EXAMINING THE MULTISCALE INTERRELATIONSHIP BETWEEN ETHANOL AND AGRICULTURAL COMMODITIES[1]

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Abstract

This paper investigates the multiscale interdependence between ethanol and three agricultural commodities—corn, wheat, and soybeans—used as feedstock for ethanol production. Two wavelet approaches are applied in the analysis: wavelet coherence and wavelet cross-correlation. The first method reveals the strength of the connection, while the second indicates the leading (or lagging) interconnection between assets. According to the wavelet coherence results, the link between ethanol and agricultural commodities is relatively weak in the short term but progressively strengthens as the time horizon increases. In the short-term horizon, the strongest link is observed between ethanol and corn. Wavelet cross-correlation indicates that the short-term connection is only relevant for ethanol and corn due to their relatively strong short-term relationship. Conversely, all long-term interdependencies are relevant since strong correlations are found at higher wavelet scales. According to the results, larger agricultural markets tend to lead the smaller ethanol market in most cases.

Key words: *ethanol, multiscale interlink, wavelet methodologies.*

Introduction

Global warming and CO_2 emissions are pressing global challenges, with biofuels seen as a viable path toward a sustainable energy future. However, because biofuel production relies on organic materials and agricultural commodities that also serve as essential food sources for both humans and animals, it is intricately linked to

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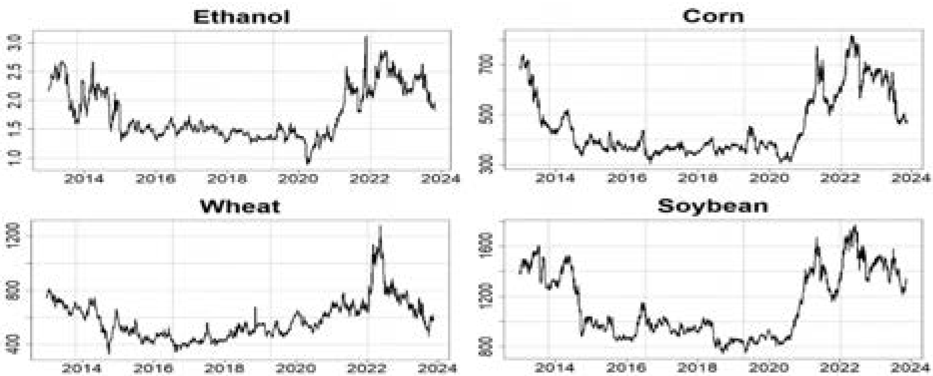
the agricultural sector (Sarmiento et al., 2012). Ethanol, in particular, stands out as a major renewable energy source derived from biomass, making its relationship with agricultural commodities inevitable.

Understanding the connection between ethanol and agricultural prices is essential for several reasons. First, this close relationship affects the volatility of agricultural prices; fluctuations in biofuel demand can lead to price changes in the agricultural sector (Wu et al., 2023). Second, farmers' incomes are influenced by crop prices, and any shifts in the demand for crops used in ethanol production can directly impact their profitability (Leonardo et al., 2015). Additionally, agricultural investors must account for biofuel demand trends, as these influence crop prices and, consequently, inform decisions on resource allocation and risk management. Increased demand for crops in ethanol production also drives changes in farming practices, as noted by Lundberg et al. (2023). Consequently, understanding ethanol impact on agricultural commodities enables farmers to make informed choices about crop planning and production levels, manage risks through hedging and crop insurance, and explore diversification opportunities that may enhance income stability.

Based on the above, this study aims to determine the strength of the interdependence between ethanol and three agricultural commodities—corn, wheat, and soybeans—used as feedstocks in ethanol production. Figure 1 displays the empirical price dynamics of ethanol and these three agricultural assets over a period of more than 10 years. The similarity in their price movements suggests that a relatively strong correlation may exist between ethanol and these grains.

Figure 1. *Empirical dynamics of four commodities*



Note: The price of ethanol is in USD per gallon, while corn, wheat and soybean are in USD cents per bushel.

Source: *Author's calculation.*

The analysis utilizes a multiscale framework, enabling the assessment of correlation strength across multiple time horizons. This approach is essential as different stakeholders – speculators, farmers, traders, portfolio managers, and policymakers – have varying time preferences. For example, market participants who seek profits from price volatility prioritize short-term interdependencies, while farmers and commodity traders, who aim to mitigate price risk, find long-term relationships more valuable for their hedging strategies.

