z_t \sigma_t$ and $z_t \sim N(0,1)$, i.e., are standardized residual returns. ω, α_i and β_j are the parameters to be estimated. In order for the variance to be positive, the necessary condition is that $\omega > 0$, $\alpha_i > 0$ ≥ 0 α i (for i = 1,..., q) and $\beta_j \geq 0$ (for j = 1,..., p). One of the most used and simple models is the GARCH (1,1) process, for which the conditional variance is represented as a linear function of its lags (Miaha and Rahman, 2016).

The classic linear regression model assumes that the error variance is constant, known as homoscedasticity. In other words, it assumes that var $(\varepsilon_t = \sigma^2)$. On the other hand, if the variance of the errors is not constant, this would be known as heteroscedasticity. It's expected that the variance of the errors will not be constant over time, so a model that does not assume that the variance is constant is more appropriate (Costa, 2017).

The GARCH model estimates the conditional variance of a time series based on its past values and the past values of the residuals or the difference between the actual values and the predicted values. It assumes that the conditional variance of the series is a function of the past variance and the past squared errors.

A significant drawback of GARCH models is how they react to changes in the variance behavior of a time series. Traditionally, they have absurd delays in the experiential processing of volatility, which is particularly evident when dealing with abrupt changes in the mean-variance, volatility level, or in case of structural discontinuity (Hwang and Valls Pereira, 2008; Oliveira and Pereira, 2017). Furthermore, finding the appropriate probability distribution for the residuals is extremely difficult since return series often have long tails and excess kurtosis. Hence, the standard normal distribution is upside down (Engle and Patton, 2001). Finally, a critical drawback is the model's reliability, which cannot be directly measured by means of samples. Almost all methods suggest that the model's reliability be checked by comparing the actual values of the process with its forecasts. However, it is impossible to observe the volatility of the forecasts, so most of the methods are careless and impractical (Reis, Perobelli, Mattos and Corrêa, 2013).

2.3 Wavelet Approach

This study has chosen to employ wavelet analysis to study the volatility of sugar prices. While this approach is relatively new in the realm of finance literature, it has the potential to yield insightful results. A new statistical procedure has the purpose of adding one or more gains, which would be estimated for new situations, improving the efficiency of the estimate or reducing biases, increasing robustness to modeling errors, or providing new insights. That is, the ability to apply new insight to inspect relationships in economics or finance holds great promise for the development of the discipline (Ramsey, 2002).

Wavelets are mathematical functions for analyzing signals and data in various fields, including engineering, physics, and finance. The wavelet technique starts from the principle of decomposing the series of returns into timescale components and finally represents the variability and structure of stochastic processes scale by scale (Bouri, Shahzad, Roubaud, Kristoufek and Lucey, 2020). The Wavelet function is a small wave and can be manipulated (stretched or compressed over time) to extract the frequency components of a complex signal. In other words, they are an essential function that can represent signals as a sum of different wavelets with different frequencies and scales.

A function $\Psi(t) \in L^2(R)$, is called wavelet, if your Fourier Transform $\widehat{\Psi}(w)$ meets the condition:

$$\int_{-\infty}^{\infty} \frac{|\widehat{\Psi}(w)|^2}{|w|} dw < \infty$$

In the analyses, wavelet $\Psi(t)$ is called wavelet mother. It is associated with a scale function φ(t) and is generated through translations and dilations of this scale function. The translation and dilation operations applied to the mother wavelet are performed to calculate the wavelet coefficients, representing the correlation between the wavelet and a localized signal section. The wavelet coefficients are calculated for each wavelet segment, giving a timescale function relating the wavelet's correlation to the signal. This process of translation and dilation of the mother wavelet is depicted below in Figure 4.

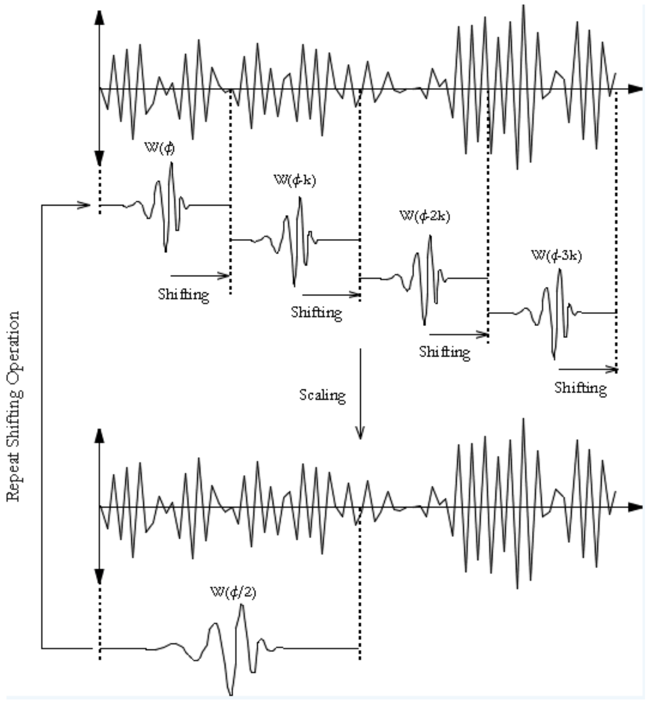

Figure 4. The Scaling and Shifting Process of the Wavelet

Source: TradeWays (2023).

Some commonly used mother wavelets include the Haar wavelet, the Daubechies wavelet, the Morlet wavelet, and the Mexican hat wavelet. Each wavelet has a different shape and properties, such as the number of vanishing moments and the degree of smoothness. These properties determine the wavelet's ability to capture different signal features, such as edges, oscillations, and singularities. In this work, it will be used the Daubechies wavelet: This family of wavelets is characterized by a finite support and a finite number of vanishing moments and is often used in the analysis of financial time series data due to its ability to capture both smooth and non-smooth features in the data.

The continuous wavelet transforms of a function f(t), assuming a chosen mother wavelet, is defined by Equation 1 (Burrus, Gopinath and Guo, 1997):

$$W_{f(a,b)} = \int_{-\infty}^{\infty} f(t)|a|^{-p}\ \Psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

The Daubechies-type wavelet is defined by Equation 2, and its scale function is defined by Equation 3:

$$\Psi_N(t) = \sum_{k=0}^{2N-1} (-1)^k\ \alpha_{2N-1-k}\ \varphi_N(2t-k) \tag{2}$$

$$\varphi_N(t) = \sum_{k=0}^{2N-1} \alpha_k\ \varphi_N(2t-k) \tag{3}$$

Daubechies defined the wavelet families with values of N between 2 and 10. The values of α are called filter coefficients, where N is half of α (Daubechies, 1992).

In this way, a time series dataset of sugar prices with high-frequency data will be applied to the Daubechies wavelet transform using the software MATLAB. The results will be interpreted to identify patterns and trends by analyzing the wavelet coefficients, looking for specific frequency bands or time intervals where price volatility is exceptionally high or low. The data results will be shown as graphs for the analysis.

