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Risk Transfer in an Electricity Market

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Abstract: Energy is traded using different products; long-term contracts or electricity forward contracts can assure the future transaction price. However, due to the difficulties in storing electrical energy for long periods and in large amounts, risks must be incorporated when defining contract prices through a Forward Risk Premia (FRP). This study analyzes the transfer of uncertainty from electricity market variables to the FRP in long-term contracts. We evaluate a type of econometric risk with the construction of Autoregressive Distributed Lag contagion models for the FRP using electricity demand, spot price, power generation via different technologies, and the Oceanic Niño Index. As a case study, we consider the Colombian electricity market. Our results show empirical models where the FRP has a short-term response with the following variables: hydropower generation, coal power generation, electricity demand, and Oceanic Niño Index, even though its transaction is reflected one or two years after the occurrence of the event.

Keywords: electricity market; Forward Risk Premia (FRP); contagion model; ARIMAX

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1. Introduction

Forward electricity contracts are the most common financial product to trade energy. These contracts are agreements to set the price of a certain amount of electrical energy delivered at a future date. To define both the price and the amount to be traded [1], buyers and sellers must take into account the peculiarities of the electricity market, such as the difficulty of creating sufficient inventories to mitigate price fluctuations [2] and the possibility that some agents can use their market power to obtain economic benefits [3].

Forward electricity agreements include two important moments: 1. when the deal takes place at the beginning and 2. the maturity moment when the delivery is required. In the beginning, the agents agree on both forward price and quantities; meanwhile, buyers and sellers settle accounts [4]. However, the forward price depends on the spot price expectations due to the difficulties of storing electrical energy; and those expectations vary due to the market drivers such as climate circumstances, load variability, network configurations, and oil prices. These uncertainty conditions reflect a Forward Risk Premia (FRP). Then contango or backwardation conditions are observed in the market.

The FRP has been studied by [5,6] through autoregressive vectors and by [7] using linear models for price changes. Reference [8] found evidence of the FRP in other types of energy commodities and [7] did so for the Colombian electricity market. For their part, ref. [1] examined the perception of risk in the future through the FRP. Moreover, the works by [9,10] stand out in the literature. In this study, we seek to identify how sources of market uncertainty lead to the definition of market risk valuation.

Reference [11] shows the different methods for the analysis of energy variables with market variables using econometric contagion models. In said methodology, price variables were explained by other market variables in the time series, thus showing the transfer of market uncertainty from hydropower generation to the energy spot price in Colombia. For this purpose, the author used Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) models, which allowed him to estimate the reference models for each time series. Subsequently, he employed Auto Regressive Integrated Moving Average with Exogeneous Input (ARIMAX) models (also known as ADL) to determine the influence of the exogenous variables on the endogenous variable.

The principal motivation of this study is to present a contagion model to describe how risks are transferred from different electricity market variables to FRP values, with the main objective of calculating the risk of long-term forward contracts based on exogenous market variables and determining its risk relationship with and impact on those contracts with risk forecasting models. To that end, we propose contagion models for the FRP using information regarding electricity demand, power generation via various technologies, and the Oceanic Niño Index (ONI). As a case study, we consider the Colombian electricity market between 2006 to 2019.

In Section 1, we study the power generation variables and the ONI, examine their behavior, and conduct stationarity and causality analyses required for developing the methodology proposed by [11,12]. In Section 2, we identify and develop the contagion models that rule out variables that are not efficient in the Autoregressive Distributed Lag (ADL) model. As a result, variables related to hydropower generation, coal power generation, electricity demand, and ONI provide reliable results in estimating the ARIMA and pre-whitening models, helping us to establish the initial parameters of the transfer function models. Section 3 selects the models with the best transfer parameters (b, r, s) using the effiency criterion. In Section 4, through Mean Absolute Percentage Error (MAPE) criteria and statistical analysis of residuals, we define the appropriate transfer function models for each series versus the FRP. Finally, we present the analysis results, draw some conclusions, and provide recommendations to guide future work on the subject.

