International Journal of Management Economics and Business, Vol. 19, No. 1, 2023
Uluslararası Yönetim İktisat ve İşletme Dergisi, Cilt 19, Sayı 1, 2023

Research Article / *Araştırma Makalesi*

THE CAUSALITY BETWEEN AGRICULTURAL RAW MATERIALS AND ECONOMIC POLICY UNCERTAINTY: EVIDENCE FROM THE TIME-VARYING GRANGER CAUSALITY

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ABSTRACT

This paper aims to examine the time-varying dynamics of the causal interaction between agricultural raw materials commodity prices and the US economic policy uncertainty (EPU). To this end, we use monthly data for the period spanning from January 1992 to November 2021. We employ a time-varying Granger causality test to provide empirical evidence on the time-varying dynamics of the causality interaction and thereby revealing potential heterogeneities of these interactions during major historical events. The results show that causality running from EPU to agricultural raw materials, as well as causality running from agricultural raw materials to EPU, exhibits time-varying dynamics. More specifically, the findings reveal that causality generally tended to run from agricultural raw materials to EPU for most of the 2000-2014 period but reversed with the US-China trade war and the Covid-19 pandemic period. This result highlights the importance of modeling the potential causality interactions in the economic uncertainty-commodity prices nexus within a dynamic framework and implies that these interactions cannot be considered independently of the prevailing economic, political and global conditions.

Keywords: *Economic Policy Uncertainty, Agricultural Raw Materials, Time-Varying Granger Causality, Covid-19.*

TARIMSAL HAMMADDELER VE EKONOMİ POLİTİKASI BELİRSİZLİĞİ NEDENSELLİK İLİŞKİSİ: ZAMANLA DEĞİŞEN GRANGER NEDENSELLİK TESTİNDEN KANITLAR

ÖZET

Bu çalışma, tarımsal hammadde emtia fiyatları ile ABD ekonomi politika belirsizliği (EPU) arasındaki nedensellik etkileşiminin zamanla değişen dinamiklerini incelemeyi amaçlamaktadır. Bu amaçla, Ocak 1992 - Kasım 2021 dönemini kapsayan aylık veriler kullanılmıştır. Nedensellik etkileşiminin zamanla değişen dinamiklerine ilişkin ampirik kanıtlar sağlamak ve böylece önemli tarihsel olaylar sırasında bu etkileşimlerin potansiyel heterojenliklerini ortaya çıkarmak için zamanla değişen bir Granger nedensellik testi kullanıyoruz. Sonuçlar, EPU'dan tarımsal hammaddelere uzanan nedenselliğin yanı sıra tarımsal hammaddelerden EPU'ya uzanan nedenselliğin de zamanla değişen dinamikler

www.ijmeb.org ISSN:2147-9208 E-ISSN:2147-9194
http://dx.doi.org/10.17130/ijmeb.1186996
Received: 10.10.2022, Accepted: 10.01.2023

sergilediğini göstermektedir. Daha spesifik olarak, bulgular 2000-2014 döneminin büyük bir bölümünde nedenselliğin genellikle tarımsal hammaddelerden EPU'ya doğru gitme eğiliminde olduğunu, ancak bu durumun ABD-Çin ticaret savaşı ve Covid-19 pandemi dönemi ile tersine döndüğünü ortaya koymaktadır. Bu sonuç, ekonomik belirsizlik-emtia fiyatları ilişkisindeki potansiyel nedensel etkileşimlerin dinamik bir çerçeve içinde modellenmesinin önemini vurgulamakta ve bu etkileşimlerin hakim ekonomik, politik ve küresel koşullardan bağımsız olarak düşünülemeyeceğini ima etmektedir.