Dominant methodological approaches, such as GARCH models and other time series techniques, effectively capture specific aspects of price volatility. However, these models fail to identify dynamic patterns at different time scales or to reveal long-term structural changes. Although still scarce, studies using wavelets demonstrate this technique's potential to disaggregate volatility signals, allowing for more granular and comprehensive analysis.

This analysis method is better known than other methods widely used in the literature because it offers some important advantages. Wavelet analysis can measure the relationships between different groups and see how these relationships change over time. In addition, this method does not require the data to follow the concept of stability, so it is flexible (Khalfaoui, Boutahar and Boubaker, 2015). The simultaneous integration of time and frequency quantities characterizes wavelet transformation. Thus, it is possible to simultaneously analyze how variables relate for different reasons and how this relationship changes over time (Boubaker and Raza, 2017).

3. Methodology

The data series was obtained from globally recognized websites, namely Macrotrends and Investing. These websites are renowned for providing historical data, including stock prices, market indices, dividend data, and other relevant financial information.

For the first part, the series of sugar prices are daily settlement prices, 5 days per week, from November 29, 1962, through May 08, 2023; that was all the data information available to be downloaded on the website then. The price series is comprehensive and long, with 15.137 observations. The price is in U.S. dollars per pound. For the second part, the sugar and ethanol prices series have the same length, spanning monthly data from January 1, 2005, to January 9, 2023, encompassing 6,582 observations.

3.1 Data – Sugar Price Volatility

The data analysis can be initiated through simple analyses and visualizations, yielding initial insights and enabling a data-driven narrative. These preliminary findings can help you formulate research questions, identify areas of interest, and guide more sophisticated analyses. It also helps understand the data's overall structure, patterns, and characteristics and identifies data quality issues such as missing values, outliers, or inconsistencies.

Figure 5 displays the trend of the data curve; it is possible to note that during the 1970s (1973 until 1976), there was a noticeable increase in the price of sugar. The production of ethanol as a fuel substitute for gasoline in Brazil was one of the factors that contributed to the increase in sugar prices. The Brazilian government implemented the National Alcohol Program (Proálcool) in 1975, which aimed to reduce the country's dependence on imported oil by promoting the production and use of ethanol as a fuel. This program led to a significant increase in demand for sugarcane, the primary raw material used to produce ethanol in Brazil. As a result, the increased demand for sugarcane for ethanol production also led to a rise in sugar prices.

The Figure 6 shows the absolute value percentage returns. The return series is more volatile than others in some periods, especially from 1980 until 1990. From 1980 to 1990, Brazil went through significant political and economic changes. In the early 1980s, the country experienced a severe economic crisis due to high inflation and foreign debt. The government implemented a series of economic policies and reforms to address these issues, including a new currency, the Real Plan, in 1994. During this period, Brazil transitioned from a military dictatorship to a democratic government in 1985 with the election of Tancredo Neves as president, followed by José Sarney. This period marked significant social and political changes, economic challenges, and reforms.

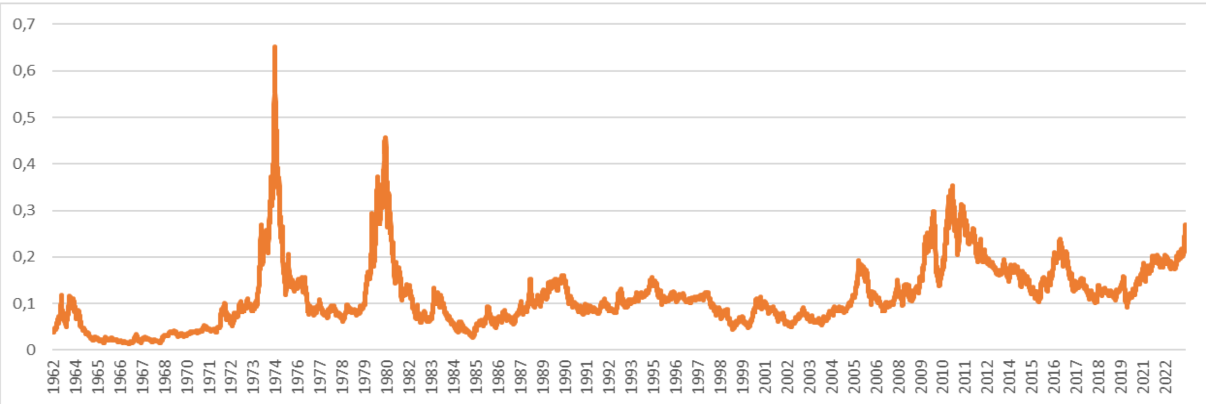

Figure 5. Price Fluctuations of Sugar Over Time

Source: Prepared by the authors (2023).

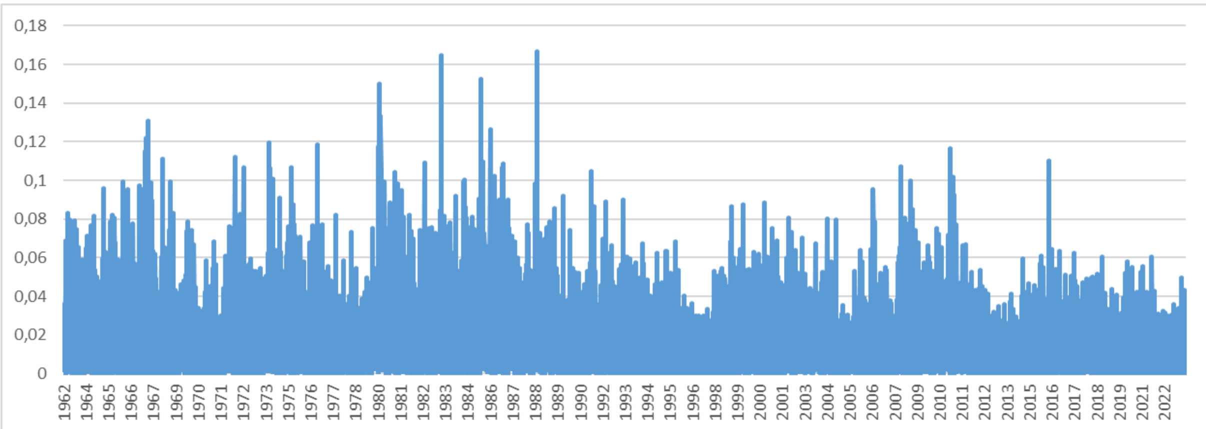

Figure 6. Absolut Percent Return of Sugar Over Time

Source: Prepared by the authors (2023).

3.2 Data – Ethanol and Sugar Prices Volatility

In a comparative analysis, sugar and ethanol prices from 2005 to 2023 were examined, with the data standardized for uniform scaling, illustrated in Figure 7. However, this initial assessment only reveals the relationship between the prices of ethanol and sugar and highlights the most significant years. It needs to be clarified in this visualization. To clarify this complex association, more robust tools are necessary. This study employs the wavelet approach as a potent tool for in-depth analysis.

