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Co-movement of commodity price indexes and energy price index: a wavelet coherence approach

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Abstract

This research sheds light on the causal link between commodity price indexes, i.e., the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index, in the global market, using wavelet coherence, Toda–Yamamoto causality, and gradual shift causality tests over the period 1992M1 to 2019M12. Findings from the wavelet power spectrum and partial wavelet coherence reveal that: (1) there was significant volatility in the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index between 2004 and 2014 at different frequencies; and (2) commodity price indexes significantly caused the energy price index at different time periods and frequencies. It is noteworthy that the outcomes of the Toda–Yamamoto causality and gradual-shift causality tests are in line with the results of wavelet coherence.

Keywords: Energy price, Commodity price, Wavelet coherence, Causality

JEL Classification: Q4, Q2, E3, C3

Introduction

Commodities play a key role in global trade, connecting nations around the world. The trade of an item is affected by numerous factors, which have been studied from various perspectives. It can be challenging when the prices of commodities fluctuate in the markets, making it difficult to sustain the smooth flow of trade. Globalization has contributed to the interconnections of prices among many items, whose trade has become easier through globalization. Over the last century, commodities have become popular tools of investment portfolios. For example, while corn is an agricultural commodity and food, it is also a source of ethanol, and thus biodiesel, which is a commodity in the energy market, and it is an investment tool for speculators in financial markets. The lack of a thorough understanding of the relationships between commodities and their prices bring challenges to producers, traders, investors, and policy-makers when making decisions. If the price of a commodity has a causal relationship with the price of another, then it is possible to predict price fluctuations in the other. This is important since it can

enable more accurate planning and smoother operations in the management of supply and demand in a global context.

Scholars have shown substantial interest recently in the price relationships between energy commodities and various non-energy commodities. This is due to the clear co-movement of oil and food prices during the global financial crisis from 2006 to 2008. It is important to understand the price movements since they contain useful information, and in some cases are transmitted to other prices. This can be viewed as a contagious process whose effects are transferred from one market to another. To make predictions in different markets, participants and regulators need to understand how the influence of one market transmits to another via different channels. For example, speculators would want to know about price movements and their connections in order to speculate in futures markets for risk management, hedging strategies, and asset pricing (Kou et al. 2014, 2020; Chao et al. 2020), while traders would want to know the nexus between prices of certain commodities so that they can predict their price movements. Although it sounds appealing, to merely consider the physical links between commodities is not sufficient to forecast price movements in the markets, as there may be some nonlinearity issues.

Our approach differs from those of other researchers in two ways. First, we use a different method to examine the co-movement of energy and non-energy commodity prices. The wavelet coherence method is rarely used in this field, and it has some advantages over other methods. Pal and Mitra (2017) discussed these advantages and argued that they originate from statistical physics and combine information about both time and frequency. This method uniquely allows the decomposition of unidimensional time data into the bidimensional time–frequency sphere. Second, the data we use represent the global price indexes and have not been extensively used in such analysis.

A vast amount of empirical literature exists on co-movement, particularly between oil and food (agricultural commodity) prices in many markets. As oil is the commodity most commonly used as an energy source, it has linkages to almost all other commodities through energy costs, and thus production costs. Therefore, oil prices have a spillover effect on many other commodities. This increases the importance of oil prices in the global economy, such as through production costs, domestic inflation, and exchange rates. The findings of this particular strand of the literature are mixed. While some researchers have found evidence of co-movement between oil and commodity prices, others have supported the neutrality hypothesis of no relationship. For example, Zhang and Reed (2008) studied the causal effect of world oil prices on the Chinese agricultural commodity market and found no evidence that oil prices co-moved with some agricultural commodity prices in China over the period of the study. Esmaeili and Shokoohi (2011) analysed the co-movement of the food price index with the macroeconomic and oil price indexes, and reported that the oil price index has an influence on the food price index, whereas the macroeconomic index has an influence on the food price index. Nazlioglu and Soytaş (2011) studied the oil-agricultural commodity relationship, concentrating on nonlinear causality, and found nonlinear feedbacks between oil and agricultural commodity prices, while there was a persistent unidirectional nonlinear causality from oil to certain agricultural commodities. However, their causality analysis, similar to those of Yu et al. (2006), Nazlioglu and Soytaş (2011), and Reboredo

(2012), among others, supported the neutrality hypothesis. In other words, agricultural commodity prices are neutral to the effects of oil price movements in the long run. In another study, Nazlioglu et al. (2013) considered the volatility transmission between oil and selected agricultural commodity prices using a sample divided into pre-and post-crisis periods (before and after 2006–2008). They found no risk transmission during the pre-crisis period, whereas the dynamics of volatility changed significantly during the post-crisis period, and risk transmission emerged as a new dimension of their relationship. Similar to Nazlıoglu et al. (2013), Wang et al. (2014) reported that in the pre-crisis period, oil shocks could explain the minor changes in agricultural commodity prices. However, both during and after the crisis, the explanatory ability of oil prices on agricultural commodity prices was much higher. They argued that in the pre-crisis period, most of the variation in agricultural prices came from the demand side. Avalos (2014) argued that after the Energy Policy Act of 2015 was implemented in the US, oil prices become a relevant factor in certain agricultural commodity markets such as corn. This is due to the use of corn-based ethanol as a biofuel, which creates a physical link between the oil and agricultural commodity markets. Thus he found a two-way feedback relationship between the prices of oil and agricultural commodities. Koirala et al. (2015) stated that biodiesel, diesel, corn oil, and gasoline prices affect energy producers. As also explained by Avalos (2014), to link agricultural commodities to oil by regulation allowing the use of ethanol as biodiesel is expected to create a causal link between the prices of commodities and oil. Ultimately, they found that agricultural futures, commodity prices, and energy futures prices are highly correlated and show a significant relationship. Hence they concluded that an increase in energy prices increases agricultural commodity prices. Kapusuzoğlu and Ulusoy (2015) studied the effect of Europe Brent and West Texas Intermediate oil prices on selected agricultural commodity prices and discovered a unidirectional causality running from oil prices to agricultural commodity prices. Lucotte (2016) also studied the co-movement of oil and agricultural commodity prices for a sample consisting of two periods, pre- and post-crisis, and found strong evidence that in the post-crisis period, there was a strong positive co-movement between crude oil and agricultural commodity prices. De Nicola et al. (2016) conducted a comprehensive study on the price returns of energy and agricultural commodities and found a strong correlation between them. Furthermore, they revealed that the co-movement among the commodities increases with the use of biofuels. Fowowe (2016) studied the links between oil and agricultural commodity prices for South Africa. He found no relationship between them, and therefore his findings supported the neutrality hypothesis. Pal and Mitra (2017) studied the co-movements of crude oil prices and the world food price index. Their findings supported the view that oil prices co-move with food prices and are also led by oil prices.