Anahtar Kelimeler: *Ekonomi Politika Belirsizliği, Tarımsal Hammaddeler, Zamanla Değişen Granger Nedensellik, Covid-19.*

1. Introduction

Since the beginning of the 21st century, global economic activity has faced many challenges, such as the Global Financial Crisis (GFC), the oil price collapse of 2014, the US-China trade war, the ongoing Covid-19 pandemic, and the Russia-Ukraine war. While some of these events were directly related to the commodity markets, others were triggered by economic, political, and global events that were mainly independent of commodity markets. For example, the GFC started as a subprime crisis in the US and later deepened into a global financial meltdown. The effect of the GFC on agricultural commodity markets was the rise in agricultural commodity prices as a result of the countries' modifications to their agricultural policies. Rising export barriers reduced supply on the one hand; on the other, lowering import tariffs increased demand and as a result, agricultural commodity prices rose sharply (Sun et al., 2021). With a 70% drop in oil prices, the oil price collapse of 2014 was one of the worst oil price shocks in modern history and, unlike the GFC, it was mainly driven by commodities markets (World Bank, 2018). This drop in oil prices spread rapidly to other commodity markets and agricultural commodity prices experienced sharp declines.

However, there is a consensus in the existing literature that Covid-19 is a different type of shock compared to other economic and financial shocks. Because unlike the previous shocks, which were mainly driven by economic and financial shocks and linked to one sector of the economy, the Covid-19 pandemic caused severe disruptions in global economic activity, affecting both demand and supply conditions (Bouri et al., 2021; Sharif et al., 2020). The public health measures such as travel restrictions and lockdown policies imposed by countries around the world to minimize the spread of Covid-19 have reduced economic activity, resulting in a significant disruption in the global supply chain (Leduc & Liu, 2020; Ahmed & Sarkodie, 2021). With the Covid-19 pandemic, the decline in global economic activity and the high pressure on commodity markets are estimated to be more severe than that caused by the GFC (Yakubu & Sarkodie, 2021). Due to concerns about disruptions in the global supply chain, agricultural commodity prices rose sharply, hitting their highest level since the 2008 spike in this commodity class (Yan et al., 2021). As markets began to recover following Covid-19, the outbreak of the Russia-Ukraine war significantly increased spillover effects among individual agricultural commodities, exacerbating the impact on agricultural markets (Just & Echaust, 2022).

Despite their various origins, the most basic common feature of these shocks is that they have an uncertainty shock as a second moment component (Bloom, 2009, 2016; Baker

& Bloom, 2013). As well documented by the existing literature, the uncertainty shock caused by the GFC contributed significantly to the depth of the crisis (Bloom, 2009; Stock & Watson, 2012; Bloom, 2014; Antonakakis et al., 2014). However, Covid-19 has created an enormous burst of uncertainty which is far exceeding the level caused by the GFC. Moreover, just like in the case of the GFC, this burst of uncertainty caused by the pandemic has contributed significantly to the depth of the crisis in terms of both moment and duration (Baker et al., 2020; Bouri et al., 2021; Leduc & Liu, 2020). Because the effects of the decline in aggregate demand and the disruptions in the supply chain have been intensified by the burst of uncertainty related to the pandemic (Bakas & Triantafyllou, 2020). In response to concerns about disruptions in the supply chain caused by Covid-19, some countries responded by implementing export restrictions on agricultural products, which in turn drove world prices higher. In addition to high pressure on agricultural commodity prices, these restrictions seriously affect international trade and hence the global agricultural income (Udmale et al., 2020).

Fluctuations in commodity prices are early signals of the potential shifts in aggregate demand (Barsky & Kilian, 2004; Kilian, 2009). Besides, as commodities, especially primary ones, are crucial inputs into the production process, commodity prices are also strictly associated with the supply conditions (Kaldor, 1987; Garner, 2017). Due to their strict associations with economic activity, commodity prices contain important information about the state of the economy and hence they respond quickly to uncertainty shocks (Wang et al., 2015; Bannigidadmath & Narayan, 2021). Therefore, in addition to the causality running from commodity prices to economic uncertainty, it is of great importance to investigate the reverse causality running from economic uncertainty to commodity prices.

Despite the immense literature on the economic uncertainty - energy commodity prices nexus (Antonakakis et al., 2014; Kang & Ratti, 2013a, 2013b; Hailemariam et al., 2019; Sun et al., 2020; Apergis et al., 2021; Shi & Shen, 2021; Tunc et al., 2022), the literature focusing on the agricultural markets is quite limited. This study intends to fill this gap in the literature by examining the time-varying dynamics of the causal relationship between the US economic policy uncertainty and agricultural raw material commodity prices. In this context, our paper is innovative in some aspects. First, some early attempts focused on the pre-Covid-19 pandemic period, whereas more recent studies focused on the Covid-19 period in examining the link between commodity prices and economic uncertainty. However, this article covers the last three decades, during which both the US EPU and agricultural raw materials prices have been subjected to various shocks.