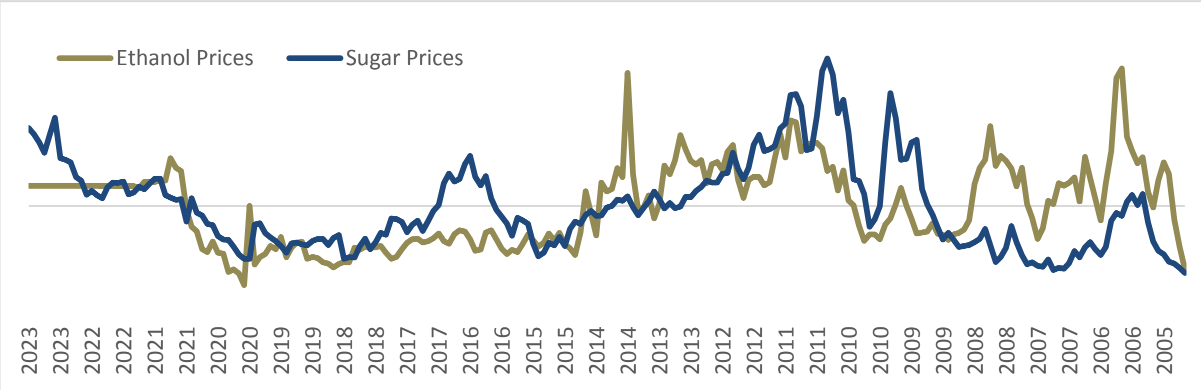

Figure 7. Comparison of Sugar and Ethanol Prices from 2005 to 2023

Source: Prepared by the authors (2023).

4. Results and Discussions

This section highlights the primary discoveries achieved by utilizing the Wavelet function to identify notable fluctuations in sugar prices over the years and to demonstrate the correlation between sugar prices and ethanol prices.

4.1 Sugar Price Volatility

In this part of the results, applying wavelet analysis to the nearly 60-year sugar price series will illustrate how it aids in understanding historical price fluctuations over time. Consider Figure 8, which plots the wavelet coefficients for sugar volatility at various scale indices and over time to illustrate the localization in scale and time captured by the wavelet decomposition.

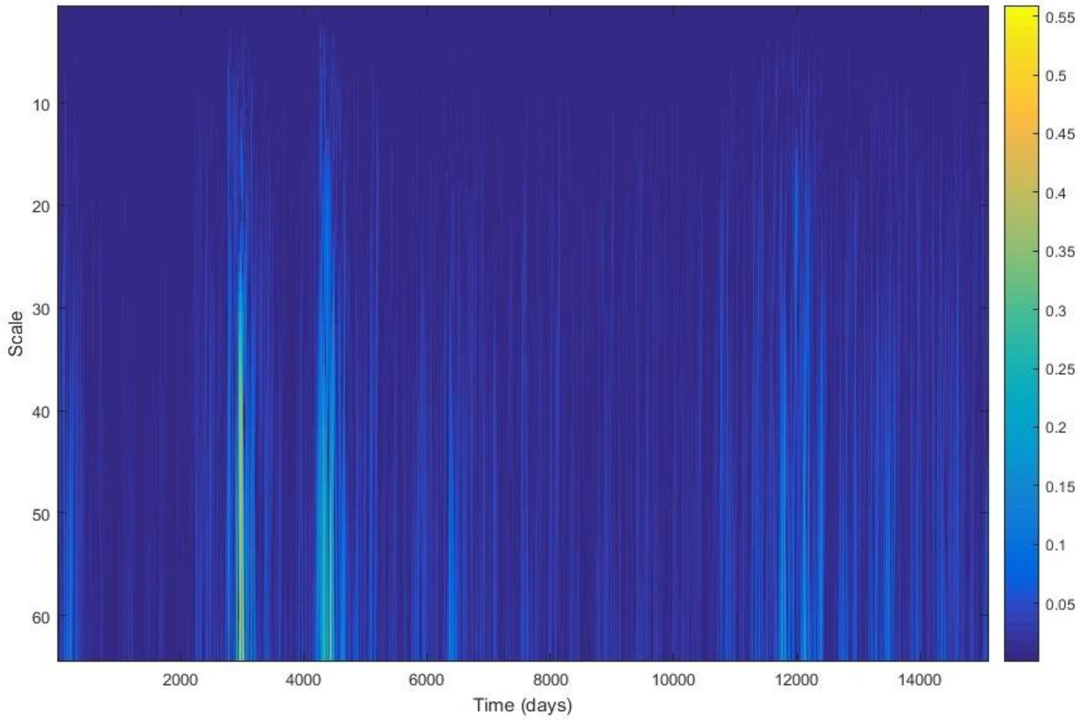

Figure 8. Commodity Sugar volatility: Wavelet Coefficient Plot (Own Source)

Source: Prepared by the authors (2023).

First, note the localization of sugar volatility in terms of time and scale. Although spectral analysis decomposes a signal into frequencies, wavelet analysis decomposes a signal by scale and time, utilizing colors to illustrate the magnitude of the wavelet coefficients at various time scales. Next, note the repeating cones of wavelet coefficients. These cones illustrate repeating patterns at high and low scales, consistent with the self-similarity property of long memory (Elder and Jin, 2007).

It is easier to identify it, especially in 2000 days, 4000 days, and 12000 days. The data start in 1962, then 1971, 1975, and 1995 respectively. In the 1970s, notable occurrences affected the sugar market. The oil crisis triggered by geopolitical events in the Middle East led to a significant increase in oil prices. As a result, there was a growing interest in alternative energy sources, including sugarcane-based ethanol. The increased demand for sugarcane to produce ethanol could have impacted the price of sugar as resources were diverted to ethanol production. In addition, during this period, Brazil was under a military dictatorship, and in 1971, the Brazilian government introduced a series of economic reforms known as the economic miracle. These reforms aimed to stimulate economic growth and modernize the country's infrastructure. They included policies such as fiscal discipline, currency stabilization, and attracting foreign investment. The emphasis on promoting agribusiness and modernizing agricultural practices influenced sugar production. Technological advancements, increased efficiency, and government support for the agricultural sector may have contributed to the growth and productivity of the sugar industry, potentially affecting the price of sugar.

In 1995, said that the volatility in sugar prices could be explained by implementing a series of economic reforms in Brazil, known as the Real Plan, which aimed to control hyperinflation and stabilize the economy. The Real Plan successfully brought down inflation rates and restored confidence in the Brazilian currency, the Real. This implementation was made by Fernando Henrique Cardoso, who was elected as the Brazilian president in 1994; his presidency marked a shift towards market-oriented reforms and economic stabilization. Looking at the world perspective, in 1995, the General Agreement on Tariffs and Trade (GATT) was replaced by the World Trade Organization (WTO). The establishment of the WTO aimed to promote global trade liberalization, resolve trade disputes, and facilitate international cooperation on trade policies. The establishment of the WTO in 1995 signaled a continuation of international trade liberalization efforts. It provided a framework for negotiations on agricultural trade, including sugar. WTO agreements, such as the Agreement on Agriculture, aimed to address trade barriers and subsidies in the agricultural sector, which could indirectly impact the global sugar market.

