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Climate Shocks and Electricity Prices in a Hydropower-Based System with Thermal Backup: Evidence from a Developing Economy

Choques climáticos y precios de la electricidad en un sistema basado en energía hidroeléctrica con respaldo térmico: datos de una economía en desarrollo

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ABSTRACT

Objective: To examine the impact of extreme climate events, specifically El Niño and La Niña, on electricity prices in energy systems that rely primarily on hydropower generation with thermal backup.
Design/Methodology: A Vector Autoregressive (VAR) model is employed to analyze shock transmission and the resulting price volatility. The analysis is extended using a Quantile Vector Autoregressive (QVAR) model. While the VAR model captures the average dynamic interactions among variables, the QVAR model provides a more nuanced assessment by estimating heterogeneous effects across different quantiles of the electricity price distribution.
Findings: The empirical findings show that extreme climate events such as El Niño and La Niña have a statistically significant impact on electricity prices. Importantly, these effects are not evenly distributed across all price levels. Higher quantiles exhibit stronger responses, indicating that electricity prices are more sensitive to climate shocks during periods of elevated prices.
Conclusions: The findings highlight the importance of incorporating climate risk into energy market models and decision-making processes. In hydropower-dependent systems, extreme climate events can trigger price spikes, which may jeopardize market stability and energy security. Therefore, adaptive planning and energy diversification strategies are crucial for managing future climate-related uncertainties.

Keywords: extreme climate events, hydropower-based systems, electricity prices, thermal generation backup, developing economies, quantile analysis.

Highlights

- Extreme climate events increase electricity price volatility.
- Higher quantiles of the price distribution exhibit greater sensitivity to climate shocks.
- Energy mix diversification reduces vulnerability to climate-related risks.

RESUMEN

Objetivo: Examinar el impacto de los fenómenos climáticos extremos, concretamente El Niño y La Niña, en los precios de la electricidad en sistemas energéticos que dependen principalmente de la generación hidroeléctrica con respaldo térmico.
Diseño/metodología: Se emplea un modelo de vectores autorregresivos (VAR) para analizar la transmisión de los choques y la volatilidad de los precios resultante, y se amplía el análisis mediante un modelo de vectores autorregresivos por cuantiles (QVAR). Mientras que el modelo VAR capta las interacciones dinámicas medias entre las variables, el modelo QVAR ofrece una evaluación más matizada al estimar efectos heterogéneos en los diferentes cuantiles de la distribución de los precios de la electricidad.
Resultados: Los resultados empíricos muestran que los fenómenos climáticos extremos, como El Niño y La Niña, tienen un impacto estadísticamente significativo en los precios de la electricidad. Cabe destacar que estos efectos no se distribuyen de manera uniforme en todos los niveles de precios. Los cuantiles más altos muestran respuestas más intensas, lo que indica que los precios de la electricidad son más sensibles a los choques climáticos durante los períodos de precios elevados.
Conclusiones: Los resultados ponen de relieve la importancia de incorporar el riesgo climático en los modelos del mercado energético y en los procesos de toma de decisiones. En los sistemas que dependen de la energía hidroeléctrica, los fenómenos climáticos extremos pueden provocar picos de precios, lo que puede poner en peligro la estabilidad del mercado y la seguridad energética. Por lo tanto, la planificación adaptativa y las estrategias de diversificación energética son cruciales para manejar las futuras incertidumbres climáticas.

Palabras clave: fenómenos climáticos extremos, sistemas basados en energía hidroeléctrica, precios de la electricidad, generación térmica de respaldo, economías en desarrollo, análisis de cuantiles.

Highlights

- Los fenómenos climáticos extremos aumentan la volatilidad del precio de la electricidad.
- Los cuantiles más altos de la distribución de precios muestran una mayor sensibilidad a los choques climáticos.
- La diversificación de la matriz energética reduce la vulnerabilidad ante los riesgos climáticos.

1. INTRODUCTION

Energy production is the primary source of emissions contributing to climate change underscoring the urgent need for a transition towards a renewable energy-based system (Osman et al., 2023). Electricity generation and its improvement are key elements in the transformation of the energy sector aimed at ensuring a secure and sustainable future for all populations (Cohen & Stanhill, 2016). Global energy demand continues to rise driven mainly by economic growth, which in turn intensifies energy consumption worldwide (Restrepo Londoño & Sepúlveda Rivillas, 2016). However this increase is not explained by economic growth alone. In developing economies rising energy demand is also associated with population growth, urbanization, industrial expansion, higher household income, increasing access to electricity and the electrification of productive and transportation activities. These factors place additional pressure on electricity systems and make it necessary to understand not only whether energy demand is increasing, but also how and why this growth occurs**.** This growth is particularly pronounced in developing countries (Jiang & Hu, 2018). Energy demand is projected to increase by 56 % by 2040 (Rahman et al., 2022) and if the current reliance on fossil fuels persists, this growth will lead to a proportional rise in greenhouse gas emissions thereby accelerating climate change.

This research focuses on Colombia a hydro-dependent electricity system in which approximately 70 % of generation comes from hydroelectric sources and around 25 % from thermal plants while the remaining share is supplied by other generation technologies including non-conventional renewable sources and minor generation units. The generation structure makes the Colombian electricity market high sensitive to hydrological particularly during climate anomalies associated with the El Niño- Southern Oscillation (ENSO)**.** This research analyzes the impact of climate variability on electricity price changes in a system where hydroelectric generation plays a dominant role and thermal plants operate as backup during periods of hydrological stress. In this context El Niño events can reduce rainfall, water inflows, and reservoir levels limit hydroelectric generation and increase the need for fossil fuel-based thermal generation. This substitution mechanism raises marginal generation costs and may lead to significant increases in electricity prices.

This study understands thermal generation as a mechanism that increases domestic electricity costs and contributes marginally to global greenhouse gas emissions, rather than as a direct driver of ENSO dynamics. The main research question addressed in this study is the following: how does climate variability, particularly El Niño and La Niña events, affect electricity price changes in a hydro-dependent electricity market, and through which generation mechanisms do these effects occur? To address this question, we employ Vector Autoregressive (VAR) models and their extensions to analyze the dynamic interactions among climate conditions, hydroelectric generation, thermal generation, and electricity prices. Rather than analyzing the transmission of volatility, this study examines how shocks in climate-related variables and generation sources are associated with changes in the level of electricity prices over time**.** Additionally, we use a Quantile Vector Autoregressive (QVAR) model to assess the behavior of electricity prices across different quantiles of the conditional distribution. This approach allows us to determine whether the effects of climate variability are stronger during extreme price episodes than under normal market conditions.

Based on this framework, the study proposes four main hypotheses. First, climate variability has a significant effect on electricity price changes in Colombia's hydro-dependent electricity market. Second, El Niño events exert a stronger upward effect on electricity prices than La Niña events, reflecting the asymmetric nature of climate impacts. Third, reductions in hydroelectric generation increase the use of fossil-fuel-based thermal generation, raising marginal generation costs and electricity prices. Fourth, the relationship between climate variability and electricity prices is nonlinear, meaning that the magnitude of the effect is greater during extreme hydrological or market conditions than under normal conditions.

This study makes a novel contribution to the literature by providing empirical evidence of a nonlinear relationship between climatic phenomena, particularly El Niño and La Niña, and electricity price changes in a hydro-dependent energy system. Our findings align more closely with recent studies that highlight the asymmetrical impact of climate shocks on electricity markets. Moreover, while European-based research has emphasized threshold effects in temperature and precipitation on electricity pricing (Mosquera-López et al., 2024) this study extends such insights to the Colombian context, where limited reservoir capacity and strong reliance on hydroelectricity magnify the influence of climatic variability. Methodologically, the combination of impulse-response functions with connectedness analysis based on the Diebold and Yilmaz (2012) approach allows for a dynamic understanding of how shocks in climate conditions, hydroelectric generation, and fossil-fuel-based generation are associated with changes in electricity prices.