We contribute to the existing literature on the nexus between economic uncertainty and commodity prices in several ways. Firstly, considering the importance of agricultural raw materials as an industrial input, we specifically focus on this commodity class. Secondly, in addition to the causality running from agricultural raw materials, we examine the existence of the causality running from economic uncertainty. Thirdly, we employ the time-varying Granger causality methodology proposed by Shi et al. (2018, 2020). In this way, we provide a comparative assessment of the potential heterogeneities exhibited by the causal relationship between economic uncertainty and agricultural raw materials over the past three decades. This comparison might provide an understanding of the existence, direction, and potential heterogeneities that any possible causal relationship can display.

This study is constructed as follows: Section 2 reviews the literature. Section 3 documents the TVGC methodology. Section 4 presents the empirical findings. Section 5 concludes the study.

2. Literature

Since the GFC, higher fluctuations in agricultural commodity prices have drawn considerable attention to the relationship between agricultural commodity prices and economic uncertainty (Sun et al., 2021). Because similar to other commodity markets, agricultural commodity markets are highly sensitive to uncertainty shocks (Bakas & Triantafyllou, 2018). The first strand of the literature focuses on a large group of commodity markets in examining the nexus of economic uncertainty-commodity markets. For example, Joëts et al. (2017) found that agricultural commodity prices are more sensitive to long-term uncertainty, whereas the energy market is more sensitive to short-term uncertainty. Bakas & Triantafyllou (2018) found that the volatility of agricultural, energy, and metals commodity prices increases significantly in response to economic uncertainty shocks.

Huang et al. (2021) focused on a large group of commodity markets and examined the relationship between commodity prices and economic uncertainty for the period from 1990:04 to 2018:06. Their findings reveal that economic uncertainty exerts negative responses to energy, agricultural and metals commodities prices. Compared to the major historical events, the greater negative responses of commodity prices coincide with the GFC period. Yin & Han (2014) investigated the correlations between commodity prices and economic uncertainty for the period from January 1991 to March 2013. Their findings reveal that rises in economic uncertainty lead to increases in the volatility of commodity prices. Besides, the correlation between commodity prices and economic uncertainty has strengthened in the post-2003 period.

The second strand of the literature focuses on the Covid-19 period. For example, the US Department of Agriculture (USDA) investigated the impacts of the Covid-19 pandemic and policy restrictions implemented by governments on global agricultural trade. The findings show that decreasing human mobility and policy restrictions account for approximately a 10% decrease in global agricultural trade. Moreover, the effects exhibit some differences across various commodities. More specifically, agricultural raw materials and higher-value products are the most affected commodity classes (USDA, 2021). In a similar vein, Yan et al. (2021) investigated the effects of trade restrictions on the volatility of agricultural commodity prices. They used panel data covering 71 countries for the period spanning from January 2020 to July 2021. The findings show that trade restrictions caused around a 22% rise in price volatility. Additionally, rises in volatility are far more pronounced in countries that depend heavily on agricultural imports.

Performing a bootstrap causality test, Sun et al. (2021) examine the bidirectional causality between agricultural commodity prices and trade policy uncertainty in China. Their results indicate that trade policy uncertainty Granger causes agricultural commodity prices during the GFC, the US-China trade war, and the Covid-19 pandemic. In addition, the reverse causality episode, such as the US-China trade war, during which causality runs from agricultural commodity prices to trade policy uncertainty was reported in the study. Just & Echaust (2022) focused on the Russia-Ukraine war using daily data covering the period from 2000 to 2022.

They report a significant peak in the spillover effects for individual agricultural commodities during the Russia-Ukraine war.