Other researchers have analysed the links between oil prices, food prices (agricultural commodity prices), and exchange rates, as there is a channel through which oil prices transmit to local agricultural markets via exchange rates. Nazlioglu and Soytas (2012) studied world oil prices and agricultural commodity prices, accounting for changes in the relative strength of the US dollar. They found evidence of the impact of world oil price changes on agricultural commodity prices. Furthermore, their findings confirmed the positive impact of a weak dollar on agricultural commodity prices.

Scholars have also researched the nexus between oil prices, food prices, metal prices, and exchange rates. Industrial metal prices are important in developed and developing economies since they represent one of the main inputs of industrial production. Precious metals such as gold, silver, platinum, and palladium are used as investment and hedging tools for international investors, as do currencies. Because of international trading of these commodities, exchange rates play a key role, since most world trade is priced in US dollars or euros. The exchange rate is one of the main channels through which the international price volatilities of commodities are transmitted to local economies. Using monthly data for the period 1973–1996, Chaudhuri (2001) reported that real commodity prices and real oil prices are co-integrated. His findings revealed that oil is used as an intermediate commodity in the production of agricultural commodities and metals and that the rise in oil prices has an impact on the real prices of other commodities via the real exchange channel. Sari et al. (2010) studied the relationship between the spot prices of some precious metals, oil prices, and the US dollar/euro exchange rate. They found a weak long-run equilibrium relationship but strong feedback in the short run, indicating that those commodities may not be sensitive to common economic factors in the long run, and investors may benefit from diversification into precious metals. Furthermore, exporters can benefit from weak long-run relationships by shifting their exports into other precious metals, thus diversifying the price fluctuation risk of the future. Ji and Fan (2012) argued that the link between the crude oil market and the agriculture and metal markets has increased. They studied the pre-and post-2008 periods and found that the overall level of correlation strengthened in the latter. The crude oil market showed significant volatility spillover effects on non-energy markets. Their findings also revealed that the influence of the US dollar on commodity markets weakened in the post-crisis period. Jain and Ghosh (2013) studied the post-crisis period for India. They researched the link between global oil prices, precious metal prices, and the rupee/US dollar exchange rate. Their findings showed that the global oil prices transmitted to the Indian economy via the exchange rate channel since India is an importer of both precious metals and oil. Wang and Chueh (2013) studied the US dollar interest rates, US dollar, and oil and gold prices. Their data covered the period between 1989 and 2007. Therefore, the research focused largely on the pre-crisis period of 2006–2008. Their findings revealed that interest rates had a positive influence on future crude oil prices and a negative influence on future gold prices. Also, gold and oil prices positively influenced each other. In the long run, a relationship exists whereby interest rates influence the US dollar, which in turn influences international crude oil prices. Furthermore, there is a price transmission relationship from interest rates to gold prices, which is an important insight for speculators. Mensi et al. (2013) investigated the return links between volatility transmission between the S&P 500 and commodity price indexes for energy, food, gold, and beverages for the period between 2000 and 2011. Their findings showed significant transmission among the S&P 500 and commodity markets in terms of return and volatility spillover. Klotz et al. (2014) studied the case of China and found a causality running from economic activity to energy and industrial metal prices. Their findings further revealed that energy and industrial metal prices respond positively to interest rates in China. When the exchange rate system is relaxed, industrial metal prices tend to be higher. Balcilar et al. (2015) researched the transmission dynamics between oil spot prices, precious

metals spot prices, and the US dollar/euro exchange rate for the period 1987–2012. They considered high- and low-volatility regimes and found that silver and oil were the most volatile, while gold was considered a safe haven for investors. Gold prices were found to be the most informative among all the assets, while palladium prices had a negative impact on the exchange rate. Rafiq and Bloch (2016) studied commodity and oil prices using nonlinear models, using data from 1900 to 2011. They found a long-run relationship using both linear and nonlinear models. Oil prices were found to have a low impact on most agricultural commodity prices, but a substantial impact on metal prices. Kang et al. (2017) studied the dynamics of return and volatility spillover indexes to reveal the intensity and direction of transmission during the 2006–2008 global financial and European sovereign debt crises, focusing on crude oil, precious metals, and agricultural commodity futures markets. Their findings showed that during the crises, the correlation between the commodities' futures market returns increased sharply. During the crisis period, the benefits of international portfolio diversification diminished for investors. Furthermore, there was a strong volatility spillover across commodity futures markets. Gold and silver were found to be information transmitters, while others were receivers. Karabulut et al. (2020) explored the linkage between commodity prices and world trade uncertainty using a wavelet coherence approach. They found a positive correlation between commodity prices and world trade uncertainty.

