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Time Frequency and Co-movements between Global Economic Policy Uncertainty, Precious Metals and Agricultural Prices: A Wavelet Coherence Analysis and Bootstrap Rolling Window Granger Causality

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ABSTRACT

Examining the links between economic uncertainty and precious metals allows us to explore the interconnectedness of various economic factors and their potential impact on markets, investments, and global trade. Precious metals such as gold and silver have historically been used as safe havens during times of economic uncertainty. Understanding how these metals interact with fluctuating economic policies can help assess their role as a safe haven and their importance to investors. Analyzing the links between precious metals, economic uncertainty, and agricultural prices can help policymakers design measures to mitigate negative impacts on the economy and foster financial and food stability. The main objective of this paper is to examine the co-movements between global economic policy uncertainty and each commodity such as oil, precious metals and agricultural prices. We employ two empirical approaches such as wavelet coherence and bootstrap rolling window Granger causality. The dynamic causality according to the bivariate framework between variables is analyzed. We used monthly data during the period span from January 2004 to September 2022. Empirical results indicate the evidence of unidirectional, bidirectional and absence of causality between variables. In addition, the co-movements between GEPU and each variable are positive and negative.

Keywords: global economic policy uncertainty, oil, precious metals, agricultural prices, Wavelet coherence, Bootstrap rolling window.
JEL Classifications: F21, C22

1. INTRODUCTION

The relationship between global economic policy uncertainty, oil prices, precious metals, and agricultural prices is an important topic because these factors are all interconnected and can significantly impact the global economy. Economic policy uncertainty can affect investor and business decisions on spending and investment, which in turn can affect economic growth. Oil prices also have a major impact on the global economy as energy is a critical resource for many industries. Fluctuations in oil prices can have ripple effects on production and transportation costs, while precious metals and agricultural prices are often influenced by economic conditions and can impact inflation rates and consumer spending.

Economic policy uncertainty can affect investor and business spending and investment decisions, which can impact economic growth. Precious metals are often considered safe assets in times of economic uncertainty and can be used as a hedge against inflation. Oil prices also impact the global economy, as energy is a critical resource for many industries. Fluctuations in oil prices can affect production and transportation costs, which can impact food prices. Agricultural prices, on the other hand, can be influenced by economic and climatic conditions, as well as by trade policies. They can also have an impact on inflation and household consumption, as food is a basic expense for many people.

There are several causal links between precious metals and economic policy uncertainty. First, precious metals, such as gold and silver, are often considered safe assets in times of economic and political uncertainty. Investors can buy these metals as a means of protecting their portfolio against economic and financial risks. Additionally, economic uncertainty can also increase the demand for precious metals as a hedge against inflation. When interest rates are low, investors can buy gold and other precious metals to hedge against potential inflation. This is because precious metals tend to maintain their value over time, which can make them a hedge against a decline in the value of the currency.

Finally, economic policies, such as monetary and fiscal policies, can also affect precious metal prices. For example, if an aggressive monetary policy is put in place to stimulate the economy, it can lead to a depreciation of the currency and an increase in the prices of precious metals.

The main contributions of this article are as follows: first, we consider the causal links between global EPU and commodities and agricultural prices. Whose assets are strongly affected during periods of crises such as the global financial crisis and the sovereign debt crisis as well as for the period of Covid-19 and currently the war in Ukraine. Second, we employ the wavelet coherence to study the Co-movements among GEPU, oil, precious metals and agriculture at different time scales and different periods. The key advantage of this method is to decompose the time series of global economic policy uncertainty and commodities into the frequency domain to assess whether the timing of GEPU overlaps with the timing of strong Co-movement in the commodities as suggested. On the other hand, we employ the time-varying causality test that has the advantage of localizing periods of causality over time. Specifically, we employ the bootstrap Granger causality test and the rolling window estimation to study the time-varying dependence between each pair of time series.

The layout of the present study is as follows. Section 2 displayed a related literature of some theoretical and empirical considerations. Section 3 presents the data and empirical methodology. The empirical results are displayed, analyzed and discussed in section 4. Section 5 reports the concluding remarks and policy implications.

2. RELATED LITERATURE

In this section, we examine the causal links between economic policy uncertainty, oil price, precious metals and agriculture prices following theoretical and empirical reviews.

2.1. Nexus between Economic Policy Uncertainty and Oil Price

In literature, the relationship between economic policy uncertainty and WTI oil prices has become increasingly. On one hand, economic policy uncertainty can have an impact on WTI oil prices. Government decisions regarding economic policies, such as levels of government spending, tax rates, and monetary policies, can influence the global economy and subsequently, the demand for oil. For instance, an expansionary monetary policy that boosts investment and consumption can lead to higher demand for oil, which can drive up prices. On the other hand, oil prices can also have an impact on economic policies. Changes in oil prices can affect inflation, economic growth, and interest rates, which can, in turn, impact government decisions regarding economic policies. For example, a sudden surge in oil prices can cause inflation to rise, prompting central banks to increase interest rates to control inflation. Moreover, WTI oil prices can also impact political uncertainty. For instance, a rapid and significant increase in oil prices can create geopolitical tensions due to the economic and security concerns that it raises.

In the empirical context, the relationship between economic policy uncertainty and oil price has been discussed in both directions. A first part tried to study the influence of oil prices on economic uncertainty. For example, Kang et al. (2017) explored the effects of oil production shocks from both the US and non-US on EPU. They found that US oil production shocks have a positive impact on EPU, but non-US oil production shocks do not have a significant effect. On the other hand, Hailemariam et al. (2019) used a nonparametric panel data method to study the impact of global oil prices on EPU over time. Their research demonstrated that when there is a surge in global aggregate oil demand, global oil prices negatively influence EPU. In the same year, Kang et al. discovered that EPU's response to global oil prices is asymmetric.

The second category of literature focuses on the impact of EPU on global oil prices. Yao and Sun (2018) discovered that higher global oil prices are connected to higher EPU. In addition, Reboredo and Uddin (2016) concluded that there is no co-movement or Granger causality between EPU and global oil prices shocks. Aloui et al. (2016) used copula estimation to study the impact of EPU on global oil prices returns and found that EPU has a positive effect on oil returns during the financial crisis, but the impact becomes negative over the entire sample period. Zhang and Yan (2020) supported the claim that EPU has a negative effect on oil prices returns, and this effect is asymmetric, as Ji et al. (2018) noted. Meanwhile, Bonaccolto et al. (2018) used non-parametric methods and quantile forecasts to demonstrate that EPU has separate negative and positive effects on the lower and upper quantiles of global oil prices returns.

2.2. Interactions between Precious Metals and Economic Policy Uncertainty

Economic policy uncertainty can affect precious metal prices. Government decisions on economic policy, such as levels of government spending, tax rates and monetary policies, can impact investor confidence and the global economy. As safe-haven assets, precious metals may become more attractive to investors, leading to increased demand and higher prices.

Precious metal prices can also influence economic policies. Fluctuations in gold, silver and platinum prices can impact interest rates, inflation and economic growth, which can affect governments' decisions on economic policy. For instance, a significant rise in the price of gold may indicate a decline in confidence in the global economy, leading the central bank to lower interest rates to boost economic growth.

Political uncertainty can also impact precious metal prices. Geopolitical tensions, armed conflicts and political uncertainties can disrupt the global economy and increase the attractiveness of precious metals as safe-haven assets, leading to increased demand and prices. Precious metal prices can also influence political uncertainty. Fluctuations in the prices of gold, silver and platinum can affect investor confidence and the global economy, which can have an impact on geopolitical tensions and political uncertainties.

Frequently, various countries issue economic policies to maintain their economic stability, which, in turn, increases the uncertainty surrounding economic policies (Baker et al., 2016). Economic policy uncertainty has significant implications for the entire economy (Lee et al., 2021). Due to the safe-haven nature of precious metals, a considerable amount of capital has been invested in the precious metal market, resulting in an increase in precious metal prices and earnings. Economic policy comprises of monetary, fiscal, and regulatory policies, all of which require frequent adjustments (Adjei and Adjei, 2017; Raza et al., 2018). Economic policy uncertainty may affect precious metal returns through various channels. First, it can alter the decisions made by economic agents, including consumption and investment (Gulen and Ion, 2016). Second, it impacts supply and demand, leading to a contraction of investment and the economy, which might affect financing and production expenditures (You et al., 2017). Third, it can also influence the interest rate, inflation, and expected risk premiums (Pastor and Veronesi, 2013).

Various empirical works have tried to study the causal links existing between precious metals and the economic policy uncertainty. For example, Shafiee and Topal (2010) investigated the factors that influence gold prices and found that the safe-haven role of gold was a crucial factor in increasing gold prices during times of financial instability. Similarly, Białkowski et al. (2015), Van et al. (2016), and Lau et al. (2017) reached similar conclusions. Building on this research, Bouoiyour et al. (2018) presented evidence of a significant positive effect of economic policy uncertainty on gold returns when the uncertainty peaks. Additionally, Huynh (2020) used multilayer perception neural network nonlinear Granger causality and transfer entropy models to examine the prices of four representative precious metals and concluded that gold remained the primary "safe-haven" asset for hedging uncertainty.

