A New Perspective on Energy Contagion in Colombia: Evidence from Wavelet Analysis and Co-Movement Dynamics*

Una nueva perspectiva del contagio financiero energético en Colombia: evidencia del análisis de ondas y dinámicas de comovimientos

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Abstract

Objective: This study examined the existence of energy contagion from the most important energy indicators—oil, natural gas, and coal—to electricity spot prices in Colombia.
Design/Methodology: The methodology employed here was correlational, with a quantitative approach. Daily data from February 2011 to December 2018 were used, excluding the 2008 financial crisis and the COVID-19 pandemic. The data were sourced from Refinitiv and XM. Wavelet analysis and co-movement dynamics were applied. Additionally, cross-correlation was used to analyze financial contagion from energy indicators to electricity spot prices.
Findings: This study demonstrated that there are significant long-term correlations between energy indicators and electricity spot prices. It also determined the presence of energy contagion from natural gas and Brent crude oil to electricity spot prices during crisis periods. Regarding coal, there was no clear evidence of contagion. These findings are relevant for understanding how changes in the global energy market can affect electricity prices in the long term in an emerging economy like Colombia.
Conclusions: Energy contagion impacts the global economy, especially in energy-dependent emerging markets. This study emphasizes the need to understand and mitigate risks in the energy market, offering key information for companies, investors, and policymakers.
Originality: Advanced methods were employed to analyze the impact of international fuel prices on the Colombian electricity market, identifying contagion periods and highlighting the vulnerability of emerging economies to changes in the global energy market.

Keywords: energy contagion, co-movements, wavelet analysis, electricity spot price, global energy market.

JEL classification: G00, G1, G15

Highlights

- Energy contagion is a financial phenomenon that can have a significant impact on the global economy—in particular, on emerging markets that usually have less diversified economies and are highly dependent on energy exports or imports.
- Wavelet analysis can be used to study financial contagion at different time scales, providing a detailed and dynamic picture of the transmission of volatility in stock markets.
- Unexpected events in the oil market, such as sharp falls in prices, can have significant impacts on currency exchange rates. This has consequences for companies that conduct international transactions and the economy as a whole.
- Understanding the connection between energy indicators and electricity spot prices provides crucial information for policymakers and participants in the financial and energy market in an emerging economy such as Colombia.

Resumen

Objetivo: examinar la existencia de contagio financiero energético desde los principales indicadores de desempeño energético: petróleo, gas natural y carbón sobre los precios *spot* de energía en Colombia.

Diseño/metodología: la metodología empleada en este estudio fue de tipo correlacional, con un enfoque cuantitativo. Se emplearon datos diarios de febrero de 2011 a diciembre de 2018, excluyendo la crisis financiera de 2008 y la pandemia por COVID-19. Los datos provienen de Refinitiv y XM. Se aplicó el análisis de ondas (*wavelets analysis*) y dinámica de comovimientos (*co-movimientos dynamics*). Además, se utilizó la correlación cruzada para el análisis de contagio financiero entre los indicadores de desempeño energético y los precios *spot* de energía.
Resultados: la investigación demostró que existen correlaciones significativas a largo plazo entre los indicadores de desempeño energético y los precios spot de energía. Además, determinó la presencia de contagio del gas natural y del petróleo brent sobre los precios *spot* de energía durante periodos de crisis. Con respecto al carbón, no hay evidencia clara de contagio. Estos hallazgos son relevantes para comprender cómo los cambios en el mercado global de la energía pueden afectar los precios de esta a largo plazo en una economía emergente como la colombiana.
Conclusiones: el contagio financiero energético impacta la economía global, especialmente en mercados emergentes dependientes de energía. Este estudio resalta la necesidad de comprender y mitigar riesgos en el mercado energético, ofreciendo información clave para empresas, inversores y formuladores de políticas.
Originalidad: se emplearon métodos avanzados para analizar el impacto de los precios internacionales de combustibles en el mercado energético colombiano, identificando periodos de contagio y subrayando la vulnerabilidad de economías emergentes frente a cambios en el mercado global de la energía.

Palabras clave: contagio financiero energético, comovimientos, análisis de ondas, precio *spot* de energía, mercado global de energía.

Clasificación JEL: G00, G1, G15

Highlights

- El contagio financiero energético es un fenómeno que puede tener un impacto significativo en la economía global, particularmente en mercados emergentes, que a menudo, poseen economías menos diversificadas y altamente dependientes de exportaciones o importaciones de energía.
- El análisis de wavelets permite abordar el contagio financiero energético en diferentes escalas temporales, proporcionando una visión detallada y dinámica de la transmisión de volatilidad en los mercados financieros.
- Los eventos inesperados en el mercado del petróleo, como bruscas caídas de precios, pueden generar impactos significativos en las tasas de cambio. Esto repercute en las empresas con transacciones internacionales, teniendo consecuencias directas en la economía en su conjunto.
- Comprender la conexión entre el rendimiento energético y los precios spot de energía, proporciona datos cruciales para formuladores de políticas y participantes del mercado financiero y energético en una economía emergente como la colombiana.

1. INTRODUCTION

The growing importance of oil prices in the economy has prompted financial contagion studies to analyze the correlations between energy and stock markets (Wen et al., 2012). According to Kilian and Vigfusson (2011), financial contagion from energy prices can have a significant impact on the world economy, and it is particularly relevant in emerging markets. Usually, these countries have less diversified economies and are highly dependent on energy exports or imports, which makes them particularly vulnerable to fluctuations in energy prices and the effects of volatility transmission.

Originally, energy contagion studies focused on oil as an energy indicator and co-movement dynamics. Some remarkable works in this area were published by Ghorbel and Boujelbene (2013), Pan et al. (2015), Guesmi et al. (2018), Mahadeo et al. (2019), and Zhao et al. (2021). They analyzed the contagion from oil to stock market indices in Europe, North America, and Asia, as well as emerging countries. Later, several authors (Li et al., 2019; Algieri & Leccadito, 2017; Hergety, 2012) addressed other commodities (e.g., ethanol, coal, copper, and other metals) as energy indicators to measure contagion.

Subsequent works applied wavelet analysis as a method to measure the contagion from oil to stock markets. This line of research includes Reboredo and Rivera-Castro (2014), Boubaker and Raza (2017), Lin et al. (2019), and Hamdi et al. (2019), who examined contagion in Europe, North America, Asia, and emerging countries. It should be highlighted that no study in the published literature has addressed the relationship between energy indicators and stock markets using wavelet analysis combined with co-movement dynamics. These research gaps indicate promising areas for future studies that can provide a more detailed and constantly evolving picture of the interaction between energy and stock markets. In this context, this study aims to develop a new perspective focused on the comprehensive understanding of the propagation of disturbances between energy indicators and electricity spot prices (Díaz et al., 2019). Such perspective combines co-movement dynamics and wavelet analysis, which is a novel contribution to financial and energy studies.

As financial contagion can have a significant impact on emerging markets, it is important to understand the factors involved in this phenomenon. Therefore, this study makes a contribution to the literature in this area because it introduces a new perspective on energy contagion in Latin American countries using several energy indicators: the futures contracts prices of Brent and West Texas Intermediate (WTI) crude oil, Natural Gas (NG), and coal. First, crisis and non-crisis periods were identified using two methods taken from rule-based algorithms: one employs the criterion of duration (Pagan & Sossounov, 2003); and the other one, the magnitude of price change (Lunde & Timmermann, 2004). Second, the effects of the fundamental factors of electricity spot prices were decomposed. Third, tests were conducted to measure contagion adopting the perspective of co-movement dynamics and wavelet analysis. Finally, the results of these two approaches are discussed.

In the energy market, it is essential to consider a diversity of investment horizons, which produce flows of dynamic information in different time frames and also contribute to the variability observed in said market. A detailed understanding of the dynamic relationship between different energy assets can be achieved by decomposing market prices at different time scales. As a result, co-movement dynamics and wavelet analysis emerge as appropriate tools to decompose these data at several time scales without imposing restrictions on the structure of the Underlying Asset Return (Roy et al., 2023).

The rest of this paper is structured as follows. Section 2 presents a general overview of the financial literature in this area. Section 3 describes the data used in this study. Section 4 details the methodology. It shows the modeling of the electricity spot prices and international energy indicators; explains the econometric tools used to measure the degree of interdependency between the Colombian energy market and the international fuel markets of interest; and discusses the strategies employed to identify crisis and non-crisis market conditions. Section 5 reports the results. Finally, Section 6 draws the conclusions.