4.2 Ethanol and Sugar Prices Volatility

To complete the analysis, the wavelet analysis of sugar prices can be compared with that of ethanol prices. Starting with examining potential patterns between them, Figure 9 presents the coefficients observed for Sugar Prices, while Figure 10 displays the coefficients for Ethanol Prices. The graphic that plots the wavelet coefficients' length (or scale) on the x-axis and their corresponding values on the y-axis is commonly called a "Wavelet Coefficient Plot". This type of graphic is used to visualize the wavelet coefficients at different scales, allowing for the examination of how the signal's details are distributed across various frequency scales; it is a valuable tool for understanding the structure and characteristics of a time series.

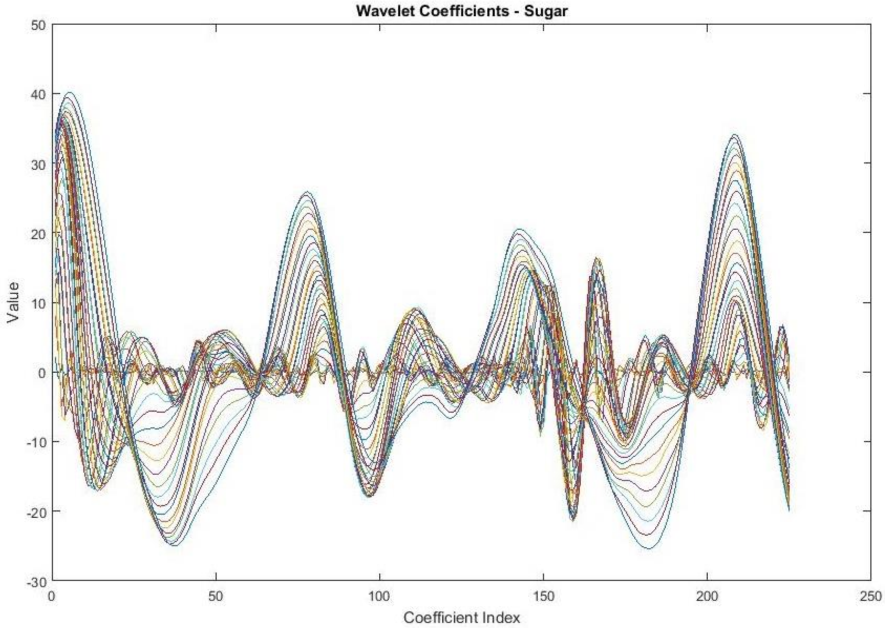

Figure 9. Coefficient Index – Sugar Prices (Own Source)

Source: Prepared by the authors (2023).

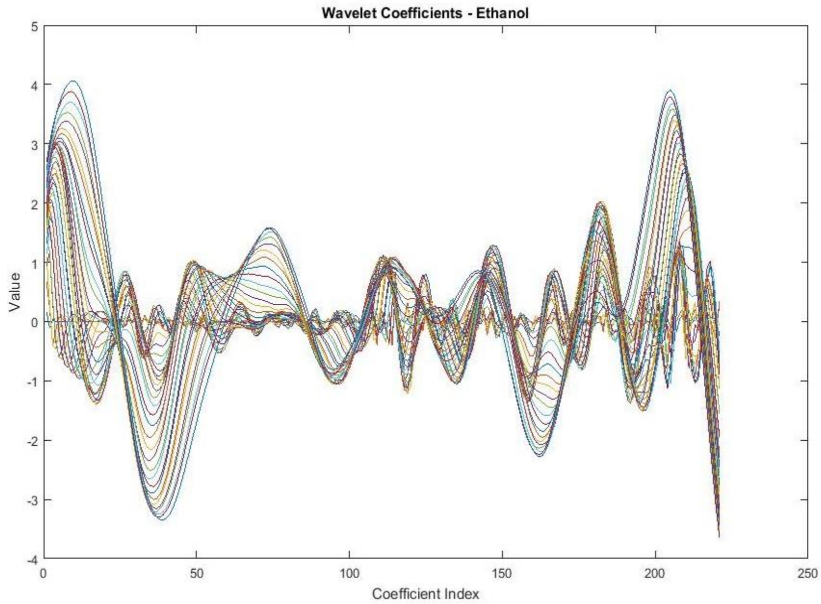

Figure 10. Coefficient Index – Ethanol Prices (Own Source)

Source: Prepared by the authors (2023).

By inspecting the figures, it becomes evident that the curves closely resemble each other in their shape, particularly when considering the magnitude of the coefficients. Notably, both the ethanol and sugar curves exhibit higher volatility at the beginning and end of the data series. However, moving further into the signal, sugar experiences more pronounced fluctuations with more excellent spreads, whereas the ethanol curve displays comparatively fewer variations and oscillations. To delve deeper into this analysis, the data has now been plotted with time and frequency scales to pinpoint the specific time intervals where sugar and ethanol prices demonstrate correlations.

Figure 11 and Figure 12 show the Wavelet Power Spectrum for sugar and ethanol prices, respectively. The graphics display the wavelet results with power on the y-axis, frequency on the x-axis, and time on the z-axis. This type of graphic provides a visual representation of how the power of a signal varies with both time and frequency, making it helpful in identifying patterns, trends, and correlations in time series data.

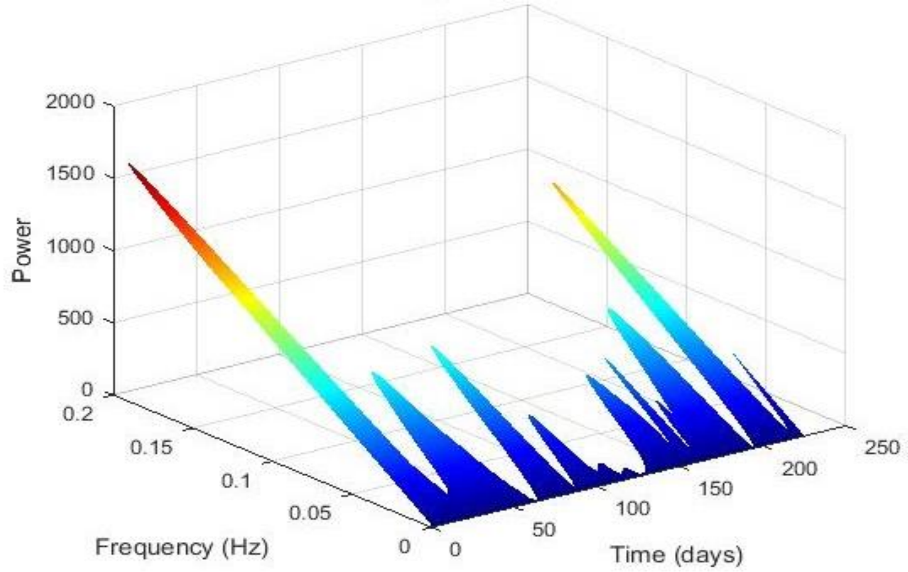

Figure 11. Wavelet Power Spectrum of Sugar Prices (Own Source)

Source: Prepared by the authors (2023).