The relevance of this study lies in explaining how climate variability particularly extreme events such as El Niño, affects electricity prices within a predominantly hydroelectric system. Although hydropower is generally considered a low carbon source of electricity its dependence on water availability makes hydro-dominated electricity systems highly vulnerable to climatic shocks. When water scarcity reduces hydroelectric generation, the system requires increased support from fossil fuel based thermal plants which are generally more expensive and carbon intensive. The substitution not only increases electricity prices but also reveals the economic vulnerability of hydro dependent systems under climate stress. By identifying these mechanisms, the study provides new evidence on the dynamic, asymmetric and nonlinear interactions between climate variability, generation composition and electricity prices in an emerging electricity market.

2. THEORETICAL FRAMEWORK

Electricity markets are increasingly exposed to climate-related factors because electricity generation demand and prices are closely linked to weather conditions and the availability of natural resources. Previous studies have shown that variables such as temperature, precipitation, wind speed, solar radiation, hydrological inflows, reservoir levels, electricity demand and installed generation capacity can influence electricity price dynamics (Butchers et al., 2022, Russo et al., 2022). In systems with a high participation of renewable energy sources especially hydropower these effects become more relevant because generation capacity depends directly on climatic and hydrological conditions. For instance, changes in precipitation and water inflows can alter the availability of hydroelectric generation while temperature changes may affect electricity demand for cooling or heating, (Mello et al., 2021; Rübbelke & Vögele, 2013).

The literature has documented that weather conditions can influence electricity prices through both supply-side and demand-side mechanisms. On the supply side climate conditions affect the availability of renewable sources such as hydropower, wind, and solar energy. On the demand side temperature variations can increase electricity consumption especially during periods of extreme heat or cold. Studies such as Do et al. (2019), Manowska and Nowrot (2019), Mosquera-López et al. (2017) and Mosquera-López et al. (2024) show that the effect of weather variables on electricity prices may differ depending on market conditions generation structure and the position of prices within their distribution.

A central concept in this literature is the existence of nonlinear relationships between climate variables and electricity prices. In this study a nonlinear relationship is understood as a relationship in which the effect of a climate-related variable on electricity prices is not constant, proportional or identical across all hydrological and market conditions (Sasana et al., 2023; Teotónio et al., 2017). In other words, the effect of a climate shock may depend on the initial state of the electricity system. For example, under normal reservoir levels a moderate reduction in rainfall may have only a limited effect on electricity prices (van Vliet et al., 2016). However during El Niño episodes, a severe reduction in water availability may significantly reduce hydroelectric generation and increase the need for fossil-fuel-based thermal generation leading to stronger increases in electricity prices.

This nonlinear behavior is especially relevant in hydro-dependent electricity systems. Hydropower is generally considered a low-carbon electricity source but its dependence on water availability makes it highly sensitive to climate variability. When reservoir levels and water inflows are sufficient hydroelectric generation can supply electricity at relatively low marginal costs. When water availability decreases the system may require greater participation from thermal plants which usually have higher marginal costs because they depend on fossil fuels such as natural gas, coal, or oil (Ugurlu et al., 2018).

ENSO is one of the most relevant sources of climate variability for hydroelectric systems in Latin America. El Niño events are often associated with reductions in rainfall and hydrological inflows in several regions while La Niña events may be associated with increased precipitation and higher water availability, (Venturini, 2022). In countries where electricity generation depends heavily on hydropower these events can alter the balance between hydroelectric and thermal generation. During El Niño periods lower water availability may reduce hydroelectric generation and increase the need for thermal backup. This substitution mechanism can raise marginal generation costs and generate upward pressure on electricity prices (Téllez Gutiérrez et al., 2018).

Several studies have examined electricity price formation using weather-related and generation-related variables. For example, studies on electricity price prediction use variables such as temperature, wind speed, precipitation, hydrological inflows, and solar radiation to explain price changes. These variables are relevant because they affect both electricity demand and the availability of renewable generation. In hydrothermal systems hydrological conditions are particularly important because they determine the opportunity cost of water and the need to activate thermal plants. Oviedo-Gómez et al. (2021) and Billé et al. (2023), for instance, analyze electricity price fundamentals in hydrothermal markets and highlights the importance of generation structure and climatic conditions in price formation.

The use of quantile-based methods has become relevant in this field because the relationship between climate variables and electricity prices may differ across the distribution of prices. Traditional mean-based models can identify average effects but they may fail to capture what happens during extreme price episodes. Quantile approaches allow researchers to examine whether climate shocks have stronger effects when prices are already high or when the system is under stress. This is consistent with studies such as Do et al. (2019), Manowska and Nowrot (2019) and Mosquera-López et al. (2024), which show that electricity price responses can differ across quantiles.

Therefore, the notion of nonlinearity is central to this study because it allows us to analyze whether climate shocks have stronger effects during extreme price episodes than under normal market conditions. In a hydro-dependent system the same climatic shock may produce different price effects depending on reservoir levels, hydrological inflows, demand conditions and the availability of thermal generation. The literature also connects energy prices with broader economic outcomes. Dechezleprêtre and Sato (2017) discuss how environmental regulation climate pressures and energy costs may affect firms' competitiveness and labor market outcomes. In this context changes in electricity prices should be understood as one possible economic channel through which climate related pressures on energy systems may influence production costs and indirectly employment dynamics. This relationship should not be interpreted as implying that electricity prices are the only or the main mechanism through which climate change affects labor markets**.** A more precise causal sequence is that climate change and climate variability can alter energy system conditions.

This discussion is particularly relevant because the electricity system depends strongly on hydropower. This structure provides important environmental advantages under normal hydrological conditions but it also increases exposure to climate variability. When hydrological conditions deteriorate especially during El Niño events the system may require greater thermal generation to guarantee electricity supply (Tian et al., 2022). The central argument of this study is that these relationships are nonlinear and asymmetric. El Niño and La Niña may not affect prices with the same intensity or direction and their effects may be stronger during extreme hydrological or market conditions. This provides the theoretical basis for using VAR and QVAR models to analyze both average dynamic interactions and heterogeneous responses across the conditional distribution of electricity prices.

3. METHODOLOGY

This research aims to identify how different climatic scenarios affect electricity price changes in a hydro-dependent electricity system where approximately 70 % of electricity generation comes from hydroelectric plants. To achieve this objective, we employ VAR models and their extensions originally proposed by Sims (1972), to analyze the dynamic interactions among electricity prices, climate variables, hydroelectric generation, thermal generation and other relevant system variables.

The VAR framework is appropriate for this study because it treats the variables included in the system as jointly endogenous. This means that each variable may be affected by its own past values and by the past values of the other variables in the system**.** In addition, we use the Diebold and Yilmaz (2012) connectedness approach based on generalized forecast-error variance decompositions. This approach allows us to quantify the degree of statistical connectedness among the variables of the system, identifying how much of the forecast-error variance of one variable is explained by shocks to other variables. Since the generalized VAR framework is used, the results are invariant to the ordering of the variables.

Finally, we use a QVAR, following Chatziantoniou et al. (2021), to examine whether the relationships among the variables differ across the conditional distribution. This allows us to graph the quantile-dependent connectedness among the system variables and identify the scenarios in which statistical connectedness is stronger. In this context, connectedness refers to statistical dependence based on forecast-error variance decompositions, not to the physical interconnection of the electricity system.

VAR model

Let $\mathbf{z}_t$ be a $K \times 1$ vector of endogenous variables observed at time t. In this study, $\mathbf{z}_t$ may include electricity price changes, climate indicators, hydroelectric generation, thermal generation, and other relevant electricity system variables. A reduced-form VAR(p) model can be written as:

$$\boldsymbol{z}_t = \boldsymbol{c} + \sum_{i=1}^{p} \boldsymbol{A}_i\, \boldsymbol{z}_{t-i} + \boldsymbol{u}_t, \qquad (1)$$

where $\mathbf{z}_t$ is a $K \times 1$ vector of endogenous variables, $\mathbf{c}$ is a $K \times 1$ vector of intercepts, $\mathbf{A}_i$ is a $K \times K$ matrix of autoregressive coefficients for lag i, p is the number of lags, and $\mathbf{u}_t$ is a $K \times 1$ vector of reduced-form innovations. The innovations satisfy:

$$\mathrm{E}(\mathbf{u}_t) = \mathbf{0}, \mathrm{E}(\mathbf{u}_t\mathbf{u}_t') = \mathbf{\Sigma}, \qquad (2)$$

where $\mathbf{\Sigma}$ is the $K \times K$ variance-covariance matrix of the innovations.