2. THEORETICAL FRAMEWORK

Globalization has enabled communication and interdependence between markets in different countries (Centeno et al., 2015; Briones Pinargote, 2023). This has produced linkages that have been studied to establish if they show evidence of financial contagion. Pericoli and Sbracia (2003) reviewed five definitions of *contagion* that have been adopted in the literature and the corresponding measurements used in empirical studies. They suggest that, during a crisis, there is a change in the transmission mechanism. Along the same lines, Dornbusch et al. (2000) and Kaminsky and Reinhart (2000) made a distinction between two types of contagion: fundamentals-based (indirect) contagion and pure (direct) contagion. Calvo et al. (1996) defined fundamentals-based contagion as the transmission of a shock between countries and/or markets as a result of real linkages and the integration of stock markets in crisis and non-crisis periods. Eichengreen et al. (1999) and Bae et al. (2003) defined pure contagion as the excess transmission of a shock between countries beyond what should be expected after the fundamentals have been controlled. Hence, the definition of contagion works well as long as a financial crisis can be identified and excess transmission can be estimated. Pericoli and Sbracia (2003) hold that a financial crisis is a source of falls in the stock market index or increases in the price volatility of financial assets. Samarakoon (2011) indicates that an increase in cross-market correlation in a crisis period (as opposed to in a non-crisis one) is interpreted as contagion. However, Forbes and Rigobon (2002) claim that these correlations are biased by the increase in market volatility during crisis periods, generating heteroskedasticity. Thus, they proposed an adjusted correlation coefficient and defined financial contagion as a significant increase in cross-market correlations after a shock.

The first contagion studies were conducted by Sharpe (1964) and Grubel and Fadner (1971), and a variety of methodologies can be used to evaluate evidence of contagion. Based on the adjusted correlation model proposed by Forbes and Rigobon, (2002), Fry-McKibbin et al. (2014) proposed a contagion test using adjusted linear correlation, assessing the significance of the adjusted correlation in crisis compared to non-crisis periods. Fry et al. (2010) introduced a coskewness-based test of contagion that evaluates the differences between market correlations in crisis and non-crisis periods as a function of changes in coskewness. There is evidence of contagion in two situations: (1) when the average behavior of a market affects another's volatility and (2) when a market's volatility affects another's average behavior. Fry-McKibbin and Hsiao (2018) developed a test for co-volatility contagion, evaluating the differences between market correlations in crisis and non-crisis periods as a function of changes in co-volatility. There is evidence of contagion when the volatility of a market affects that of another.

Recent studies on financial contagion have turned their attention to analyzing the correlations between energy indicators and stock markets. Wen et al. (2012) mentioned the growing importance of oil price in the economy, which has become an energy indicator. They applied time-varying copulas to analyze the effect of the energy contagion between the WTI oil price and Chinese stock market indices. Fang and Egan (2018) studied the contagion effects between Brent crude oil and Chinese stock market sectors. Zhao et al. (2021) investigated the energy contagion effect and bubbles between (international and Chinese) oil prices and Chinese stock markets. Other authors, such as Pan et al. (2015), have extended Hong et al.'s (2007) model-free test to analyze contagion between (Brent and WTI) crude oil y and the S&P 500 index (US), FTS 100 (UK), and the DAX index (Germany). Guesmi et al. (2018) tested for the existence of energy contagion between oil price fluctuations and stock markets in the European Monetary Union (EMU), Asia-Pacific (AP), the Non-European Monetary Union (NEMU), and North America (NA).

In this research area (i.e., energy contagion), some studies have investigated emerging markets. Ghorbel and Boujelbene (2013) employed GARCH-class models to test for the existence of energy contagion between the volatility of crude oil prices and Brazil, Russia, India, and China (BRIC) stock markets. Mahadeo et al. (2019) analyzed the effects of energy contagion from Brent crude oil prices to the Trinidad and Tobago Stock Exchange using contagion tests with linear correlation, co-skewness, and co-volatility. Nevertheless, energy contagion tests are not limited to analyzing the correlations between oil prices (as an energy indicator) and stock markets. As mentioned by Li et al. (2019), coal has dominated the energy supply in China as a substitute for crude oil, and it could be related to other markets. Other studies have evaluated the presence of contagion between other energy indicators and stock markets. Algieri and Leccadito (2017) analyzed the contagion between WTI crude oil futures; ethanol as a proxy for biofuels; metal and food markets; indices; and the S&P 500 index (US). Hergety (2012) studied contagion between the prices of raw materials (i.e., oil, copper, and coffee); macroeconomic variables; external factors; and the Brazil, Mexico, Chile, and Peru stock markets.

The literature on financial contagion has not been limited to analyzing significant increases in the correlations between markets after a shock by testing for co-movement. For instance, Ghosh et al. (2020) and Shrestha et al. (2018) delved into the evolutionary dynamics inherent in financial and energy markets by means of wavelet analysis to estimate the conditional correlation between markets at different time scales. Wavelet analysis is a quantitative modeling tool that can be used to conduct multiresolution analysis of non-stationary time series and separate new relationships from financial time series taking into account the time and frequency dimensions (Ranta, 2013). On this regard, Ftiti and Hadhri (2019) provided solid evidence that using the wavelet approach produces significantly more robust results than conventional time-scale techniques.

Among the pioneering studies that first examined the effects of contagion between stock markets using wavelet analysis, Gallegati's (2012) stands out, proving the existence of contagion between the market indices of G7 countries plus Brazil and Hong Kong. Benhmad (2013) showed the contagion dynamics between the S&P 500 index (US) and the stock market indices of G7 countries (without Italy) plus other nations, such as Switzerland, Australia, India, South Korea, Russia, and China. Both studies focused on the 2007 subprime mortgage crisis. More recently, Cărăuşu et al. (2018) investigated how and when contagion occurs between ten stock markets in central and eastern Europe and financial markets in western Europe and the US. Zhou et al. (2018) analyzed the contagion effect between stock markets in countries in Asia, Europe, and America. Dash and Maitra (2019) studied the sentiment contagion effect between developed and emerging markets.

Wavelet analysis is also employed to study energy contagion. Reboredo and Rivera-Castro (2013) analyzed the relationship between crude oil prices and the US Dollar exchange rate. Later, Reboredo and Rivera-Castro (2014) examined the relationship between crude oil and stock markets in Europe and the US. Both studies analyzed the global financial crisis. Boubaker and Raza (2017) examined the secondary effects and shocks between crude oil prices and stock markets in BRICS countries during the 2007–2009 financial crisis. Lin et al. (2019) investigated contagion between Brent crude oil, the London gold market, and stock markets in China and European countries. Hamdi et al. (2019) examined the extent of volatility between oil price and sectoral indices in the Gulf Cooperation Council (GCC) countries by using wavelet nonlinear denoised based quantile and Granger-causality analysis. Multiple studies have investigated the relationship between other energy indicators and stock markets employing wavelet analysis. Lahmiri et al. (2017) examined the relationship between 14 stock exchanges, two kinds of exchange rates, and twelve commodity markets before and after the financial crisis. Although they did not focus on energy contagion, they indirectly analyzed contagion between crude oil, natural gas, metals, food commodities, and financial markets in the US, Europe, and Asia. In a more recent study, Ghosh et al. (2020) analyzed the co-movement dynamics and the dynamic correlation between the Bombay Stock Exchange (BSE) Energy Index; Crude Oil; Natural Gas; and the DJIA and NIFTY indices. They used fractal modeling, wavelet analysis, and DCC-GARCH. However, their study did not evaluate contagion in particular either.

Other relevant studies have examined the interaction between oil prices and stock markets using wavelet analysis. Belhassine and Karamti (2021) studied the interdependence between oil and stock markets, highlighting long-term asymmetries and hedging opportunities in India and China. Zhu et al. (2022) focused on the asymmetric effects of oil prices on BRICS markets, emphasizing the short term and the influence of financial volatility. Mensi et al. (2023) addressed global co-movements, supporting the idea of *recoupling* during a crisis, with persistent dependency and greater portfolio risk. This diversity of approaches enriches our understanding of how these factors impact markets, which is relevant for investors and policymakers in the area of risk management and strategic financial decisions.

Based on the above, it is clear that, nowadays, there is a growing interest in researching how energy indicators impact equity markets (Boako et al., 2020) using different methodologies. However, there is a lack of studies that apply wavelet analysis to examine energy contagion, especially beyond crude oil. In addition, Latin America has been little explored in this regard, and no studies so far have investigated contagion between energy indicators and electricity prices in this region. To address this gap, this study analyzes energy contagion from Brent and WTI crude oil, natural gas, and coal to electricity prices in Colombia using co-movement tests and wavelet analysis. Two crisis periods were identified using two cutting-edge empirical strategies.