In recent times, an increasing amount of literature has focused on investigating the impact of economic uncertainty on commodity prices. However, the results of the existing studies have been mixed and often conflicting, despite the abundance of evidence provided. For instance, Kang and Ratti (2013) utilized a structural vector autoregressive (SVAR) model to observe a negative relationship between the unanticipated increase in policy uncertainty and real stock returns of energy-exporting countries like Canada. Nicolau and Palomba (2015), on the other hand, employed a bivariate battery VAR to study the dynamic relationship between spot and futures prices of energy commodities, namely crude oil, natural gas, and gold. They discovered evidence of diverse interactions between spot and futures prices and prices of these commodities. In particular, they found strong exogeneity operating in natural gas, weak exogeneity for crude oil, and no evidence of valid forecasting between spot and futures prices for gold commodity. Using the SVAR model, Kang et al. (2017b) recorded evidence of a significant negative interaction between policy uncertainty and oil price shocks of the stock returns of oil and gas companies.

In their study, Bilgin et al. (2018) utilized the global economic policy uncertainty (EPU) index to argue that an increase in economic policy uncertainty leads to a rise in gold prices, using the NARDL model. Badshah et al. (2019) studied a large set of commodities included in the Dow Jones commodity index and discovered a positive effect of economic policy uncertainty on stock-commodity correlations, with notably stronger effects in the case of energy and industrial metals, by employing the DCC- and ADCC-GARCH models. The effect of economic policy uncertainty was observed to be more significant during weak economic conditions, while VIX, a proxy of market uncertainty, was generally found to be insignificant.

Sharma and Paramati (2021) conducted a panel analysis of 97 commodities imported to India and reported that economic uncertainty resulted in higher imports of commodities, albeit with a dampening effect in the long run. Meanwhile, Apergis et al. (2020) contended that economic uncertainty affects the price performance of commodities, with the effects clustering around the tail of their conditional distribution.

2.3. Economic Policy Uncertainty and Agriculture

Economic policy uncertainty can affect agriculture by creating uncertainty around prices and demand. Government decisions on economic policies such as agricultural subsidies, taxes, and regulations can impact farmers, producers, and consumers, and can lead to uncertainty around price and demand.

Economic policies can also impact agricultural production. Government decisions on public spending, interest rates, and monetary policies can influence investment levels and capital flows, which can affect agricultural production and demand for agricultural products. Fluctuations in the prices of agricultural products can also impact economic policies. Price increases in crops like cotton and bananas can lead to increases in inflation, which can prompt the central bank to raise interest rates to control inflation and impact economic policies.

Research has investigated the impact of economic policy uncertainty (EPU) on agricultural trade. In particular, Xiao et al. (2019) found that China's EPU affects different agricultural markets in varying ways, with a greater influence on the future prices of maize and soybean compared to wheat. Meanwhile, Li and Li (2021) utilized a Time-Varying Parameter Stochastic Volatility Vector Autoregressive model and confirmed that China's EPU has a negative effect on the sustainability of its net grain imports, although they did not provide a quantitative measure of this impact.

3. DATA AND EMPIRICAL METHODOLOGY

This paper study the interaction between GEPU, oil price (WTI), precious metals (SILVER, GOLD and Platinum) and agriculture prices (BANANAS and COTTON) from January 2004 until September 2022. In total, there are 225 observations. The Gross Domestic Product (GDP) weighted average of economic and policy uncertainty indices of 21 countries are represented by the GEPU index on a global scale. The index is determined by analyzing the relative frequency of newspaper articles in each country that cover terms related to economic, policy, or uncertainty news, as described by Davis in 2016. The Eikon platform was used to obtain commodity data, while the GEPU index was obtained from its website. WTI is sourced from www.eia.gov and precious metals and agriculture prices are extracted from the website: World Bank commodity market.

To analyze the co-movements between each time series, we employ the wavelet coherence analysis to detect the sign of correlation (positive or negative). In addition, we examine the causality between GEPU, oil price, precious metals and agriculture prices by considering the bootstrap rolling window Granger causality with bivariate VAR. the key advantage of this approach is to detect the sense of causality during some economic and financial crises.

3.1. Continuous Wavelet Transform

The mathematical technique known as the continuous wavelet transform (CWT) is employed for the analysis of non-stationary signals, including time series data, through the decomposition of the signal into its frequency components at varying time scales. To carry out this analysis, the CWT employs a wavelet function, which is a small oscillating wave-like function that is localized, and used to study the signal.

The fundamental concept underlying the CWT is the convolution of the signal with the wavelet function, executed at different positions and scales over time. The resulting convolution is utilized to compute the wavelet coefficients that quantify the correlation strength between the wavelet function and the signal at each scale and position.

Generally speaking, the wavelet transform function is used for the purpose of dividing the time series into sub-series which are derived from the main or parent wavelet. The latter is broken down into two fundamental parameters, namely time (i) and scale (s). These parameters are defined as follows:

$$\varnothing_{i,s}\left(t\right)=\sqrt{s}^{-1}\varnothing\left(t-i\right)(s^{-1}),\varnothing\left(.\right)\in L^{2}\left(\mathrm{R}\right) \tag{1}$$

We specify the parameter (i) to provide the exact position of the wavelet. It is the location parameter. (s) indicates how the wavelet is stretched. It is the scale dilation parameter. To justify that the unit variance of the wavelet $\text{Ø}_{i,s}(t)^2 = 1$, we specify the normalization factor namely, $\sqrt{s}^{-1}$ The Morlet wavelet can be defined as follows:

$$\varphi^{M}\left(t\right)=\pi^{-1/4}e^{iw_{0}t}e^{-t^{2}/2} \tag{2}$$

Where; ω_0 is the central frequency of the wavelet. $\omega_0\,\omega_0$ is set at 6, following Rua and Nunes (2009) and Vacha and Barunik (2012). Respecting to a selected mother wavelet, a time series x (t) can be decomposed as follow:

$$\omega_{x}\left(i,s\right)=\int_{-\infty}^{+\infty}x(t)\sqrt{s}^{-1}\varnothing(\frac{t-i}{s})\ \mathrm{dt} \tag{3}$$

$\omega_x(i,s)$ is obtained by projecting the specific wavelet Ø(.) onto the selected time series. The key advantage of continuous wavelet transform is the ability to decompose and reconstruct the function x (t) ∈ L^2 (R).

$$x(t)=\frac{1}{C_{\varphi}}\int_{0}^{\infty}\left[\int_{0}^{\infty}\omega_{x}\left(i,s\right)\varnothing_{i,s}\left(t\right)di\right]\frac{ds}{s^{2}},s>0\,, \tag{4}$$

3.2. Wavelet Coherence

Wavelet coherence is a technique used to analyze the relationship between two non-stationary signals by decomposing them into their frequency components at different time scales using the continuous wavelet transform (CWT). It provides a way to measure the similarity of the frequency content of two signals at different time scales and can help identify patterns and relationships between the signals.

Wavelet coherence is computed by first applying the CWT to both signals to obtain their wavelet coefficients at different scales and positions in time. The wavelet coefficients are then used to compute the cross-spectrum and auto-spectra of the two signals. The cross-spectrum represents the coherence between the two signals at each scale and position in time, while the auto-spectra represent the power of each individual signal at each scale.

Through a comparison with classical spectral methods, one can obtain the WPS (wavelet power spectrum) on a well-determined and specific time series from the absolute squared value of $\omega_x(i,s)$. The WPS is specified as follows:

$$WPS_{x}\left(i,s\right)=\omega_{x}\left(i,s\right)^{2} \tag{5}$$

Li et al (2022) add that WPS has various limitations in low frequency oscillations. Thus, to study the Co-movements and dependence structures between global economic policy uncertainty, oil price, precious metals and agriculture prices and to reduce the bias of WPS, we employ the cross-wavelet transform tool developed by Ng and Chan (2012). The CWT describing covariance in the time frequency domain is defined as follows:

$$W_{xy}=W_{x}\left(i,s\right)W_{y}^{*}(i,s) \tag{6}$$

* indicates a complex conjugate, $\omega_x(i,s)$ and $\mathrm{W_y}^*(\mathrm{i,s})$ denote the cross-wavelet of series x(t) and y(t). The cross-wavelet transform shows the area in time space with high common power.

i and *s* are position and scale, and * alludes to the compound consolidate. Last but not least, we use a wavelet termed wavelet coherence which may be defined as a squared coherence wavelet to assess the coherence of the CWT in the time–frequency domain:

$$R_t^t(s) = \frac{\left|S(s^{-1}w_t^{xy}(s)\right|^2}{S\left(s^{-1}\left|w_t^x(s)\right|^2\right)S(s^{-1}\left|w_t^y(s)\right|^2} \quad (7)$$

The smoothing parameter, s, is represented by the wavelet coherence, which can be thought of as a correlation coefficient with a value ranging from zero to 1. The WC will be equal to 1 in the case where there is no easing. Additionally, the squared wavelet coherence coefficient ranges from 0 to 1, with values close to 0 indicating weak correlation and values close to 1 indicating the existence of strong correlation. Consequently, WC is a useful tool for measuring the co-movement of the selected parameters over time (Mishra et al. 2022).

