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Revealing Multiscale Interdependence between Ethanol and Corn

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Abstract: *One of the key issues nowadays is global warming, while biofuels have been seen as potential solution for this problem. In the recent years, corn is used as a primary raw material for ethanol production, which means that these two commodities could be highly interconnected. In this regard, this paper investigates time and frequency interdependence between corn and ethanol markets, using the wavelet coherence methodology. As a preliminary result, wavelet power spectrum reveals that increased volatility in the corn and ethanol markets is present up to 16 days and around the two major crisis. The wavelet coherence results clearly indicate that high interconnection does not exist in the short time-horizons, even at the time of the pandemic and the war in Ukraine. This means that various external shocks affect differently the two markets in the short-run. However, the areas of very high coherence are found in the time-horizons from 32 days onwards, which means that the movements of the two markets are pretty much synchronized in the longer time-horizons. This happens because longer time-horizons characterize the lack of idiosyncratic price oscillations, which means that external factors affect the two markets relatively aligned in the long-run. Future studies may use different wavelet techniques, such as wavelet correlation and cross-wavelet correlation, in order to overcome deficiencies of the wavelet coherence method.*

Keywords: *Corn and Ethanol; Multiscale Interconnection; Wavelet Coherence Methodology.*

Introduction

Global warming and climate change are some of the most important global topics nowadays. In this regard, biofuels are seen as a promising alternative to help replace fossil resources, which should lead to a sustainable energy system (Petković et al., 2020). However, the transition from food production to biofuel production may adversely affect the supply and price of commodities such as sugarcane, sugar beet, cassava, corn, rapeseed, soybeans, palm oil, and wheat, as Subramaniam et al. (2020) argued. Corn is one of the most produced agricultural commodities in the world and also the key raw material in ethanol production (see e.g. Zhang et al., 2023). This means that prices of corn and ethanol are inevitably intertwined, which steams their interdependence. In particular, the demand for corn as a feedstock for ethanol production can have a significant impact on agricultural practices, including land use, crop rotation, and farming methods (Kuzman et al., 2021). This, in turn, affects food prices and availability. Besides, fluctuations in corn prices can affect the economics of ethanol production and the price of ethanol at fuel stations. Both corn and ethanol are globally traded commodities, and their interdependence can have international ramifications. For instance, changes in the U.S. ethanol production can affect global corn markets and prices, influencing food security and trade dynamics in various countries. Therefore, understanding the relationship between corn and ethanol prices is vital for both consumers and the biofuel industry to anticipate and manage price volatility. Several papers studied the corn-ethanol relationship, confirming the presence of the nexus. For instance, in their 2013 study, Zhang et al. (2013) reported estimates ranging from 5 per cent to 53 per cent for the expected increase in maize prices by 2015 that can be attributed to biofuel policies. On the other hand, Condon et al. (2015) asserted that a one billion gallon expansion of the US corn ethanol mandate in the year 2015 would lead to a three to four percent increase in corn prices. Bilgili et al. (2022) contended that a public concern worldwide is present in recent years regarding the potential effects of biofuel production on food security.

According to the above, this paper tries to contribute to the international debate on the interrelationship between corn and ethanol. This question is additionally important because both corn and ethanol prices have gone through serious oscillations in recent years due to the pandemic and the war in Ukraine. Heavy price swings of these two commodities are clearly visible on Figure 1. In addition, it can be seen that dynamics of both prices is relatively equalized, i.e. the prices of both commodities started to rise when the pandemic erupted and have maintained a high level during 2021 and 2022. In 2023, both prices started to fall. Based on both plots it can be assumed that the commodities are interrelated, and the task of this paper is to figure out how strong this interlink is.