All variables included in the VAR must be stationary. Therefore, before estimating the model, unit root tests should be applied, and non-stationary variables should be transformed when necessary, for example by using first differences or growth rates. The stability of the VAR is verified by checking that the eigenvalues of the companion matrix lie inside the unit circle. This condition ensures that the moving-average representation of the model exists.

Structural and reduced-form representation

A structural representation of the VAR can be written as:

$$\mathbf{B}\mathbf{z}_t = \boldsymbol{\delta}_0 + \sum_{i=1}^{p} \boldsymbol{\delta}_i\, \mathbf{z}_{t-i} + \boldsymbol{\varepsilon}_t, \qquad (3)$$

where $\mathbf{B}$ is a $K \times K$ matrix that captures contemporaneous relationships among the variables, $\boldsymbol{\delta}_0$ is a $K \times 1$ vector of constants, $\boldsymbol{\delta}_i$ is a $K \times K$ matrix of structural lag coefficients, and $\boldsymbol{\varepsilon}_t$ is a $K \times 1$ vector of structural shocks.

To obtain the reduced-form representation, both sides of equation (3) are multiplied by $\mathbf{B}^{-1}$:

$$\mathbf{z}_t = \mathbf{B}^{-1}\boldsymbol{\delta}_0 + \sum_{i=1}^{p} \mathbf{B}^{-1}\, \boldsymbol{\delta}_i\mathbf{z}_{t-i} + \mathbf{B}^{-1}\boldsymbol{\varepsilon}_t. \qquad (4)$$

Thus, the reduced-form VAR can be expressed as:

$$\mathbf{z}_t = \mathbf{c} + \sum_{i=1}^{p} \mathbf{A}_i\, \mathbf{z}_{t-i} + \mathbf{u}_t, \qquad (5)$$

where:

$$\mathbf{c} = \mathbf{B}^{-1}\boldsymbol{\delta}_0, \mathbf{A}_i = \mathbf{B}^{-1}\boldsymbol{\delta}_i, \mathbf{u}_t = \mathbf{B}^{-1}\boldsymbol{\varepsilon}_t. \qquad (6)$$

This correction clarifies why the matrix Bdisappears in the reduced-form equation: it is not omitted but absorbed into the reduced-form parameters after premultiplying by B^{-1}.

Bivariate illustration

For illustration, a bivariate VAR(1) model can be written as:

$$y_t = \alpha_1 + a_{11}y_{t-1} + a_{12}x_{t-1} + u_{1t}, \quad (7)$$
$$x_t = \alpha_2 + a_{21}y_{t-1} + a_{22}x_{t-1} + u_{2t}. \quad (8)$$

In matrix form:

$$\begin{bmatrix} y_t \\ x_t \end{bmatrix} = \begin{bmatrix} \alpha_1 \\ \alpha_2 \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ x_{t-1} \end{bmatrix} + \begin{bmatrix} u_{1t} \\ u_{2t} \end{bmatrix}. \quad (9)$$

Unlike the previous version, this formulation avoids classifying $x_t$as exogenous. In a VAR model, both $y_t$and $x_t$are treated as endogenous variables.

Moving-average representation

If the VAR is stable, it can be represented as an infinite vector moving-average process:

$$\mathbf{z}_t = \sum_{h=0}^{\infty} \mathbf{\Psi}_h \, \mathbf{u}_{t-h}, \quad (10)$$

where $\mathbf{\Psi}_h$is a $K \times K$matrix of moving-average coefficients at horizon h. The initial matrix is:

$$\mathbf{\Psi}_0 = \mathbf{I}_K, \quad (11)$$

where $\mathbf{I}_K$is the $K \times K$identity matrix. For $h < 0$, we define:

$$\mathbf{\Psi}_h = \mathbf{0}. \quad (12)$$

The moving-average coefficients are obtained recursively as:

$$\mathbf{\Psi}_h = \sum_{i=1}^{p} \mathbf{A}_i \, \mathbf{\Psi}_{h-i}, h = 1,2, \ldots \quad (13)$$

The index h is used for the impulse-response horizon, while $i$is reserved for the lag order of the VAR. This avoids mixing indices in the summations.

Impulse-response functions

Impulse-response functions (IRF) are used to trace the dynamic response of one variable to a shock in another variable over time. In this study IRF are interpreted as dynamic responses conditional on the estimated VAR model and the adopted shock-identification strategy. They do not eliminate endogeneity; rather, they summarize how shocks propagate through the system once the VAR has been estimated.

The generalized impulse-response function can be expressed as:

$$GIRF_{ij}(h) = \frac{\mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \mathbf{e}_j}{\sqrt{\sigma_{jj}}}, \qquad (14)$$

where $\mathbf{e}_i$ is a $K \times 1$ selection vector with one in the i-th position and zeros elsewhere, $\mathbf{e}_j$ is the corresponding selection vector for variable j, $\boldsymbol{\Psi}_h$ is the moving-average coefficient matrix at horizon h, $\boldsymbol{\Sigma}$ is the variance-covariance matrix of the innovations, and σ_{jj} is the j-th diagonal element of $\boldsymbol{\Sigma}$.

Forecast-error variance decomposition and connectedness

Following Diebold and Yilmaz (2012), the generalized forecast-error variance decomposition is used to measure the contribution of shocks in variable j to the H-step-ahead forecast-error variance of variable i. The generalized variance decomposition is defined as:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \mathbf{e}_j\right)^2}{\sum_{h=0}^{H-1} \left(\mathbf{e}_i' \boldsymbol{\Psi}_h \boldsymbol{\Sigma} \boldsymbol{\Psi}_h' \mathbf{e}_i\right)}, \qquad (15)$$

where $\theta_{ij}^{g}(H)$ measures the share of the H-step-ahead forecast-error variance of variable i attributable to shocks in variable j. Here, σ_{jj} is the j-th diagonal element of $\boldsymbol{\Sigma}$.

Since the elements of the generalized variance decomposition are not necessarily row-normalized, they are normalized as follows:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{K} \theta_{ij}^{g}(H)}. \qquad (16)$$

Thus:

$$\sum_{j=1}^{K} \tilde{\theta}_{ij}^{g}(H) = 1, \sum_{i,j=1}^{K} \tilde{\theta}_{ij}^{g}(H) = K. \qquad (17)$$

The total connectedness index is calculated as:

$$C^{g}(H) = \frac{\sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{\theta}_{ij}^{g}(H)}{K} \times 100. \qquad (18)$$

This index measures the overall degree of statistical connectedness among the variables of the system. It replaces the previous expression “total volatility spillover index” because the purpose of this study is to analyze connectedness among changes in electricity prices, climate variables, and generation variables, rather than volatility in the strict statistical sense.

Directional connectedness

The directional connectedness received by variable $i$from all other variables is defined as:

$$C_{i\leftarrow\cdot}^{g}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{K} \tilde{\theta}_{ij}^{g}(H)}{K} \times 100. \quad (19)$$

The directional connectedness transmitted by variable $i$to all other variables is defined as:

$$C_{i\rightarrow\cdot}^{g}(H) = \frac{\sum_{\substack{j=1\\ j\neq i}}^{K} \tilde{\theta}_{ji}^{g}(H)}{K} \times 100. \quad (20)$$

The net directional connectedness of variable $i$is:

$$C_{i}^{g}(H) = C_{i\rightarrow\cdot}^{g}(H) - C_{i\leftarrow\cdot}^{g}(H). \quad (21)$$

A positive value of $C_{i}^{g}(H)$indicates that variable $i$is a net transmitter of shocks to the system, while a negative value indicates that it is a net receiver.