3.3. Bootstrap Rolling Window Granger Causality

The rolling window Granger causality technique is an econometric approach that assesses the causality between two time series by employing sliding windows of data to estimate the parameters of a VAR model in a bivariate context. Financial and economic series often exhibit temporal variations, making this method a valuable tool for investigating causal relationships between two variables. This method involves generating bootstrap samples by resampling the data in sliding windows. This feature allows for the estimation of the distribution of Granger causality statistics for each window and the computation of confidence intervals for the results.

The bivariate VAR model's parameters can be estimated concurrently for both variables, allowing for the study of dynamic interactions between the variables. Generally, the rolling window Granger causality approach, using the bivariate VAR model, provides a robust analysis of the correlation between two time series, considering the variables' interactions and changes over time.

3.4. Bootstrap full-Sample Causality Test

We utilize the rolling window Granger bootstrap causality test introduced by Balcilar et al. (2010). This method has been applied in various empirical studies, including those by Su et al. (2021), Sun et al. (2021), and MK Minlah and Zhang. (2021). We employ the Engle and Granger (1987) test for non-causality, which is based on the bivariate VAR model. This test aims to determine whether information related to one variable can enhance the prediction of another variable and vice versa. However, classical Granger causality test statistics, such as the Wald test, LR likelihood ratio test, and Lagrange multiplier (LM) test, do not follow a standard asymptotic distribution when the series is I(1) or not stationary at the level.

In this paper, we discuss the methodology for testing Granger causality between global economic policy uncertainty, oil price, precious metals and agriculture prices using a rolling window approach. We use the modified Wald test of the bivariate VAR model on rolling window subsamples to estimate the parameters of the VAR model, and then perform the residual-based (RB) bootstrap method to obtain asymptotic critical values for the causality test.

The bivariate VAR model is specified in equation (8)

$$y_0 = \varnothing_0 + \varnothing_1 y_{t-1} + \ldots + \varnothing_p y_{t-p} + \varepsilon_t, \quad t = 1, 2, \ldots T \quad (8)$$

where y_t is a vector of the four variables (global economic policy uncertainty, oil, precious metals and agriculture prices), $\varnothing_0$ is a constant term, $\varnothing_p$ are the coefficients for the lagged values of the variables, and ε_t is the error term. The lag length p is chosen based on the SBIC information criterion.

$y_t = (EPU_t, OP_t, PM_t, AP_t)$. Where, EPU is the economic policy uncertainty, OP is the oil price (WTI), PM are the precious metals and AP is the agriculture prices. Using four sub-vectors, equation (8) is written as follows:

$$\begin{Bmatrix} EPU_t \\ OP_t \\ PM_t \\ AP_t \end{Bmatrix} = \begin{Bmatrix} \varnothing_{10} \\ \varnothing_{20} \\ \varnothing_{30} \\ \varnothing_{40} \end{Bmatrix} + \begin{Bmatrix} \varnothing_{11}(L)\varnothing_{12}(L) \\ \varnothing_{21}(L)\varnothing_{22}(L) \\ \varnothing_{31}(L)\varnothing_{32}(L) \\ \varnothing_{41}(L)\varnothing_{42}(L) \end{Bmatrix} \begin{Bmatrix} EPU_t \\ OP_t \\ PM_t \\ AP_t \end{Bmatrix} + \begin{Bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \varepsilon_{3t} \\ \varepsilon_{4t} \end{Bmatrix} \quad (9)$$

Where $\varnothing_{ij}(L) = \sum_{k=1}^{p} \varnothing_{ij,k} L^k$ and the lag operator (L) is expressed as follows: $L^k x_t = x_t =$

$\varnothing_{12,k} = 0$ and $\varnothing_{21,k} = 0$, $\varnothing_{31,k} = 0$ and $\varnothing_{14,k} = 0$ and $\varnothing_{41,k} = 0$ which represent the causal effect of oil price on global economic policy uncertainty and vice versa, the causal effect of precious metals on GEPU and vice versa and the causal effect of agriculture price on GEPU and vice versa respectively. If these coefficients are zero, then there is no Granger causality in that direction.

3.5. Parameter Stability Tests

The empirical literature suggests that when structural changes are present in the full sample data, the VAR model parameters may indicate instability (Su et al., 2019). Balcilar and Ozdemir (2013) further argue that a large number of observations in the sample can lead to structural mutations in the component variables, resulting in an unstable effect in the interaction between the two variables over the sampling period. To address this instability problem, stability tests of short-term parameters such as Sup-F, Exp-F, and Mean-F (Andrews, 1993; Andrews and Ploberger, 1994) as well as stability test Lc with long-term parameters (Nyblom, 1989; Hansen, 1992) should be performed. If the parameters vary over time, it indicates the need to use subsample tests to examine the causal Granger relationship between global economic policy uncertainty and WTI, GEPU and precious metals and GEPU and agriculture prices.

3.6. Bootstrap Sub-sample Rolling-window Causality Test

We use a modified RB-based LR test (Balcilar et al. 2010) and subsample testing to examine the causal relationship between GEPU and WTI, GEPU and precious metals and GEPU and agriculture prices. The method involves dividing the time series into subsamples using a sliding window width l and estimating the impact of oil, precious metals and agriculture on global economic policy uncertainty and vice versa using bootstrap estimates from VAR models. Wang et al. (2020a) note that this approach accounts for temporal variations in the causal relationship between the variables and the presence of instability resulting from structural changes. The average of these estimates is computed, and the 5th and 95th quantiles of each estimate are used to construct confidence intervals. Bootstrap P-values and LR statistics are used to identify any temporal variations in the causal relationship between each two series.

This approach is useful in capturing the variations in the causal relationship between GEPU, oil, precious metals and agriculture and the instability that may result from structural changes. As a result, it provides a more nuanced understanding of the relationship between these variables, which can be critical for effective decision-making.

$N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{12,k}^{\;*}$ and $N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{21,k}^{\;*}$, $N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{13,k}^{\;*}$ and $N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{31,k}^{\;*}$ and $N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{14,k}^{\;*}$ and $N_b^{-1}\sum_{k-1}^{p}\hat{\varnothing}_{41,k}^{\;*}$ denote the average of a large number of estimates, indicating the impact of global economic policy uncertainty on WTI and the effect of WTI on global economic uncertainty; the effect of GEPU on precious metals and the effect of precious metals on GEPU and the impact of GEPU on agriculture price and the impact of agriculture price on GEPU respectively. Bootstrap estimates from VAR models are $\hat{\varnothing}_{12,k}^{\;*}$, $\hat{\varnothing}_{21,k}^{\;*}$, $\hat{\varnothing}_{13,k}^{\;*}$, $\hat{\varnothing}_{31,k}^{\;*}$, $\hat{\varnothing}_{14,k}^{\;*}$, $\hat{\varnothing}_{41,k}^{\;*}$.

N_b represent the number of bootstrap repetitions. We calculate the 90% confidence intervals, where the lower and upper bounds are equal to the 5th and 95th quantiles of each of the $\hat{\varnothing}_{12,k}$ and $\hat{\varnothing}_{21,k}$, $\hat{\varnothing}_{13,k}$, $\hat{\varnothing}_{31,k}$ and $\hat{\varnothing}_{14,k}$, $\hat{\varnothing}_{41,k}$.

4. EMPIRICAL RESULTS

In Table 1, the descriptive statistics of precious metals and agricultural prices, along with global economic policy uncertainty (GEPU), are presented. Overall, the mean values are positive. However, each series display asymmetrical behavior, as indicated by negative skewness values for GOLD and BANANAS. Conversely, WTI, SILVER, PLATINUM, and COTTON exhibit positive asymmetry coefficients. The distributions are leptokurtic, with kurtosis values greater than 3, indicating the presence of extreme values and thick tails. The normality assumption is significantly rejected for precious metals and global uncertainty, according to the Jarque-Bera test except for BANANAS.