3. METHODOLOGY

This study employed daily data from February 23, 2011, to December 31, 2018. This period was selected for two reasons. First, the big 2008 financial crisis was deliberately avoided because this paper focuses on another object of analysis and said crisis has been thoroughly addressed in previous research. Second, the period of the COVID-19 pandemic was left out because it was characterized by a series of extreme movements in a wide range of variables, which involved not only financial but also economic, social, and health-related aspects—this is beyond the scope of the financial contagion that this study aims to analyze. The data were sourced from two platforms: Refinitiv Financial Solutions and XM. Refinitiv is a leading platform thanks to its thorough coverage of financial data in real time. It is recognized by its outstanding accuracy and advanced analysis tools that put investors in a privileged position with excellent information search and powerful analytical capabilities. In turn, XM provides access to essential data on the management of the Colombian wholesale electricity market. This broad range of information is highly attractive for those who seek to conduct transactions in real time and manage, in an effective manner, their exposure to risk in stock and energy markets.

The wavelet analysis applied in this study is a widely employed technique in signal processing and data analytics to research the relationship between two variables, particularly when the data have complex structures in the time and frequency domains.

The so-called *wavelet* functions bear some resemblance to base functions employed in techniques such as Principal Component Analysis (PCA) or the Fourier transform. However, they are especially designed for analyzing non-stationary signals with local (rather than global) characteristics. These mathematical functions are characterized by their localization capacity in the time as well as the frequency domain, which makes them ideal tools to detect local changes in a signal.

As a complement, this methodology employed cross-correlation analysis, which can be used to identify relationship patterns between two signals at different time and frequency scales. This approach is particularly relevant in the context of the analysis proposed in this study because the phenomenon of financial contagion is inherently local, manifesting itself at specific moments of financial crises and involving different scales or frequencies. As demonstrated in the *Results* section, significant correlations were observed at small as well as larger scales.

Several time series were employed: indicators of the Colombian energy market, type of exchange, foreign economic activity, and energy market performance. In addition, variables were used to decompose the effects of fundamental factors of the electricity spot prices. The indicator of energy market performance was based on three variables: the closing futures prices in dollars of (Brent and WTI) crude oil, natural gas, and coal. The indicator of type of of exchange was the Real Effective Exchange Rate (REER) in Colombia. The measure of foreign economic activity was the short-term shadow rate of the US stock market (SSR_US). The indicator of energy market performance was the national electricity spot price (P_spot). The variables employed to decompose the effects of the fundamental factors of electricity spot prices were excess demand measured using the total predicted demand for day t divided by the installed capacity of hydropower plants (river contribution in kw/h). In addition, an indicator was used to show if there was El Niño phenomenon on day t. Finally, missing data (due to holidays or other reasons) were replaced with the immediately previous value.

As stated above, when authors address contagion, they refer to the emergence of transmission channels (that did not exist previously), which strengthen the relationship between a couple of markets in moments of crisis compared to a non-crisis scenario. As a result, traditional transmission channels (i.e., those that are predominant in non-crisis scenarios) should be left out. In econometrics, this is achieved by modeling the temporal evolution of each one of the variables of interest using a well-specified regression and, immediately after, extracting the residual (which is the part not explained by the model). These residuals (called *pseudoreturns* in this study) are expected to reflect non-traditional channels, if there are any.

The following subsection explains the econometric tools used here to measure the degree of interdependency between the Colombian energy market and the international markets of fuels of interest. It also provides evidence in favor of the contagion hypothesis if these measures of interdependency increase significantly in moments of crisis. The third subsection explains the way crisis and non-crisis periods were identified in this study. Considering all this, contagion is summarized in a graph showing a time series that reflects the degree of interdependency over time and, in addition, crisis and non-crisis periods. The existence of contagion is determined when, in crisis periods, the time series mentioned above reaches local maxima.

Obtaining the pseudoreturns

Modeling the electricity spot price

According to XM (s.f.), in normal operating conditions, the electricity spot price is the highest ask price by the generating units with centralized dispatch that have been scheduled to generate electricity in the optimal dispatch and do not present inflexibility. This reveals that the price asked by each one of the dispatched companies is the main component of the market price. In addition, as shown by Garcia and Pérez-Libreros (2019), the price that each company/plant asks is essentially determined by their marginal costs and their net position in the contracts market. Based on this, this study proposes a functional way to relate the observed electricity spot price to fundamental factors that determine marginal costs. Since the Colombian energy matrix is mainly composed of hydropower and thermal power plants, the following factors were selected:

- Installed capacity of hydropower plants, approximated using river contribution in kWh hour $(\mathrm{O_t})$.
- Total predicted demand $(\mathrm{D_t})$.
- Natural gas price: international futures price of natural gas in US$/BTU $(\mathbf{natural\ gas_t})$.
- Coal price: international futures price of coal in US$/tons $(\mathbf{coal_t})$.
- Oil price: international futures price of crude oil in US$/Bar $(\mathbf{Brent_t})$.
- COP/USD exchange rate: Colombian Pesos to US Dollars official exchange rate in the Colombian currency exchange market, which is known as TRM in Colombia $(\mathbf{trm_t})$.

In turn, Equation (1) is a functional form that may describe the temporal evolution of the electricity market price:

$$\mathrm{Spot} = \alpha + \beta_1 \ln \mathrm{D}^* + \beta_2 \ln \mathrm{D}^* \mathrm{x} \ln \mathrm{gas} + \beta_3 \ln \mathrm{D}^* \mathrm{x} \ln \mathrm{carbon} + \beta_4 \ln \mathrm{D}^* \mathrm{x} \ln \mathrm{brent} + \epsilon \qquad (1)$$

where D^* is the ratio between $\mathrm{D_t}$ and $\mathrm{O_t}$ $\left(\frac{\mathrm{D_t}}{\mathrm{O_t}}\right)$. This functional form captures the main characteristic of the Colombian energy matrix. This matrix is hydro-dominated, and, for that reason, the main factor that determines the price is excess demand in relation to the installed capacities of the hydropower plants added together. When this ratio is low, the marginal costs of these plants essentially determine the price. However, the higher this ratio (i.e., the more residual demand satisfied by thermal power plants), the more important the prices of their consumable goods. All of this is captured when these prices interact with excess demand. The specification is improved by including two more factors in the model:

- A binary variable that indicates if El Niño phenomenon occurs at moment **t**.
- Spot price lags.

It is well known that El Niño phenomenon has a strong effect on electricity production costs because its occurrence implies a considerable fall in the generation capacity of hydropower companies. Certainly, the D_t^* variable partially captures this fact. However, the occurrence of El Niño may cause a structural change in the functional form of the model. This is controlled by including the binary variable mentioned above in the model. Furthermore, non-observable components of marginal costs may exist and, in addition, exhibit persistence—which means that ϵ_t is autocorrelated. This is controlled by including price lags in the model, as seen in Equation (2).

$$\mathrm{Spot}_t = \alpha + \beta_1 \ln \mathrm{E}(D_t^*|\Gamma_{t-1}) + \beta_2 \ln \mathrm{E}(D_t^*|\Gamma_{t-1}) \,\mathrm{x} \ln \mathrm{gas}_{t-1} + \\ \beta_3 \ln \mathrm{E}(D_t^*|\Gamma_{t-1}) \,\mathrm{x} \ln \mathrm{carbon}_{t-1} + \beta_4 \ln \mathrm{E}(D_t^*|\Gamma_{t-1}) \,\mathrm{x} \ln \mathrm{brent}_{t-1} + \sum_{j=1}^{H} \gamma_j I_j \mathrm{Spot}_{t-j} + \epsilon_t \qquad (2)$$

This equation explicitly considers that the spot price on day t is determined based on the prices asked by different companies/plants on the previous day. Likewise, it should be highlighted that, when a price is offered, the companies observe $\mathrm{E}(D_t^*|\Gamma_{t-1})$, which is the demand forecast based on a set of information Γ available at $t-1$[†].

In Equation (2), H represents the maximum number of lags to be included in the equation, and I_j is an indicator variable that takes a value of 1 when the lag (j) is actually included in the model. The set of lags to be included is selected so that it minimizes the information criterion AIC. In particular, the procedure is the following. First, H is determined. This is done by recursively estimating the equation of interest, every time including one more lag, until the estimated model produces non-autocorrelated residuals. In this case, H equals 40. Since this procedure results in an overidentified model because many of the 40 lags are not significant, genetic algorithms are used to find the combination of lags that minimizes the AIC in the model[‡]. That is, the optimization by a genetic algorithm determines which among the 40 I_j lags take a value of 1 and which ones take a value of 0. Importantly, after the redundant lags are excluded, the model still generates non-autocorrelated residuals. After the model has been estimated, the term ϵ_t is extracted to conduct the contagion analysis. In this article, ϵ_t is referred to as the *domestic pseudoreturn.*

[†] The Mining and Energy Planning Unit of Colmbia (Unidad de Planeación Minero-Energética, UPME) does the calculations and then provides this information to different plants.

