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Directional Spillover of Fossil Fuels Prices on a Hydrothermal Power Generation Market

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ABSTRACT

The Colombian electricity market is based on a hydrothermal power generation market with a strong dependence on exogenous variables such as fossil fuel prices and climatology factors. Besides, the Colombian economy is characterizable by relevant mining-energy activities. Therefore, the main objective of this research was to evaluate the directional spillovers between the electricity spot prices and gas, coal, and crude oil prices and thus provide relevant information for the electricity market agents to identify the risk related to energy commodity price fluctuations. The dataset used in this research consists of monthly logarithmic returns of energy prices between September 2009 and December 2019. The main finding shows that the system's average connectedness is 13.6%. Besides, the electricity spot prices are net shock receivers of volatility, and 20% of their dynamic is related to fossil fuel price fluctuations.

Keywords: Directional Connectedness, Hydrothermal Power Generation Markets, Volatility Spillovers, Energy Prices, Vector Autoregression Model
JEL Classifications: C32, Q35, Q43

1. INTRODUCTION

The Colombian electricity matrix is structured by 68% of hydric sources and 31% of thermal sources. Besides, renewable sources such as wind and solar represent only 0.21% (Oviedo-Gómez et al., 2021b). Therefore, this electricity market is defined as a hydrothermal market, which is characterized by significant differences in the marginal costs of the generation sector, a heavy dependency on weather factors and fossil fuel prices, and a small renewable generation capacity (Fernández-Blanco et al., 2017; Mosquera-López et al., 2017). According to Werlang et al. (2021) and Wang et al. (2013), fuel prices are a driver of electricity prices because their shocks impact the opportunity costs of hydropower plants and increase the uncertainty of operation in the electricity system.

On the other hand, Colombian exportations are based on mining-energy commodities such as crude oil, coal, and nickel. According to Oviedo-Gómez and Candelo-Viafara (2020), the volatility of energy commodities' prices causes significant effects on macroeconomic variables such as economic activity, investment, the trade balance, and the real exchange rate. Hence, it leads us to ask whether there is a relationship between electricity and fossil fuel prices due to the Colombian economy and electricity market characteristics. Besides, several authors observed a bidirectional relationship between electricity and fossil fuel prices. The first link describes that coal, natural gas, and oil prices increase the running cost of thermal plants. For example, it is observed a negative and high relationship between electricity and gas prices. Therefore, natural gas prices are a determinant of electricity prices even in an electricity market with significant renewable energy sources (Abban and Hasan, 2021; Chevallier et al., 2019; Moutinho et al., 2022; Mwampashi et al., 2021; Uribe et al., 2022). The second link shows that the electricity prices' peaks impact natural gas, coal, and oil prices in the short term (Mjelde and Bessler, 2009;

Mohammadi, 2009; Moutinho et al., 2011; Scarcioffolo and Etienne, 2021).

Therefore, the objective was to evaluate the directional spillovers between the Colombian electricity spot prices and the prices of the three most relevant sources of thermal sources: gas, coal, and crude oil. The methodology applied was proposed by Diebold and Yilmaz (2009; 2012; 2014), and it allows the volatility connectedness to be analyzed. The method is based on the variance decomposition of the forecast error of the generalized vector autoregression model (VAR) with n-dimensions and does not depend on Cholesky identification. Besides, it offers information about the size, target, and source of spills (Restrepo et al., 2018). The most relevant result showed that the electricity spot prices are pure shock receivers of fuel fossil price fluctuations. Consequently, the study provides information on the risk of fossil fuel prices and their volatility for the electricity system.

The paper is structured, after section 1, as follows: In section 2, the methodology applied is described. Section 3 presents the dataset, and in section 4, the main findings and discussion are reported. Section 5 presents the conclusions.

2. METHODOLOGY

The relationship of volatility connectedness between the energy prices in a hydrothermal power generation market was analyzed by the method proposed by Diebold and Yilmaz (2009; 2012; 2014). The methodology is based on the variance decomposition of the forecast error of a generalized VAR model proposed by Koop et al. (1996), and Pesaran and Shin (1998). Therefore, the generalized VAR model does not depend on Cholesky identification, and it allows invariant decomposition to the ordering of the variables.