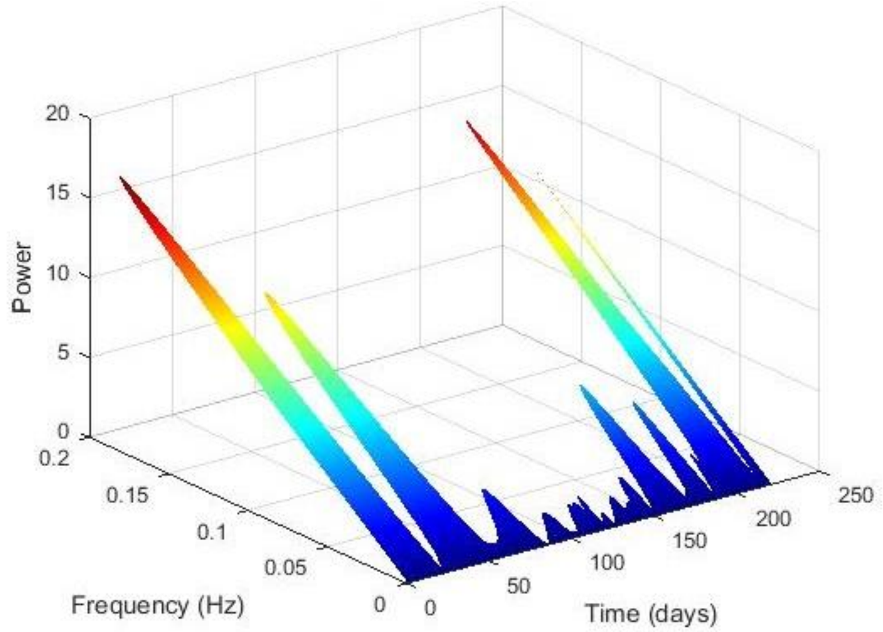

Figure 12. Wavelet Power Spectrum of Ethanol Prices (Own Source)

Source: Prepared by the authors (2023).

Simply by observing the images, it becomes evident that the curves of ethanol and sugar prices share remarkable similarities. This prompts us to explore the more significant economic and global factors that may have contributed to the correlation between these behaviors.

In the graphs, time zero represents 2005, when the data begins. At that point, ethanol and sugar prices were very high. After this, in the years around 2012, while sugar prices dropped significantly, ethanol prices were still high in comparison. Over the following years, sugar prices fluctuated with ups and downs but not as sharply upward as before, while ethanol prices had fewer fluctuations. In 2017 (at 150 days on the graph), sugar and ethanol prices surged simultaneously. Fast forward to 2023 (at 200 days on the graph), a peak in both ethanol and sugar prices is notable. Connecting to the prior examination of sugar prices presented in the first part of the results, Table 1 serves as a valuable resource for comprehending the observed behaviors of sugar and ethanol prices mentioned earlier.

Table 1. Important Phases in the History of Brazilian Ethanol

Phase 1: 1975-1978	- *Proálcool* programme initiated - Ethanol and gasoline mixing begins with the so-called E20 blend (1 part ethanol to 4 parts gasoline) - Expansion of distilleries - Production of E20-powered cars by the automobile industry
Phase 2: 1979-1985	- Hydrous ethanol production initiated under *Proálcool* - Cars powered exclusively by hydrated ethanol launched on the Brazilian market
Phase 3: 1985-1990	- Hydrated ethanol consumption increases due to a significant increase in ethanol-driven vehicles. - Rises in international sugar prices and the end of ethanol subsidies
Phase 4: 1988-2001	- Deregulation of the sugar and ethanol sector marks the end of the government's direct intervention
Phase 5: 2002-2009	- Increasing oil prices - Global concern for GHG emissions - Development of flex fuel engines - Renewed expansion of ethanol production
Phase 6: 2008-2013	- International financial crisis and reduction in investments - New government incentives attempt to improve competitiveness of ethanol, but an uncertain future lies ahead

Source: Ninô de Carvalho (2013).

In 2005, Phase 5, the Brazilian government, connecting with global warming issues, took proactive steps to promote the development of flex-fuel (FFV) technology. This innovation allows engines to operate on various combinations of ethanol and gasoline. The government's efforts included implementing forward-thinking legislation, providing tax incentives, comprehensive consumer education initiatives, and substantial investment in research and development. Consumers met These measures with widespread acceptance, leading to a significant increase in ethanol consumption within the domestic market. This marked the beginning of a new era, opening opportunities for the substantial growth of the ethanol industry in Brazil.

This time was growing global concern about greenhouse gas (GHG) emissions, particularly carbon dioxide (CO2), and their contribution to climate change. This heightened awareness led to a significant focus on sugarcane ethanol as a more environmentally friendly alternative to fossil fuels. Sugarcane ethanol offers several advantages, including high yields in production and efficient biofuel conversion processes, resulting in significantly lower GHG emissions than gasoline (Ninô de Carvalho, 2013). The carbon dioxide emitted when burning ethanol was roughly balanced by the amount absorbed by sugarcane during its growth, creating a closed carbon cycle and reducing its impact on climate change. Additionally, the energy required for sugarcane ethanol production was relatively low compared to the energy it provided, resulting in a positive energy balance.

Furthermore, ethanol's biodegradability reduced its long-term environmental impact. Overall, 2005 marked a crucial point in the global awareness of GHG emissions and their environmental impact. It set the stage for increased international cooperation and efforts to address climate change in the following years.

During the global financial crisis 2010, the government introduced new measures to make ethanol more competitive. These incentives were an attempt to improve the competitiveness of ethanol. However, another factor affected sugar prices. India had a bumper sugarcane harvest, resulting in a surplus of sugar production, as shown in Figure 13. This abundance was primarily due to favorable weather conditions and increased sugarcane acreage. With so much sugar available, the prices dropped significantly.

Another consideration highlighted in certain studies is that the fluctuation in sugar prices has a more pronounced impact on the sugar cane industry's production. The modeling suggests that the sugar cane market is more responsive to changes in sugar prices than ethanol prices. Essentially, the market prefers producing sugar for the external market rather than ethanol for the domestic market (Melo and Sampaio, 2016).

Figure 13. India Sugar Exports in the Last 10 years

Source: KGS Sugar & Infra Corporation (2023).