The impact of the 2006–2008 oil price shocks on local economies has also been studied (Farzanegan and Markwardt 2009; Tang et al. 2010; Cunado and de Gracia 2015; Coronado and Rojas 2016; Morana 2017; Alekhina and Yoshino 2019). The transmission channels of oil price shock are: (a) supply-side shock effect due to increases in production costs by oil price shock; (b) wealth transfer effect due to the marginal consumption rate of petrodollars and that of ordinary trade surplus; (c) inflation effect due to increased inflation rates from increased oil prices; (d) real balance effect due to changes in money demand and monetary policy due to increased oil prices; (e) sector adjustment effect due to the adjustment cost of industrial structure from increased oil prices; and (f) uncertainty over the oil price and its impact on local economies (Tang et al. 2010). Findings were mixed.

This study investigates the causal link between the commodity price indexes, namely Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index for the global market. We employ the Toda–Yamamoto causality, Fourier Toda–Yamamoto causality, and wavelet coherence tests to answer the following questions: (1) Is there any causal link between the commodity price indexes and the energy price index? (2) If yes, in which direction(s)?

Data

Because the main aim, as well as the innovation of the present study, is to investigate the time–frequency dependency between commodity price indexes—namely, the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index—in the global market using wavelet power spectrum and partial wavelet coherence approaches, a unique dataset is used, which was obtained from the International Monetary Fund (IMF), covering the period 1992M1 to 2019M12.

Table 1 Descriptive statistics

Variable	Energy price index	Agriculture raw material index	Industry input price index	Metal price index
Code	EPI	API	IPI	MPI
Source	IMF	IMF	IMF	IMF
Time	1992M1-2019M12			
Mean	118.128	86.927	97.386	80.230
Median	109.485	80.361	87.977	70.182
Maximum	312.413	140.146	221.183	179.729
Minimum	30.923	56.496	43.777	30.420
Std. Dev	67.951	21.519	43.940	44.440
Skewness	0.5831	0.419	0.575	0.410
Kurtosis	2.232	2.002	2.264	1.775
Jarque–Bera	27.283	23.766	26.113	30.441
Probability	0.000	0.000	0.000	0.000

Energy Price Index is constructed by the Crude oil (petroleum), Natural Gas, Coal Price and Propane Indices while the Metal Price Index is constructed by the Metal Price Index (Base Metals) and Precious Metals Index. However, the Industry Input Price is constructed by the Index Agricultural Raw Materials and Base Metals Price Indices, while the Agriculture Price Index is constructed by the Food and Beverages and Agriculture Raw Materials Price Indices

The descriptive statistics of the time series variables and their codes are presented in Table 1. The pattern of the time series variables is illustrated in Fig. 1.

Methodology

In this study, the DF-GLS, KPSS, and Z-A unit root tests are employed to explore the order of integration of the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index. Also applied is the more recent unit root test of Cavaliere et al. (2011), which "allows for a possible structural break and non-stationary volatility, where the volatility includes both single and multiple abrupt breaks in variance, polynomially trending volatility, piecewise trending volatility, and smooth transition variance breaks" (Ghoshray 2019).

Consistent with the main aim of the study, the partial wavelet coherence approach is used to capture the co-movement commodity price indexes and Energy Price Index. The wavelet coherence approach was initially developed by Goupillaud et al. (1984). This allows the decomposition of one-dimensional time data into the bi-dimensional time–frequency sphere (Grinsted et al. 2004; Adebayo and Odugbesan 2020; Adebayo and Beton Kalmaz 2020; Kirikkaleli 2021), and therefore facilitates the investigation of the long- and short-term causal linkage between commodity price indexes and the Energy Price Index. In other words, a multi-scale decomposition technique creates a natural framework to illustrate frequency-dependent behaviour to explore the linkage between the commodity price indexes and the Energy Price Index. The wavelet (ψ) used in this paper is part of the Morlet wavelet family. It has the equation $\psi(t) = \pi^{-\frac{1}{4}} e^{-i\omega_0 t} e^{-\frac{1}{2}t^2}$, p(t), t = 1, 2, 3..., T, where ψ is applied on narrow observations.

As discussed by Kirikkaleli (2019) and Adebayo (2020), time (represented by k) and frequency (represented by f) are the main two elements of the wavelet approach. "The k parameter has an important role in detecting the exact location of a wavelet by

relocating the wavelet over time, while f monitors the distended wavelet for localizing different frequencies" (Orhan et al. 2019). The transformation of the wavelet ψ equation with k and f elements is shown as

$$\psi_{k,f}(t) = \frac{1}{\sqrt{h}}\psi\left(\frac{t-k}{f}\right), k, f \in \mathbb{R}, \quad f \neq 0. \tag{1}$$

The continuous wavelet transformation, which can be obtained from ψ as a function of k and f, is

$$W_p(k,f) = \int_{-\infty}^{\infty} p(t)\frac{1}{\sqrt{f}}\psi\left(\overline{\frac{t-k}{f}}\right)dt. \tag{2}$$

Equation 2 with time series p(t) and coefficient ψ can be written as

$$p(t) = \frac{1}{C_\psi}\int_0^\infty \left[\int_{-\infty}^\infty |W_p(a,b)|^2 da\right]\frac{db}{b^2}. \tag{3}$$

To obtain information about the behaviour of the time series, we used the wavelet power spectrum (WPS) in the present paper,

$$WPS_p(k,f) = |W_p(k,f)|^2. \tag{4}$$

As stated by Kirikkaleli and Gokmenoglu (2019), Alola and Kirikkaleli (2020) and Zhang, et al. (2021) unlike traditional causality tests, the wavelet approach combines time and frequency approaches in order to investigate the link between the time series p(t) and q(t). The cross-wavelet transform (CWT) of the time series is

$$W_{pq}(k,f) = W_p(k,f)\ \overline{W_q}(k,f), \tag{5}$$

and the squared wavelet coherence of $W_{pq}(k,f)$ is

$$R^2(k,f) = \frac{\left|C\left(f^{-1}W_{pq}(k,f)\right)\right|^2}{C\left(f^{-1}|W_p(k,f)|^2\right)C\left(f^{-1}|W_q(k,f)|^2\right)}, \tag{6}$$

where c represents the smoothing process over time, with $0 \leq R^2$ (k, f) ≤ 1. When the value of R^2(k, f) approaches 0, it shows no correlation between p(t) and q(t), and this is indicated in blue. When the value of R^2(k, f) approaches 1, meaning that p(t) and q(t) are correlated, it is shown in red and surrounded by a black line in the wavelet figures.