The net pairwise connectedness from variable $i$to variable $j$is defined as:

$$C_{ij}^{g}(H) = \left(\frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{K}\right) \times 100. \quad (22)$$

This formulation replaces the ambiguous expressions "from $i$to j" and "from $j$to i" with explicit notation for received, transmitted, net, and pairwise connectedness.

Quantile VAR model

To analyze whether the relationships among variables differ across the conditional distribution, we estimate a Quantile VAR model.

Let $q \in (0,1)$ denote a quantile. The conditional quantile function of $\mathbf{z}_t$given the information set $\mathcal{F}_{t-1}$is defined as:

$$Q_{\mathbf{z}_t}(q \mid \mathcal{F}_{t-1}) = \boldsymbol{\mu}(q) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(q)\mathbf{z}_{t-j}. \quad (23)$$

The QVAR(p) model can be written as:

$$\mathbf{z}_t = \boldsymbol{\mu}(q) + \sum_{j=1}^{p} \boldsymbol{\Phi}_j(q)\mathbf{z}_{t-j} + \boldsymbol{\varepsilon}_t(q), \quad (24)$$

where $\mathbf{z}_t$is a $K \times 1$vector of endogenous variables, $\boldsymbol{\mu}(q)$is a $K \times 1$vector of quantile-specific intercepts, $\boldsymbol{\Phi}_j(q)$is a $K \times K$matrix of quantile-specific autoregressive coefficients, $p$is the number of lags, and $\boldsymbol{\varepsilon}_t(q)$is a $K \times 1$vector of quantile-specific errors.

The error term satisfies the quantile restriction:

$$Q_{\varepsilon_t(q)}(q \mid \mathcal{F}_{t-1}) = \mathbf{0}. \qquad (25)$$

The word "quantile" is used instead of "quartile" because the model can be estimated at any point of the conditional distribution, such as $q = 0.05$, $q = 0.50$, or $q = 0.95$, not only at the three quartiles. In addition, the coefficients $\Phi_j(q)$depend on the quantile q, which allows the relationships among the variables to change across low, median, and high-price scenarios.

Following the connectedness framework, the generalized forecast-error variance decomposition can be computed for each quantile. This allows us to obtain quantile-dependent connectedness measures and evaluate whether the statistical connectedness among electricity prices, climate variables, hydroelectric generation, and thermal generation is stronger during extreme scenarios than under normal market conditions.

Data

The data utilized in this study are monthly frequency observations spanning a specific period from May 2002 to July 2024 comprising a total of 267 observations. The data were sourced from the wholesale electricity market administrator in Colombia and the National Oceanic and Atmospheric Administration (NOAA) (see Table 1). The Southern Oscillation Index (SOI) measures the surface atmospheric pressure gradient between Darwin, Australia and Tahiti. This index is employed to reflect the strength of atmospheric circulation in the tropical Pacific. A positive SOI value indicates the presence of La Niña, whereas a negative value signifies the presence of El Niño. Conversely the Oceanic Niño Index (ONI, its acronym in English) is based on sea surface temperature anomalies in the central and eastern regions of the equatorial Pacific. An ONI of +0.5°C or higher sustained over several consecutive months indicates the presence of El Niño, while an ONI of -0.5°C or lower indicates La Niña.

Table 1. Variable definitions

Tabla 1. Definiciones de las variables

Variable	Description	Units	Source
PB	Electricity spot prices	COP/KWh	XM - Wholesale energy market administration
SOI	Southern Oscillation Index	Sea level pressure differentials (SLP)	NOAA Physical science laboratory
ONI	Ocean Niño Index	Anomalies in the Niño 3.4 region (5°N-5°S, 120°-170°W)	NOAA National weather service
CF	Fossil fuel generation	GWh (Gigawatt-hour)	XM - Wholesale energy market administration
VOL	Useful volume of energy	GWh (Gigawatt-hour)	XM - Wholesale energy market administration
DE	Energy demand of the National Interconnected System (SIN)	GWh (Gigawatt-hour)	XM - Wholesale energy market administration
HI	Generation by hydraulic source	GWh (Gigawatt-hour)	XM - Wholesale energy market administration

Source: own elaboration.

The energy matrix is characterized by a high dependency on hydropower generation which accounts for 78 % of the total electricity generation (see Figure 1). This predominance is attributed to the abundance of water resources in the country allowing hydropower to play a central role in meeting energy demand. To complement and ensure the stability of supply 16.17 % of generation derives from fossil fuel-based sources demonstrating the necessary diversification to address seasonal or climatic variations, such as those caused by the El Niño phenomenon (Restrepo-Trujillo et al., 2022). This combination of sources ensures a flexible and adaptive response to the energy needs of the country particularly during periods of water stress.

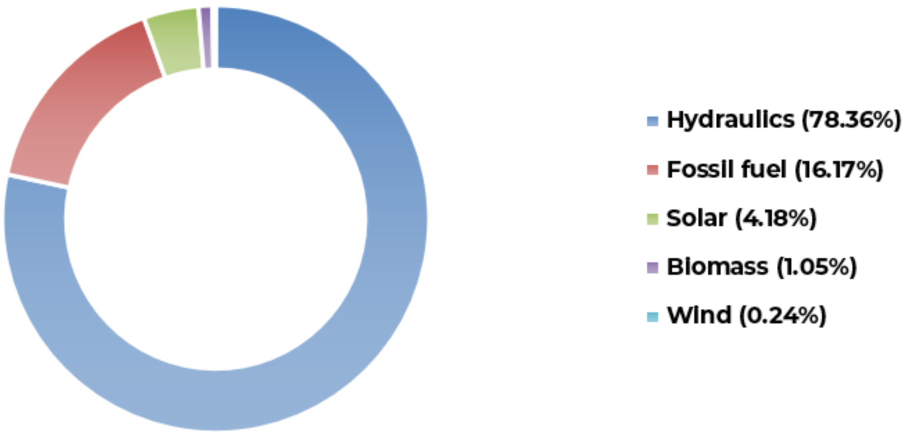


Figure 1. Colombia's energy matrix
Figura 1. Matriz energética de Colombia
Source: own elaboration based on XM data.

Figure 2 displays the normalized variables over time illustrating the anomalies of SOI and ONI in relation to the energy generation sources in Colombia. During the period of 2015-2016 a significant alteration in the energy sources utilized is observed attributed to shifts in the SOI and ONI indices which explains a notable episode of the El Niño phenomenon. Figure 2 depicts the evolution of reservoir volumes, electricity demand, and electricity prices. It is evident that pronounced fluctuations in electricity prices were recorded during the periods of 2015-2016 and 2023-2024 correlating with variations in the ONI Index during those same intervals.