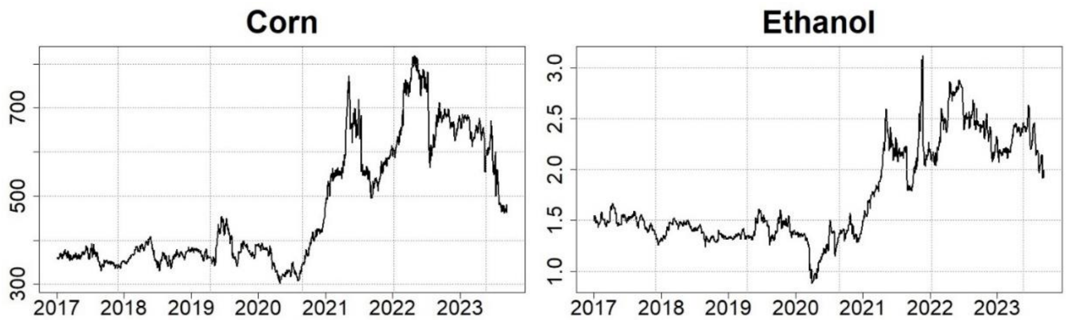

Fig. 1. Empirical dynamics of corn and ethanol prices

Note: The price of corn is expressed in US cents per bushel, while the price of ethanol is in US dollars per gallon.

Source: Author's calculation.

In the real world, different stakeholders (producers, traders, investors, speculators, policymakers) meet their goals in different time horizons. For instance, those agents who want to make a profit on the price change must act quickly and for them the short-term relationship is more important than the long-term one (Živkov et al., 2021a). On the other hand, for those who care about protecting themselves from the risk of price changes, knowing the long-term interdependence is more important. In order to take into account the different aspirations of market participants over different time horizons, the paper uses the wavelet coherence methodology. This technique is effective in measuring the strength of the bond between two different elements over different periods of time throughout the observed sample, and the strength of the coherence is presented via colour pallet (Chen and Li, 2016; (Živkov et al., 2021b). Wormer colours indicate stronger coherence, while cooler colours point to weaker coherence. This methodology efficiently deals with the problem of sample size reduction when observes different time horizons because created wavelet time-series preserve all empirical information. This trait of wavelet coherence is found very appealing by many researchers who investigated various phenomena in different time-horizons (see e.g. Pal and Mitra, 2017; Li and Gençay, 2017; Belhassine and Karamti, 2021; Živkov et al., 2023).

As for the existing papers that researched the connection between corn and ethanol, Yoon (2022) used cointegration and quantile Granger causality analysis to examine the long- and short-term relationships between fossil fuel, biofuel, and agricultural food commodity prices. Tanaka and colleagues tested the theory that ethanol production strengthens the link between food and energy prices in their 2023 study. In addition to a wavelet coherence approach, they used a hybrid method combining the Dynamic Conditional Correlations (DCC) with Mixed-Data Sampling (MIDAS) model during the period of 2005 to 2020. Guo and Tanaka (20-22) used the spillover index and partial wavelet coherence methods to study the interrelationships among three commodity markets - ethanol, gasoline and corn - from January 2001 to December 2020.

Gardebroek and Hernandez (2013) investigate the transmission of volatility in oil, ethanol and corn prices in the United States between 1997 and 2011 using a multivariate GARCH approach to assess the degree of interdependence and the dynamics of volatility between these markets. They found a higher interaction between the ethanol and corn markets in recent years, particularly after 2006, when ethanol became the only substitute oxygenate for gasoline.

Apart from the introductory section, the structure of the paper consists of several distinct sections. The second section describes the research methodology used. The third section presents the data set and provides descriptive statistics. The fourth section presents the results of the wavelet coherence analysis between corn and ethanol. The potential implications of these results for various market participants are discussed in the fifth section. Finally, the last section summarises the research findings.

Research Methodology – Wavelet Coherence

In this paper, the wavelet coherence method is used to reveal the multi-scale strength of the link between corn and ethanol. This approach provides insights into the strength of the correlation across different wavelet scales and across the sample data. In their study, Tao et al., 2018) detailed the wavelet coherence method as an instrument for evaluating the local linear correlation between two stationary time series across multiple scales. Further, in their 1998 study, Torrence and Compo (1998) introduced W_xy (u,s) = W_x (u,s) W_y^* (u,s) as the cross-wavelet transform of two time series, x(t) and y(t). In this formula, W_x and W_y represent the wavelet transforms of x and y, respectively. The variables u and s represent position and scale index, while the asterisk (*) signifies a complex conjugate. The equation (1) further details the squared wavelet coherence coefficient.

$$R^2(u,s) = \frac{\left|\mathbb{S}\left(s^{-1}W_{xy}(u,s)\right)\right|^2}{\mathbb{S}(s^{-1}|W_x(u,s)|^2)\mathbb{S}\left(s^{-1}|W_y(u,s)|^2\right)} \tag{1}$$