2.1. Correlated Shocks

From a reduced-form VAR model (Sims, 1980):

$$y_t = v + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t, \tag{1}$$

where y_t is a K-dimensional vector of endogenous variables, v is a fixed K-dimensional vector of intercept terms, A_i is a coefficients matrix with K x K dimensions, u_t is a K-dimensional white noise, i.e., $E(u_t) = 0$, $E\left(u_t u_t'\right) = \Sigma_u$ and $E\left(u_t u_s'\right) = 0$ for s ≠ t. The covariance matrix Σ_u is assumed to be nonsingular if not otherwise stated.

Besides, the VAR (p) model can be written in the companion VAR(1) form as follows:

$$Y_t = v + AY_{t-1} + U_t, \tag{2}$$

Where $Y_t := \begin{pmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{t-p+1} \end{pmatrix}$, $\boldsymbol{v} := \begin{pmatrix} v \\ 0 \\ \vdots \\ 0 \end{pmatrix}$, $\boldsymbol{A} := \begin{bmatrix} A_1 & A_2 & \ldots & A_{p-1} & A_p \\ I_K & 0 & \ldots & 0 & 0 \\ 0 & I_K & 0 & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \ldots & I_K & 0 \end{bmatrix}$, and $U_t := \begin{pmatrix} u_t \\ 0 \\ \vdots \\ 0 \end{pmatrix}$. On the other hand, if it assumes the VAR(p) models as stable, then its moving average (MA) representation can be obtained by successive substitution for Y_{t-i}. Therefore, it can be written as follows:

$$\begin{aligned} y_t &= A(L)^{-1} v + A(L)^{-1} u_t = A(L)^{-1} v \\ &+ \sum_{i=1}^{\infty} J\boldsymbol{A}^i J' J U_{t-i} = \mu + \sum_{j=1}^{\infty} \Phi_i u_{t-i} \end{aligned} \tag{3}$$

Where J = $[I_K, 0_{K \times K(p-1)}]$ is the selection matrix and $A(L)^{-1} = \sum_{i=0}^{\infty} \Phi L_i = J\boldsymbol{A}^i J$ for i = 0,1,…. Thus, these matrices are recursively computed as $\Phi_0 = I_K$, and $\Phi_i = \sum_{j=1}^{i} \Phi_{i-j} A_j$ for i = 1,2,…, with $A_j = 0$ for $j > p$. The matrix $\Phi_i = [\phi_{kj,i}]_{K \times K}$ is also called the response of the variables k to unit shock u_{jt}, j = 1,2,…K, with i periods.

According to Lütkepohl (2005), the forecast error variance decomposition (FEVD) at the hth horizon is:

$$\begin{aligned} FEVD_j^k(h) &= E\left(y_{k,t+h} - y_{k,t}(h)\right)^2 \\ &= \sum_{j=1}^{K} \left(\theta_{kj,0}^2 + \ldots \theta_{kj,h-1}^2\right) = \sum_{i=0}^{h-1} \left(e_k' \Theta_i e_j\right)^2, \end{aligned} \tag{4}$$

If one decomposes $\Sigma_u = E(u_t u_t') = P\Sigma_w P'$ with $\Sigma_w = I_K$ then defines $\Theta_i = \Phi_i P$ such that $\Theta_0 = \Phi_0 P = P$, and $\Theta_{i \geq 1} = \Phi_i P = JA^i J'$.