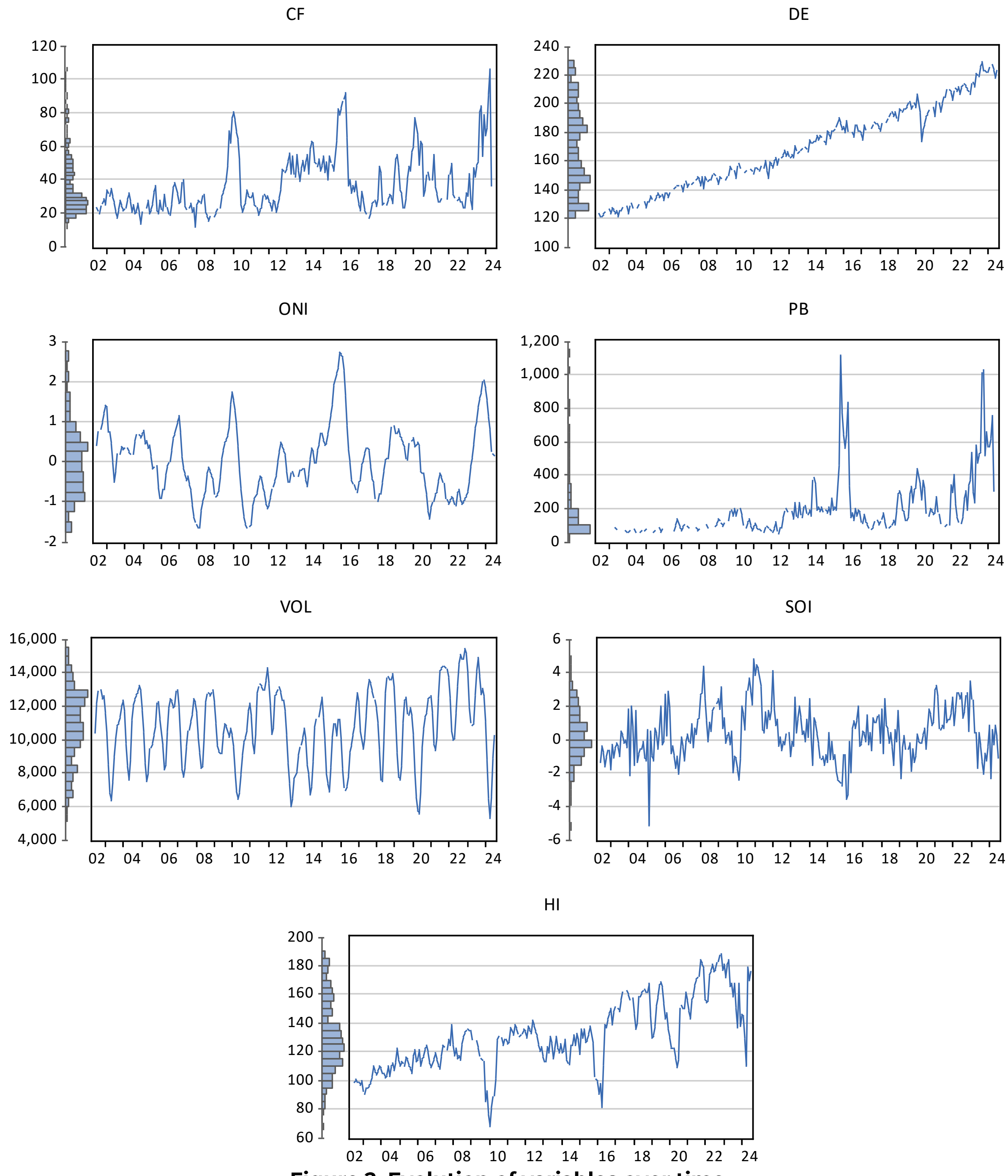


Figure 2. Evolution of variables over time

Figura 2. Evolución de las variables en el tiempo

Source: own elaboration.

Logarithmic difference transformations were applied to the variables CF: Climate Factor, HI: Hydrological Index, DE: Electricity Demand, PB: Electricity Spot Price, and VOL: Energy Volume, ensure the stationarity of the series. Figure 3 presents these variables on a normalized scale revealing significant patterns, pronounced fluctuations in electricity prices are observed during the periods of 2015-2016 and 2023-2024 suggesting potential shocks or structural changes in the energy market.

Additionally, a marked decrease in energy demand is observed in 2020 attributable to the economic contraction resulting from the measures implemented to mitigate the spread of Covid-19.

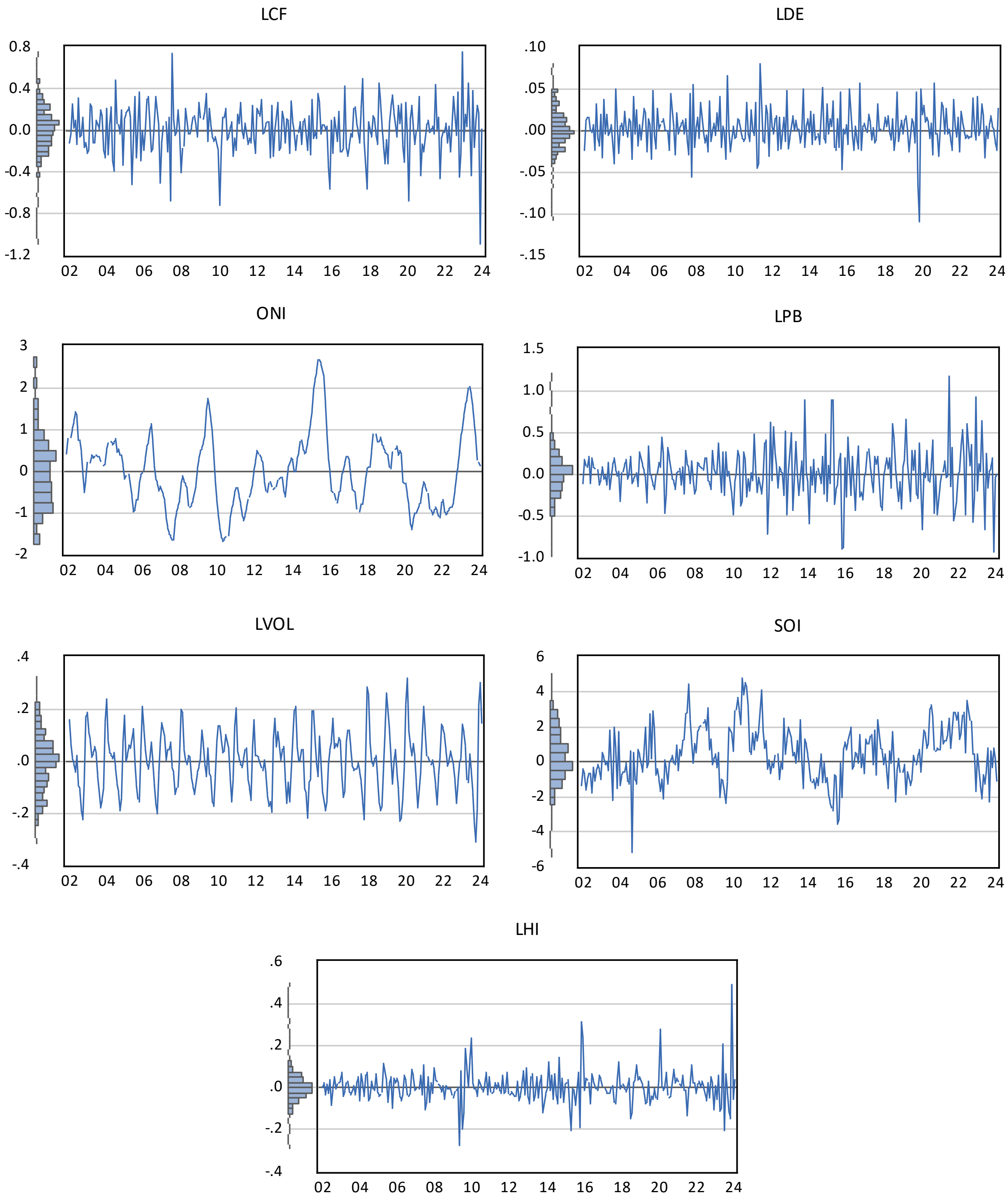


Figure 3. Returns of variables over time

Figura 3. Retornos de las variables a lo largo del tiempo

Source: own elaboration.

Table 2 presents the descriptive statistics and stationarity tests of the series used in this study, panel A reports the descriptive statistics. SOI exhibits the highest dispersion with a standard deviation of 1.54, followed by the ONI and spot electricity prices (LPB) with standard deviations of 0.87 and 0.30 respectively. Regarding distributional asymmetry all variables display some degree of skewness with Natural logarithm of the Hydrological Index (LHI) showing the most pronounced positive skewness (1.20) and Natural logarithm of the Climate Factor (LCF) exhibiting the most marked negative skewness (-0.54). In terms of kurtosis LHI presents the highest value (8.32) indicating a distribution with heavier tails relative to the normal distribution, assuming that standard kurtosis is reported.

The variables expressed in positive economic or energy units were transformed using the natural logarithm in order to reduce scale differences smooth large fluctuations and allow changes to be interpreted approximately in percentage terms. This transformation was applied to variables such as S In contrast, SOI and ONI were not transformed into logarithms because they are standardized climate indices that can take positive, negative, or near-zero values making a logarithmic transformation unsuitable from both a mathematical and interpretative perspective.