4.1. Wavelet Coherence Analysis between Oil Price and Economic Policy Uncertainty

Figure 1 displays the wavelet coherency-based co-movements between crude oil price (WTI) and global economic policy uncertainty. The plot indicates short-term co-movements in the 2-8 month period, medium-term co-movements in the 8-32 month period, and long-term co-movements in the 32-64 month period. The absence of the power of WTI price over global uncertainty is represented by blue color, while the dominance of power is shown by red color. The green and yellow colors denote the average power. Additionally, the white outline represents the statistical significance at a threshold of 5% for short, medium, and long term co-movements.

For the co-movement between the oil price and global uncertainty (GEPU), results indicate that the co-movements are negative and significant in the short term for the frequencies (1-8 months). Indeed the arrows are oriented to the right and down. WTI leads the GEPU. Otherwise the power of uncertainty is absorbed. When there is heightened uncertainty regarding global economic policies, investors become more cautious and seek to minimize their risk exposure. Therefore, they are less inclined to invest in risky assets such as commodities, including oil. In addition, changes in oil demand and supply can also affect prices in the short term. When economic uncertainty is high, it is more difficult to predict fluctuations in demand and supply, which can lead to lower oil prices.

On the other hand, in the medium term, the correlation between uncertainty and the price of oil is positive since the arrows are directed upwards on the right. In this case, GEPU lead the WTI. Increased uncertainty about economic policies is prompting investors to look for assets to hedge against inflation or against economic risks. Oil, as a commodity, can be considered as a hedging asset, which can lead to an increase in demand for oil and, therefore, an increase in prices in the medium term.

Table 1: Descriptive statistics

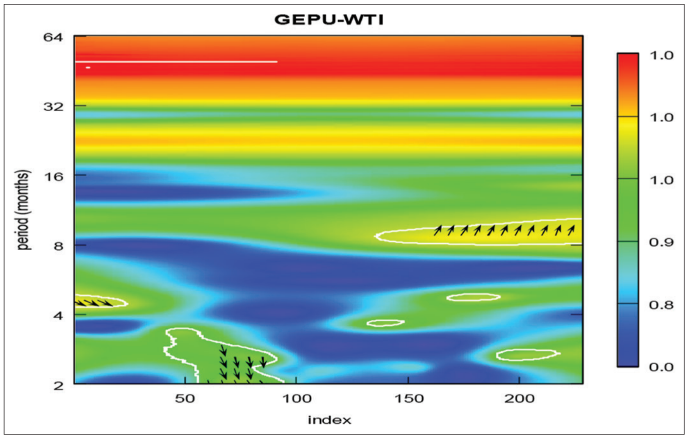
Variables	Mean	SD	Skewness	Kurtosis	J-Bera	Observations
Global EPU						
GEPU	150.5472	76.1762	0.9973	3.5327	39.9622***	225
Oil price						
WTI	69.4797	22.8870	0.9632	2.3778	8.7416***	225
Precious metals						
Silver	18.2421	7.4039	0.7579	3.5099	23.9807***	225
Gold	1195.060	433.6632	−0.2827	2.1731	9.4075***	225
Platinum	1180.870	319.0474	0.7443	2.5477	22.6928***	225
Agriculture prices						
Bananas	0.9422	0.2289	−0.0256	3.2204	0.4801	225
Cotton	1.8397	0.6242	2.2853	10.0906	667.2040***	225

***Significance at 1% level. EPU: Economic policy uncertainty, GEPU: Global EPU

4.2. Wavelet Coherence Analysis between Precious Metals and Economic Policy Uncertainty

By referring to the co-movements existing between precious metals such as SILVER, GOLD, Platinum and GEPU (Figure 2), we admit the existence of negative (out phase) and positive (in phase) correlations. Indeed, during the short term and the medium term (1-16 months), the arrows point down and right in the short term and right up in the medium term. The power of uncertainty is absorbed. However, in the medium term, GEPU lead the silver price.

Figure 1: Wavelet analysis of global economic policy uncertainty and WTI



We note that the correlation between platinum and global uncertainty is negative (out phase) in the short term and in the medium term for different frequencies (1-4 months) and (32-64 months). Indeed the arrows are directed to the left downwards.

Investors may seek safe, low-risk assets like gold, silver, and platinum, which are considered safe havens, when faced with economic uncertainty. This surge in demand for precious metals can result in short-term price increases. However, economic uncertainty linked to an economic crisis or recession may cause an overall decrease in demand for precious metals, as businesses and consumers reduce their purchases and investments. This can lead to lower precious metal prices in the short term.

Due to their scarcity and intrinsic value, precious metals, particularly gold, are viewed as a long-term store of value. Consequently, investors may choose to purchase gold as a hedge against inflation and currency devaluation during times of high economic uncertainty. This can lead to higher prices for gold and other precious metals over the long term.

4.3. Wavelet Coherence Analysis between Agricultural Prices and Economic Policy Uncertainty

Figure 3 illustrates the co-movements between global uncertainty and agricultural prices (BANANAS and COTTON). it is assumed that the correlation between the GEPU and the BANANAS is

Figure 2: Wavelet analysis of global economic policy uncertainty and precious metals

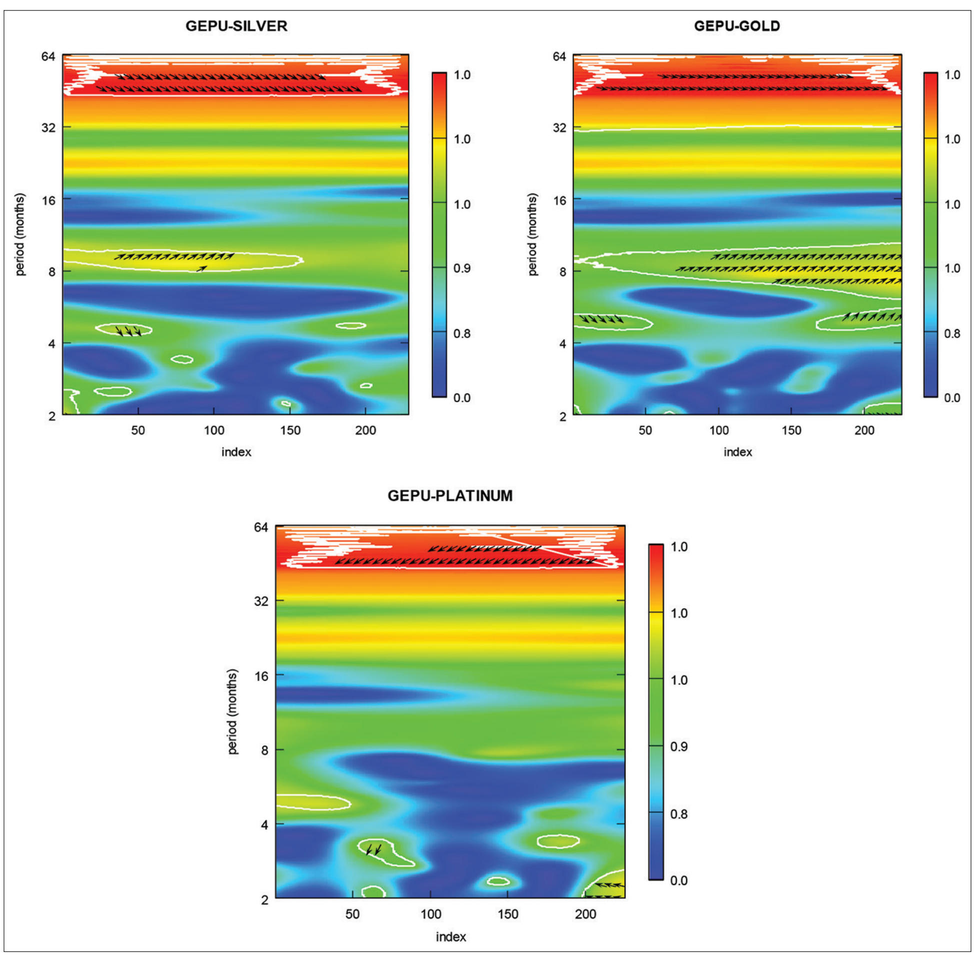
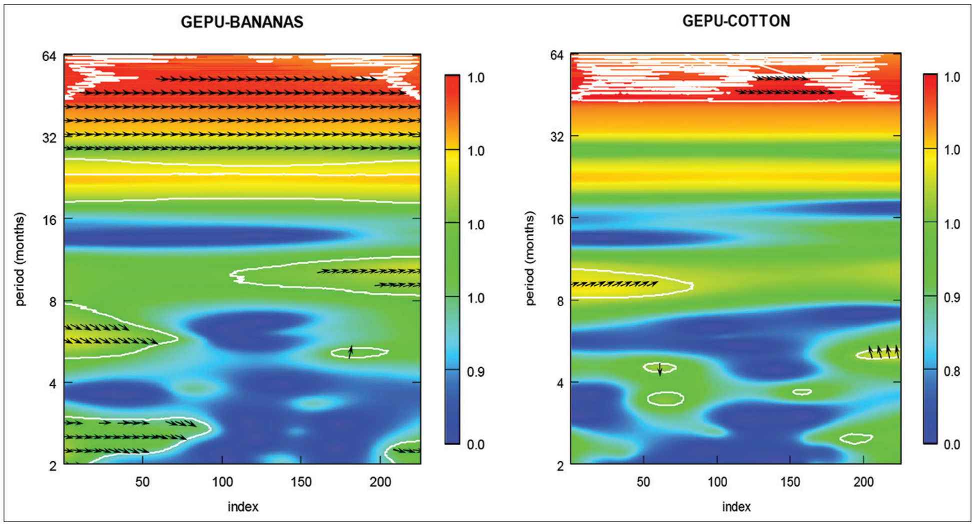


Figure 3: Wavelet analysis of global economic policy uncertainty and agriculture prices



positive (in phase) in the short term, medium term and long term. Indeed the arrows are directed horizontally to the right. In addition, the correlation between cotton and GEPU is positive (arrows pointing up and to the right). On the other hand, it is negative in the short term (arrows pointing up and to the left).