In this context, $\mathbb{S}(.)$is represents the smoothing operator. The squared coefficient of the wavelet coherence, denoted by R^2 (u,s), varies between 0 and 1. The key to comprehending these correlations lies in the phase difference, which is denoted by phase arrows within the wavelet coherence diagrams. Following the methodology outlined by Torrence and Webster (1999), the calculation of the wavelet coherence phase difference is detailed in equation (2):

$$\phi_{xy}(u,s) = tan^{-1}\left(\frac{\Im\{S(s^{-1}W_{xy}(u,s))\}}{\Re\{S(s^{-1}W_{xy}(u,s))\}}\right) \tag{2}$$

In the argumentation, $\Im$ and $\Re$ denote the imaginary and real components of the smoothed power spectrum, respectively. It is suggested that the time series are in phase, indicating a positive correlation, when the arrows in the analysis point to the right.

Dataset and Descriptive Statistics

This study uses daily near-maturity futures prices for corn and ethanol. Futures prices were chosen over spot prices because they react more quickly to external shocks than spot markets. The analysis covers the period from January 2017 to August 2023, with data sourced from the stooq.com website. The time series for both commodities are transformed into log returns using the formula: $r_{(i,t)} = 100\times\log(P_t/P_{(t-1)})$, where P is the price of either corn or ethanol.

Table 1 presents descriptive statistics for ethanol and corn, including the first four moments, Jarque-Bera normality test, and DF-GLS stationarity test. The data show a relative riskiness in both series, as indicated by the standard deviation levels. A significant negative skewness in both series indicates a greater concentration of returns to the left of the mean. High kurtosis values for both assets indicate the presence of outliers and extreme values, which is not unexpected given that the sample period includes two crises that caused significant market turbulence. The third and fourth moments show non-normal characteristics, implying that both series deviate from a normal distribution, as confirmed by the Jarque-Bera test. Stationarity in both series, as indicated by the DF-GLS test, is essential for an accurate estimation of the wavelet coherence.

Table 1. Descriptive statistics of ethanol and corn futures time-series

	Mean	St. dev.	Skewness	Kurtosis	JB	DF-GLS
Ethanol	0.004	0.751	-1.801	22.689	28128.3	-4.976
Corn	0.010	0.801	-1.526	20.650	22524.6	-8.889

Note: JB stands for p-value of Jarque-Bera coefficients of normality. 1% and 5% critical values for DF-GLS test with 10 lags assuming only constant are -2.566 and -1.941, respectively.

Source: Author's calculation.

The paper examines multiscale interdependence, so it is useful to inspect areas of high volatility in different time horizons. In this regard, Figure 2 shows wavelet power spectrum of the two time-series. According to the plots, high volatility of corn occurred in 2021 and 2022, which can be linked with the sharp drop of corn price due to counter-COVID measures and steep rise of corn price at the beginning of 2022 as a result of the war in Ukraine. Similar pattern can also be found on the ethanol plot, but with the difference that high volatility is present in 2020, which can be explained by the significant drop of ethanol price due to global slowdown caused by the pandemic (see Figure 1). It is interesting to note that red colour can be found only up to 16 days in both plots. This means that high volatility in the markets does not last for an extended period of time, but dissipates relatively quickly. This is also an indication that the markets absorb and imbed new information from external shocks in relatively short time. High volatility implies high activity in the markets, where each market reacts to external shocks in its own way. Due to the idiosyncratic characteristics of both markets, it could be hypothesized that interdependence between the markets is weak in short run. This assumption is tested in the next section, when wavelet coherence is calculated.

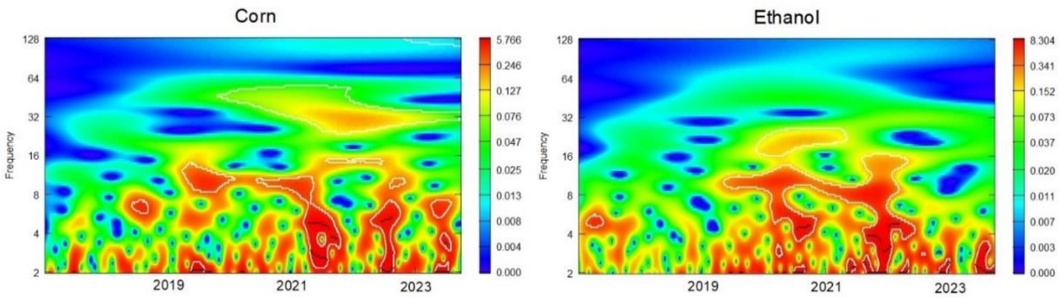

Fig. 2. Wavelet power spectrum of the two time-series

Source: Author's calculation.