This study applies two advanced wavelet-based methodologies: wavelet coherence (WTC) and wavelet cross-correlation. WTC captures the strength of interdependence across both time and frequency domains, visualized on a color-coded surface map, though it lacks precise numerical values for coherence (Singh et al., 2022). On the other hand, wavelet cross-correlation provides insights into leading and lagging relationships among assets across different time frames. Identifying lead-lag connections can aid in forecasting, as a leading asset may signal changes in a lagging one. By combining these methods, a well-rounded perspective of the interdependence between ethanol and its agricultural feedstocks emerges.

Regarding existing literature, Bilgili et al. (2022) analyzed the interdependencies between corn and ethanol in the U.S. using wavelet analysis. They found that the connection between ethanol production and corn prices exists over both short and long terms; specifically, since 2010, increases in corn prices have been followed by increases in ethanol production in U.S. markets. Tanaka et al. (2023) examined whether ethanol production strengthens the link between energy and food prices using a DCC-GARCH-MIDAS model and wavelet coherence approach. Their findings revealed positive linkages between ethanol-crude oil, crude oil-corn, and ethanol-corn, indicating that dynamic correlations between ethanol and corn can influence ethanol production across short and long horizons. Subramaniam et al. (2020) assessed the impact of biofuels on food security across 51 developing countries using a dynamic generalized method of moments, concluding that the link between environmental quality and biofuels significantly enhances food security. Finally, Guo and Tanaka (2022) explored interrelations among ethanol, gasoline, and corn markets, specifically examining wholesale and producer prices. By applying the spillover index and partial wavelet coherence methods, they observed that ethanol and gasoline prices are positively correlated with corn prices in the short term.

Material and methods

Wavelet coherence

The initial method employed to analyze the connection between ethanol and agricultural commodities is wavelet coherence. This approach offers localization in both time and frequency, enabling us to observe how the relationship between two-time series changes across various time scales. Unlike Fourier-based methods, wavelet coherence can detect nonlinear connections between time-series, capturing nuances that might otherwise be overlooked (Hung, 2022). Given that our dataset spans a substantial time period with frequent outliers and extreme values, the wavelet approach is especially suitable due to its robustness against noise. The squared wavelet coherence is calculated as shown in equation (1):

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

whererepresents a smoothing operator and *s* indicates wavelet scale. The squared wavelet coherence coefficient ranges $0 \le R^2(u,s) \le 1$, where values near zero point to weak correlation, while values near one indicate to strong correlation.

Wavelet cross-correlation

Wavelet cross-correlation further enriches the analysis by identifying which asset leads and which lags across different time horizons. This insight is particularly valuable for short-term investors, as it helps them understand the origin and direction of market shocks (Živkov et al., 2023). While this method also examines two time series, it incorporates the lagged correlation function (ρ_τ) with lag τ, enabling the construction of a symmetric lagged correlation profile ($\rho_\tau = \rho - \tau$). Symmetry is disrupted when significant deviations arise between $\rho_\tau$and $\rho - \tau$, introducing asymmetry in the information flow. In cases of asymmetry, the leading asset demonstrates predictive power over the lagging asset. Based on Gencay et al. (2002), the MODWT cross-correlation equation for scale j and lag τ is represented as follows:

$$\rho_{x,y,j,t,\tau} = \frac{COV(\widehat{D}_{x,j,t}, \widehat{D}_{y,j,t+\tau})}{\left(Var(\widehat{D}_{x,j,t})Var(\widehat{D}_{y,j,t+\tau})\right)^{1/2}}, \quad (2)$$

whereVar and COV are variance and covariance, respectively, and cross-correlation takes value $-1 \le \rho_{x,y,j,t,\tau} \le 1$.

Dataset and descriptive statistics

This paper utilizes daily near-maturity futures prices for ethanol and three key agricultural commodities – corn, wheat, and soybeans. Futures markets were selected for their higher liquidity, which makes these prices more representative than spot prices. The dataset spans a substantial period, from January 2013 to December 2023. Each commodity's prices were converted to log-returns using the formula: , where represents the price at a specific time. All time series data were sourced from stooq.com, with each agricultural commodity synchronized with ethanol to create three equal-length pairs. Table 1 provides descriptive statistics for these assets.