2. Materials and Methods

2.1. Forward Risk Premia

According to [4], at the time of maturity T, the agent that purchased the electricity for the price of the contract at the moment t_o should pay an underlying value, F_{t_oT}, and, in return, receive the energy valued at the spot price, PB_T. This scenario shows as a forward derivative (1) contract seller (short position) will receive the same net benefit as the buyer but with an opposite sign. In this case, the seller is the one who benefits from the contract.

$$\Pi_T = F_{t_oT} - PB_T \tag{1}$$

Therefore, it is more convenient for electricity forward contract sellers to have a spot price (PB_T) below the contract price. If, on the contrary, the spot price is above the contract price, electricity generators (sellers) will suffer losses, coercing them to be the ones who pay to stabilize the price in the contract market. Hence, the phenomenon known as Forward Risk Premia (FRP) can be defined as the difference between the expected spot price and the contract price (2).

$$FRP_{tT} = E(PB_T) - F_{tT} \tag{2}$$

A positive value of FRP_{tT} indicates a contract price agreed below the expected market price and that the selling agent pays for the contract coverage, while a negative value suggests that the contract price is greater than the market expectation and the purchasing agent pays for the coverage [1,12].

2.2. Contagion Model and Transfer Function

According to the methodology implemented by [11,13,14], in the estimation of the ADL model, a relationship between an exogenous time series X_t and an endogenous time series Y_t is established, as shown in Equation (3).

$$Y_t = \frac{\omega_s(L)}{\delta_r(L)} X_{t-b} + \eta_t;\ \eta_t = \frac{\theta(L)}{\phi(L)} a_t, \tag{3}$$

where ω_s and δ_r are polynomials of the transfer function with components $(b,\ r,\ s)$; η_t, an ARIMA process, which is specified by the lag polynomials θ and ϕ; and a_t, a white noise process. In this study, the FRP is the endogenous variable. For instance, when analyzing a transfer function model in which the exogenous variable is coal power generation (COAL), the general transfer function is given by Equation (4).

$$FRP_t = \frac{\omega_{COALs}(L)}{\delta_{COAL_r}(L)} COAL_{t-b} + \eta_{COALt}; \eta_{COALt} = \frac{\theta_{COAL}(L)}{\phi_{COAL}(L)} a_{COALt} \tag{4}$$

To estimate the model, we use the process proposed by [13], shown in Figure 1. This process consists of five steps:

i. Initial conditions: shows a descriptive statistics review of variables that influence the FRP, those statistics identify whether they present information of high variance, this information is in the data description section.
ii. Stationarity identification: ADF, KPSS, and PP to determine stationarity in the series are necessary for the ADL models; later, the Granger test is applied to identify whether the series are the spurious or present level of causality level X to Y.
iii. Identification of the impulse–response function: this procedure consists of two parts, a pre-whitening the X variables as described in Equation (1) and a process of identification of the impulse–response function (IRF) as shown as an example in Equation (2).
iv. Estimation of ADL models: in this step, the components (b, r, s) will be fit to find the best estimable model according to the IRF information, looking for the white noise process in residuals, and if not, the theory of [11,12] suggest to create an additional ARIMA or SARIMA model on the residuals to fit the pure white noise.
v. Post-estimation review: MAPE is used to verify the level of fit of each estimated model.

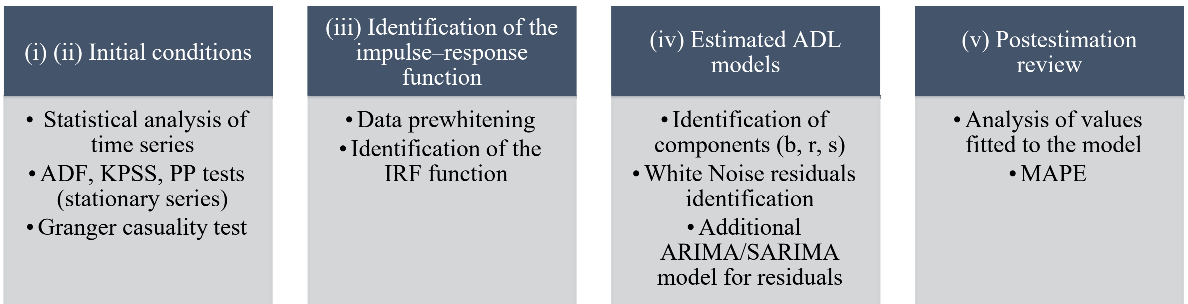

Figure 1. Process to estimate ADL models.