In recent years, particularly after 2017, ethanol and sugar prices have experienced a notable surge. This surge can be attributed to several factors. Firstly, a severe drought in 2019 significantly impacted sugarcane production, marking it the second most severe drought in South America since 2002 (Gomes, de Albuquerque Cavalcanti and Müller, 2021). The lack of rainfall during the summers of 2019 and 2020 affected sugarcane growth and increased the risk of sugarcane fields catching fire. This issue was particularly pronounced in the Brazilian Pantanal region, where fires consumed extensive areas and had serious socio-ecological and economic consequences (Marengo *et al.*, 2021). The El Niño–Southern Oscillation (ENOS) phenomenon was identified as a critical driver of these climatic anomalies, significantly compromising agricultural yields on a large scale across various regions in Brazil (Sentelhas and Pereira, 2019).

Another factor that impacted the market and the lives of everyone was the lockdown during the COVID-19 pandemic that started in early 2020. During the lockdowns imposed in response to the COVID-19 pandemic, there were notable shifts in consumption patterns, including sugar-related ones. With more people staying at home, there was an increase in home cooking and baking, which led to a surge in the demand for sugar as a key ingredient in various recipes. Additionally, some individuals turned to comfort foods during this period, which may have contributed to higher sugar consumption. On the other hand, closing restaurants, cafes, and other food service establishments led to decreased demand for sugar in the commercial sector. This last factor holds significant weight when predicting consumption trends. The consumption of sugar outside of the home is likely to decrease even more than sugar consumption within households. With restrictions on visiting shops, cinemas, sports events, and bars, sugar intake, primarily through sugary drinks, fast food, and treats, is also expected to decrease. This thesis is supported by the noticeable impact on soft drink sales, especially by lockdown measures and the decrease in social gatherings (Czarnikow, 2023). The consumption of sugar year by year is illustrated in Figure 14.

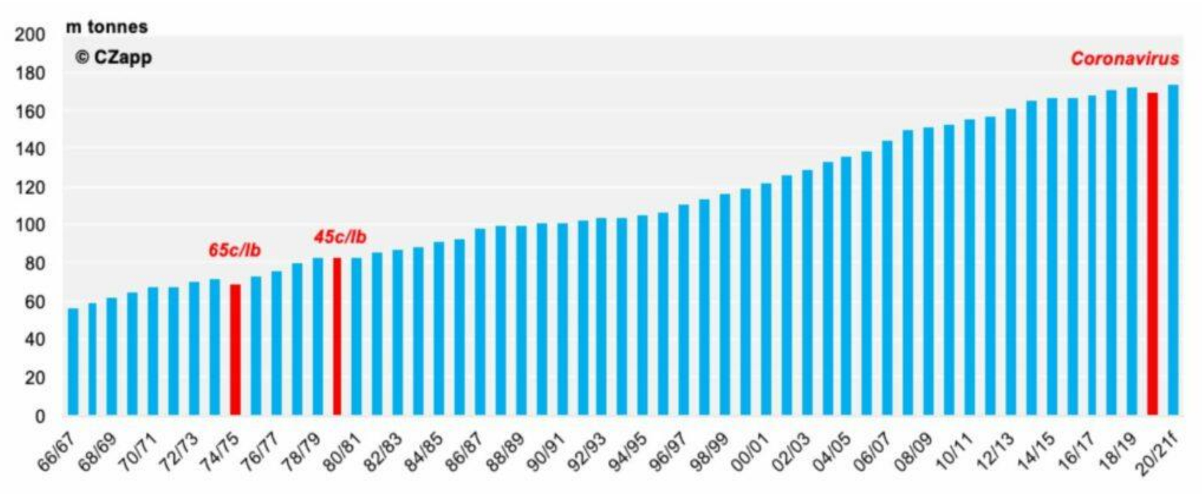

Figure 14. Coronavirus has interrupted the upward trend in consumption

Source: Czarnikow (2023).

It is essential to mention that the price of ethanol was affected during the lockdown. The reduction in economic activity and travel restrictions resulted in a dramatic drop in the demand for oil and its derivatives, such as gasoline and jet fuel. Fewer people were commuting to work, and international travel virtually stopped. This sudden and severe drop in oil demand put significant pressure on oil prices. In April 2020, an extraordinary event occurred in the oil market. Oil futures contracts for May turned negative, meaning sellers were essentially paying buyers to take oil off their hands. This historic plunge into hostile oil prices resulted from oversupply, lack of storage capacity, and the unique dynamics of oil futures trading, as illustrated in Figure 15. Concurrently, there was an oil price war between major oil-producing countries, particularly Saudi Arabia and Russia. This disagreement led to a flood of oil supply into an already oversupplied market, exacerbating the price decline.

Ethanol, often blended with gasoline, decreased its prices with oil prices. Reduced demand for gasoline, coupled with the drop in oil prices, affected the ethanol industry. Additionally, with fewer people driving and gasoline consumption decreasing, the need for ethanol as an oxygenate in gasoline blends also diminished.

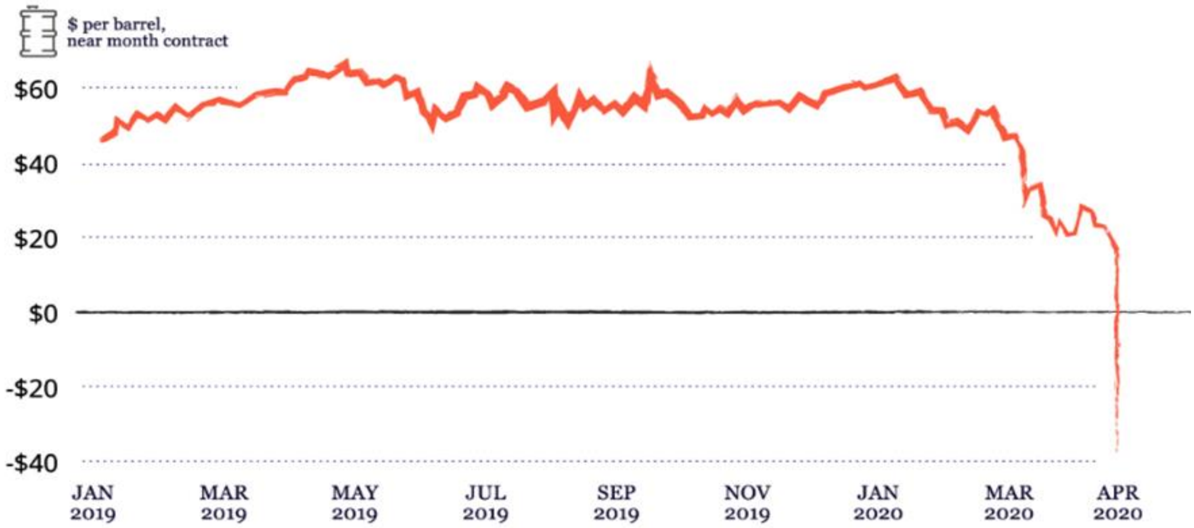

Figure 15. Going below zero

Source: Desjardins (2020).