Panel B of Table 2 reports the panel unit root tests used to verify the stationarity of the variables. The Levin, Lin and Chu test, which assumes a common unit root process, rejects the null hypothesis of a unit root, with a statistic of -9.14 and a p-value of 0.00. Pesaran and Shin, ADF-Fisher and PP-Fisher tests which allow for individual unit root processes also reject the null hypothesis with p-values equal to 0.00. These results provide statistical evidence that the series included in the model are stationary and therefore suitable for VAR estimation.

Finally, the coefficient of variation is not reported for variables whose mean is close to zero or can take negative values, such as The Southern Oscillation Index (SOI) and the Oceanic Niño Index (ONI), or for transformed variables where the mean may be very small. In these cases, the coefficient of variation can produce negative or extremely large values that are difficult to interpret and may lead to misleading conclusions. For this reason, the analysis of dispersion is based mainly on the standard deviation, skewness, and kurtosis (see table 3).

Table 1. Descriptive statistics*

Tabla 2 Estadísticas descriptivas

	LPB	SOI	ONI	LCF	LVOL	LDE	LHI
Valid	266	266	266	266	266	266	266
Median	0.02	0.30	-0.07	0.01	6.87e-3	3.77e-4	-3.51e-4
Mean	7.41e-3	0.38	-1.84e-3	1.73e-3	-2.68e-5	2.25e-3	2.19e-3
Std. Deviation	0.30	1.54	0.87	0.23	0.11	0.02	0.08
Coefficient of variation	39.87	4.03	-470.60	133.12	-4182.12	10.30	34.62
Skewness	0.22	0.15	0.55	-0.54	0.08	-0.06	1.20
Kurtosis	1.89	0.41	0.31	2.51	-0.09	2.01	8.32
Minimum	-0.93	-5.20	-1.69	-1.09	-0.31	-0.11	-0.28
Maximum	1.17	4.80	2.71	0.75	0.32	0.08	0.49

Source: own elaboration.

* SOI and ONI data show no changes.

Table 3. Stationarity analysis: panel unit root tests

Tabla 3. Análisis estacionario: pruebas de raíz unitaria en panel

Method	Statistic	Prob.	Cross-sections	Obs
Null: Unit root assumes common unit root process				
Levin, Lin & Chu t*	-9.14	0.00	7	1831
Null: Unit root assumes individual unit root process				
Im, Pesaran and Shin W-stat	-25.51	0.00	7	1831
ADF - Fisher Chi-square	465.19	0.00	7	1831
PP - Fisher Chi-square	509.53	0.00	7	1858

Source: own elaboration.

The Pearson correlation analysis (see Figure 4) reveals significant patterns among the variables studied. A strong positive correlation (0.71) is observed between spot electricity prices (LPB) and fossil fuel generation (LCF). Conversely, a substantial negative correlation (-0.62) is evident between LPB and hydroelectric generation (LHI). The most pronounced negative correlation (-0.79) occurs between LCF and LHI, reflecting the substitution relationship between energy sources. Additionally, the climatic indices SOI and ONI demonstrate a significant negative correlation (-0.72), consistent with their inverse relationship.

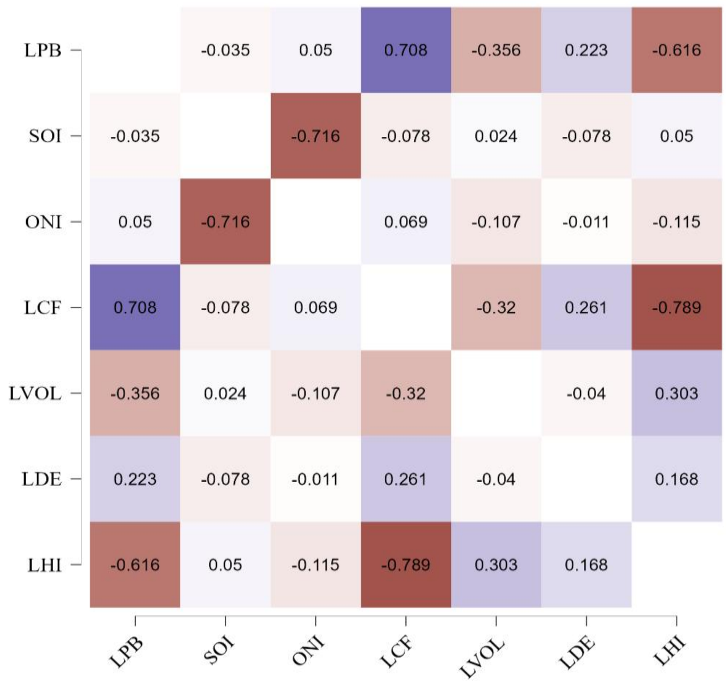


Figure 4. Heatmap of Pearson correlation coefficients

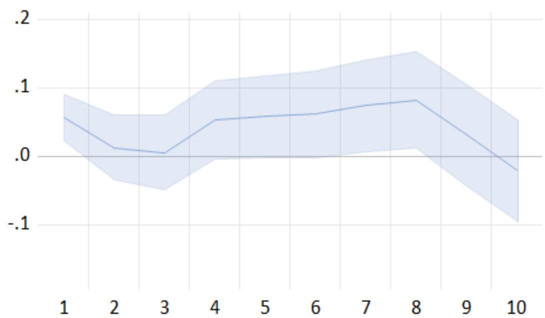
Figura 4. Mapa de calor de coeficientes de correlación de Pearson

Source: own elaboration.

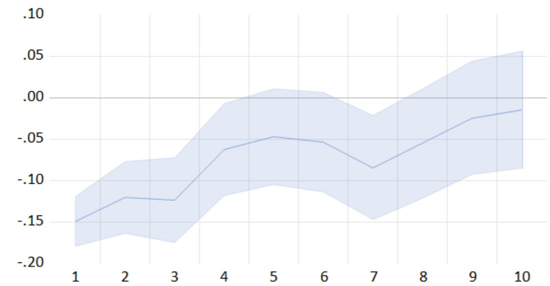
4. RESULTS

Figure 5 presents the accumulated generalized impulse-response functions of spot electricity prices to shocks in the variables included in the VAR system. The VAR model was estimated with 12 monthly lags, and the diagnostic tests indicate no evidence of residual autocorrelation or heteroskedasticity. The impulse-response functions are estimated using generalized impulse-response functions (GIRFS) rather than Cholesky-orthogonalized responses; therefore, the results do not depend on a recursive ordering of the variables in the VAR system. The responses are accumulated over a horizon of $H = 10$ months.

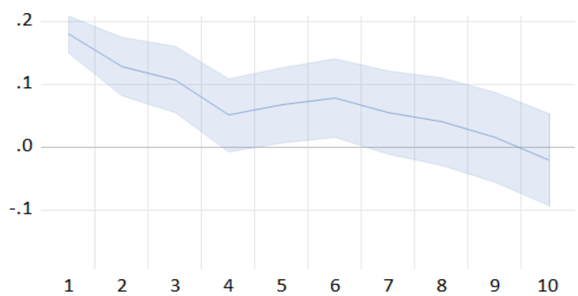
Panel A: Accumulated Response of LPB to LDE Innovation



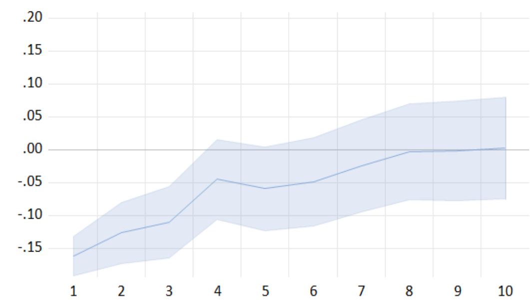
Panel B: Accumulated Response of LPB to LVOL Innovation