The primary advantage of the wavelet methodology is showing interdependencies between assets in different time-horizons. In other words, the short-term horizon is presented up to 8 wavelet scale, midterm horizon observes the scales between 8-64 days, while the long-term horizon is depicted by the scales between 64-128 days,

Wavelet Coherence Results

This section uses wavelet coherence methodology to explore the relationship between the two commodities through a time and frequency lens. The intensity of their connection is shown on a colour-coded surface, with warmer tones indicating stronger and cooler tones indicating weaker connection. The interdependence is observed up to 128 days, which is relatively long time period.

According to Figure 3, the assumption from the previous section that the connection is weak in the short time horizon turned out to be correct because the green colour dominates up to 2 days and even up to 4 days. This means that very feeble connection exist between the markets in the very short time-horizon, i.e. they behave pretty much independent. The reason probably lies in the specific characteristics of the two markets and the behaviour of the market participants in these markets that do not allow their congruence in short run.

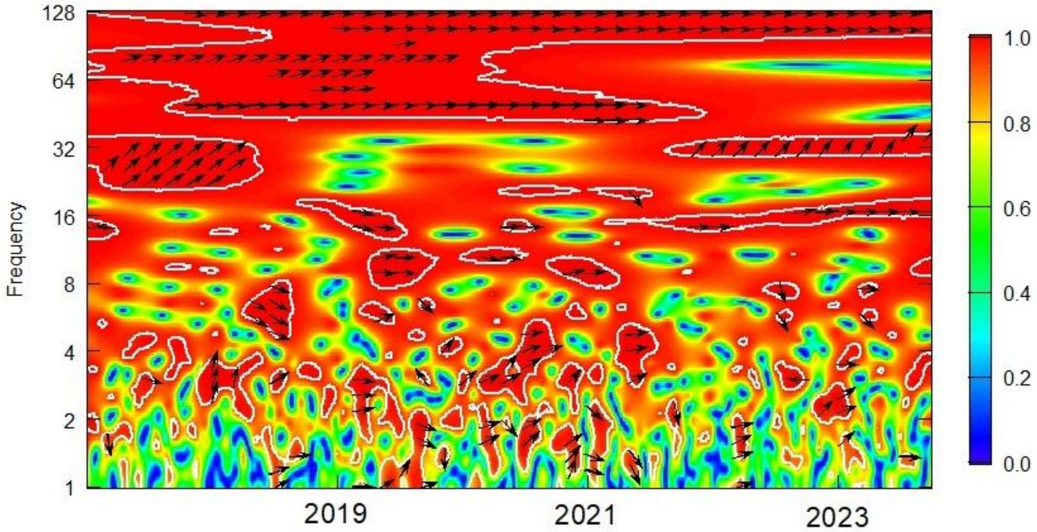

Fig. 3. Wavelet coherence plot between corn and ethanol

Source: Author's calculation.

On the other hand, as wavelet scales increase, the red colour begins to take upper hand. This means that stronger connections between the markets start to emerge as time horizons get longer. In other words, specific characteristics of markets start to dissolve in the longer time-horizons, while the effect of fundamental factors on markets becomes more and more unison. This suggests that markets react relatively equally on external shocks in the long time-horizons, which strengthens the interdependence between the two markets. In the very long time-horizons, from 64 days onwards, delineated areas of very high coherence exist, which means that connection between the markets is really strong at very long time-horizons. In regions where coherence is high, phase arrows are also present. These arrows not only signify the direction of the interdependence between variables but also highlight the lead-lag relationship between them. Most of the arrows point to right, which means that positive coherence exist between corn and ethanol markets in long term. This indicates that external shocks drive both markets in the same direction, which is expected. In addition, some phase arrows are point to up and right, which means that second variable in the computational process (ethanol) lags the first one. In other words, corn market reacts faster to external shocks than ethanol market. The findings of this study are closely aligned with those of Bilgili et al. (2022), who also employed a wavelet methodology to examine the co-movement between the same markets. Their research also revealed a pattern of pronounced coherence over longer time horizons, which contrasts with a markedly lower degree of coherence over shorter time horizons.