The statistics indicate that all assets have an average value close to zero, suggesting that, on average, prices remained stable over the observed period. As depicted in Figure 1, there were notable price peaks in 2013, 2014, 2021, and 2022, while prices stayed comparatively low from 2015 to 2020, resulting in a near-zero average. The standard deviation reflects relatively high risk, with ethanol displaying the highest volatility. Negative skewness in ethanol, corn, and soybeans reveals a greater frequency of negative returns. High kurtosis, particularly for ethanol, indicates the occurrence of extreme returns. According to the Jarque-Bera test, none of the assets follow a normal distribution. The DF-GLS test confirms the absence of a unit root in each time series, meeting a key requirement for wavelet analysis.

Table 1. *Descriptive statistics of the selected assets*

	Mean	**St. dev.**	**Skew.**	**Kurt.**	**JB**	**DF-GLS**
Ethanol	-0.003	0.883	-3.338	43.189	188166.2	-46.824
Corn	-0.006	0.726	-1.482	19.424	32181.810	-27.577
Wheat	-0.005	0.839	0.489	8.848	4102.268	-25.926
Soybean	-0.001	0.583	-0.689	8.951	4345.385	-53.378

Notes: JB stands for value of Jarque-Bera coefficients of normality, while DF-GLS is unit root test where 1% and 5% critical values are -2.566 and -1.941, respectively.

Source: *Authors' own calculation based on data from stooq.com (2023).*

The paper researches the nexus in a multiscale environment *via* six wavelet scales. These scales represent different time-horizons:scale 1(2-4 days), scale 2(4-8 days), scale 3(8-16 days), scale 4 (16-32 days), scale 5(32-64 days) and scale 6(64-128 days). The first four scales represent the short-term horizon, whereas the fifth and sixth scales are regarded as midterm and long-term, respectively.

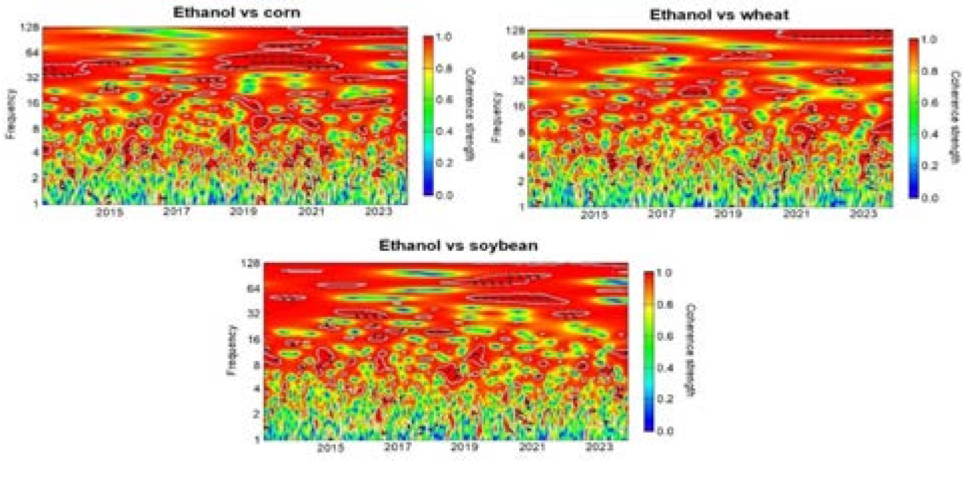
Results and discussion

Wavelet coherence

This section presents the wavelet coherence results for each of the three pairs, illustrated in Figure 2. Wavelet coherence offers an intuitive visual of the relationship between two-time series across both time and frequency domains, capturing complex interaction patterns that other analyses might miss. The horizontal axis represents time, while the left vertical axis shows frequency scales, expressed in days from 1 to 256, to represent different time horizons. The color-coded surface depicts the strength of the coherence between the two-time series, with cooler colors indicating weaker connections and warmer colors signaling stronger coherence. Dark-red areas denote very high coherence between variables.

As seen in the plots, cooler colors dominate at lower wavelet scales, suggesting weak short-term linkages between ethanol and the three agricultural commodities. This likely reflects the impact of various unique factors that drive each market, leading to relatively independent price movements in the short run. In contrast, warmer colors appear more prominently at higher wavelet scales, indicating that price dynamics between these markets become more synchronized over longer time horizons. This synchronization occurs because fundamental factors tend to influence global markets more uniformly over extended periods, resulting in more aligned price trends. However, wide bands of high coherence are generally absent, except in the ethanol-corn pair during the pandemic period.