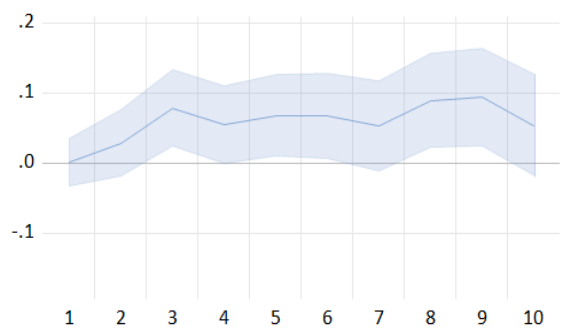
Panel C: Accumulated Response of LPB to LCF Innovation



Panel D: Accumulated Response of LPB to LHI Innovation



Panel E: Accumulated Response of LPB to ONI Innovation



Panel F: Accumulated Response of LPB to SOI Innovation

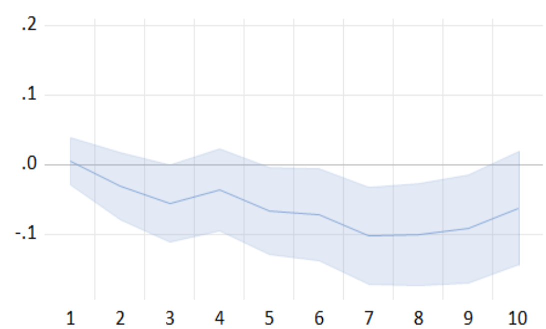


Figure 5. Impulse response functions for spot electricity prices

Figura 5. Funciones de respuesta al impulso para los precios *spot* de la electricidad

Source: own elaboration.

Each panel in Figure 5 represents the accumulated response of spot electricity prices to a one-standard-deviation innovation in a specific variable of the system. The solid line shows the estimated accumulated response, while the light-blue shaded areas represent the 95 % confidence intervals. These intervals indicate the statistical uncertainty around the estimated responses, and a response is interpreted as statistically significant when the confidence interval does not include zero.

Among the findings, an increase in electricity demand leads to a rise in spot electricity prices during months 1 and 8 (Panel A). An increase in fossil fuel generation raises electricity prices from month 1 to month 4 and again in month 6 (Panel C), after which the effect dissipates over time. Conversely, an increase in hydroelectric generation reduces electricity prices over three periods, reflecting the lower marginal cost of hydroelectric production. The onset of El Niño is interpreted as a one-standard-deviation positive innovation in the ONI and is associated with an increase in electricity prices over several periods. In contrast, a shock associated with La Niña reduces electricity prices. Finally, an increase in the available volume of usable energy significantly lowers spot electricity prices, consistent with the role of water availability in reducing the need for more expensive thermal generation.

Table 4 illustrates the connectedness among the variables using the methodology proposed by Diebold and Yilmaz (2012). The table should be interpreted as follows: the diagonal elements represent the share of each variable's forecast-error variance explained by its own shocks, while the off-diagonal elements represent the share explained by shocks from the other variables. The column "From" indicates the connectedness received by each variable from the rest of the system, whereas the row "To" indicates the connectedness transmitted by each variable to the rest of the system.

For LPB, the own variance share is 16.12 %, while 83.88 % of its forecast-error variance is explained by shocks from the remaining variables. The variables that contribute most significantly to changes in electricity prices are LHI and fossil fuel generation (LCF), accounting for 20.41 % and 18.87 %, respectively. Similarly, the SOI and the available energy volume (LVOL) explain 12.69 % and 11.92 %, respectively. These are followed by the ONI and electricity demand (LDE), which account for 10.49 % and 9.52 % of the forecast-error variance of electricity prices, respectively. Collectively, these variables explain 83.88 % of the forecast-error variance of spot electricity prices, according to the "From" column.

Table 4 further shows the role of hydropower and fossil fuel generation in the connectedness structure of the Colombian electricity system. LHI and LCF are the main transmitters of shocks to the system, with "To" values of 121.51 and 112.15, respectively. Their net connectedness values are also positive, with LHI showing the highest net value at 42.44 and LCF the second highest at 31.06. This indicates that these variables act as net transmitters within the system. Therefore, the relevance of hydropower generation should not be inferred from its diagonal value of 20.93 %, since this value represents the own variance share of LHI. Instead, its role as a transmitter is identified through the "To" and "NET" measures.

In addition to generation sources, LDE and LVOL emerge as important receivers of connectedness, with "From" values of 89.15 % and 87.79 %, respectively. This means that a large proportion of the forecast error variance of these variables is explained by shocks from the rest of the system. Results suggest that demand and available energy volume are highly responsive to variations in generation sources and climate-related variables.

The net connectedness values show that the system is characterized by bidirectional dynamic relationships among energy and climate variables. LHI, LCF, and LPB present positive net connectedness values of 42.44, 31.06, and 10.38 respectively indicating that they behave as net transmitters of shocks. By contrast, LDE, ONI, LVOL, and SOI present negative net connectedness values of -31.99, -24.66, -16.60, and -10.65 respectively indicating that they behave mainly as net receivers.

The Total Connectedness Index (TCI) is 85.12 %, indicating a high degree of dynamic connectedness among the variables in the system. The value 595.86 corresponds to the aggregate off-diagonal connectedness before normalization and should not be interpreted as a percentage by itself. The standard TCI is obtained after normalization and corresponds to 85.12 %. The corrected Total Connectedness Index (c TCI) is 99.31 % adjusted by the factor $K/(K-1)$. Finally, the net Pairwise Transmission (NPT) row reports the number of net pairwise transmission relationships for each variable. LHI presents the highest NPT value with 6 net pairwise transmissions followed by LCF with 5 and LPB with 4. This reinforces the role of hydropower generation, fossil fuel generation, and electricity prices as relevant transmitters within the system.

From an economic perspective, these results reflect the operational structure of a hydro-dependent electricity market. Hydropower generation behaves as the main net transmitter because changes in water based generation directly affect the marginal cost of electricity and the need for thermal backup. When hydroelectric availability decreases, the system relies more heavily on fossil fuel generation, which is generally more expensive and therefore amplifies price responses. The positive net connectedness of LPB also indicates that electricity prices do not only respond to shocks but also transmit information to the rest of the system, reflecting their role as a market signal for generation decisions and resource scarcity. In contrast, variables such as demand, available energy volume, ONI, and SOI behave mainly as net receivers because they absorb the effects of shocks transmitted through the generation mix and market conditions. Overall, the high TCI suggests that the Colombian electricity market is strongly integrated, so climatic, hydrological, and generation shocks are rapidly reflected across the system.

Table 4. Volatility transmission across variables[†]

Tabla 4. Transmisión de volatilidad entre variables

	LPB	LCF	LVOL	LDE	LHI	SOI	ONI	From
LPB	16.12	18.87	11.92	9.52	20.41	12.69	10.49	83.88
LCF	16.13	18.92	11.8	9.86	20.17	12.41	10.71	81.08
LVOL	15.47	18.67	12.21	9.62	20.42	12.9	10.72	87.79
LDE	15.59	18.65	11.68	10.85	19.95	12.58	10.69	89.15
LHI	15.71	18.66	11.94	9.63	20.93	12.55	10.57	79.07
TO	94.26	112.15	71.19	57.16	121.51	75.91	63.68	595.86
Inc, Own	110.38	131.06	83.4	68.01	142.44	89.35	75.34	CTCI/TCI
NET	10.38	31.06	-16.6	-31.99	42.44	-10.65	-24.66	99.31/85.12
NPT	4	5	2	0	6	3	1	

Source: own elaboration.

[†] The model was run within a 24-month window and an 18-month forecast horizon.

Figure 6 illustrates the degree of interconnection across different quantiles following the methodological approach applied by Chatziantoniou et al. (2021). In this figure, red denotes a high level of interconnectedness, yellow represents a medium level and light yellow indicates low interconnectedness. The graph reveals that the system maintains a strong degree of interconnection across nearly the entire distribution with a modest decline in the middle quantiles. This reduction is not pronounced as interconnection at the median remains at a medium-high level. In contrast, the upper and lower quantiles exhibit intensified interconnection, suggesting that during periods of extreme economic conditions whether positive or negative the system becomes more tightly linked.