[‡] This step uses differential evolution, which is a specific method in the family of genetic algorithms. See, for example, Chakraborty (2008) for a complete description of the method.

Modelling the returns of international energy prices

According to Mahadeo et al. (2019), it is assumed that the temporal evolution of the returns of the international fuel prices is explained by its own lags and the shadow short rate of the US stock market (SSR) as follows in Equation (3):

$$r_{it} = \alpha_0 + \alpha_1 r_{it-1} + \alpha_2 SSR_{t-1} + \omega_{it} \tag{3}$$

where r_{it} is the international return of fuel i (coal, natural gas, or oil) at moment t. The term ω_{it} (referred to as *international pseudoreturn*) is used to conduct the contagion analysis.

Local correlations

Local regression and correlation

After this point, r_i and r_d represent the international and domestic pseudoreturns, respectively, observed in periods $t = 1, \dots, T$. The objective is to have a linear function $f_s(r_i)$ that, for a fixed s belonging to interval $[1, T]$, minimizes the following weighted sum of squared residuals in Equation (4):

$$S_s = \min_{f_s} \sum_t \theta(t-s)[f_s(r_i) - r_d]^2 \tag{4}$$

where $\theta(.)$ is the moving-average Gaussian weighting function, which depends on the distance, in terms of time periods, between r_t and r_s. From this, we deduce that the local regression function takes the following form in Equation (5):

$$f_s(r_i) = Z_i\beta_s, \qquad Z_i = r_i - \overline{r_i}$$

$$S_s = \min_{\beta} \sum_t \theta[y - Z_i\beta]^2$$
$$\frac{dS_s}{d\beta} = -\sum_t 2\theta(y - z\beta)z = 0$$

$$\sum_t \theta(y - z\beta)z = 0$$
$$\sum_t (\theta y - \theta z\beta)z = 0$$
$$\sum \theta yz - \beta \sum \theta z^2 = 0$$

$$\beta = \frac{\sum \theta yz}{\sum \theta z^2}$$

$$\beta = \frac{\Sigma\left(\theta_i^{\frac{1}{2}} y_i\right)\left(\theta_i^{\frac{1}{2}} z_i\right)}{\Sigma\left(\theta^{\frac{1}{2}} z\right)^2} \tag{5}$$

where $\overline{r_1}$ is the value of the international return in s. The vector of coefficients and its matrix of variances and covariances are obtained using the structure of the weighted least square estimator in Equation (6):

$$\widehat{\beta_s} = \left[\sum_t \theta(t-s) Z_{st} Z'_{st}\right]^{-1} \sum_t \theta(t-s) Z_{st} r_{sd}$$
$$V(\widehat{\beta_s}) = \sigma_s^2 [\textstyle\sum_t \theta(t-s) Z_{st} Z'_{st}]^{-1} \tag{6}$$

where σ_s^2 represents the local variance of the model's error in the proximity around r_s. Applying this procedure to each moment s, we obtain T local regressions, $\hat{f}_s(r_i) = Z_i \beta_s$, and the corresponding weighted sum of squared residuals $RwSS_a = \sum \theta(t-s) \left[Z_{st}\widehat{\beta_s} - r_d\right]^2$. Based on this weighted sum, we calculate the series of coefficients of determination as in Equation (7):

$$R_s^2 = 1 - \frac{RwSS_s}{TwSS_s}, \qquad s = 1, \dots, T$$

$$TwSS_s = \textstyle\sum_t \theta(t-s) r_{si}^2 \tag{7}$$

Local correlation using wavelets

Wavelets can be used to quantify the strength of the relationship between the domestic and the international return for each moment and time scale, which enables us to observe the dynamics of the relationship and distinguish between the short, medium, and long term. In particular, this study used the Maximal Overlap Discrete Wavelet Transform (MODWT), one of the most popular transforms (Fernández-Macho, 2018). In addition to its popularity, there are at least two more facts that justify why it was selected: (1) the discrete nature of the data and (2) the energy preservation property (Fernández-Macho, 2018), which is particularly important for the objective of this paper.

Let w_{1jt} and w_{2jt} be the coefficients at a λ_t scale obtained when the MODWT was applied to a pair of returns (the domestic one and an international one). The series of local correlations $\left(\psi_s(\lambda_j)\right)$ is obtained as shown in Equation (8):

$$\psi_s(\lambda_j) = \mathrm{Corr}\left([\theta(t-s)]^{\frac{1}{2}} \omega_{1jt}, [\theta(t-s)]^{\frac{1}{2}} \widehat{\omega}_{1jt}\right) \tag{8}$$

where $\mathrm{Corr}(x, y)$ represents the Pearson correlation between a pair of variables x and y. That is, the local wavelet correlation at moment s is obtained by calculating the Pearson correlation between the domestic return coefficients ω_{1jt} and their predicted value $\widehat{\omega}_{1jt}$. Each observation is weighted according to $\theta(t-s)$. $\widehat{\omega}_{1jt}$ is obtained by performing a local regression (such as that described in the previous section) of ω_{1jt} in w_{2jt} (the international return coefficients). Applying this procedure to each moment s, we obtain T local wavelet correlations.

Identifying crisis and non-crisis conditions in the energy market

Two strategies were used to identify crisis and non-crisis periods in energy indicators (oil, natural gas, and coal). Rule-based algorithms were employed to identify the periods of rise/fall as proxies of non-crisis/crisis periods. These periods are expressed as binary variables to apply contagion tests, where 0 is non-crisis and 1 is crisis.

Criterion: state duration

In this approach, it is important to determine the inflection points in energy indicators. We used the model developed by Pagan and Sossounov (2003), who defined a $T_{window} = 8\ \text{months}$ due to the lack of smoothing of the series and established $t_{censor} = 6\ \text{months}$ and $t_{phase} = 4\ \text{months}$ to decide on the minimum time they can be in any phase based on the Dow theory.

Criterion: magnitude of price change

In this approach, it is important to determine the change (in percentage) in a market that goes from a crisis scenario to a non-crisis one λ_1 and from a non-crisis to a crisis λ_2. We used the model developed by Lunde and Timmermann (2004), who considered a filter with $\lambda_1 = 20\%$ and $\lambda_2 = 15\%$ to explain changes in non-crisis periods in the market, which works against finding many bear markets.

4. RESULTS

Coal

Figure 1 presents the non-crisis and crisis periods identified using the two criteria mentioned above. The two techniques produced a similar classification and only differed notoriously toward the end of the period under study. It is also noteworthy that the longest crisis occurred in early 2014 and ended in the first months of 2016.

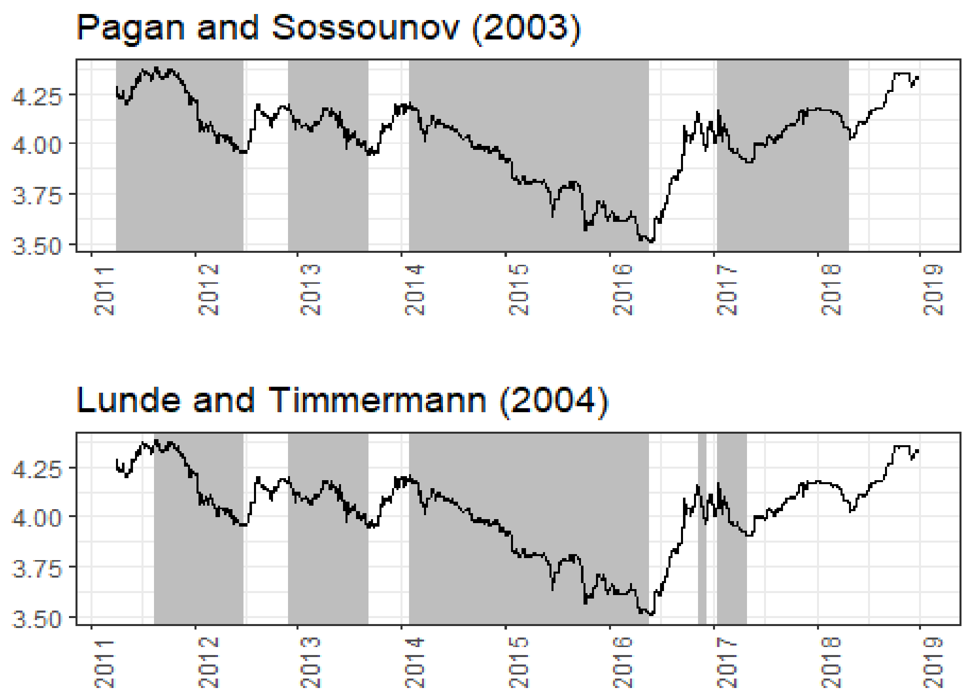

Figure 1. Non-crisis and crisis periods in the international coal market
Figura 1. Momentos de calma y crisis en el mercado internacional del carbón
Source: Own work.