3. Methodology and Data

3.1. Methodology

The time-varying causality relationship between the US EPU index and the agricultural raw materials price index is investigated in this study by utilizing the procedure proposed by Shi et al. (2018; 2020). Relying on the lag-augmented VAR (LA-VAR) model, the causality test for an integrated variable, y_t, can be tested using the following compact form of the LA-VAR model:

$$Y = \eta\Gamma' + X\Theta' + B\Phi' + \varepsilon, \tag{1}$$

where

$$Y = (y_1, y_2, ..., y_T)_{TXn'}, \eta = (\eta_1, \eta_2, ..., \eta_T)_{TX2'}, \eta_t = (1, t)_{2X1'}, X = (x_1, x_2, ..., x_T)_{TXnp'},$$
$$x_t = (y_{t-1'}, y_{t-2'}, ..., y_{t-p'},)_{npx1'}, \Theta = (\alpha_1, \alpha_2, ..., \alpha_p)_{nxnp}, B = (b_1, b_2, ..., b_T)_{Txnd'},$$
$$b_t = (y_{t-p-1'}, y_{t-p-2'}, ..., y_{t-p-d'},)_{ndx1'}, \Phi = (\alpha_{p+1}, \alpha_{p+1}, ..., \alpha_{p+d})_{nxnd}, \varepsilon = (\varepsilon_1, \varepsilon_2, ..., \varepsilon_T)_{Txn'}$$

and d is the lag addition parameter.

The Shi et al. (2018; 2020) approach utilizes supremum (sup) Wald statistic sequences. The Wald statistic over $[f_1, f_2]$ that has a sample size fraction of $f_w = f_2 - f_1 \geq f_0$ is given by $W_{f2}(f_1)$. The sup Wald statistic is given as

$$SW_f(f_0) = \frac{\sup}{(f_1, f_2) \in \Lambda_0, f_2 = f}\{W_{f_2}(f_1)\} \tag{2}$$

where $\Lambda_0 = \{(f1, f_2): 0 < f_0 + f_1 \leq f_2 \leq 1, and\, 0 \leq f_1 \leq 1 - f_0\}$, and $f_0 \in (0,1)$ represents the reduced sample size to estimate the VAR system. For a basic switch scenario, the dating rules are defined by the following procedures:

- *rolling*

$$\begin{aligned} f_e &= \frac{inf}{f \in [f_0, 1]}\{f: W_f(f - f_0) > cv\}, and \\ f_f &= \frac{inf}{f \in [f_e, 1]}\{f: W_f(f - f_0) > cv\} \end{aligned} \tag{3}$$

- *recursive evolving*

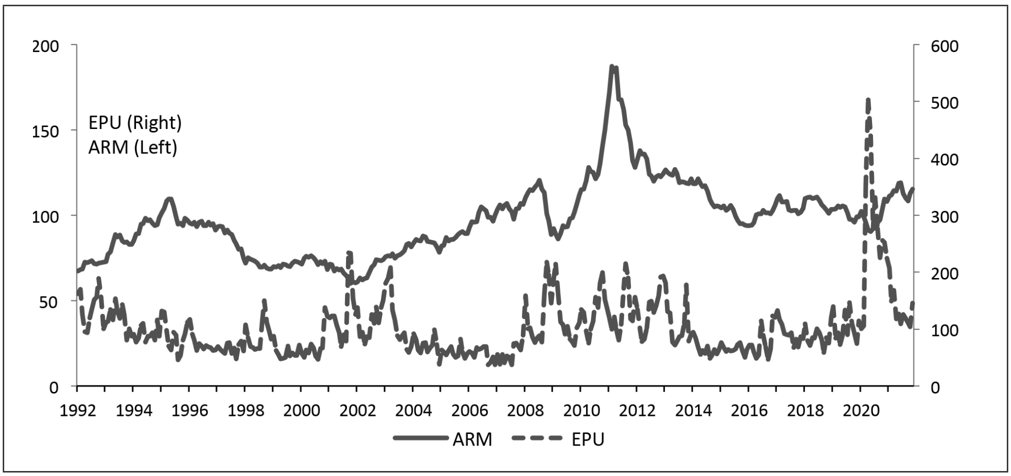
$$\begin{aligned} f_e &= \frac{inf}{f \in [f_0, 1]}\{f: SW_f(f_0) > scv\}, and \\ f_f &= \frac{inf}{f \in [f_e, 1]}\{f: SW_f(f_0) > scv\} \end{aligned} \tag{4}$$

where f_e and f_f represent the first chronological estimated observations for which the test statistics exceed or fall below the critical values in the causal relationship, respectively. cv refers to the critical value of W_f, and scv refers to the critical value of SW_f statistics.