Figure 2. *Wavelet coherence plots*



Source: *Authors' own calculation based on data from stooq.com (2023).*

Wavelet cross-correlation results

To enhance the analysis, this section presents the pairwise wavelet cross-correlation results between ethanol and the three agricultural commodities. This method uncovers the lead and lag relationships between the markets, identifying the source of market shocks and the recipient of those shocks. Such insights can be valuable for market participants seeking to mitigate the impact of shocks from related markets. Table 2 summarizes the wavelet cross-correlation results for the three pairs, while Figure 3 provides visual representations of these findings. In the analysis, ethanol is treated as the first variable, while the respective agricultural commodity is the second. This distinction is crucial because negative (positive) lagged correlations correspond to ethanol (the agricultural commodities) in Figure 2.

The wavelet cross-correlation analysis indicates lead-lag relationships based on the orientation of the cross-correlation curve. If the curve tilts to the left, it signifies that the first time series leads the second, and vice versa. At lower wavelet scales, the tilt of the cross-correlation curve may not be distinctly visible, which is why the cross-correlation values are also included in Table 2. In interpreting the results, only the fifth cross-correlation values, highlighted in bold, will be discussed.

Table 2. *Wavelet cross-correlation results*

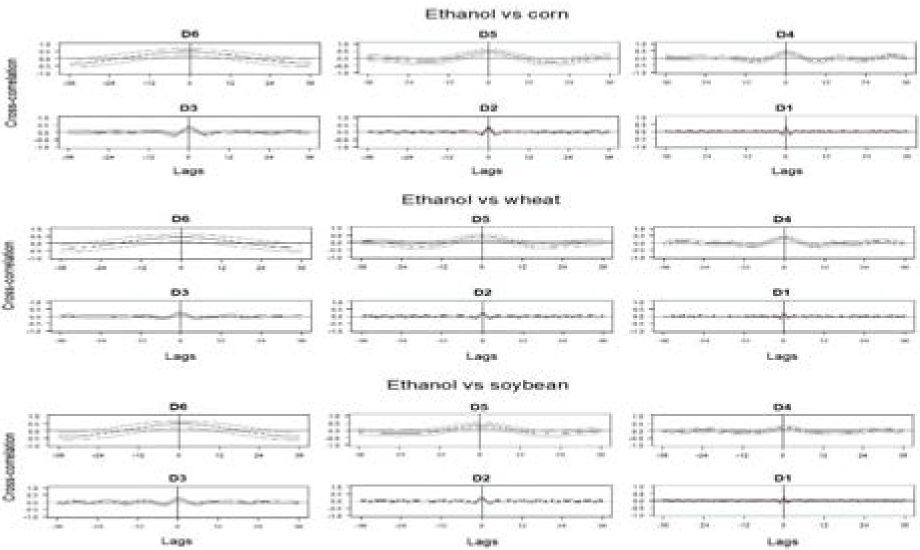
		Negative lagged correlations				Positive lagged correlations			
		-20	-15	-10	-5	5	10	15	20
Ethanol vs corn	D1	0.023	0.023	-0.017	**0.018**	**0.019**	0.025	-0.003	-0.011
	D2	0.031	-0.002	-0.044	**-0.013**	**0.036**	0.001	-0.029	-0.031
	D3	0.016	-0.007	0.037	**-0.205**	**-0.167**	-0.005	0.046	-0.012
	D4	-0.007	-0.035	-0.184	**-0.011**	**0.049**	-0.199	-0.002	-0.063
	D5	-0.235	-0.195	0.043	**0.304**	**0.302**	0.014	-0.252	-0.298
	D6	0.052	0.219	0.365	**0.458**	**0.432**	0.312	0.159	-0.004
Ethanol vs wheat	D1	-0.001	-0.006	-0.020	**-0.025**	**0.004**	0.022	0.006	-0.028
	D2	0.019	-0.004	0.000	**-0.004**	**0.032**	-0.031	-0.013	-0.008
	D3	-0.012	0.015	0.005	**-0.122**	**-0.110**	-0.033	0.073	-0.054
	D4	-0.037	-0.062	-0.180	**0.041**	**0.021**	-0.180	-0.040	-0.052
	D5	-0.229	-0.219	0.000	**0.272**	**0.278**	0.013	-0.203	-0.230
	D6	-0.015	0.144	0.291	**0.394**	**0.395**	0.290	0.148	-0.007
Ethanol vs soybean	D1	0.027	0.009	0.013	**-0.021**	**0.015**	0.002	0.034	0.017
	D2	0.034	-0.023	-0.017	**-0.016**	**0.023**	-0.025	-0.054	-0.005
	D3	0.055	-0.079	0.089	**-0.168**	**-0.126**	0.030	0.008	-0.035
	D4	0.020	-0.068	-0.102	**-0.007**	**0.072**	-0.084	-0.051	-0.079
	D5	-0.168	-0.116	0.068	**0.253**	**0.282**	0.071	-0.141	-0.223
	D6	-0.090	0.098	0.285	**0.425**	**0.456**	0.330	0.152	-0.040