Figure 2 presents a series of correlations estimated by applying regressions to the pseudoreturns of the electricity spot prices and coal, along with their respective confidence intervals at 95%. It can be observed that many of the estimated correlations are significant. This confirms the existence of transmission channels that are not captured by the models mentioned above—and this should be stressed. The correlations were estimated with the pseudoreturns, that is, the error term of the models described above, i.e., the part of the returns that is not explained by the models. Therefore, the correlations shown in the figure represent phenomena that were not captured by traditional models or transmission channels. In addition, the series has three local maxima, although one of them (the second one) is not significant (the confidence interval includes zero). Figure 3 presents the same series of correlations, but this time indicating the crisis and non-crisis periods. Two of the local maxima occur in moments of crisis. However, the second one is not significant, so it does not count as evidence of contagion. In turn, the third local maximum occurs in a non-crisis period. Therefore, conclusive evidence of contagion was not obtained. This time, evidence of contagion was found only during the 2013 crisis.

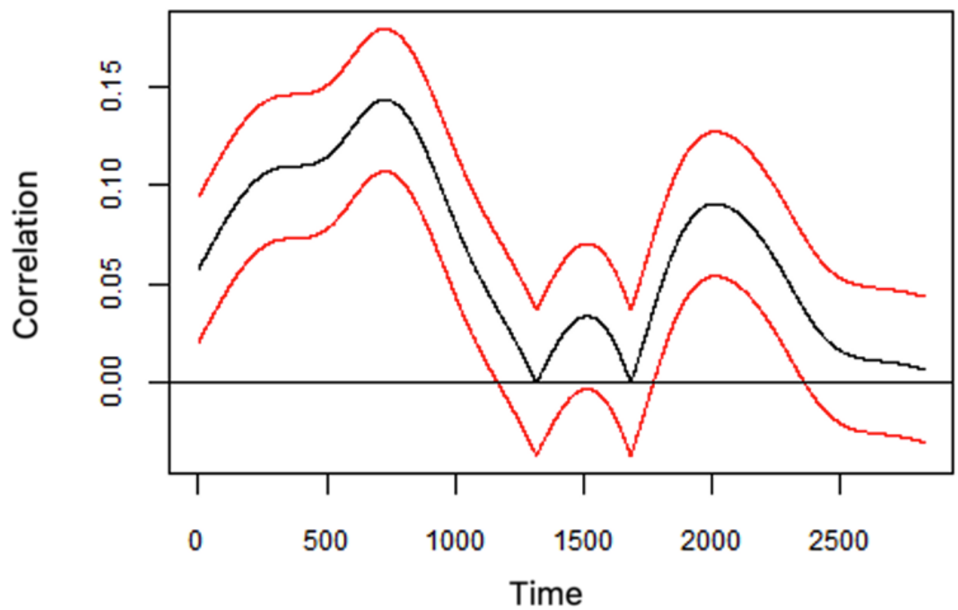

Figure 2. Local correlation between coal and electricity spot prices in crisis and non-crisis periods
Figura 2. Correlación local entre el carbón y el precio *spot* en momentos de calma y crisis
Source: Own work.

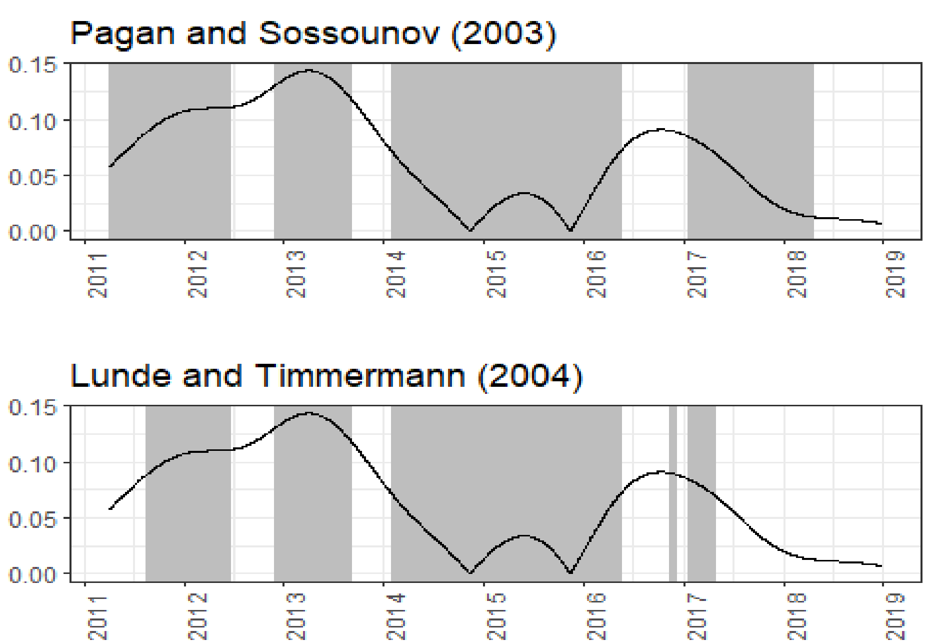

Figure 3. Local correlation between coal and electricity spot prices in crisis and non-crisis periods
Figura 3. Correlación local entre el carbón y el precio *spot* en momentos de calma y crisis
Source: Own work.

Finally, Figure 4 presents a map of correlations estimated using wavelets. In this case, in addition to the variation over time (x-axis), it shows the correlation in different periods or scales (y-axis). It can be seen that strong correlations are found in high periods, which reflects the existence of a medium- and long-term relationship between the returns of interest. The first two contours of high correlations coincide approximately with the first two crises, which provides evidence in favor of the contagion hypothesis specifically for these time periods.

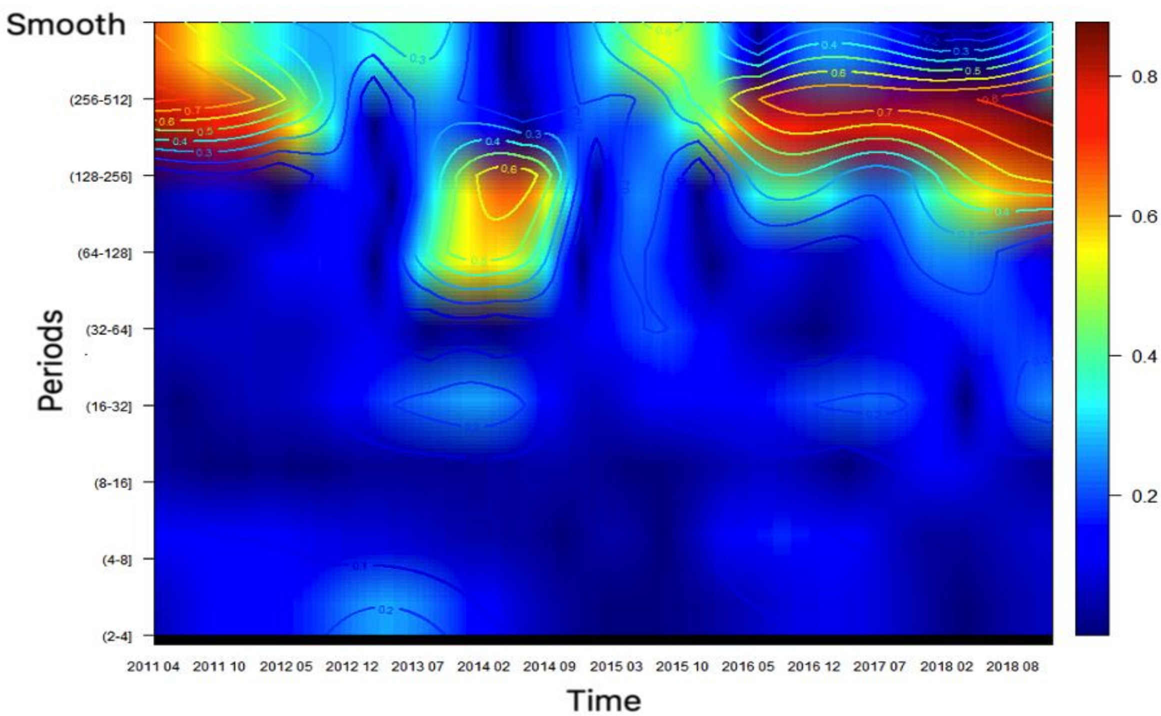

Figure 4. Local wavelet correlation between coal and electricity spot prices in crisis and non-crisis periods
Figura 4. Correlación local *wavelet* entre el carbón y el precio *spot* en momentos de calma y crisis
Source: Own work.