To better highlight the behavior of the system during crisis episodes, specific quantile regions are emphasized using circular markers as proposed by Joaqui-Barandica and Manotas-Duque (2023). This graphical enhancement aims to identify whether the energy market exhibits similar patterns of heightened interconnectedness during crises, as observed in financial markets. By doing so, the analysis allows for a more nuanced understanding of the transmission of shocks under conditions of economic stress.

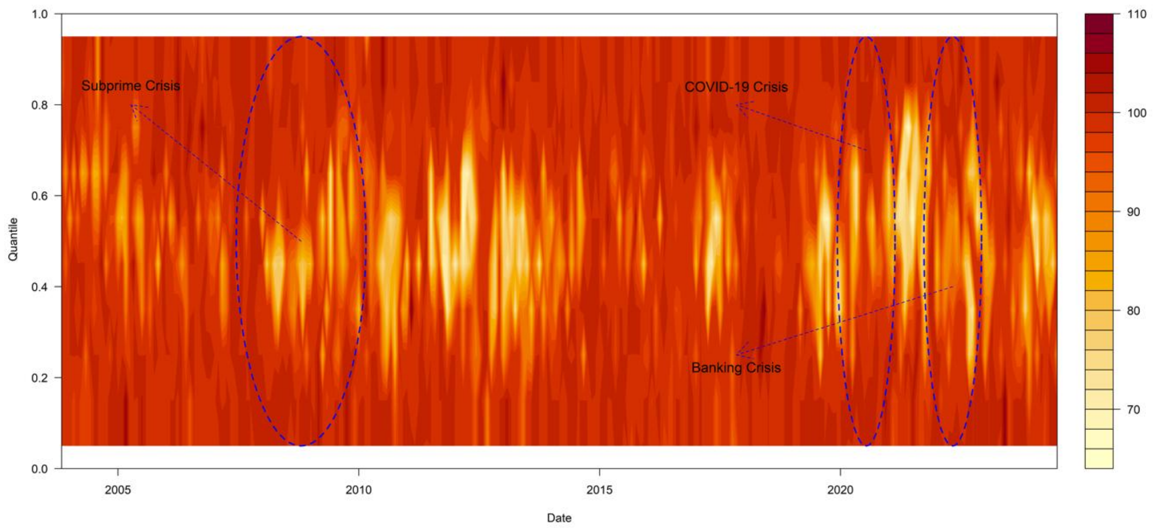


Figure 6. Interactions among variables across quantiles

Figura 6. Interacciones de variables por los cuantiles

Source: own elaboration.

5. DISCUSSION

The results are consistent with the theoretical mechanisms identified in the literature on climate-sensitive electricity markets. Previous studies show that electricity prices respond to weather conditions, hydrological availability, electricity demand, and the generation mix (Do et al., 2019, Manowska and Nowrot, 2019; Mosquera-López et al., 2017; Mosquera-López et al., 2024). Our findings extend this evidence to the Colombian electricity market, whose main structural feature is its high dependence on hydropower and its reliance on thermal generation as backup during hydrological stress.

The results identify five transmission channels. First, the demand channel shows that higher electricity demand increases spot prices in months 1 and 8. Second, the thermal generation channel indicates that fossil fuel generation raises prices between months 1 and 4 and again in month 6. Third, the hydrological-hydroelectric channel shows that hydroelectric generation reduces prices over three consecutive monthly periods. Fourth, the ENSO channel shows that a positive ONI shock interpreted as a one-standard-deviation innovation associated with El Niño conditions, increases electricity prices while La Niña-related conditions tend to reduce them. Fifth, the available energy volume channel confirms that higher reservoir availability lowers spot prices by reducing the need for thermal backup.

These findings also allow us to assess the hypotheses proposed in the introduction. The first hypothesis that climate variability affects electricity price changes in Colombia is supported by the significant response of prices to ENSO-related shocks.

The second hypothesis that El Niño exerts a stronger upward effect on prices than La Niña is also supported, since ONI shocks increase prices over several monthly periods whereas La Niña-related conditions are associated with price reductions. The third hypothesis that lower hydroelectric availability increases reliance on fossil-fuel-based thermal generation and raises prices is consistent with the positive price response to fossil generation and the negative price response to hydroelectric generation and useful energy volume. Finally, the fourth hypothesis that the climate-price relationship is nonlinear is supported by the QVAR results which show that the effect of climate and generation shocks varies across the conditional distribution of electricity prices.

The connectedness results reinforce this mechanism. Hydropower generation and fossil fuel generation are the main net transmitters of shocks indicating that the Colombian market is strongly driven by the interaction between low-cost hydroelectric supply and higher-cost thermal backup. This reveals a structural vulnerability as hydropower reduces costs and emissions under normal hydrological conditions but its dependence on rainfall, inflows and reservoir levels exposes the market to price increases during ENSO-related stress periods.

This study contributes to the literature in three ways. First extends evidence on weather-related electricity pricing to a hydrodependent emerging market where the climate-price relationship operates through water availability and thermal backup rather than mainly through fossil fuel prices. Second it identifies the specific channels through which ENSO-related variability affects electricity prices: demand, useful energy volume, hydroelectric generation, thermal generation and climate shocks. Third, it combines impulse response functions Diebold and Yilmaz (2012) connectedness analysis based on generalized forecast-error variance decomposition and QVAR models to capture average dynamic effects, system-wide connectedness and heterogeneous responses across the price distribution.

From a policy perspective the results suggest that resilience in Colombia requires reducing the electricity system's exposure to climate-dependent generation. This implies diversifying the energy matrix with complementary sources that are less directly affected by rainfall, reservoir levels, and ENSO-related shocks. Greater participation of non-conventional renewable sources such as solar and wind, together with storage technologies, demand-response mechanisms and improved reservoir management could reduce dependence on hydropower during dry periods and limit the need for fossil-fuel-based thermal backup. In this sense, diversification would not only improve energy security but also reduce the sensitivity of electricity prices to extreme climate events. ENSO-based early-warning systems may also support decisions on reservoir use thermal dispatch, forward contracting, and demand management.

6. CONCLUSIONS

The results of this study indicate that climatic phenomena particularly El Niño and La Niña are major drivers of electricity price volatility. These events affect both the availability of water for hydroelectric generation and patterns of electricity demand resulting in significant fluctuations in market prices. Notably the relationship between temperature and electricity prices is nonlinear, both extreme heat and cold exert upward pressure on prices due to their respective impacts on supply constraints and increased demand for cooling or heating.

In the Colombian context where the electricity matrix is predominantly hydro based hydrological variability plays a decisive role in market stability, fluctuations in river flows directly influenced by climatic anomalies contribute to heightened price uncertainty, especially considering the limited storage capacity of the country's reservoirs. This vulnerability underscores the structural dependence of Colombia's energy system on climatic conditions. The spillover analysis confirms that electricity generated from both fossil fuels and hydro sources are the main transmitters of price shock, the strong interdependence between electricity generation and climatic variables suggests that disturbances in supply or demand can trigger amplified and systemic effects on prices, this dynamic reflects the complexity and sensitivity of the electricity market to environmental shocks.

These findings highlight the intricate and asymmetric interactions between climate variability, electricity generation and market volatility. As the energy sector faces growing exposure to climate risk understanding these linkages is critical for designing resilient policy frameworks and energy systems, future research could explore the direct contributions of thermal power generation particularly those relying on fossil fuels such as oil, coal, and natural gas to climate change as well as assess the broader environmental and economic implications of continued reliance on these energy sources.

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CONFLICTS OF INTEREST

The authors declare no financial, professional, or personal conflicts of interest that could have inappropriately influenced the results or interpretations presented in this study.

AUTHOR CONTRIBUTIONS

All authors contributed significantly to the development of this article:

Juan Manuel Candelo Viáfara: developed the main idea of the study, was responsible for the methodological analysis, data processing, and validation of the results.

Maria del Pilar Rivera Diaz: conducted the literature review and wrote the first draft of the manuscript.

Juan Esteban Orrego Reyes: participated in the modeling and discussion of the results.

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