3.2. Data Description

We use monthly data on the US economic policy uncertainty index of Baker et al. (2016) and the agricultural raw materials price index obtained from the IMF database. The agricultural raw materials price index is a weighted average of the prices of some important industrial inputs such as timber, cotton, wool, natural rubber, and hides (see IMF, 2022). Both time series cover the period from 1992:01 to 2021:11, and descriptive statistics are given in Table 1. The sample period covers major historical events such as the Asian financial crisis of 1997, the 9/11 terrorist attacks, the 2003 invasion of Iraq, the GFC, the US presidential elections, the 2014 oil price collapse, the US-China trade war, and the ongoing Covid-19 pandemic period. It should be noted that while some of these events, such as the 2014 oil price collapse and the US-China trade war, were directly related to commodity markets, some evolved mainly independently of commodity markets and caused considerable swings in the US EPU index.

Figure 1: Original Time Series of the Variables



As seen in Fig. 1, except for the 1996 grain price shock, the agricultural raw materials prices remained relatively stable from the beginning of the sample period until 2002 and then experienced sharp increases throughout the 2002-2008 period. The GFC prompted countries to modify their trade policies, and, as a result, agricultural commodity prices rose sharply due to reduced import tariffs and higher export barriers and then declined as a result of demand shortage caused by the economic downturn (Sun et al., 2021). In the following years, agricultural raw materials prices quickly compensated for the sharp declines caused by the GFC, hitting new highs in mid-2011. But towards the end of 2014, the world economy experienced one of the biggest oil price shocks, with a 70% drop in oil prices. The drop in oil prices triggered significant decreases in other commodity markets as well, but the agricultural markets were relatively less affected.

Table 1: Descriptive Statistics

	EPU	ARM
Mean	101.671	97.263
Median	87.490	96.354
Std. Dev.	54.860	21.756
Skewness	2.816	0.994
Kurtosis	16.074	5.116
J-B	0.000[a]	0.000[a]
Obs.	359	359

Notes: This table displays the descriptive statistics of the time series, namely the US economic policy uncertainty index (EPU), and the agricultural raw materials price index (ARM). [a] indicates the significance level at 1%.

We check the stationarity of the variables using traditional unit root tests, such as the ADF, the PP and the KSS tests, and the results of these tests are displayed in Table 2. However, since these tests do not take the structural breaks into account, we apply two additional unit root tests of Clemente et al. (1998), which allow for two structural breaks. Table 3 displays the test results of these unit root tests. Since the time-varying Granger causality methodology does not require a priori knowledge about the stationarity properties (see Shi et al., 2020), it should be noted that the main aim of this step is to find the maximum order of integration of the series.

Table 2: Results of Unit Root Tests

	ADF		PP		KSS	
	Intercept	Trend& Intercept	Intercept	Trend& Intercept	Intercept	Trend& Intercept
Panel A. Level unit root test						
EPU	-5.486[a] (1)	-5.673[a] (1)	-5.685[a] [5]	-5.866[a] [5]	-2.987[b] (1)	-3.488[b] (1)
ARM	-2.018 (3)	-2.453 (3)	-2.023 [6]	-2.245 [6]	-2.403 (3)	-2.625 (3)
Panel B. First difference unit root test						
ΔEPU	-12.151[a] (3)	-12.139[a] (3)	-22.506[a] [5]	-22.486[a] [5]	-3.576[a] (3)	-3.608[a] (3)
ΔARM	-8.696[a] (2)	-8.677[a] (2)	-15.042[a] [6]	-15.028[a] [6]	-5.187[a] (2)	-5.198[a] (2)

Notes: The optimal lag length for the ADF and KSS is chosen based on SIC and displayed in parentheses. Similarly, the optimal lag length for the PP is chosen according to Newey & West (1987) and displayed in square brackets beside the t-statistic. [a], [b], and [c] indicate the significance levels at 1%, 5%, and 10%, respectively.