Source: *Authors' own calculation based on data from stooq.com (2023).*

Examining the ethanol-corn pair reveals an absence of a consistent leading or lagging pattern, as the leading asset shifts across different wavelet scales. At certain scales, the cross-correlation values are nearly identical, indicating a lack of a clear pulling effect. Specifically, at the D1 and D5 scales, the cross-correlation values are so similar that it becomes difficult to identify any lead-lag interdependence. However, at the D2 and D4 scales, corn demonstrates a leading position, while ethanol leads at the D3 and D6 scales. These results suggest that, in the short term, shocks from the corn market influence the ethanol market, whereas, in the long term, ethanol shocks become more dominant.The short-term advantage of corn can be attributed to its significantly larger futures market in terms of liquidity, as indicated in Table 4. This greater liquidity allows external shocks to be processed more swiftly in the corn market. Consequently, it is plausible that external shocks are first identified in the corn market before they are transmitted to the ethanol market. Conversely, the relationship shifts over the long term, likely because corn is the primary feedstock used in ethanol production.

When analyzing wavelet cross-correlation, it is crucial to assess the level of correlation at specific scales. Higher interdependence between the variables enhances the reliability of the cross-correlation findings. In this case, the wavelet correlations between ethanol and corn remain relatively strong even at the lowest scales, lending further credibility to the short-term wavelet cross-correlation results.

Figure 3. *Wavelet cross-correlation plots*



Source: *Authors' own calculation based on data from stooq.com (2023).*

Table 3. *Average trading volumes of the selected assets*

	Ethanol	Corn	Wheat	Soybean
Trading volumes	315	409,476	120,663	211,636

Note: Average trading volumes are observed in 2019 in order to avoid possible biasedness that can be caused by the pandemic and the war in Ukraine.

Source: *stooq.com website*

In examining the ethanol-wheat and ethanol-soybean pairs, the wavelet correlations are lower than those found in the ethanol-corn relationship, prompting a focus on the long-term connections rather than short-term cross-correlations in these cases. Notably, at the D5 and D6 scales, wheat exhibits a slight leading edge over ethanol, indicating that the wheat market tends to lead in the long term. As highlighted in Table 3, the liquidity in the wheat market is significantly higher than that of the ethanol market, suggesting that external shocks can be absorbed and processed more rapidly in the wheat market. This factor accounts for the observed influence of wheat on ethanol.

For the ethanol-soybean pair, only the long-term cross-correlations warrant discussion due to the relatively weak short-term wavelet connection. According to Figure 3 and Table 2, the cross-correlation curve tilts noticeably toward soybean, indicating that soybean leads ethanol in both midterm and long-term time frames. This finding aligns with expectations, as the soybean market is the second largest in terms of liquidity (refer to Table 3), making it likely that external shocks are recognized more swiftly in the soybean market compared to the ethanol market. This dynamic underscores the leading role of soybean in this relationship.

Conclusion

This study examines the multiscale interdependence between ethanol and three major grains that serve as raw materials in its production. The analysis employs two wavelet techniques: wavelet coherence and wavelet cross-correlation. While the first method assesses the strength of interdependence, the latter identifies the lead-lag dynamics between the assets. The findings from wavelet coherence, indicate that the strongest short-term connection exists between ethanol and corn, with correlations significantly exceeding 30%. In contrast, the correlations between ethanol and the other two grains are weaker. These results align with expectations, given that corn is the primary feedstock for ethanol production.