It is interesting to note that high coherence areas are not present in short-term during the period of the two crisis. This is a strong indication that despite of the devastating effects of the two crisis, the two markets retain pretty much independent course in the short-run during this period.

Implications of the Results

Wavelet coherence indicates that the weaker interdependence exists up to eight day, and the stronger connection onwards. These results bear several implications for ethanol and corn producers, investors and portfolio managers in the corn and ethanol markets.

First, for ethanol producers, the long-term connection is more important. Wavelet coherence results indicate that strong price connection exists in the long-term horizons, which means that changes in the price of corn can substantially affect the cost of producing ethanol. In other words, if global corn prices rice, for whatever reason, this makes production of ethanol more expensive because corn is the primary feedstock for ethanol production. Also, if corn price rises, this makes ethanol less competitive with gasoline or other alternative fuels in terms of price. This may affect consumer choices and the market share of ethanol in the transportation fuel sector. On the other hand, long-term connection between the assets can be beneficial for farmers. In particular, if the price of oil rise, the prices of biofuels follow, which means that corn prices will probably rise as well, because more corn feedstock is intended for ethanol production.

Second, for investors, speculators and portfolio managers that are active in the corn and ethanol markets, the short-term connection is more important. The results indicate that weak price connection exists between corn and ethanol, and this is good for the short-term investors in the portfolio combined of corn and ethanol. Low correlated assets in a portfolio increase diversification and lower the risk of a portfolio. On the other hand, investors who combine corn and ethanol in the same portfolio, should avoid keeping this combination in the longer time-horizons because higher interdependence is bad for diversification efforts. Short-term speculators, who want to profit on the price changes, cannot use the developments in one market for predicting developments on the other market. On the other hand, the stronger connection is present in the longer time-horizons, where wavelet coherence suggests that ethanol prices lag corn prices in the long-run. This can be used by long-term investors in ethanol to predict the movements of ethanol prices, looking at the dynamics of corn prices.

Conclusions

The global warming phenomenon and biofuels have become one of the top topics in the international community. In this respect, biofuels and commodities that are used for their production are interlinked. In this regard, this paper researches the nexus between corn and ethanol prices in a multiscale framework, which gives an information about the strength of interdependence across the sample and various time-horizons. Wavelet coherence methodology is used in this process.

As a preliminary result, wavelet power spectrum reveals that increased volatility in the corn and ethanol markets is present up to 16 days and around the two major crisis – the pandemic and the war in Ukraine. Somewhat higher volatility is detected on the ethanol market in 2022, which is strong indication that the war in Ukraine had an impact on the global energy market, which also refers to the ethanol market. Wavelet power spectrum shows that higher volatility does not prevail in the longer time-horizons in both markets.

On the other hand, the wavelet coherence results clearly show that high interconnection does not exist in the short time-horizons, even at the time of the two crisis. This means that idiosyncratic behaviour of the two markets do not allow that various external shocks affect at the same way the two markets in the short-run. This leaves small room to find high interdependence between the two markets, which is good for short-term portfolio investors, who combine corn and ethanol in the same portfolio. However, in the long-run, the story is completely different. In other words, the areas of very high coherence are found in the time-horizons from 32 days onwards, which means that the movements of the two markets are pretty much synchronized in the longer time-horizons. This happens because longer time-horizons characterize the lack of idiosyncratic price oscillations, which means that external factors affect the two markets relatively aligned in the long-run. This is why areas of high coherence are found at longer time horizons and not at shorter time horizons. These results may be used for predicting price movements in one market, tracking the price on the other market. In particular, ethanol producers can use the prices of corn to create a picture in which direction the prices of ethanol will go because ethanol prices lag corn prices.

Wavelet coherence has the disadvantage of not being able to display exact values of wavelet coherence between two assets, which may lead sometimes to wrong conclusions. In this regard, future studies may use different wavelet techniques, such as wavelet correlation and cross-wavelet correlation, which serve as a complementary analysis, to disclose the exact levels of multiscale interdependence between corn and ethanol.

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