Economic uncertainty can have both positive and negative impacts on the prices of agricultural products such as bananas and cotton, depending on the time horizon. In the short term, an increase in economic uncertainty can lead to a decrease in demand for these commodities, as consumers may be uncertain about their future income and reduce their purchases. This can lead to lower prices for bananas and cotton. However, in the medium term, if economic uncertainty is linked to stronger economic growth, this may lead to an increase in demand for agricultural products, including bananas and cotton. As the supply of these commodities cannot be quickly adjusted, this increase in demand can lead to higher prices.

In the long term, structural factors such as technological innovations and climate change can have a significant impact on the production and costs of agricultural products. If economic uncertainty is linked to adverse structural changes, such as a decrease in the availability of arable land or an increase in extreme weather events, this can reduce the supply of bananas and cotton and increase production costs. As a result, this can lead to higher prices for these commodities in the long term.

4.4. Causality Analysis: Full Sample

In the first part of empirical analysis, we perform the unit root tests (ADF) at level and first difference for global economic policy uncertainty (GEPU) and all series such as precious metals an agriculture prices. Stationarity is displayed in Table 2. Empirical results indicate that uncertainty, WTI, BANANAS and Cotton are stationary in level (I(0)). For the first difference, all variables are I (1).

Balcilar et al. (2010) have suggested an econometric analysis approach for evaluating the significance of results in terms of both econometric and economic implications. The method is based on a rolling window Granger causality analysis, which utilizes a bootstrap technique. To execute this method, the data is divided into windows of fixed-size, and Granger regression is used to estimate the regression coefficients for each window. To determine the significance of causality, a bootstrap technique is employed, where many replications of the original sample are generated by randomly drawing samples with replacement. For each replication, the regression coefficients and causality statistics are calculated. Finally, the distribution of these statistics is used to determine the significance of causality.

To investigate the causal relationship between global economic policy uncertainty, precious metals, and agricultural prices, a bivariate VAR model is utilized by referring to equation (9). An optimal lag of order 1 is adopted based on the SBIC information criterion. In this study, a window size consisting of 24 observations is chosen, with the optimal window size being dependent on the subsample size and persistence. While a large window size can enhance the validity of the estimate, a small window size can reduce the effect of potential heteroscedasticity, causing larger estimated variances and weaker efficiency. According to Pesaran and Timmermann (2005), frequent interruptions can decrease the autoregressive (AR) parameter deviation, with a window width greater than 20 being considered a valid selection. The results of the modified LR tests based on RB, stability of parameters, and rolling window causality tests are interpreted for each variable pair.

Table 3 displays the results of the RB-based modified-LR tests. By referring to bootstrap p-value and considering the (GEPU-WTI) pair, we observe the absence of causality. The lack of causality between oil and the global uncertainty can be explained by factors such as the nature of the variations in the oil price, the diversity of the effects of economic uncertainty on different sectors and the management of oil production by producing countries. Global economic policy uncertainty may affect different economic sectors differently, and the oil sector may not be the most affected. For example, increased economic uncertainty may further affect financial sectors, stock markets, foreign investment, etc. Therefore, even if global economic uncertainty is correlated with the price of oil, this does not guarantee that there is direct causality.

Considering the causal relationships between GEPU, SILVER, GOLD and PLATINUM (Table 4), we see that the causality between (GEPU-SILVER) and (GEPU-PLATINUM) is unidirectional. However, we observe the absence of causality between global uncertainty and GOLD price. Economic uncertainty can affect the price of silver and platinum by increasing demand for these precious metals as hedging assets, reducing supply due to geopolitical concerns, and influencing monetary and fiscal policies.

Table 5 reports the causality between GEPU and agricultural prices. We see that the causality between global uncertainty and BANANAS is bidirectional. However, we observe the absence of causality between GEPU and cotton. It is unlikely that there is a two-way causality between global economic uncertainty and the price of bananas. The factors that influence the price of bananas are mainly related to production, transport and local demand. While global economic uncertainty may affect demand for some consumer goods, including bananas, it is unlikely to have a direct impact on production costs or local regulations affecting the banana industry.

Due to the presence of structural changes, the parameters of the full-sample VAR model for each pair may vary over time, leading to instability in the causal relationship between global uncertainty, precious metals, and agricultural prices. To address this issue, Zeileis et al. (2005) propose an extension of the rolling-window Granger causality method that includes stability tests for structural changes in causal relationships.

The proposed method involves dividing the data into fixed-size windows and estimating the regression coefficients for each window using rolling-window Granger causality. Stability tests are then performed on the regression coefficients to detect structural changes in causal relationships. These tests include the Sup-F, Ave-F, and Exp-F tests, which assess the significance of structural changes at different levels of sensitivity. The Sup-F test measures the largest difference between the regression coefficients of the different windows and the average of the coefficients of all the windows. The Ave-F test measures the average difference between the regression coefficients of the different windows and the average of the coefficients of all the windows. The Exp-F test gives more weight to the regression coefficients of the most recent windows. To verify the evidence of structural changes and to study the short-term and long-term stability of the VAR system parameters, the Sup-F, Ave-F, Exp-F, and Lc tests are employed.

The results of the parameter stability tests are presented in Table 6. For the (GEPU-WTI) pair, we observe evidence of a sudden structural change in the GEPU equation from the Sup-F and Exp-F statistics. However, for the WTI equation, structural changes are observed from the Sup-F, Ave-F, and Exp-F statistics at levels of 1% and 10%. The Exp-F statistic indicates the absence of a sudden structural change in the VAR system.

Concerning the interaction between GEPU and precious metals, we observe the presence of sudden structural changes in SILVER, GOLD, and PLATINUM. However, we do not observe structural changes in the GEPU equations. Considering the VAR system, the Sup-F statistic is significant, indicating the presence of sudden structural changes.

Table 2: Unit root tests

Variables	ADF-test (level)		ADF-test (difference)	
	Statistic	P	Statistic	P
GEPU	−4.4854***	0.0020	−19,7445***	0.0000
Oïl price				
WTI	−3.3320*	0.0638	−10,1059***	0.0000
Precious metals				
Silver	−2.1687	0.5042	−11.9519***	0.0000
Gold	−1.7081	0.7447	−12.2366***	0.0000
Platinum	−2.8311	0.1877	−10.7896***	0.0000
Agriculture prices				
Bananas	−5.3427***	0.0001	−14.3442***	0.0000
Cotton	−3.7821**	0.0192	−7.9483***	0.0000

***, *Significance at 1% and 10% level. GEPU: Global economic policy uncertainty

Table 3: Full sample granger causality tests: Bootstrap LR test: GEPU-oil price

Pair (GEPU-WTI)				
Test	H_0: GEPU does not granger cause WTI		H_0: WTI does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap lr-test	3.0006	0.2900	1.9467	0.4100

GEPU: Global economic policy uncertainty

Table 4: Full sample granger causality tests: Bootstrap LR test: Global economic policy uncertainty - precious metals

Pair (GEPU-silver)				
Test	H_0: GEPU does not granger cause silver		H_0: Silver does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap LR-test	4.6289*	0.0900	1.1567	0.5900
Pair (GEPU-gold)				
Test	H_0: GEPU does not granger cause gold		H_0: Gold does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap LR-test	4.3791	0.18000	3.1702	0.2800
Pair (GEPU-platinum)				
Test	H_0: GEPU does not granger cause platinum		H_0: Platinum does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap LR-test	6.7012*	0.0800	1.6007	0.5600

*Significance at 10%. P-values are calculated using 1000 bootstrap repetitions. GEPU: Global economic policy uncertainty

Table 5: Full sample granger causality tests: Bootstrap LR test: Global economic policy uncertainty - agriculture prices