The test results in Table 2 suggest the presence of a unit root in the ARM variable. On the other hand, the EPU variable is stationary at the level, as confirmed by all three unit root tests. We then employ the CMR test, which allows for two structural breaks. As displayed in Table 3, the results of the CMR test based on both IO and AO models indicate the acceptance of the null of unit root for the ARM variable[1].

1 This result indicates that the maximum order of integration is I(1). Hence, we set *d* to unity.

Table 3: Results of Unit Root Test With Structural Breaks

The CMR test – Clemente, Montanes and Reyes (1998)								
	IO model				AO model			
	TB_1	TB_2	t-stat	(AR-n)	TB_1	TB_2	t-stat	(AR-n)
EPU	2007:06	2020:01	-7.189[a]	0	2007:05	2020:04	-6.785[a]	0
ARM	1997:02	2012:02	-3.933	2	2010:05	2012:01	-3.721	1

Notes: IO model refers to the innovational outlier case, and the AO model refers to the additive outlier case. For both of the tests, TB_1 and TB_2 are the first and second break dates, respectively. [a], [b], and [c] indicate the significance levels at 1%, 5%, and 10%, respectively.

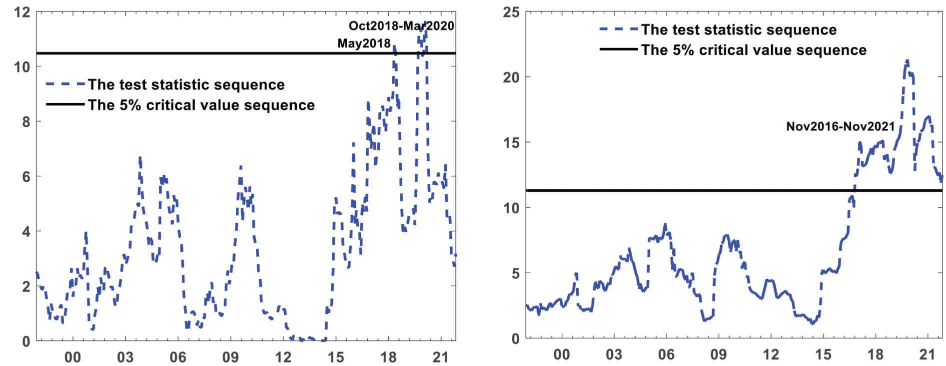
For the EPU index, both tests detect the GFC period as the first break date and the beginning of the Covid-19 period as the second break date. Despite different first break dates, both tests detect the second break date as 2012 for agricultural raw materials. This period can be accepted as a significant breakpoint because it coincides with the period during which agricultural raw materials, or commodity prices in general, peaked after the GFC period and then began to decline due to the weakening global demand.

4. Estimation Results

To examine the dynamic causality relationship between the US EPU and the agricultural raw materials price indices, we employ the time-varying Granger causality (TVGC) model of Shi et al. (2018; 2020). Figs. 2-3 display the results of the TVGC, with panels (a) the rolling window (RO) algorithms and panels (b) the recursive evolving (RE) algorithms. It should be emphasized that panels a and b of the figures exhibit some heterogeneities. The main reason behind this fact is that the RE algorithm allows for potential heteroscedasticity (see Shi et al., 2018, 2020). Hence, one might claim that the results of the RE algorithms more closely match economic expectations when compared to the results of the RO algorithm.

Fig. 2 displays the result of TVGC running from EPU to ARM. The RO algorithm detects only two short-lasting causality episodes in May 2018 and from October 2018 to March 2020 (Fig. 2a). However, the RE algorithm detects the beginning date for these causal episodes as November 2016. This long-lasting episode covers the US-China trade wars and the Covid-19 pandemic periods and lasts until December 2021, the end of the sample period (Fig. 2b).