Dividing Eq. (4) by $FEVD^k(h) = \sum_{j=1}^{K} FEVD_j^k(h)$ to give the fraction of the contribution of shock j to the forecast error variance of the variables k. Diebold and Yilmaz (2009) define the spillover index to measure the spillover connectedness across the energy prices as follows:

$$Spillover\ Index = \frac{\sum_{k,j \in \{i..K\}, k \neq j} FEVD_j^k(h)}{\sum_{k,j \in \{1..K\}} FEVD_j^k(h)}, \tag{5}$$

However, Diebold and Yilmaz (2012) used a generalized VAR model to avoid the ordering of the variables. In the generalized VAR approach, the FEVD is computed at horizon $h = H$ as follows:

$$d_{kj}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_k' \Phi_h \Sigma_u e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_k' \Phi_h \Sigma_u e_j\right)}, \tag{6}$$

where e_k is a selection vector with k^{th} element unity and zeros elsewhere, Φ_h is the coefficient matrix multiplying the h-lagged shock vector in the infinite moving-average representation of the non-orthogonalized VAR, Σ is the covariance matrix of the shock vector in the non-orthogonalized VAR, and σ_{jj} is the jth diagonal element of Σ.

2.2. Total Connectedness Table

Diebold and Yılmaz (2014) defined the total connectedness table (Table 1), which describes the different connectedness measures between the energy prices. In the table, the $N \times N$ block describes the variance decompositions, its diagonal elements represent the own energy prices spillovers, and off-diagonal elements correspond to the pairwise directional spillovers. Thus, for each row, the sum of its off-diagonal elements equals the share of the H-step-ahead forecast error variance of the interest variable coming from the other variables' shocks. The column labeled "From others" contains the row sum, and the row labeled "To others" contains the column sum.

However, generalized FEVD does not guarantee the row sum or column sum of one. Therefore, the variance decomposition must be normalized as:

$$\widetilde{d_{kj}^{H}} = \frac{d_{kj}^{H}}{\sum_{j=1}^{K} d_{kj}^{H}}, \tag{7}$$

Where, $\sum_{j=1}^{N} \widetilde{d_{kj}^{H}} = 1$ and $\sum_{k,j=1}^{K} \widetilde{d_{kj}^{H}} = K$

2.3. Directional Spillovers

Total directional connectedness "From others" to energy price i^{th} is defined as:

$$C_{i \leftarrow *} = \sum_{j=1, j \neq i}^{N} d_{ij}^{H} \tag{8}$$

By contrast, directional volatility spillovers "To others" from energy j^{th} as:

$$C_{* \leftarrow j} = \sum_{i=1, i \neq j}^{N} d_{ji}^{H} \tag{9}$$

Therefore, it is defined net total directional connectedness measures as $C_i^H = C_{* \leftarrow i} - C_{i \leftarrow *}$ and pairwise directional connectedness between energy price i^{th} and energy price j^{th} is simply $C_{ij}^H = C_{j \leftarrow i}^H - C_{i \leftarrow j}^H$.

2.4. Impulse Response Function

The impulse response functions (IRF) are estimated to describe how the electricity spot prices react over time to energy commodity prices' shocks.

3. DATA

The dataset is a balanced time-series panel with monthly frequency from September 2009 to December 2019. The sample period was selected due to the data available with no methodological changes, and the current supply scheme for the generation sector is included (CREG 051 of 2009, article 10). Likewise, 2020 data were not selected because the Colombian electricity demand decreased significantly during the first quarterly of the COVID-19 pandemic, and the fossil fuel prices slumped, especially the oil prices that reached negative values (Hendrawaty et al., 2021; Oviedo-Gómez et al., 2021b). Thus, Table 2 describes the variables, specifying data sources and units.

In contrast, Figure 1 presents the variables' dynamics during the sample period. The electricity spot prices showed high volatility, especially during 2015 and 2016, due to El Niño-Southern Oscillation (ENSO) shock, which caused a peak price. On the other hand, crude oil prices slumped in 2014 due to the demand reduction by Asian countries. Similarly, coal prices showed two relevant decreases: in 2011 by a demand reduction and in 2018 by agreements to mitigate greenhouse gas emissions. Regarding natural gas prices, their dynamic is related to supply and demand variations. Meanwhile, Table 3 shows descriptive statistics and unit root test (augmented Dickey-Fuller-ADF) of the variables after their transformation in logarithmic returns.