However, R^2 (k,f) does not allow us to distinguish between positive and negative correlation. Torrence and Compo (1998) proposed a tool to explore the wavelet coherence via deferment indicators in the fluctuation of two-time series. We can distinguish positive and negative correlation by Kirikkaleli (2020)

$$\phi_{pq}(k,f) = \tan^{-1}\left(\frac{L\{C(f^{-1}W_{pq}(k,f))\}}{O\{C(f^{-1}W_{pq}(k,f))\}}\right), \tag{7}$$

where L indicates an imaginary operator, and O is a real-part operator.

In this research, a scale of 64 is determined since the data cover the period of 1992M1 to 2019M12 (336 observations). The white cone-shaped curve represents the cone of influence in the figures of WPS, demonstrating an edge below which the wavelet power is affected because of discontinuity, while the thick black shape indicates a 5% significance level determined by Monte Carlo simulations. In the figures of wavelet coherence, while the colder coloured areas denote low dependency among the time series variables, the warmer coloured areas report high dependency. The direction of significant causality or correlation is represented by arrows surrounded by a thick black line in the figures of wavelet coherence. In the figures, the positive and negative correlation among the time series variables are represented by arrows pointing to the right and left, respectively (Torrence and Compo 1998; Kristoufek 2015; Demir et al. 2020; Alola and Kirikkaleli 2020). Arrows pointing up, right-up, or left-down denote that the second variable causes the first variable, while arrows pointing down, right-down, or left-up indicate that the first variable causes the second variable.

In addition to the wavelet coherence approach, the Toda and Yamamoto causality and gradual shift causality approaches are applied to capture the causal linkage between commodity price indexes, i.e., the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index, in the global market. Unlike the Granger causality test (Granger 1969), the Toda–Yamamoto causality test allows us to conduct vector autoregressive (VAR) estimation in levels, regardless of whether the series has the same order of integration (d). Therefore, because taking the difference of the time series data is avoided, no information will be lost. Moreover, the Toda–Yamamoto causality test can be employed if the time series variables are not co-integrated. In this test, while investigating the causal linkage between the Energy Price Index and Agricultural Raw Materials Price Index, and the Industry Input Price Index and Metal Price Index, we eliminate the pre-test bias problem by using the procedures of the Toda -Yamamoto causality test, whose standard equation is

$$y_t = \alpha \ + \ell_1 y_{t-1} + \cdots + \ell_p y_{t-p} + \cdots + \ell \ _p +_d y_{t-(p+d)} + e_t,$$

where y_t is a vector of k variables, α is a vector of intercepts, e_t is a vector of residual terms, and ℓ is a matrix of parameters.

Nazlioglu et al. (2016) recently developed a gradual shift causality test, which is also called the Fourier Toda–Yamamoto causality test. This allows us to account for both gradual and smooth structural shifts in a causality analysis. By enabling the application of a small number of low-frequency components, the Fourier approximation methodology does not require the properties of the structural breaks to be known. Hence the test overcomes the problems associated with an unknown number of structural breaks and occurrence dates that are inherent to conventional causality tests. We also employ this approach to check the causal linkage between all four commodity price indexes, i.e., the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index.

Empirical findings

As a first step, we employ the DF-GLS, KPSS, and Z-A unit root tests to capture the order of integration of the Energy Price Index (EPI), Agricultural Raw Materials Price

Table 2 Unit root tests

Variables	DF-GLS	KPSS	Z-A	DF-GLS	KPSS	Z-A
	Panel A: Unit-root tests in levels			Panel B: Unit-root test in first differences		
Including constant						
EPI	− 1.329	1.531***	− 3.512 (2013M08)***	− 10.821***	0.009	11.202*** (2008M08)**
API	− 1.317	0.816***	− 4.288 (2009M11)***	− 13.197***	0.056	− 9.695*** (2011M05)***
IPI	− 912	1.432***	− 3.461 (2005M08)***	− 11.698***	0.082	− 12.457*** (2011M03)***
MPI	− 0.885	1.484***	− 3.252 (2005M08)***	− 12.156***	0.095	− 13.174*** (2011M03)***
Including constant and trend						
EPI	− 2.388	0.184***	− 4.534 (2010M10)***	− 10.771***	0.070	− 11.183*** (2008M08)**
API	− 2.388	0.208**	− 4.762 (2009M11)***	− 13.133***	0.048	− 9.780*** (2009M04)**
IPI	− 1.993	0.186**	− 3.848 (2009M04)***	− 11.917***	0.071	− 12.514 (2011M04)***
MPI	− 1.878	0.195**	− 3.668 (2009M04)***	− 12.587***	0.084	− 13.220*** (2011M03)