Natural gas

Figure 5 presents the crisis and non-crisis periods in the international natural gas market identified using the two methods mentioned above. The two methods produced a similar classification—only differing in the fact that the second one identified short crisis periods between 2012 and 2014 and almost at the end of the period under study. Again, it is noteworthy that the longest crisis started in early 2014 and ended in the first months of 2016.

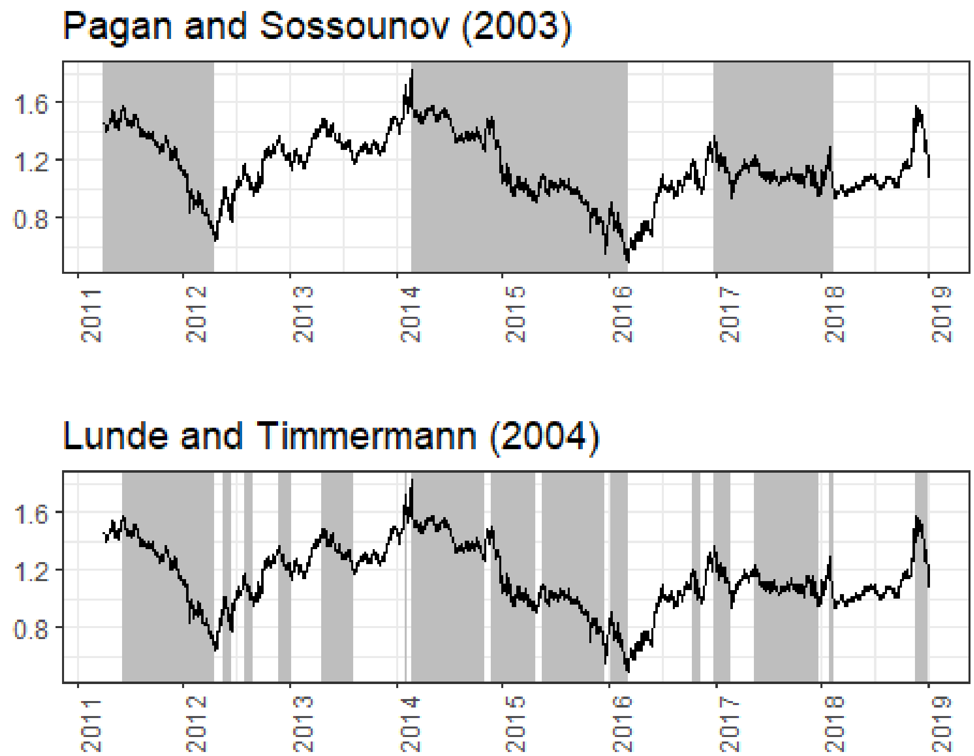

Figure 5. Crisis and non-crisis periods in the international natural gas market
Figura 5. Momentos de calma y crisis en el mercado internacional del gas
Source: Own work.

Figure 6 presents the series of correlations estimated applying regressions to the pseudoreturns of the electricity spot prices and natural gas, along with their respective confidence intervals at 95%. It can be seen that most estimated correlations are not statistically significant, which suggests that—in most periods considered in the sample—the models mentioned above adequately capture the relevant transmission channels (see Figure 7). This finding supports the robustness of the models used here because they explained significant relationships between the variables analyzed in the period under study. Nevertheless, the second peak is significant, and this occurs precisely in the middle of a crisis. Thus, in this case, evidence of contagion was found only during the crisis that started in 2014.

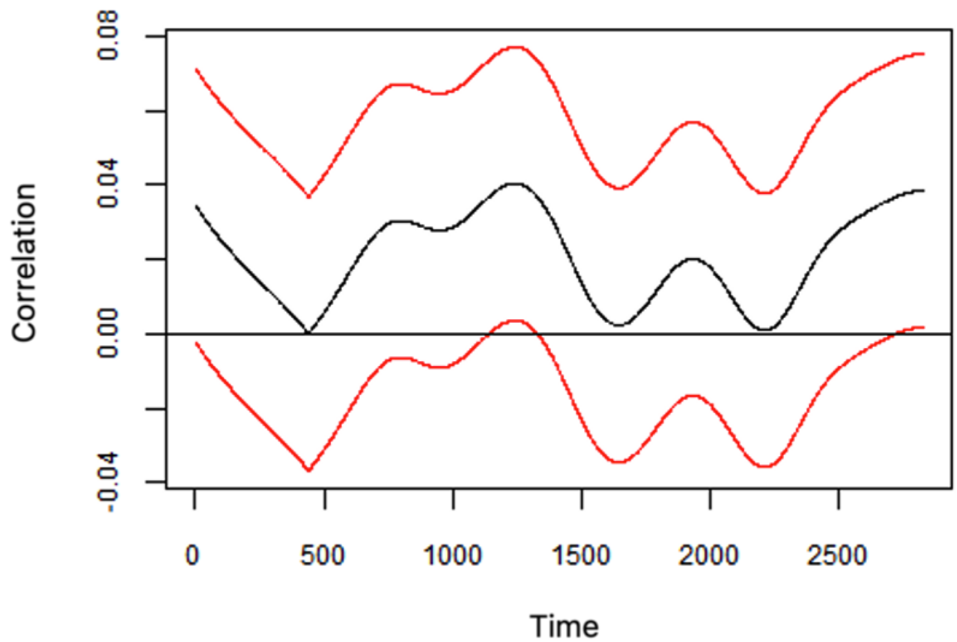

Figure 6. Local correlation between natural gas and electricity spot prices in crisis and non-crisis periods

Figura 6. Correlación local entre el gas y el precio *spot* en momentos de calma y crisis

Source: Own work.

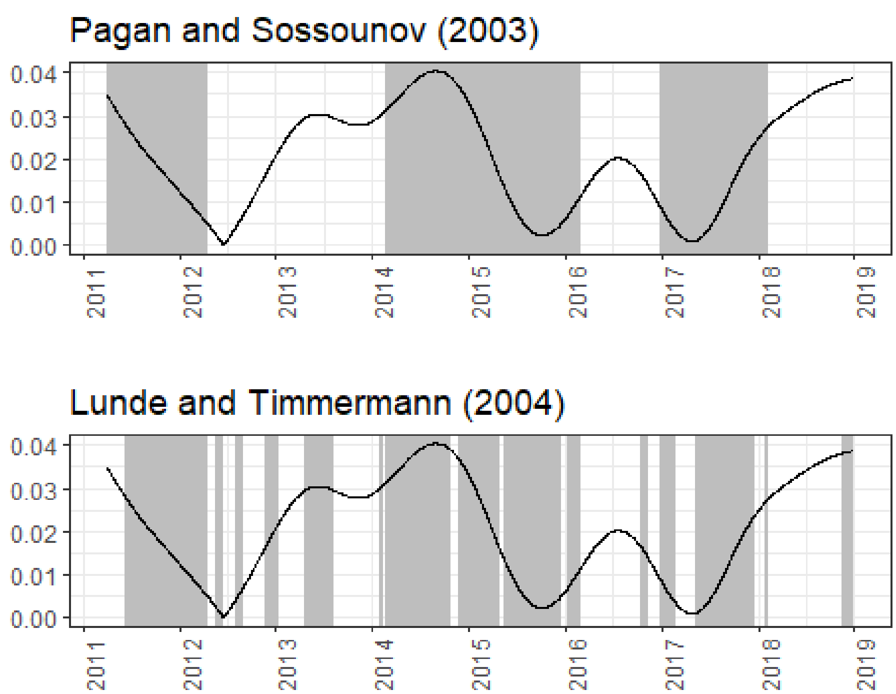

Figure 7. Local correlation between natural gas and electricity spot prices in crisis and non-crisis periods

Figura 7. Correlación local entre el gas y el precio *spot* en momentos de calma y crisis

Source: Own work.