4. EMPIRICAL RESULTS AND DISCUSSION

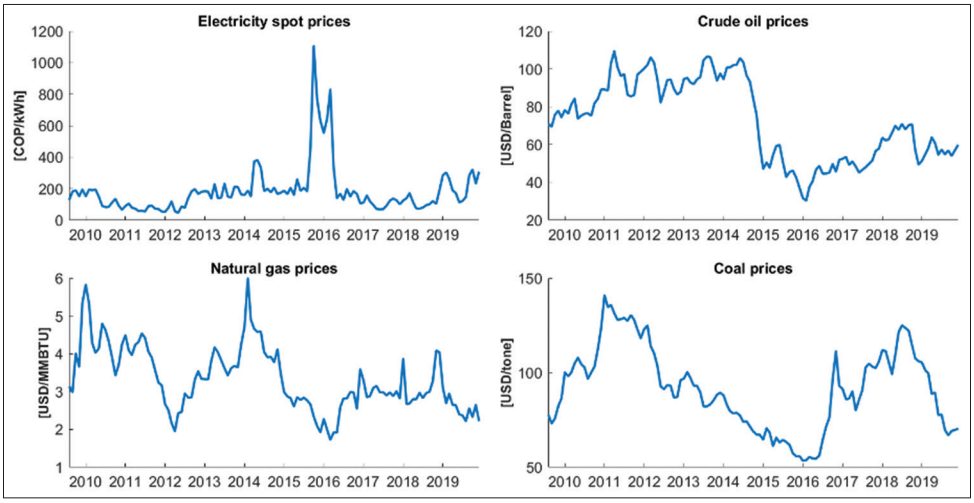
According to the Schwarz Criterion (SC), a VAR model with three lags was estimated and the forecast horizon used was 10 months ahead. Based on the FEVD, the volatility connectedness and the total dynamic volatility spillover index were constructed. Besides, Table 4 describes the total connectedness estimates of energy prices. The diagonal elements are their own variance share, and the row sum corresponds to the total directional spillovers "From

Table 1: Total connectedness table

	Energy price 1	Energy price 2	…	Energy price n	"From others"
Energy price 1	d_{11}^H	d_{12}^H	…	d_{1N}^H	$\sum_{j=\{1..N\}\setminus 1} d_{1j}^H$
Energy price 2	d_{21}^H	d_{22}^H	…	d_{2N}^H	$\sum_{j=\{1..N\}\setminus 2} d_{2j}^H$
⋮	⋮	⋮	⋱	⋮	⋮
⋮	⋮	⋮	⋱	⋮	⋮
Energy price N	d_{N1}^H	d_{N2}^H	…	d_{NN}^H	$\sum_{j=\{1..N\}\setminus N} d_{Nj}^H$
"To others"	$\sum_{k=\{1..N\}\setminus 1} d_{k1}^H$	$\sum_{k=\{1..N\}\setminus 1} d_{k1}^H$	…	$\sum_{k=\{1..N\}\setminus N} d_{kN}^H$	$\frac{1}{N} \sum_{k,j=\{1..N\}, i \neq j} d_{ij}^H$

$d_{kj}^H \equiv FEVD_j^k(h = H)$. Source: Authors' analysis.

Figure 1: Evolution of electricity spot prices and fossil fuel prices for September 2009-December 2019.



Source: Authors' construction.

Table 2: Data description

Variables	Description	Units	Source
Electricity spot prices (EP)	The monthly electricity spot price of the Colombian wholesale electricity market	COP$/kWh	XM information
Crude oil prices (OP)	West Texas Intermediate (WTI)-Cushing, Oklahoma. Not seasonally adjusted	USD/Barrel	Refinitiv
Natural gas prices (GP)	Henry Hub natural gas spot price. Not seasonally adjusted	USD/MMBTU	Refinitiv
Coal prices (CP)	Global price of Coal, Australia. Not seasonally adjusted	USD/ton	Refinitiv

Source: Authors' construction

Table 3: Descriptive statistics of electricity spot prices and energy commodity prices