Regarding lead-lag relationships, the short-term connection is particularly significant for the ethanol-corn pair, which maintains a relatively strong correlation even in the short term. Conversely, all long-term interdependencies warrant attention, as robust correlations emerge at the highest wavelet scales. The results suggest that larger agricultural markets, characterized by higher trading volumes, typically influence the smaller ethanol market. These findings have several implications. Firstly, the strong short-term correlation between ethanol and corn indicates that price fluctuations in one asset can substantially impact the other. This necessitates caution among short-term participants, including speculators and investors. In the long run, the connections among agricultural commodities and ethanol are robust, often exceeding 50%, suggesting that long-term stakeholders, such as farmers and ethanol producers, should implement hedging strategies to safeguard against rising prices in agricultural and ethanol markets.

Moreover, portfolio investors should consider avoiding the combination of ethanol and corn across all time horizons due to their high correlation, which yields poor diversification outcomes. A more favorable strategy in the short term is to pair ethanol with wheat or soybean, as these grains exhibit lower correlations with ethanol. However, for long-term portfolios, it is advisable to refrain from combining ethanol with any agricultural commodities due to their strong interconnectedness, which often surpasses 50%.

Literature

1. Bilgili, F., Kocak, E., Kuskaya, S., Bulut, U. (2022): Co-movements and causalities between ethanol production and corn prices in the USA: New evidence from wavelet transform analysis. *Energy*, 259: 124874.
2. Gencay, R., Selcuk, F., Whitcher, B.:*An introduction to wavelets and other filteringmethods in finance and economics*. Academic Press, San Diego (2002).
3. Guo, J., Tanaka, T. (2022): Energy security versus food security: An analysis of fuel ethanol-related markets using the spillover index and partial wavelet coherence approaches. *Energy Economics*, 112, 106142.
4. Hung, N.T. (2022): Time-frequency linkages between international commodities and the brics equity markets. *Economic Computation and Economic Cybernetics Studies and Research*, 56: 123-139.

5. Kinkyo, T. (2022): The intermediating role of the Chinese renminbi in Asian currency markets: Evidence from partial wavelet coherence.*North American Journal of Economics and Finance*, 59, 101598.
6. Leonardo, W.J., Florin, M.J., van de Ven, G.W.J., Udo, H., Giller, K.E. (2015): Which smallholder farmers benefit most from biomass production for food and biofuel? The case of Gondola district, central Mozambique, *Biomass and Bioenergy*, 83: 257-268.
7. Lundberg, L., Sanchez, O.C., Zetterholm, J. (2023): The impact of blending mandates on biofuel consumption, production, emission reductions and fuel prices, *Energy Policy*, 183: 113835.
8. Makutenas, V., Miceikiene, A., Svetlanska, T., Turcekova, N., Sauciunas, T. (2018): The impact of biofuels production development in the European Union. *Agricultural Economics – ZemedelskaEkonomika*, 64(4): 170-185.
9. Pal, D., Mitra, S.K. (2017): Time-frequency contained co-movement of crude oil and world food prices: A wavelet-based analysis. *Energy Economics*, 62: 230–239.
10. Percival, D.B., Mofjeld, H.O. (1997): Analysis of subtidal coastal sea level fluctuations using wavelets. *Journal of American Statistical Association*, 92:868–880.
11. Sarmiento, C., Wilson, W.W., Dahl, B. (2012): Spatial Competition and Ethanol Plant Location Decisions. *Agribusiness*, 28: 260-273.
12. Singh, S., Bansal, P., Nav Bhardwaj, N. (2022): Correlation between geopolitical risk, economic policy uncertainty, and Bitcoin using partial and multiple wavelet coherence in P5 + 1 nations, *Research in International Business and Finance*, 63: 101756.
13. Stooq (2023): Stooq. [Dataset]. Available at stooq.com (accessed Dec 15, 2023)
14. Subramaniam, Y., Masron, T.A., Azman, N.H.N. (2020): Biofuels, environmental sustainability, and food security: A review of 51 countries. *Energy Research and Social Science*, 68: 101549.
15. Tanaka, T., Guo, J., Wang, X. (2023): Did biofuel production strengthen the comovements between food and fuel prices? Evidence from ethanol-related markets in the United States. *Renewable Energy*, 217: 119142.

16. Wu, Y., Ren, W., Wan, J., Liu, X. (2023): Time-frequency volatility connectedness between fossil energy and agricultural commodities: Comparing the COVID-19 pandemic with the Russia-Ukraine conflict, *Finance Research Letters*, 55: 103866.

17. Živkov, D., Kuzman, B., Subić, J. (2023). Multifrequency downside risk interconnectedness between soft agricultural commodities. *Agricultural Economics – ZemedelskaEkonomika*, 69(8), 332-342.