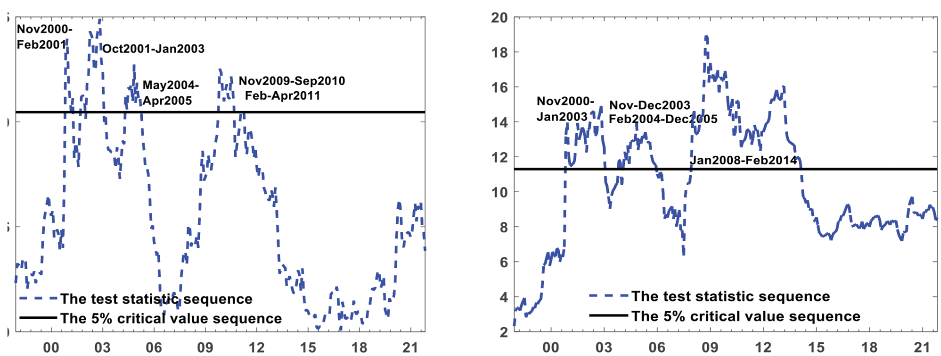
Figure 2: TVGC running from EPU to ARM



(a) Rolling window (b) Recursive evolving

As for the TVGC running from ARM to EPU, the results of the RO algorithm, given in Fig. 3a, detect significant causality episodes covering the periods from November 2000 to February 2001, from October 2001 to January 2003, from May 2004 to April 2005, and from November 2009 to September 2010. In addition to the 2001-2002 and 2004-2005 periods, the RE algorithm detects a longer period of causality starting from the beginning of 2008 to early 2014 (Fig. 3b). However, for the rest of the sample period, agricultural raw materials can not be able to predict EPU. One important fact that emerged from Figs. 2 and 3 is that causation generally tended to run from agricultural raw materials to EPU and reversed with the US-China trade wars and the Covid-19 pandemic. These findings are important as they provide complementary evidence to Sun et al. (2021), who report a two-way time-varying causality between Chinese trade uncertainty and agricultural commodity prices.

Figure 3: TVGC running from ARM to EPU



(a) Rolling window (b) Recursive evolving

In sum, while agricultural raw materials had predictive power on EPU for most of the 2000-2014 period, this commodity class has lost its predictive power as of 2014. In other words, these significant causality episodes are more evident in the 2000s and at the beginning of 2010s, during which agricultural raw materials prices experienced steady increases (except for the collapse during the GFC). This finding seems to imply that the significant explanatory power of ARM on EPU only emerges during periods of price increases in ARM. In addition, for the reverse direction, the causal episodes in which TVGC runs from EPU to agricultural raw materials coincide with the period of heightened uncertainty, such as the US-China trade wars, which have a special relevance with agricultural commodity prices, and the Covid-19 pandemic period (see Figs. 2b and 3b).

5. Conclusion

This paper aims to explore the time-varying dynamics of the causality between agricultural raw materials and the US economic policy uncertainty and focuses on the last three decades during which both of the variables have been subjected to various shocks. The empirical findings reveal that causality generally tended to run from agricultural raw materials to EPU for most of the 2000-2014 period. In other words, agricultural raw materials have predictive power on EPU for most of the 2000-2014 period. When this finding is examined with the price dynamics of agricultural raw materials, it is evident that these significant causality episodes coincide with the periods when agricultural raw material prices experienced steady increases. As for the reverse direction in which causality runs from EPU to agricultural raw materials, significant causality episodes coincide with the US-China trade war and the Covid-19 pandemic period. Due to its special relevance to agricultural and metals markets, the US-China trade war can be considered a significant breakpoint that changed the direction of the causality relationship between agricultural raw materials and the US economic policy uncertainty. Moreover, the great spike in uncertainty caused by Covid-19 seems to be responsible for the significant predicting power of economic policy uncertainty on agricultural raw materials.

Given that agricultural raw materials are one of the most essential inputs of industrial production, these results have important policy implications. As supported by our empirical evidence, the US economic policy uncertainty has significant spillover effects on agricultural markets, particularly during periods of heightened uncertainty. The most important result from this finding is that the US economic policy uncertainty is an important source of risk for international commodity markets. Moreover, agricultural markets have been exposed to various shocks, such as droughts and global warming, that are mainly independent of uncertainty shocks. As a result of the concerns about food security, major agricultural exporters often impose trade restrictions, which trigger significant fluctuations in agricultural commodity prices in the face of these shocks. Therefore, both agricultural exporters and importers should closely monitor the uncertainty dynamics of the US and follow a dynamic policy. In future investigations, expanding this study to include other commodity markets might help provide further policy implications.

Conflict of Interest

The authors have no conflicts of interest to declare.

Contribution Statement

The authors declare that they have contributed equally to this work.

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