Statistical parameters	EP	OP	GP	CP
Mean	0.0071	−0.0014	−0.0028	−0.00081
Median	0.022	0.011	−0.013	−0.0035
Maximum	0.92	0.21	0.38	0.23
Minimum	−0.92	−0.25	−0.37	−0.18
SD	0.33	0.078	0.12	0.062
Skewness	0.18	−0.62	0.58	0.48
Kurtosis	3.67	3.86	4.27	4.46
t-ADF	−11.09***	−8.51***	−11.83***	−8.62***

Data correspond to monthly logarithmic returns. *** indicates that the null hypothesis of a unit root is rejected at a 1% level. Source: Authors' analysis

Table 4: Total connectedness table

	CP	GP	OP	EP	"From others"
CP	**89.70**	2.98	4.10	3.23	10.30
GP	2.63	**86.09**	7.49	3.79	13.91
OP	6.10	2.13	**89.68**	2.09	10.32
EP	1.22	10.56	8.04	**80.18**	19.82
"To others"	9.95	15.67	19.62	9.11	13.59
Net	−0.35	1.76	9.30	−10.71	

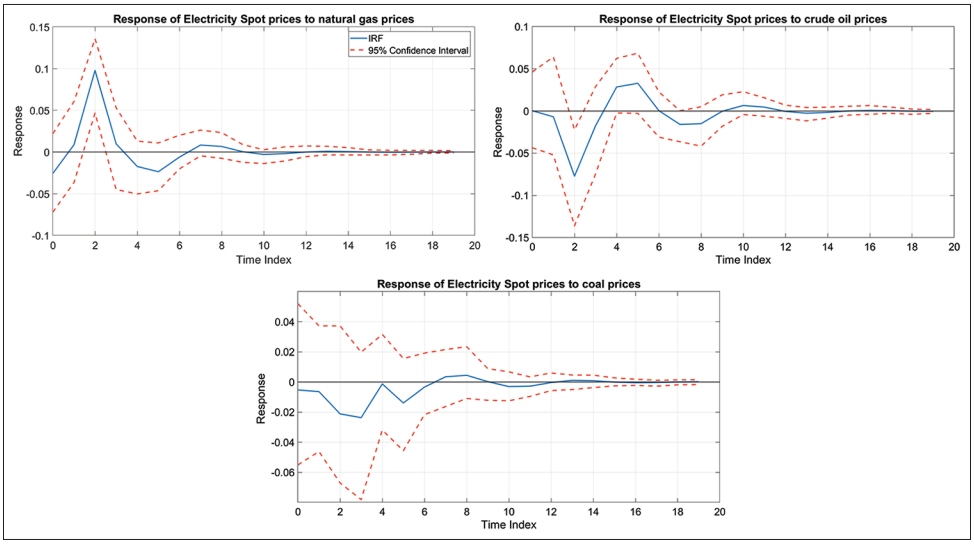
The energy price that transmits the shock is shown in the column, while the energy price that receives it is shown in the rows. The $i - j^{th}$ value is the estimated contribution to the forecast error variance of energy price i coming from innovation to energy price j. The diagonal elements (i = j) (bold type) describe their own energy price spillovers, while the off-diagonal elements ($i \neq$ j) represent the pairwise directional spillovers. The column appointed "From others" reports the total volatility spillovers received by each energy price (rows) from the rest of the system and the row appointed "To others" describes the total volatility transmitted by each energy price (columns) to the rest of the system. Source: Authors' analysis

others" to each energy price (see the last column). Therefore, the own effects range between 80.2% and 89.7%, and the total directional spillovers "From others" range between 10.30% and 19.82%.

In contrast, the row labeled "To others" describes the total directional connectedness distribution transmitted by each energy price to the rest of the system. Thus, total spillovers "To others" range between 9.11% and 19.62%. Based on the EP, it is identified the following pairwise connectedness measures: From CP to EP is 1.2%, from GP to EP is 10.56%, and from OP to EP is 8.04%. Hence, 19.82% of the electricity spot price volatility is related to fossil fuel price fluctuations. In addition, the connectedness measures show that the system's average connectedness is 13.6%.