***, **, and * denote statistically significant at 1%, 5%, and 10% levels, respectively

**Fig. 1** Commodity and energy price indexes. *Source*: International Monetary Fund
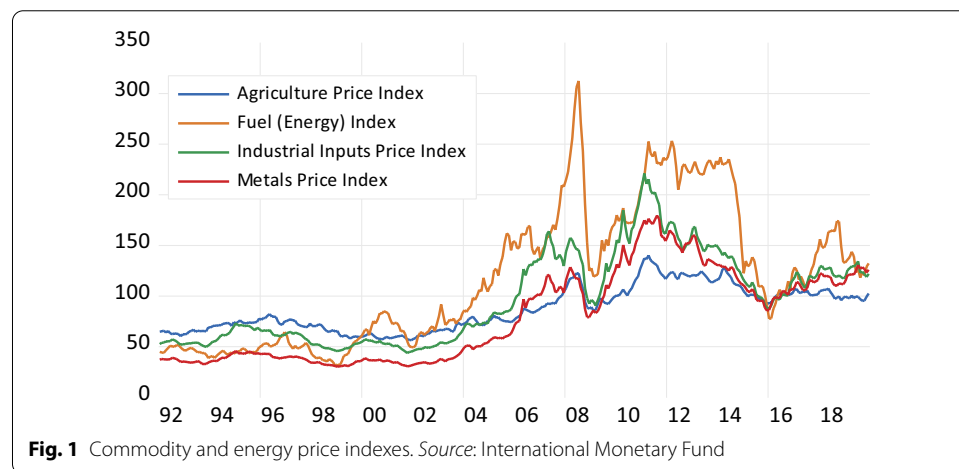
Index (API), Industry Input Price Index (IPI), and Metal Price Index (MPI) time series variables. The results of these tests are reported in Table 2, with the model including both constant and constant and trend. As can be clearly seen in Table 2, the null hypothesis that the EPI time series variable has a unit root cannot be rejected at level, but at the first difference, the variable is stationary. In other words, the order of integration of EPI is one. This situation does not differ for the API, IPI, and MPI time series variables.

The unit root test of Cavaliere et al. (2011) is also employed to capture the integration order for the variables of EPI, API, IPI, and MPI. This test "allows for a possible structural break and non-stationary volatility, where the volatility includes both

Table 3 Results of the test for unit roots in the presence of a possible break in trend and non-stationary volatility

	MZa	MZa c.v	MSB	MSB c.v	MZt	MZt c.v	t(taubar)	c.v
Panel A: Unit-root tests in levels								
EPI	− 12.790	− 23.366	0.192	0.145	− 2.453	− 3.399	− 2.408	− 3.505
API	− 10.458	− 19.552	0.215	0.159	− 2.246	− 3.106	− 2.236	− 3.182
IPI	− 7.812	− 22.709	0.249	0.146	− 1.948	− 3.364	− 1.922	− 3.466
MPI	− 5.522	− 21.920	0.300	0.150	− 1.658	− 3.289	− 1.642	− 3.384
Panel B: Unit-root test in first differences								
EPI	− 123.572	− 25.857	0.064	0.136	− 7.859	− 3.508	− 9.153	− 3.352
API	− 129.303	− 24.170	0.062	0.142	− 8.035	− 3.443	− 9.592	− 2.936
IPI	− 41.975	− 26.526	0.109	0.134	− 3.577	− 3.615	− 4.257	− 3.492
MPI	− 22.224	− 24.787	0.150	0.141	− 3.324	− 3.513	− 3.434	− 3.293

c.v. represents critical value
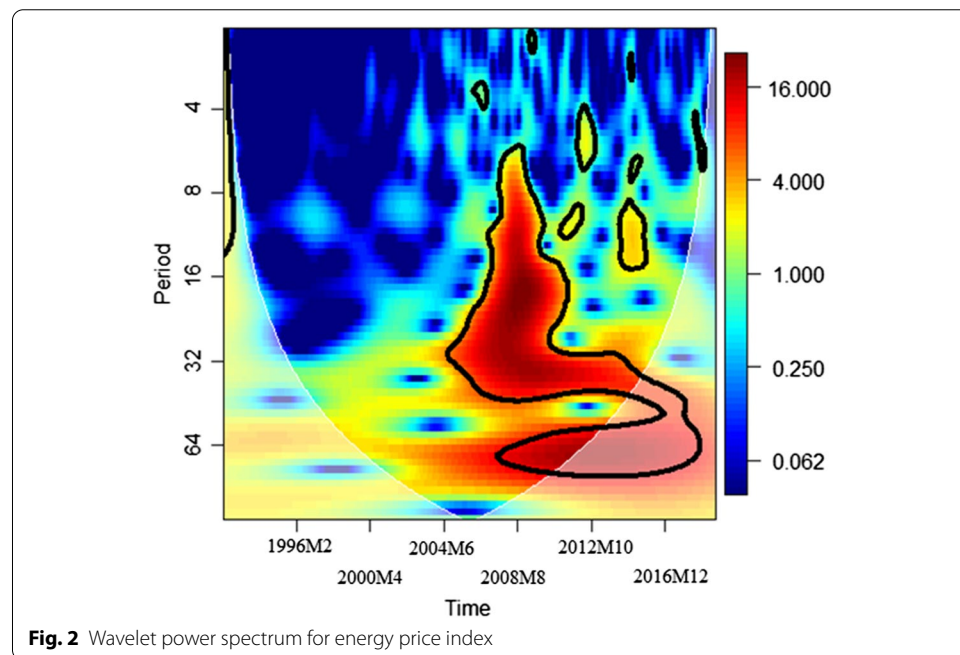
Fig. 2 Wavelet power spectrum for energy price index