Several factors contributed to the rebound in oil prices. Production cuts, implemented by oil-producing countries to address the oversupply and stabilize prices, played a pivotal role. Additionally, as regions gradually eased lockdown measures and economic activities resumed, economic conditions improved significantly. Consequently, oil prices emerged from negative territory, gradually stabilizing. While they did not immediately return to pre-pandemic levels, they did experience a significant recovery from the lows observed in April 2020.

5. Final Considerations

In conclusion, this study has ventured into the intricate world of sugar and ethanol prices, utilizing wavelet analysis as a powerful tool to unveil their volatility patterns. Several key insights have emerged while navigating through the narrative of these two markets.

Firstly, while sugar and ethanol share a common origin in sugarcane, they exhibit distinct responses to market forces. Sugar prices are sensitive to factors such as global supply and demand, weather-induced crop variations, and government policies, while ethanol prices are more directly influenced by energy market dynamics, particularly crude oil prices. This dichotomy in their behavior underscores the importance of studying them individually and in conjunction to understand their complex relationship.

Secondly, the analysis has revealed time-frequency correlations between these markets, shedding light on moments of synchronization and divergence. These findings emphasize the dynamic interplay between sugar and ethanol prices and their responsiveness to various economic and global factors.

Moreover, exploring the historical context has shown how significant economic events in Brazil, such as the initiation of the National Alcohol Program (Proálcool) in 1975, the era of military dictatorship, and the implementation of the Real Plan in 1994, have impacted sugar prices in the past. These insights offer valuable historical context for understanding the price dynamics of sugar.

Additionally, recent investigations have highlighted the correlation between ethanol and sugar prices and global concerns over greenhouse gas emissions, the advancement of flex-fuel engine technology, the impact when India became one of the largest sugar-producing and exporting countries in the world, and contemporary challenges like drought periods and the COVID-19 pandemic. These factors underscore the importance of considering domestic and global influences on these markets.

In sum, the journey through the history of these two markets using wavelet analysis provided valuable insights into their past volatility and potential trends. By better understanding the dynamics of sugar and ethanol prices, this research contributes to decision-making on subsidies, such as formulating public policies that promote market stability and industrial strategies to optimize production. Furthermore, identifying volatility patterns paves the way for helping to design more effective hedging mechanisms in a constantly evolving economic scenario.

Here are some potential future works and research directions that can be done to continue this work. Develop predictive models using machine learning techniques to forecast future sugar and ethanol prices based on the insights gained from wavelet analysis. Optimization algorithms that consider market forecasts, cost estimates, and sustainability metrics to recommend the optimal allocation of resources between sugar and ethanol production. Implement scenario analysis to evaluate the impact of different market scenarios (e.g., rising oil prices, changes in government policies) on production decisions. Moreover, it investigates risk management strategies for stakeholders in the sugar and ethanol industries. Explore how the identified patterns and correlations can be utilized to develop effective risk mitigation and hedging strategies.

References

Amrouk, E. M., & Heckelei, T. (2021). Forecasting International Sugar Prices: A Bayesian Model Average Analysis. *Sugar Tech*, 23(6), 1447-1447. https://doi.org/10.1007/s12355-021-01034-x

Atlas Big. (2020). *World Sugarcane Production by Country*. Countries by Sugarcane Production. USA. Retrieved September 7, 2023, from https://www.atlasbig.com/en-us/countries-sugarcane-production

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics*, *31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Boubaker, H., & Raza, S. A. (2017). A wavelet analysis of mean and volatility spillovers between oil and BRICS stock markets. *Energy Economics*, *64*, 105-117. https://doi.org/10.1016/j.eneco.2017.01.026

Bouri, E., Lucey, B., Saeed, T., & Vo, X. V. (2021). The realized volatility of commodity futures: Interconnectedness and determinants. *International Review of Economics & Finance*, *73*, 139-151. https://doi.org/10.1016/j.iref.2021.01.006

Bouri, E., Shahzad, S. J. H., Roubaud, D., Kristoufek, L., & Lucey, B. (2020). Bitcoin, gold, and commodities as safe havens for stocks: New insight through wavelet analysis. *The Quarterly Review of Economics and Finance*, *77*, 156-164. https://doi.org/10.1016/j.qref.2020.03.004

Burrus, C. S., Gopinath, R., & Guo, H. (1997). *Introduction to Wavelets and Wavelet Transforms* (1st ed.). Hoboken: Prentice Hall.

Carpio, L. G. T. (2019). The effects of oil price volatility on ethanol, gasoline, and sugar price forecasts. *Energy*, *181*, 1012-1022. https://doi.org/10.1016/j.energy.2019.05.067

Czapp. (2023). *Global Trade in The Food and Energy Sectors*. Trade Made Simple. USA. Retrieved September 8, 2023, from https://www.czapp.com/

Czarnikow. (2023). *Smart Supply Chain Solutions*. Sugar. USA. Retrieved September 7, 2023, from https://www.czarnikow.com/blog/sugar-consumption-update-the-first-fall-in-40-years

Daly, K. (2008). Financial volatility: Issues and measuring techniques. *Physica A: statistical mechanics and its applications*, *387*(11), 2377-2393. https://doi.org/10.1016/j.physa.2008.01.009

Daubechies, I. (1992). *Ten Lectures on Wavelets* (1st ed.). Philadelphia: SIAM.

Desjardins, J. (2020). *How Oil Prices Went Subzero: Explaining the COVID-19 Oil Crash*. Visual Capitalist. Energy. USA. Retrieved October 13, 2023, from https://www.visualcapitalist.com/subzero-oil-price-crash-covid-19/

Elder, J., & Jin, H. J. (2007). Long memory in commodity futures volatility: A wavelet perspective. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *27*(5), 411-437. https://doi.org/10.1002/fut.20260

Engle, R. F. (1982). A general approach to Lagrange multiplier model diagnostics. *Journal of Econometrics*, *20*(1), 83-104. https://doi.org/10.1016/0304-4076(82)90104-X

Engle, R. F., & Patton, A. J. (2007). What good is a volatility model?. In Knight, J., & Satchell, S. (Ed.), *Forecasting volatility in the financial markets* (3rd ed.). Oxford: Butterworth-Heinemann.