Finally, Figure 8 presents the map of correlations estimated using wavelets. Again, the evidence shows that the strongest correlations between the returns of interest occur in the medium and long term. It can also be seen that some strong correlations occur during crisis periods. Hence, (although weak) evidence of contagion was found.

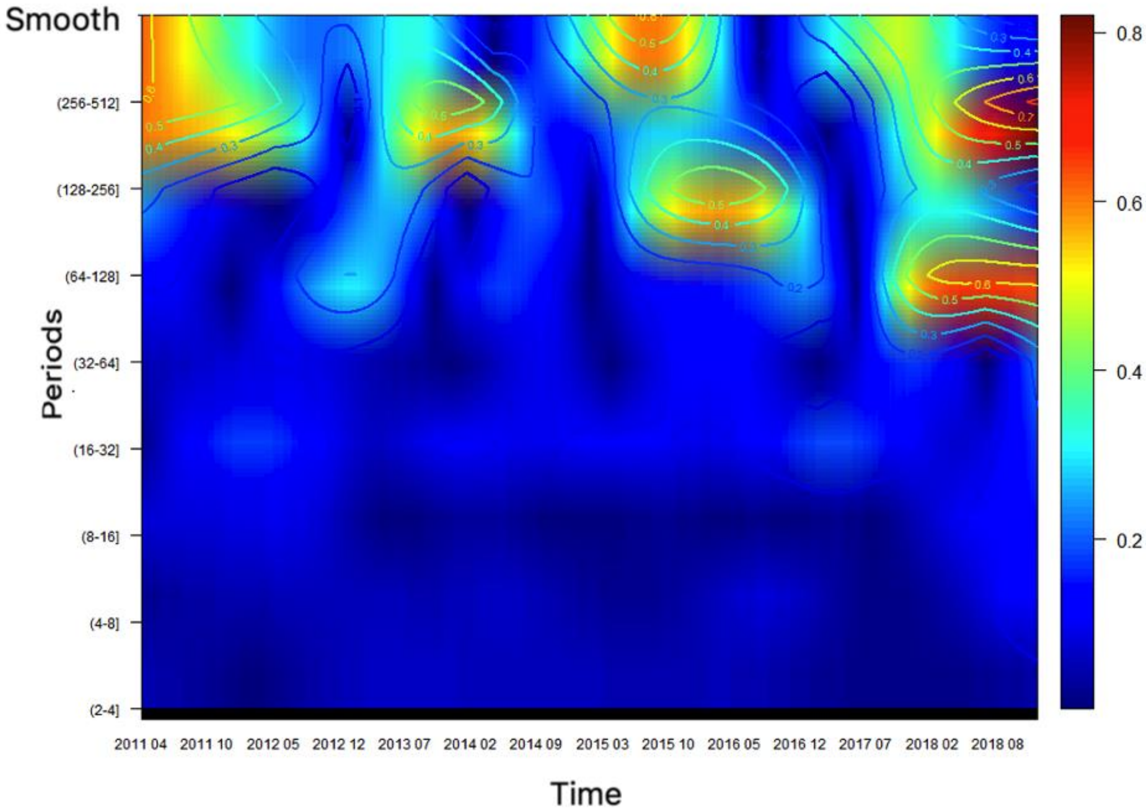

Figure 8. Local wavelet correlation between natural gas and electricity spot prices in crisis and non-crisis periods

Figura 8. Correlación local *wavelet* entre el gas y el precio *spot* en momentos de calma y crisis

Source: Own work.

Brent

Figure 9 presents the crisis and non-crisis periods of Brent oil. In this case, the two methods differed a little more. However, both indicated that the strongest crisis started in 2013.

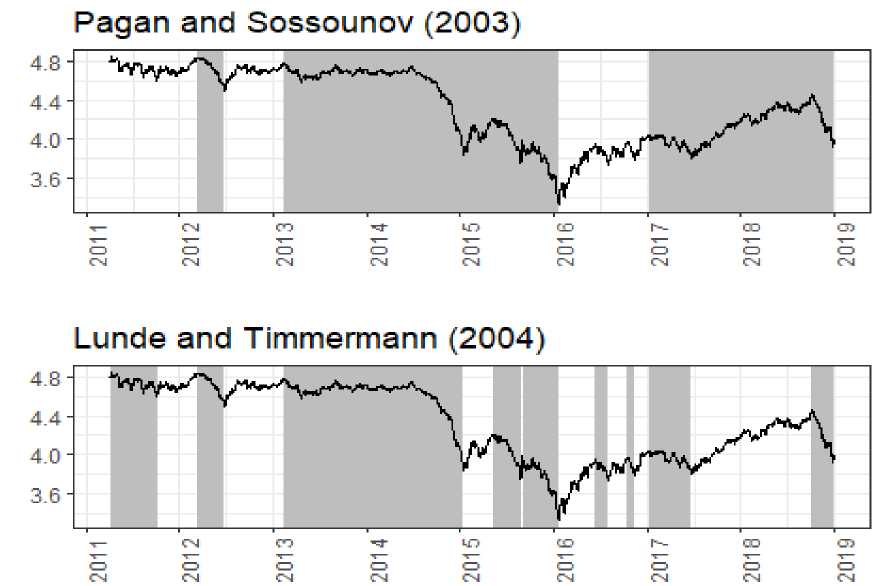

Figure 9. Crisis and non-crisis periods in the international oil market
Figura 9. Momentos de calma y crisis en el mercado internacional del petróleo
Source: Own work.

Figure 10 presents the series of correlations of this commodity. Several peaks, all significant, can be observed. At the end of the period under analysis, the correlation increased significantly.

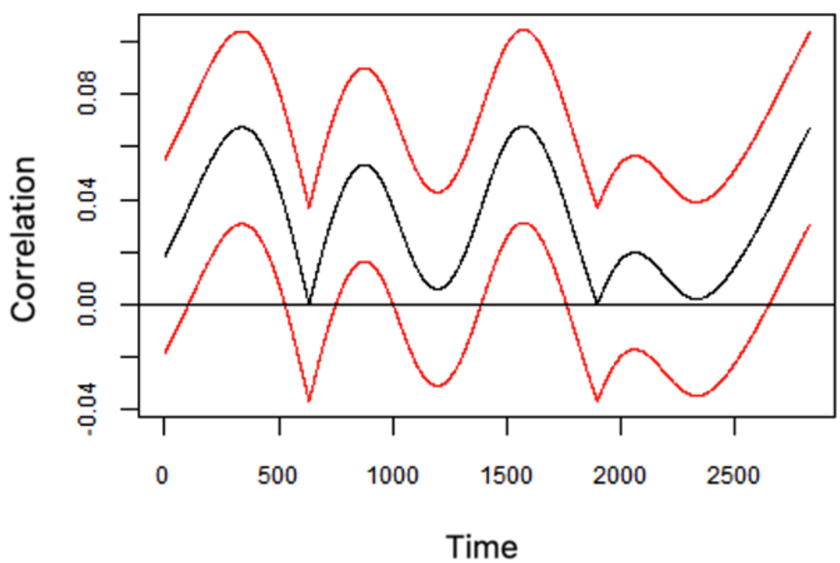

Figure 10. Local correlation between Brent oil and electricity spot prices in crisis and non-crisis periods
Figura 10. Correlación local entre el Brent y el precio *spot* en momentos de calma y crisis
Source: Own York.

Now, in Figure 11, it can be seen that each one of those peaks occurred during a crisis period. Therefore, in the case of Brent oil, we found conclusive evidence that supports the contagion hypothesis. A similar conclusion can be drawn from Figure 12, which presents the correlations calculated using wavelets, because the first two contours of strong correlations occurred during crisis periods, especially when the latter had been calculated using the method by Pagan and Sossounov (2003).