Pair (GEPU-bananas)				
Test	H_0: GEPU does not granger cause bananas		H_0: Bananas does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap LR-test	9.4000***	0.0000	14.5713***	0.0000
Pair (GEPU-cotton)				
Test	H_0: GEPU does not granger cause cotton		H_0: Cotton does not granger cause GEPU	
	Statistics	P	Statistics	P
Bootstrap LR-test	3.2112	0.2100	2.3470	0.3800

***Significance at 1%. P-values are calculated using 1000 bootstrap repetitions. GEPU: Global economic policy uncertainty

Table 6: Parameters stability tests

GEPU-WTI	GEPU equation		WTI equation		VAR system	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	27.7018***	0.0004	28.8720***	0.0002	87.7384***	0.0000
Ave-F	4.9105	0.2536	6.9257*	0.0741	36.7694**	0.0134
Exp-F	8.8689***	0.0014	10.1344***	0.0003	39.5582	0.8592
Lc					1.5368***	0.0000
GEPU-silver	**GEPU equation**		**Silver equation**		**VAR system**	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	9.7115	0.4100	39.1433***	0.0000	148.0896***	0.0000
Ave-F	3.4556	0.5392	10.6036***	0.0005	75.5151	1.0000
Exp-F	2.2871	0.5124	15.4043***	0.0000	69.9986	1.0000
Lc					1.8681***	0.0000
GEPU-Gold	**GEPU equation**		**Gold equation**		**VAR system**	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	6.7683	0.7603	28.2781***	0.0003	277.7530***	0.0000
Ave-F	3.2113	0.6011	7.7056**	0.0444	117.0435	1.0000
Exp-F	1.7152	0.7223	10.0550***	0.0004	134.4421	1.0000
Lc					1.8989***	0.0000
GEPU-platinum	**GEPU equation**		**Platinum equation**		**VAR system**	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	8.0149	0.6070	43.2509***	0.0000	199.2994	0.0000
Ave-F	3.2633	0.5877	16.3302***	0.0000	99.8835	1.0000
Exp-F	1.9259	0.6421	17.5407***	0.0000	96.1953	1.0000
Lc					1.9445	0.0000
GEPU-bananas	**GEPU equation**		**Bananas equation**		**VAR system**	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	27.5805***	0.0004	24.6517***	0.0016	131.1223***	0.0000
Ave-F	4.9748	0.2445	5.1905	0.2160	49.2421	1.0000
Exp-F	8.7664***	0.0015	8.0916***	0.0030	60.7656	1.0000
Lc					1.2226***	0.0186
GEPU-Cotton	**GEPU equation**		**Cotton equation**		**VAR System**	
	Statistics	P	Statistics	P	Statistics	P
Sup-F	31.6038***	0.0000	34.7951***	0.0000	84.0917***	0.0000
Ave-F	4.7243	0.2816	9.4006**	0.0139	29.3807***	0.0002
Exp-F	10.7422***	0.0002	13.3332***	0.0000	38.4838	0.3948
Lc					1.6342***	0.0000

***, **, *Significance at the 1%, 5%, and 10% levels, respectively. P-values are calculated using 1000 bootstrap repetitions. GEPU: Global economic policy uncertainty

For the relationships between GEPU and agricultural prices, the (GEPU-BANANAS) pair indicates the presence of sudden structural changes for the Sup-F and Exp-F statistics. Additionally, the Sup-F statistic shows the presence of a sudden structural change in the VAR system. Finally, for the (GEPU-COTTON) pair, we observe the absence of sudden structural changes (Ave-F) for the GEPU equation and the presence of structural changes for the COTTON equation.

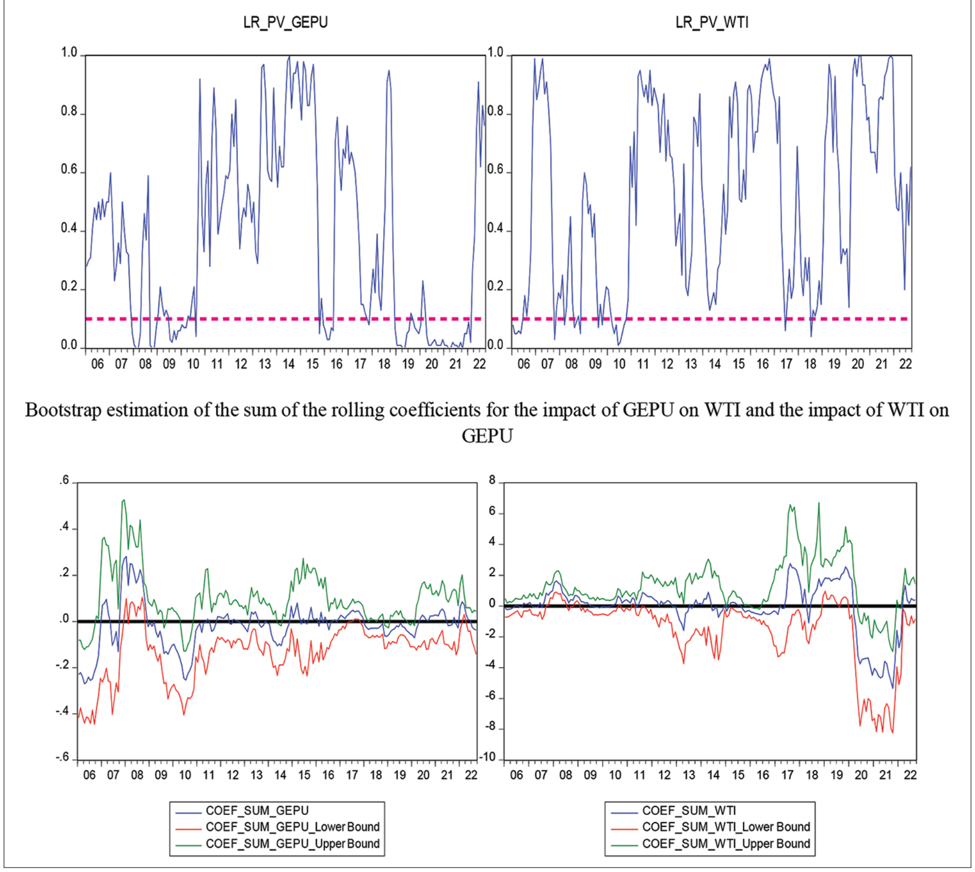
The Lc test shows that the parameters in the VAR system follow a random walk process at the 1% level. These results indicate that the parameters of the estimated VAR models using full-sample data exhibit short-term instability.

4.5. Time Varying Causality Analysis

The likelihood ratio test utilizes Bootstrap p-values to determine the significance of the difference between two models. This test compares a simpler model to a more complex model to determine which one provides a better fit to the data. The p-value derived from the likelihood ratio test represents the probability of obtaining a test statistic as extreme or more extreme than the observed test statistic, given that the null hypothesis is true. A low p-value

Figure 4: Rolling window estimation results for relationship between GEPU and WTI

Bootstrap p-values of LR test statistic testing the null hypothesis that GEPU does not Granger cause WTI and WTI does not Granger cause GEPU



indicates that the observed difference between the two models is unlikely to be due to chance and supports the alternative hypothesis that the more complex model is a significantly better fit to the data.

Bootstrap resampling involves repeatedly creating new datasets by sampling the original dataset with replacement and then fitting the model to each new dataset to estimate the distribution of the test statistic under the null hypothesis. Bootstrap p-values for the LR test statistic are calculated by comparing the observed test statistic to the distribution of test statistics obtained from the resampled datasets.

Figures 4 through 9 depict the bootstrap probability value, direction, and size of the global economic policy uncertainty (GEPU) on WTI, prices of oil, precious metals, and agricultural goods, as well as the reverse. For each pair, the impact magnitude is computed. Regarding the impact of GEPU on WTI (West Texas Intermediate) price, Figure 4 shows that the null hypothesis, which asserts that GEPU does not Granger-cause WTI price at a significance level of 10%, is rejected when the p-values (PV) fall below the horizontal dotted line in pink. This figure enables the dismissal of the causality hypothesis for the following time intervals: 2007M10-2008M02, 2018M10-2008M12, 2009M02-2010M03, 2015M10-2016M04, 2019M01-2019M10, and 2020M02-2021M12. As for the impact of WTI on GEPU, the causality hypothesis is rejected for the following periods: 2008M04-2008M05, 2006M01-2006M06, and 2010M01-2010M10.

Figure 5 shows that, by considering the GEPU-SILVER pair, the causality hypothesis is rejected for the following time intervals when examining the impact of GEPU on SILVER: 2008M06-2008M08, 2009M06-2010M04, 2012M02-2012M10, 2016M01-2016M06, and 2019M01-2019M10. However, no causality is observed for the impact of SILVER on GEPU during the following periods: 2008M02-2008M10, 2013M10-2013M12, 2016M06-2016M12, 2017M02-2017M10, and 2020M02-2021M04. These periods are notable for extraordinary occurrences like the sovereign debt crisis and the Covid-19 pandemic. Figure 5 also presents the bootstrap estimation of the sum of rolling coefficients for the effect of GEPU on WTI and vice versa. During the periods of no causality, there is a back and forth in movements, and the shock's effect is destabilizing.