single and multiple abrupt breaks in variance, polynomially trending volatility, piecewise trending volatility, and smooth transition variance breaks" (Ghoshray 2019). The results of the test are presented in Table 3 and show that the time series variables have a unit root at the level. This is consistent with the traditional unit root test reported in Table 2. However, Table 3 also indicates that we cannot reject the null hypothesis that IPI and MPI have a unit root at the first difference, indicating that the order of integration of both IPI and MPI variables is two, while the integration of order of EPI and API is one. Since we observed that the integrated order of the time series variables is a combination of I(1) and I(2), we use the wavelet coherence, Toda–Yamamoto, and gradual shift causality approaches to explore the causal linkage between EPI, API, IPI, and MPI.
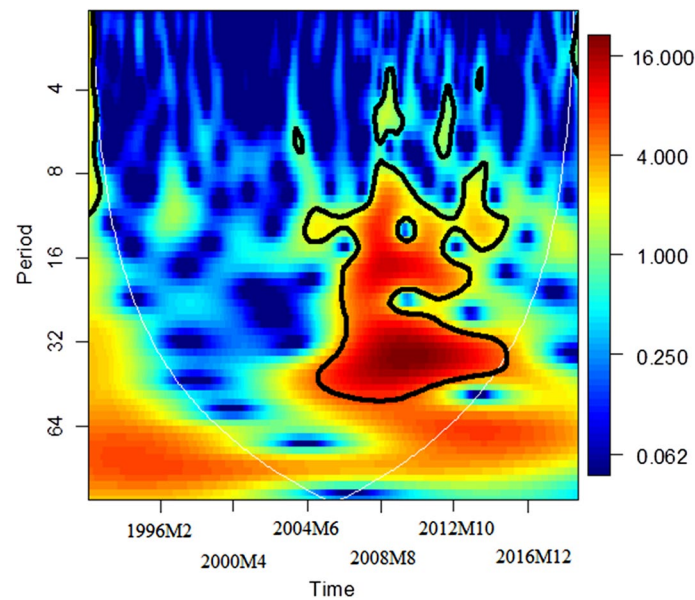
Fig. 3 Wavelet power spectrum for agricultural raw materials index
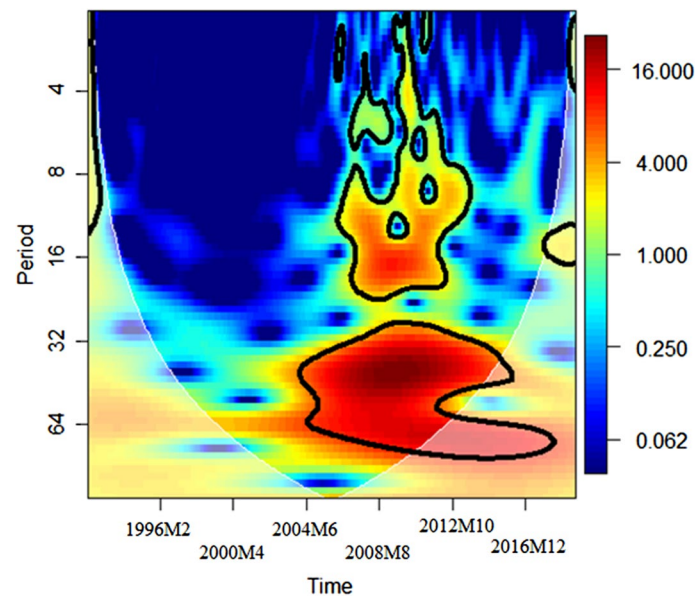

Fig. 4 Wavelet power spectrum for industry input price index

To gather information about the behaviour of the EPI, API, IPI, and MPI variables as well as the co-movement between the EPI and the API, IPI, and MPI variables, the wavelet approach is applied in this research. Figures 2, 3, 4, and 5 present the wavelet power spectrum for the EPI, API, IPI, and MPI variables, respectively. The energy price index variable appears to show significant volatility at low and medium frequencies between 2005 and 2015, as seen in Fig. 2. The behaviours of the Agricultural Raw Materials Price
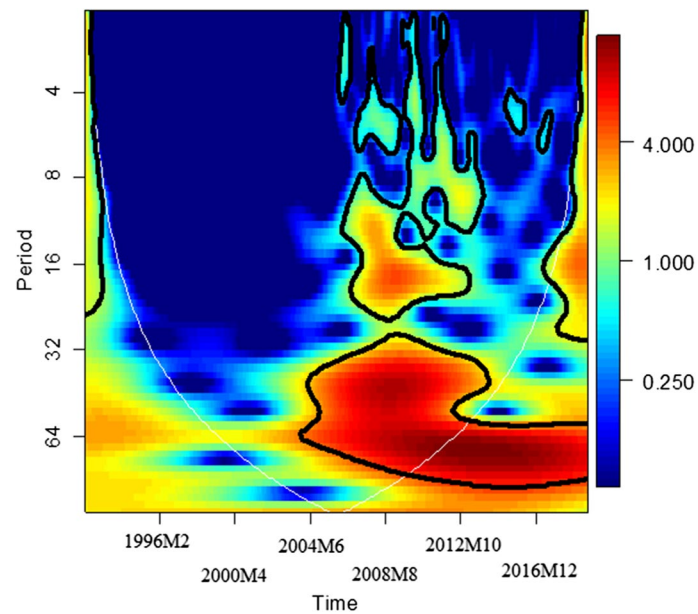
Fig. 5 Wavelet power spectrum for metal price index
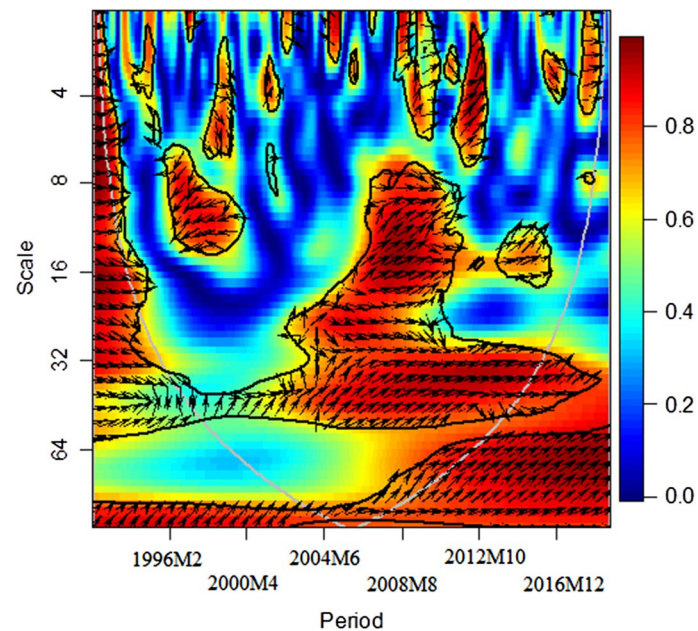
Fig. 6 Wavelet coherence between energy price index and agricultural raw materials index

Index, Industry Input Price Index, and Metal Price Index are not very different to the behaviour of the energy price index. In other words, the time series variable we use in this study was volatile between 2005 and 2015, but at different scales.