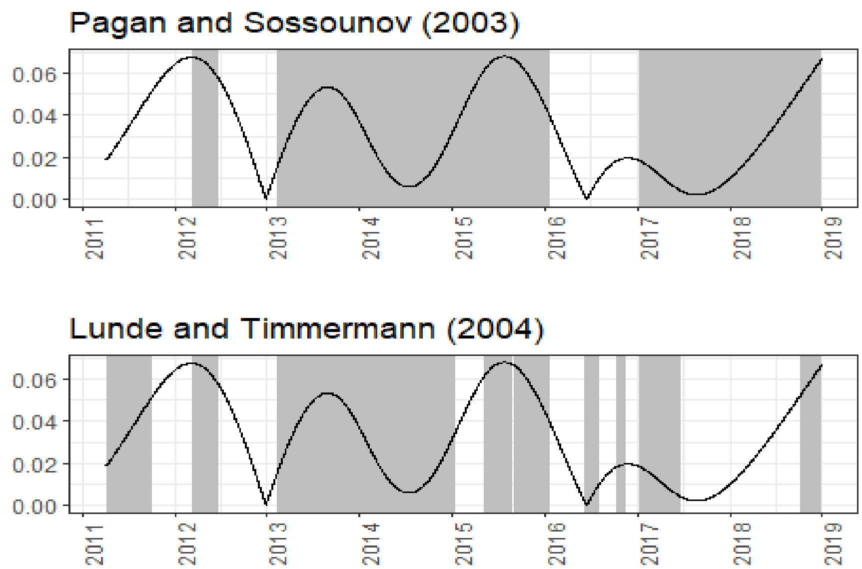

Figure 11. Local correlation between Brent oil and spot electricity prices in crisis and non-crisis periods
Figura 11. Correlación local entre el brent y el precio *spot* en momentos de calma y crisis
Source: Own work.

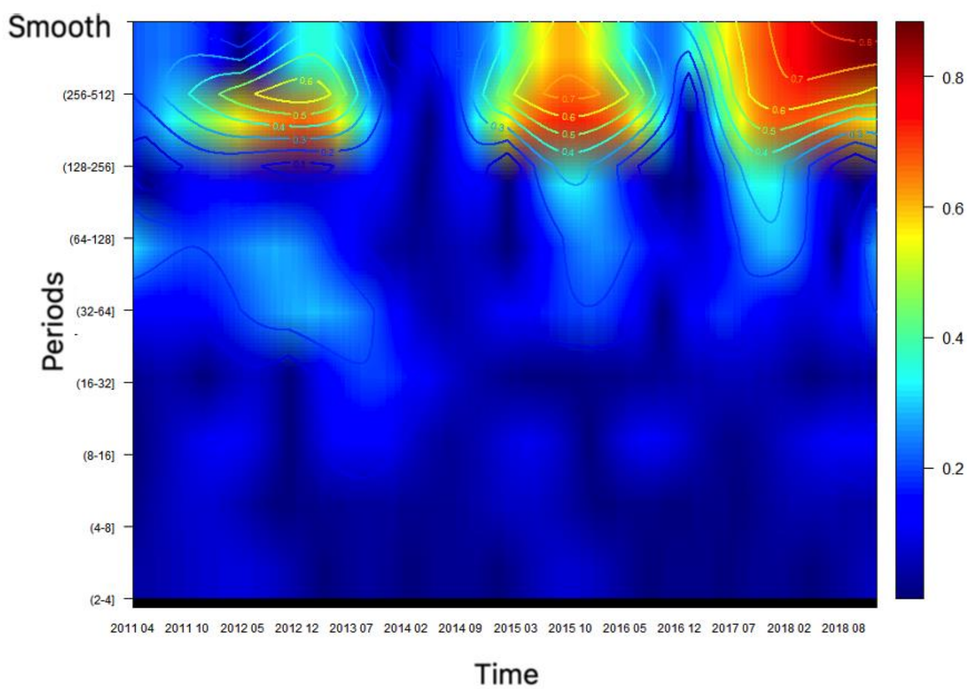

Figure 12. Local wavelet correlation between oil and electricity spot prices in crisis and non-crisis periods
Figura 12. Correlación local *wavelet* entre el petróleo y el precio *spot* en momentos de calma y crisis
Source: Own work.

5. DISCUSSION

In contrast with more conventional methods in the literature—such as copulas (Uribe, 2011) or correlation coefficients (Mahadeo et al., 2019), which have a tendency to analyze relationships in a more general manner—the wavelet technique applied in this study could simultaneously address the problem of financial contagion in its local dimension and at different scales. This was especially adequate to understand the multifaceted nature of volatility transmission in the stock markets studied here.

The results of this study—which used wavelet analysis to investigate energy contagion—match those reported by Reboredo and Rivera-Castro (2013), who analyzed the relationship between crude oil prices and the US Dollar exchange rate. They found that, before the crisis, there was no significant relationship between oil prices and exchange rates. However, during the financial crisis, they detected a negative correlation between them, without lead or lag effects before the crisis. Subsequently, during the crisis, oil prices started to influence exchange rates and vice versa. This could mean that unexpected events in the oil market (e.g., sharp price falls) may trigger significant movements in exchange rates, which, in turn, would affect economies and companies that depend on international transactions.

Additionally, the findings of this study are in line with previous research. For instance, Hergety (2012) and Boubaker and Raza (2017) examined secondary effects and shocks in crude oil prices and the BRICS stock markets during the 2007–2009 global financial crisis. Their studies have stressed the idea that countries in Latin America have currencies that are highly correlated with basic products, and, as a result, their foreign exchange markets show greater vulnerability to external influences. From a financial perspective, this suggests that investors and financial institutions who operate in Latin America should be especially aware of changes in basic product prices and global economic events because these factors can have a significant impact on foreign exchange markets and, ultimately, on their investment and risk management strategies.

The main contribution of this study is that it demonstrated that there is a significant and long-term relationship between energy indicators and electricity spot prices, as well as contagion from natural gas and Brent oil to electricity spot prices in crisis periods. However, there is no clear evidence of contagion from coal. These results are relevant to understand how changes in the energy market, and the economy in general, can affect electricity prices in the long term in an emerging economy. Furthermore, this study consolidates a theoretical, empirical, and informative body of knowledge of the industrial sector of the economy—objectively encouraging the formulation of financial and economic policy in the Colombian energy sector, as well as in its capital market.

6. CONCLUSIONS

Energy contagion has a significant impact on the global economy. And it is particularly relevant in emerging markets that usually have less diversified economies and are highly dependent on energy exports or imports, which makes them particularly vulnerable to fluctuations in energy prices and the effects of volatility transmission. This kind of studies consolidate a body of knowledge so that firms, investors, finance policymakers, and other market agents can develop strategies and actions to mitigate risks and strengthen their response capacity in crisis situations related to the international energy market.

This study analyzed the effect of the international prices of fossil fuels on electricity prices in the Colombian market. It employed time series of energy indicators, type of exchange rate, foreign economic activity, and energy market performance. It also implemented two cutting-edge econometric methods: wavelet analysis and pseudoreturn analysis (which reflects non-traditional contagion channels). Likewise, it included contagion tests using different methods to determine crisis and non-crisis periods. It was found that the method by Pagan and Sossounov (2003), as well as that by Lunde and Timmermann (2004), can be used to establish crisis periods more effectively and produce more consistent results regarding the contagion between the global market of Brent oil and Colombian stock and foreign exchange markets.

In general, the results show that there are significant long-term correlations between energy indicators and electricity spot prices during crisis periods. There is presence of contagion from Brent oil and natural gas to electricity spot prices. Regarding Brent oil, there is conclusive evidence of contagion using the two approaches. In contrast, in the case of natural gas, evidence of contagion was only observed during the oil price plunge (2014–2015) and Brexit in 2016. In relation to coal, contagion was not clearly identified employing any of the approaches analyzed in this study. However, significant long-term correlations were observed by means of wavelet analysis. These findings are relevant to understand, in a holistic way, how changes in the global energy market, and the economy in general, can affect electricity prices in the long term in emerging economies. This is specially interesting because these markets are more susceptible in terms of macroeconomic stability and the quality of life of their populations.

Future studies can expand this database so that it includes more periods of time and, thus, other important crises such as those that occurred in 2008 or 2019. Likewise, more research should be conducted on Latin American markets, where there are several economies that mainly depend on energy commodities. In addition, the efficacy of the econometric analysis of contagion largely depends on the identification of moments of stability and disturbance. Therefore, future research should include more identification methods of this kind to confirm the robustness of the results.

CONFLICTS OF INTEREST

The authors declare no conflict of financial, professional, or personal interests that may inappropriately influence the results that were obtained or the interpretations that are proposed here.

AUTHOR CONTRIBUTIONS

To carry out this study, all the authors made a significant contribution, as follows:

Luis Ángel Meneses Cerón: Project formulation, Theoretical framework, Literature review, Methodology, Results and Discussion, Writing - review & editing.

Jorge Eduardo Orozco Álvarez: Project formulation, Data collection, Model design, Writing - results & conclusions.

Juan Camilo Mosquera Muñoz: Literature review, Theoretical framework, Database, Methodological design, Statistical and econometric analyses, and Writing - original draft.

Víctor Manuel Vélez Rivera: Literature review, Theoretical framework, Methodology, Statistical and econometric analyses, and Writing - original draft.

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