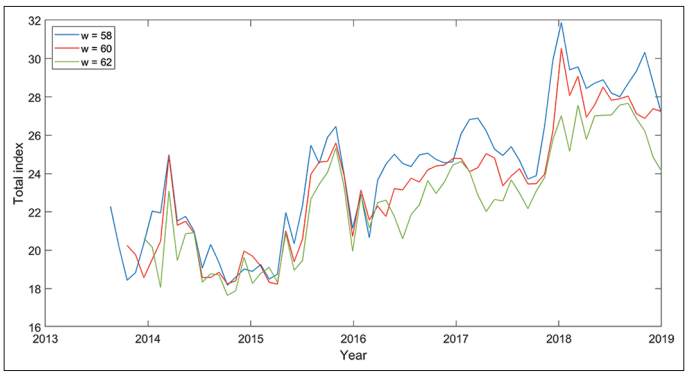
Likewise, the row labeled Net allows us to classify whether each energy price is a transmitter or a receiver of volatility shocks. The negative value of the EP (−10.71%) suggests that the electricity price is a net shock receiver of volatility from the other energy prices.

Figure 2: Electricity spot price generalized response to a positive shock of fossil fuel prices.



Source: Authors' analysis

Figure 3: Total connectedness dynamic index. The index is defined as the sum of all variance decomposition contributions "To others."



Source: Authors' analysis.

Similarly, Figure 2 shows the EP response to a fossil fuel shock through the IRF. First, is observed a significant and positive response to the natural gas price shock. Therefore, natural gas is a relevant driver for understanding electricity price changes. In Colombia, a significant proportion (12%) of the electric power generation comes from this source and their volatility dynamics impact generation costs. According to Nakajima and Toyoshima (2020) and Uribe et al. (2022), natural gas prices increase costs to a large extent, and the effect is higher when the electricity price is higher. Second, the electricity price response to the oil price shock is negative and significant because electricity suppliers absorb the crude oil price changes, mainly the lower prices than higher prices (Jantuah and Adom, 2020). Given the dependence on crude oil exportation in Colombia, this market has important implications for the economy aggregates that can mitigate the electricity spot price response. Third, the coal shock is non-significant because the electricity price does not capture the coal price dynamic in economies with high coal reserves (Elliott et al., 2019).

Meanwhile, a total index was constructed that describes the average system wide connectedness of the energy prices. It was considered three monthly window lengths: 58, 60, and 62 (Figure 3). It is observed different cycles of high volatility are related to exogenous shocks. During 2014 and 2016, the water reservoirs decreased, natural gas prices increased, and the thermal generation sector did not come into operation on time. Therefore, the electricity price reached a peak. On the other hand, during 2018 and 2019, the highest total connectedness measure (32%) was observed because of the ENSO effect and energy commodity demand and supply fluctuations (Oviedo-Gómez et al., 2021b).

5. CONCLUSIONS

The volatility spillovers between the electricity spot prices of the Colombian electricity market and fossil fuel prices were analyzed. The method allowed classifying the electricity price as net shock receivers, and the fossil fuel prices explain their volatility by 20%. The remainder of the electricity price dynamics can be explained through the reservoir levels. On the other hand, the research shows the risk network of the hydrothermal power generation market depends on external events such as ENSO shocks or thermal source price fluctuations. For this reason, the study contributes to regulatory policy design to reduce exposure to the electricity market.

Besides, the IRF showed a significant response of the electricity price to oil and natural gas price shocks. First, natural gas prices are a relevant source that increases the costs of the generation sector and consequently increases the electricity price. Second, the oil prices decrease the electricity prices because the suppliers absorbed the shock. It is relevant to clarify that the Colombian economy is based on oil exportation, and several economic aggregates can mitigate price volatility. Therefore, future research proposals should identify the mechanism by which fossil fuel prices transmit their fluctuation in the electricity market. Besides, it would be relevant to evaluate the fossil fuel price spillovers in other hydrothermal markets with different economic structures as Brazil, India, Australia, Turkey, and Canada.

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