Consistent with the aim and innovation of our study, the wavelet coherence approach is applied to capture the causal relationship between the EPI and the API,
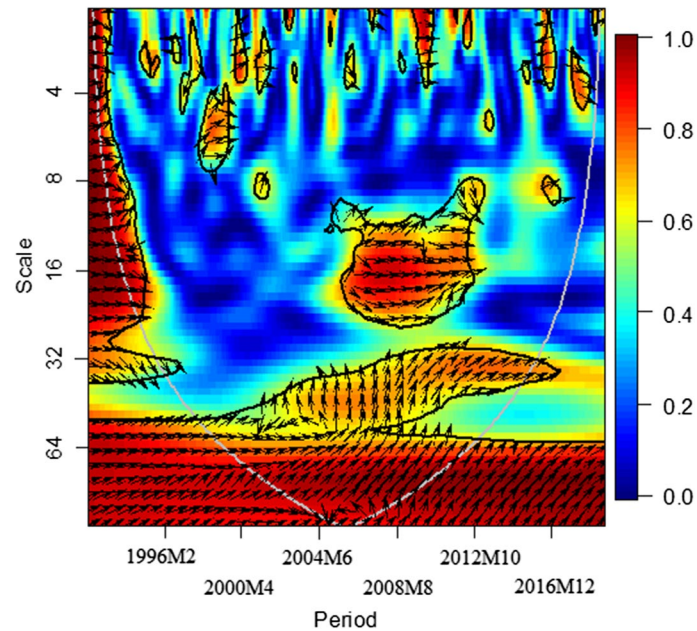
Fig. 7 Wavelet coherence between energy price index and industry input price index
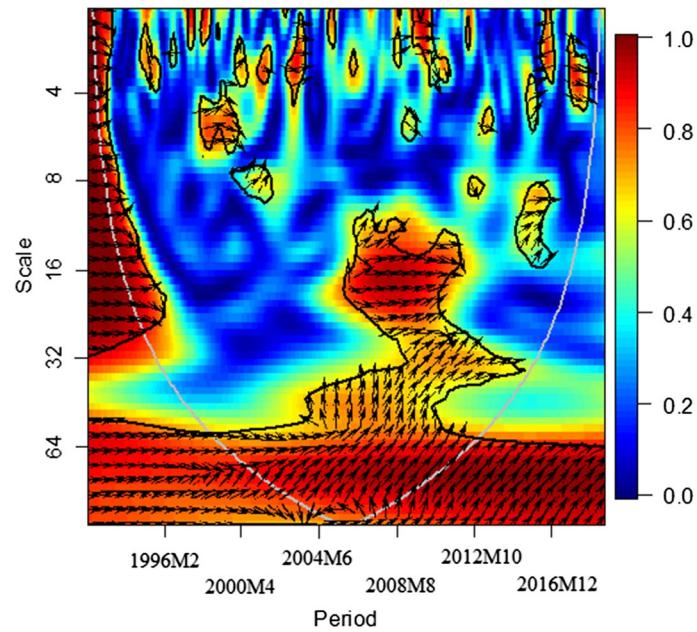

Fig. 8 Wavelet coherence between energy price index and metal price index

IPI, and MPI variables in the global market. The outcomes are reported in Figs. 6, 7, and 8. Figure 6 demonstrates wavelet coherence between the Energy Price Index and Agricultural Raw Materials Price Index. As can be seen in the figure, from scales 4 to 16, down and left-down arrows are obtained between 1996 and 2000, indicating

that in the medium term, the energy price index significantly caused the Agricultural Raw Materials Price Index in the global market. However, the direction of the causality changes between 2004 and 2015 at different frequencies, since the arrows mostly point right-up, implying that the Agricultural Raw Materials Price Index is an important predictor of the energy price index for the period between 2004 and 2015.

The time–frequency dependency between the Energy Price Index and Industry Input Price Index is reported in Fig. 7. At high frequency over the selected time period, the arrows point right at the thick black shape, which implies that the variables are in phase. Between 2005 and 2012, in the medium term, there is a positive correlation between the Energy Price Index and Industry Input Price Index. However, in the long run, the Industry Input Price Index significantly leads changes in the energy price index in the global market. Figure 8 also reports consistent results with those in Fig. 7 for the Metal Price Index, since causality is observed in the long run from the Metal Price Index to the energy price index, indicating that the Metal Price Index is an important predictor of the energy price index. However, this conflicts with some findings in the empirical literature, such as Nazlioğlu et al. (2013), Wang et al. (2014), Avalos (2014), and Pal and Mitra (2017), who argue that in the post-crisis period of 2008, there is an even stronger link between energy prices and other commodity prices, which are led by energy prices. Baumeister and Kilian (2016) provided a detailed explanation of the case in which other commodity prices may have driven the oil prices. They argued that the oil price increase between 2003 and 2008 was due to a series of small demand shocks, which came from the unexpected growth of the global economy, particularly from emerging Asian markets. For example, additional demand for inputs increased the demand for oil, which caused the price of WTI to increase from 28 to 134 USD per barrel. In February 2009, the oil price falls back to 39 USD per barrel with increased global uncertainty resulting from the 2006–2008 global financial crisis. This was the case for all the commodity prices until the first half of 2008, with the expectation of a deep recession.[1] In 2009, as a result of the relatively stable consumption component of world GDP, oil prices stabilized at around 100 USD per barrel, and non-energy commodity prices stabilized as well.