Food and Agriculture Organization - FAO. (2015). *Food Outlook May 2015 - Biannual Report on Global Food Markets*. Trade and Markets Division FAO. Rome: FAO. Retrieved from https://www.fao.org/3/I4581E/I4581E.pdf

Gomes, M. S., de Albuquerque Cavalcanti, I. F., & Müller, G. V. (2021). 2019/2020 drought impacts on South America and atmospheric and oceanic influences. *Weather and Climate Extremes*, *34*, 100404. https://doi.org/10.1016/j.wace.2021.100404

Haley, S. (2015). *Projecting world raw sugar prices*. A Report from the Economic Research Service. Washington DC: EMS/USDA. Retrieved from https://www.ers.usda.gov/webdocs/outlooks/39411/50651_sssm-317-01.pdf?v=7317.8

Hwang, S., & Valls Pereira, P. L. (2008). The effects of structural breaks in ARCH and GARCH parameters on persistence of GARCH models. *Communications in Statistics—Simulation and Computation®*, *37*(3), 571-578. https://doi.org/10.1080/03610910701812378

Investing. (2023). *Commodities*. Markets. USA. Retrieved October 24, 2023, from https://www.investing.com/commodities/

KGS Sugar & Infra Corporation. (2023). *Market Scenario*. Industry Analysis. India. Retrieved October 5, 2023, from https://www.kgssugar.in/industry-analysis.html

Khalfaoui, R., Boutahar, M., & Boubaker, H. (2015). Analyzing volatility spillovers and hedging between oil and stock markets: Evidence from wavelet analysis. *Energy Economics*, *49*, 540-549. https://doi.org/10.1016/j.eneco.2015.03.023

Macrotrends. (2023). *Commodities*. Historical Chart. USA. Retrieved October 24, 2023, from https://www.macrotrends.net/charts/commodities

Marengo, J. A., Cunha, A. P., Cuartas, L. A., Deusdará Leal, K. R., Broedel, E., Seluchi, M. E., ... Bender, F. (2021). Extreme drought in the Brazilian Pantanal in 2019–2020: characterization, causes, and impacts. *Frontiers in Water*, *3*, 639204. https://doi.org/10.3389/frwa.2021.639204

Melo, A. D. S., & Sampaio, Y. D. S. B. (2016). Uma nota sobre o impacto do preço do açúcar, do etanol e da gasolina na produção do setor sucroalcooleiro. *Revista Brasileira de Economia*, *70*(1), 61-69. https://doi.org/10.5935/0034-7140.20160004

Miah, M., & Rahman, A. (2016). Modelling volatility of daily stock returns: Is GARCH (1, 1) enough. *American Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)*, *18*(1), 29-39.

Ninô de Carvalho, P. (2013). The Story of Brazil's Ethanol Programme. *ELLA - Evidence and Lessons from Latin America*. Lima, Peru. Retrieved from https://assets.publishing.service.gov.uk/media/57a08a08ed915d622c00050b/130806_ENV_BraEthPro_GUIDE.pdf

Oliveira, A. B., & Pereira, P. L. V. (2017). Mudança de regime e efeito ARCH em volatilidade: Um estudo dos choques das cotações do Petróleo. *Revista Brasileira de Finanças*, *15*(2), 197-225.

Palacios-Bereche, M. C., Palacios-Bereche, R., Ensinas, A. V., Gallego, A. G., Modesto, M., & Nebra, S. A. (2022). Brazilian sugar cane industry–A survey on future improvements in the process energy management. *Energy*, *259*, 124903. https://doi.org/10.1016/j.energy.2022.124903

Palazzi, R. B., Meira, E., & Klotzle, M. C. (2022). The sugar-ethanol-oil nexus in Brazil: Exploring the pass-through of international commodity prices to national fuel prices. *Journal of Commodity Markets*, *28*, 100257. https://doi.org/10.1016/j.jcomm.2022.100257

Pantoja, D. E. L., Samanez, C. P. M., Castro, J. G., & Aiube, F. A. L. (2016). Economic appraisal of production flexibility in different regions of the Brazilian sugar and ethanol industry. *Revista Brasileira de Gestão de Negócios*, *18*(60), 226-244. https://doi.org/10.7819/rbgn.v18i60.2867

Ramsey, J. B. (2002). Wavelets in economics and finance: Past and future. *Studies in Nonlinear Dynamics & Econometrics*, *6*(3). https://doi.org/10.2202/1558-3708.1090

Reis, D. L. P. E., Mattos, R. S., Perobelli, F. F. C., & Corrêa, W. R. (2013). Options Pricing for Petrobras Share: A Comparison Between Realized Volatility and Conditional Heteroskedastic Estimations. In *International Workshop in Financial Econometrics*, I, Anais. Natal, Rio Grande do Norte, Brazil.

Rezende, M. L., & Richardson, J. W. (2015). Economic feasibility of sugar and ethanol production in Brazil under alternative future prices outlook. *Agricultural Systems*, *138*, 77-87. https://doi.org/10.1016/j.agsy.2015.05.004

Rua, A., & Nunes, L. C. (2009). International comovement of stock market returns: A wavelet analysis. *Journal of Empirical Finance*, *16*(4), 632-639. https://doi.org/10.1016/j.jempfin.2009.02.002

Sadik, Z. A., Date, P. M., & Mitra, G. (2019). News augmented GARCH (1, 1) model for volatility prediction. *IMA Journal of Management Mathematics*, *30*(2), 165-185. https://doi.org/10.1093/imaman/dpy004

Sant'anna, A. C., Shanoyan, A., Bergtold, J. S., Caldas, M. M., & Granco, G. (2016). Ethanol and sugarcane expansion in Brazil: what is fueling the ethanol industry?. *International Food and Agribusiness Management Review*, *19*(4), 163-182. https://doi.org/10.22434/IFAMR2015.0195

Sentelhas, P. C., & Pereira, A. B. (2019). El Niño–Southern Oscillation and its impacts on local climate and sugarcane yield in Brazil. *Sugar Tech*, *21*(6), 976-985. https://doi.org/10.1007/s12355-019-00725-w

Shikida, P. F. A. (2010). Desenvolvimento socioeconômico e agroindústria canavieira no Paraná. *Revista de Política Agrícola*, *19*(3), 67-82.

Shikida, P. F. A., & Bacha, C. J. C. (1999). Evolução da agroindústria canavieira brasileira de 1975 a 1995. *Revista Brasileira de Economia*, *53*(1), 69-90.

Thomaz, P. S., de Mattos, V. L. D., Nakamura, L. R., Konrath, A., & Nunes, G. D. S. (2020). Modelos GARCH em ações financeiras: um estudo de caso. *Exacta*, *18*(3), 626-648. Retrieved December 28 2024, from https://www.researchgate.net/publication/342855681_Modelos_GARCH_em_acoes_financeiras_um_estudo_de_caso

TradeWays. (2023). *The Wavelet Transform*. Menu. USA. Retrieved September 27, 2023, from http://www.tradeways.org/wave_1.php

União da Indústria de Cana-de-Açúcar – UNICA. (2023). *Produção*. UNICAdata. Retrieved September 18, 2023, from http://www.unicadata.com.br/

Valdes, C. (2022). Brazil's momentum as a global agricultural supplier faces headwinds. *AgEcon Search*, United States Department of Agriculture, Economic Research Service, 1-12. Retrieved from https://libkey.io/10.22004/ag.econ.338866?utm_source=ideas

Zheng, Y., dos Santos Luciano, A. C., Dong, J., & Yuan, W. (2022). High-resolution map of sugarcane cultivation in Brazil using a phenology-based method. *Earth System Science Data*, *14*(4), 2065-2080. https://doi.org/10.5194/essd-14-2065-2022