Figure 6 illustrates the Rolling window estimation results for the interaction between GEPU and GOLD price. The absence of causality for the impact of GEPU on GOLD is observed from the two periods: 2008M06-2008M10, 2009M10-2009M12, 2012M06-2012M12, 2013M10-2014M10, 2015M10-2016M04 and 2018M01-2018M12. However the absence of causality for the impact of GOLD on GEPU is detected in some periods: 2007M08-2008M10 and 2016M06-2016M10. While observing the Bootstrap estimation of the sum of the rolling coefficients for the impact of GEPU on GOLD and the impact of GOLD on GEPU, it is found that the effects are generally negative during periods of absence of causality.

Figure 5: Rolling window estimation results for relationship between GEPU and SILVER

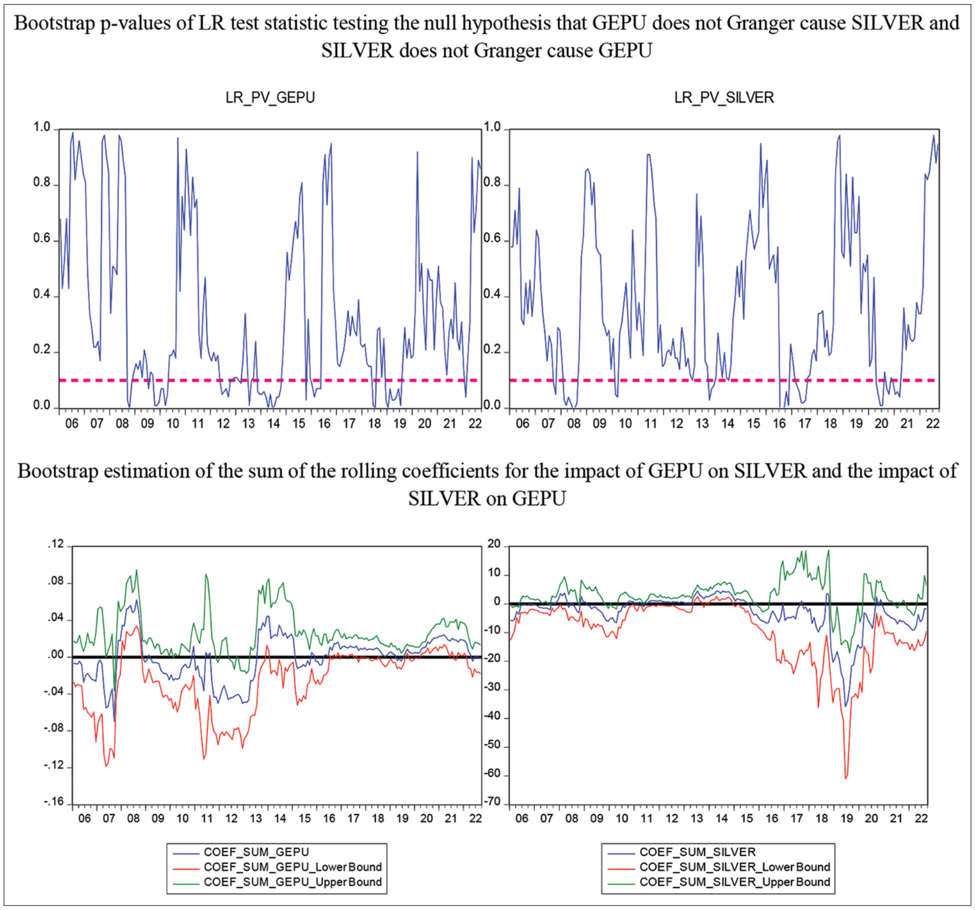


Figure 6: Rolling window estimation results for relationship between GEPU and GOLD

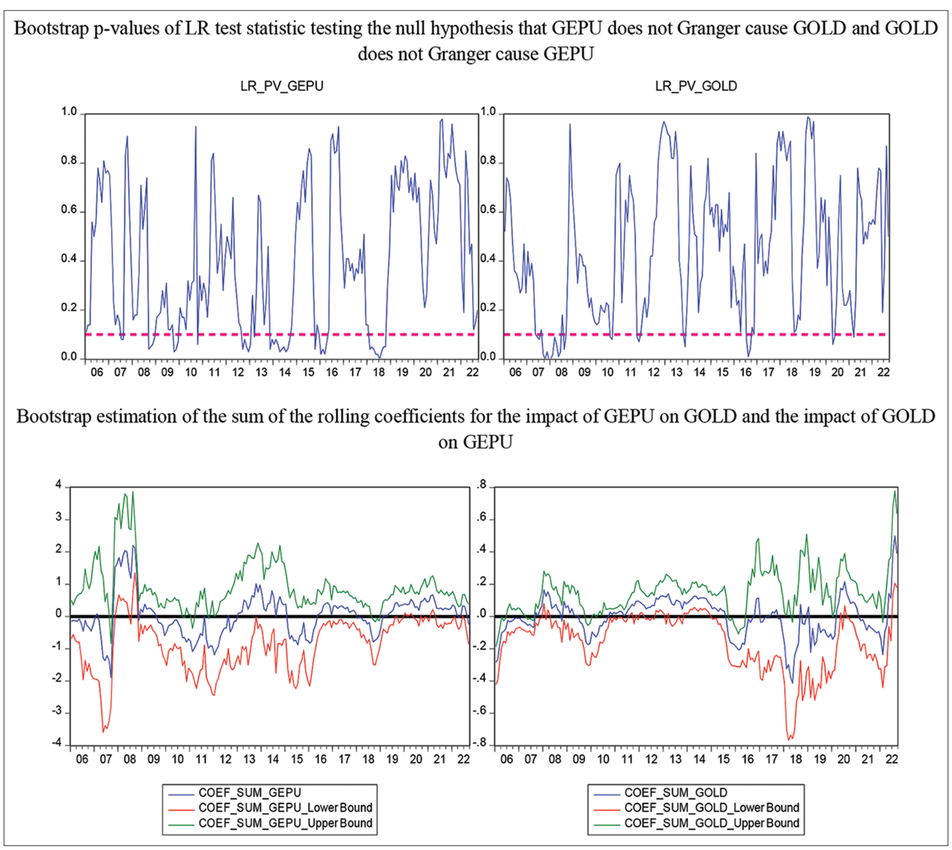


Figure 7: Rolling window estimation results for relationship between GEPU and PLATINUM

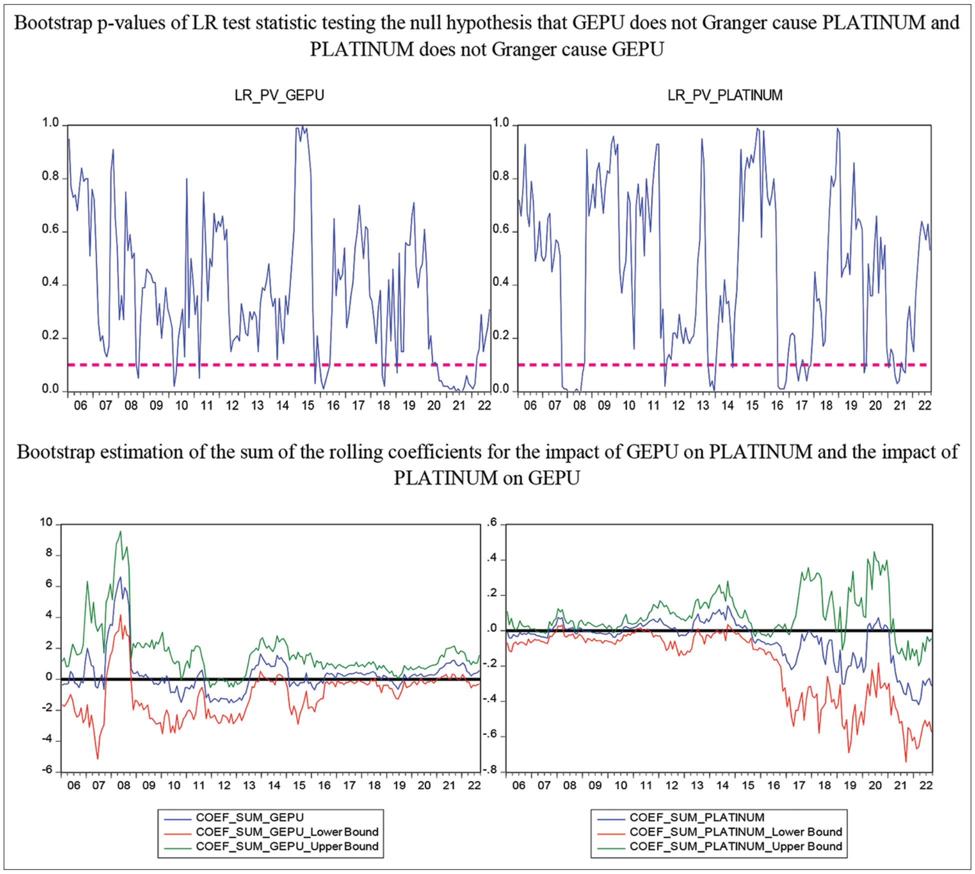


Figure 8: Rolling window estimation results for relationship between GEPU and BANANAS