Another remarkable event in 2008 was the beginning of the use of unconventional monetary policy tools (also known as quantitative easing) to tackle the zero-lower-bound interest rate problem and reverse the effects of the 2006–2008 global financial crisis. The first episode of QE in the US started on 25 November 2008, and ended on 29 October 2014. Other major central banks (ECBS, BoJ, and BoE) followed similar liquidity strategies. This common liquidity strategy had a remarkable positive impact on the industrial production and growth rates of emerging markets. Baffes and Savescu (2014) explained the role of low-interest rates and unconventional monetary policy on metal prices, claiming that this increased the prices of agricultural commodities, metals, and industrial inputs. This, in turn, caused energy prices to increase.

Therefore, in such a volatile period, two demand shocks, i.e., the Asian growth effect and quantitative easing, had a positive impact on the growth of emerging economies, with a growing demand for industrial inputs, agricultural commodities, and metals,

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[1] For example, for metal prices, see Rosen (2014); Hamilton (2009) also provides an extensive discussion on the run-up of oil prices in 2007–08.

Table 4 Causality tests

Direction of causality	MWALT	Prob
Toda–Yamamoto causality		
API → EPI	17.127	0.000***
EPI → API	1.204	0.547
IPI → EPI	8.215	0.016**
EPI → IPI	3.467	0.176
MPI → EPI	8.891	0.031**
EPI → MPI	2.744	0.432
	F-stat	**Prob**
Gradual shift causality		
API → EPI	17.303	0.000***
EPI → API	1.331	0.513
IPI → EPI	8.451	0.014**
EPI → IPI	3.558	0.168
MPI → EPI	9.292	0.025**
EPI → MPI	2.882	0.410

→ indicates the direction of causality. The optimal lag is selected using AIC

***, **, and * denote statistically significant at 1%, 5%, and 10% levels, respectively

with increasing prices. Papiez and Smiech (2012) stated that these price increases must cause a reaction in the energy prices. Our findings reveal that the prices of agricultural commodities, metals, and industrial inputs led to energy prices between 2005 and 2012. Once global conditions started to converge back to normal, such as with monetary tightening starting from 2013, the direction of causality from energy to an agricultural commodity, metal, and industrial input prices switched back, and energy prices started to cause the other prices.

To investigate the time domain causal relationship between commodity price indexes, i.e., the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index, for the period 1992M01 to 2019M12, the Toda–Yamamoto and gradual shift causality approaches are applied. Table 3 reports the outcomes of these tests. According to the Toda–Yamamoto causality results, the null hypothesis that the Agricultural Raw Materials Price Index does not cause the Energy Price Index can be rejected at the 5% significance level, implying that the Agricultural Raw Materials Price Index is an important predictor for the Energy Price Index. However, we failed to capture a reverse causality from the Energy Price Index to the Agricultural Raw Materials Price Index. Consistent with the outcome of the wavelet coherence approach, Table 4 reports that the Industry Input Price Index and Metal Price Index are important predictors for the Energy Price Index. It is remarkable that the Toda–Yamamoto causality test is assumed not to have structural breaks among the series based on the assumption that the intercept parameters are constant over time. According to Gokmenoglu et al. (2019; p. 659), "the Fourier Toda–Yamamoto causality test is applied to take possible structural breaks into account. The test can be applied without conducting a preliminary investigation on the number and form of these breaks in the series." Although the methodology of the gradual shift causality test differs from that of the Toda–Yamamoto causality test, the

outcomes of the gradual shift causality test verify the robustness of the unidirectional causality running from the commodity price indexes to the Energy Price Index in the presence of structural breaks.

Conclusion

The present study explores the time-dependency of commodity price indexes (the Agricultural Raw Materials Price Index, Industry Input Price Index, and Metal Price Index) and the Energy Price Index in the global market using wavelet coherence, the Toda Yamamoto causality test, and the gradual shift causality test over the period 1992M1 to 2019M12. The use of the wavelet approach allows the present study to (1) capture the volatility periods of the commodity price indexes and Energy Price Index; and (2) investigate the long- and short-run causal linkages between the commodity price indexes and the Energy Price Index, since the approach combines both time and frequency domain causalities. The findings from partial wavelet coherence reveal that (1) there was significant volatility in the Agricultural Raw Materials Price Index, Industry Input Price Index, Metal Price Index, and Energy Price Index between 2004 and 2014 at different frequencies; and (2) the commodity price indexes significantly caused the Energy Price Index at different time periods and frequencies, meaning that they are important predictors for the Energy Price Index. It is important to mention that the outcomes of the Toda Yamamoto causality and gradual shift causality tests are in line with the outcome of partial wavelet coherence. Our findings give support to the findings of Baumeister and Killian (2016), i.e., that the price indexes of industrial raw materials, metals, food, and energy respond to fluctuations in the global business cycle in the long run. Our findings are also in line with Papiez and Smiech (2012), who found evidence of simultaneous dependencies between the prices of energy and other commodities. Understanding the evolution of commodity prices is important in assessing macroeconomic performance. Producers, traders, investors, consumers, and policymakers are key stakeholders who have a significant interest in understanding the price evolution of energy and non-energy commodities. From the policymakers' perspective, there are some serious challenges ahead, since the energy industry is expected to experience dramatic changes in the near future due to the heavy pressures of climate change. This may make it even more difficult to understand the price formation and movements in energy markets. This transformation may further weaken the links between energy and non-energy commodities. Climate change risk and its impact on the price formation of energy and non-energy commodities seem to be one of the main areas of future research.

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