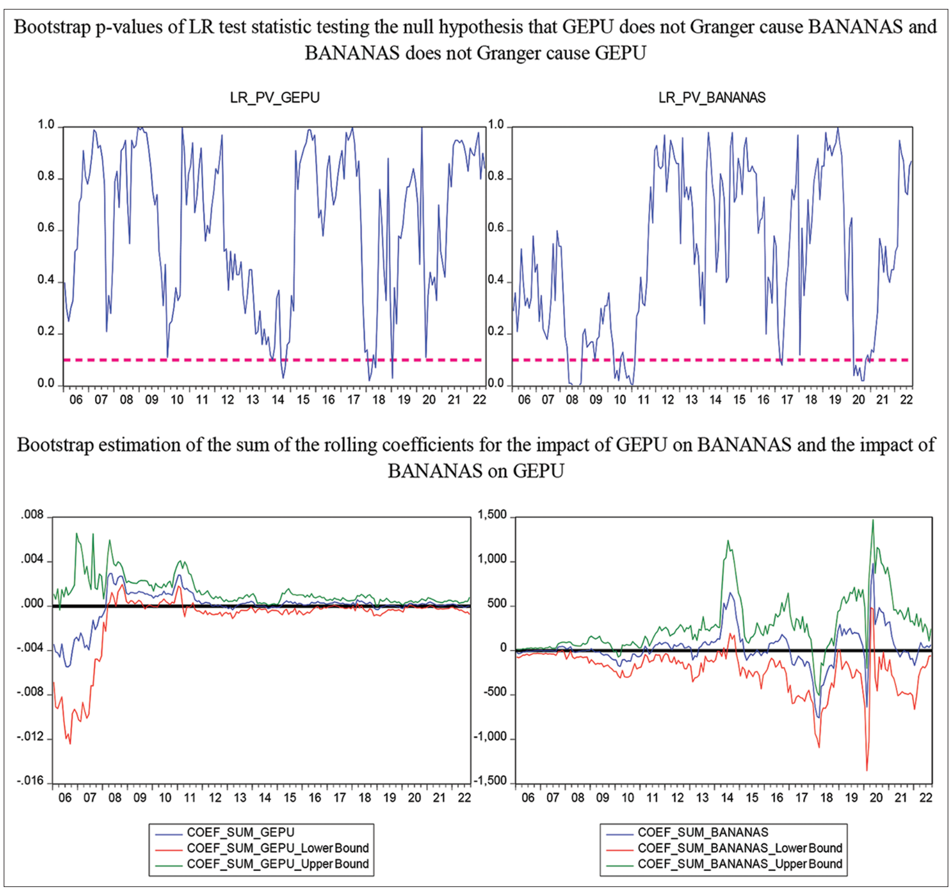
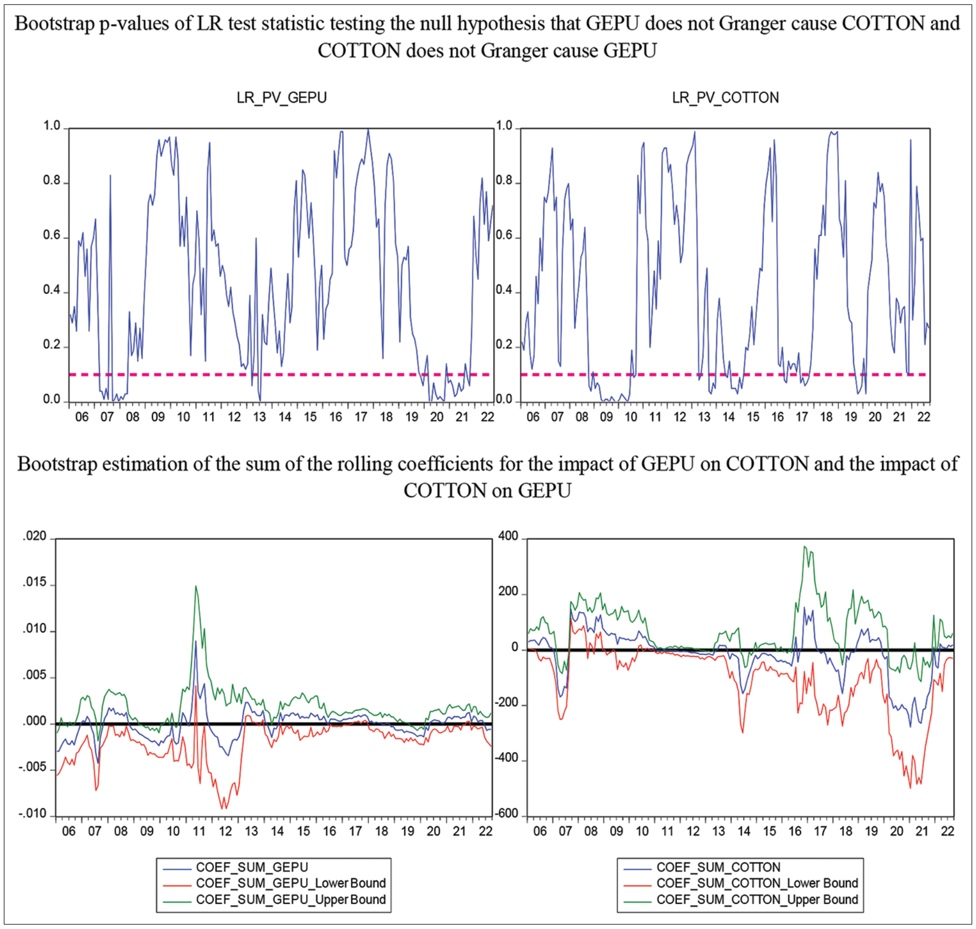


Figure 9: Rolling window estimation results for relationship between GEPU and COTTON



From GEPU-PLATINUM (Figure 7), we observe the absence of causality in these periods: 2015M10-2016M04 and 2020M06-2022M02 (impact of GEPU on PLATINUM). In addition, we see the absence of causality for the effect of PLATINUM on GEPU in periods: 2007M10-2008M10, 2013M10-2013M12, 2016M06-2016M12 and 2021M02-2021M11. Each period coincides with economic and financial crises.

Finally, from the interaction between GEPU and agricultural prices (Figures 8 and 9), we see for the impact of GEPU on BANANES and vice versa the absence of causality for these periods: 2010M02-2011M02, 2014M06-2014M10 and 2018M01-2018M04 and 2020M02-2020M12. This same figure traces the Bootstrap estimation of the sum of the rolling coefficients, in period of the absence of causality; the impact is positive and negative.

5. CONCLUSION AND POLICY IMPLICATIONS

The implications of the causal links between economic policy uncertainty, precious metals, and agricultural prices are of great significance to policy makers due to their potential impacts on economic stability, inflation, and trade policy. The movement of prices in these markets can have a ripple effect on inflation and overall economic growth. This effect can be further amplified by economic policy uncertainty, which can cause a loss of investor confidence, capital outflows, and economic stagnation.

The purpose of this study is to examine the relationship and co-movements between global economic policy uncertainty, oil prices, precious metals, and agricultural prices using two empirical methods: wavelet coherence and bootstrap rolling window Granger causality. The study focuses on certain periods of economic and financial crises, such as the subprime crisis of 2008, the sovereign debt crisis of 2011, the Covid-19 pandemic of 2020, and the recent Russian-Ukrainian conflict.

The findings from the wavelet coherence analysis reveal that the correlation between economic policy uncertainty and each of the time series is both positive and negative in the short term, medium term, and long term. On the other hand, the bootstrap rolling window analysis indicates the absence of causality between uncertainty and oil, unidirectional causality between GEPU-SILVER and GEPU-PLATINUM pairs, and bidirectional causality between GEPU and BANANAS.

Moreover, the interaction between these variables can have significant implications for international trade policy. For example, if a country relies heavily on agricultural exports and experiences volatility in these markets due to economic policy uncertainty, it may need to re-evaluate its trade policies to diversify its exports or reduce dependence on volatile commodity markets. Therefore, comprehending the relationship between economic policy uncertainty, precious metals, and agricultural prices is crucial for policy makers to make informed decisions that foster economic stability, growth, and prosperity.

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