2.2.1. Initial Conditions

Electricity generation in Colombia is predominantly hydroelectric. Therefore, climatic phenomena that could generate extreme hydrological events such as El Niño and La Niña cause nervousness in the generation market because reservoirs are limited and water supplies have a stochastic behavior, increasing the volatility of the electricity spot price and the associated risk.

The Spot Price of Electricity in Colombia is defined based on the Maximum Offer Price (MPO) of the power plants participating in the spot market. However, there is also a minimum price, which is the sum of the following terms: (i) Real Equivalent Cost of Energy (CERE): This is the payment of the Reliability Charge, understood as a demand payment to guarantee the energy service, even in periods of water shortages. (ii) Contributions: Law 99 of 1993 (Environmental Law). (iii) Secondary service or frequency control (AGC): This is the payment for the plants to control the frequency 60 Hz system. (iv) Tax contribution for Non-Interconnected Zones—FAZNI.

According to [15], the efficient functioning of the electricity market implies that all generating companies must make the best operational decisions with the best available information; therefore, electricity companies must have a thorough knowledge of the dynamics of the electricity price and the mechanisms that determine its evolution.

Before modeling, a descriptive statistical analysis is performed that helps to know better the variables, in this case, the use of the minimum (min) or maximum (max) values, quartiles (1st Q, 2nd Q (Median), and 3rd Q), standard deviation, and coefficient of variation (CV), and shows the variables distribution and their market behavior.

To perform the ADL model, the X_t and Y_t series must be stationary. This stationarity condition is verified using Augmented Dickey–Fuller (ADF), Kwiatkowski–Phillips–Schmidt–Shin (KPSS), and Phillips–Perron (PP) tests, as explained by [16]. These tests can yield two possible results for each series: stationary or nonstationary. If a is a nonstationary series, it will be differentiated d times to make it stationary, thus creating variables x_t and y_t: $x_t = \Delta^d X_t$, $y_t = \Delta^d Y_t$, with X_t and Y_t as the series in levels [17]. Subsequently, the Granger causality test is performed for x_t and y_t. In the results, there should be no evidence of a relationship between the variables, as indicated in Assumption 4 of the ADL models reported by [18]. In addition, there must be an optimal lag value in the residual's series showing the lower cointegration, considering Akaike's information criteria and the F test [19–21].

2.2.2. Identification of the Impulse–Response Function (IRF)

Data Prewhitening

Two prewhitened series, α_t and β_t, are constructed. α_t corresponds to the residuals of an ARIMA process adjusted to series x_t and whose lag polynomials are ϕ_x for the autoregressive component θ_x for the moving average components. β_t can be calculated by filtering series y_t using the same lag polynomials (ϕ_x and θ_x), as shown in Equation (5).

$$\alpha_t = \frac{\phi_x}{\theta_x} x_t;\ \beta_t = \frac{\phi_x}{\theta_x} y_t \tag{5}$$

Identification of the Impulse–Response Function

The impulse–response function ($\hat{v}_k$) is a linear relationship used in time series models, in which two stationary series (α_t and β_t) are through linear filters. To perform the IRF, the Cross-Correlation Function (CCF) (6) and the standard deviations of the prewhitened models (α_t and β_t) are used (7). For hypothesis testing, the value *int* shows the existence of the impulse–response effect of the series (alternative hypothesis) or a noncorrelation value (null hypothesis).

$$\rho_{\alpha\beta}(k) = \frac{\gamma_{\alpha\beta}(k)}{\sigma_\alpha \sigma_\beta} \tag{6}$$

$$\hat{v}_k = \frac{\sigma_\beta}{\sigma_\alpha} \rho_{\alpha\beta}(k); \quad int : \pm (T-k)^{-\frac{1}{2}}, \tag{7}$$

where $\rho_{\alpha\beta}(k)$ denotes the cross-correlation function of the prewhitened series; $\sigma_\alpha\ y\ \sigma_\beta$, their variances; and $\gamma_{\alpha\beta}(k)$, their covariance.

After calculating the impulse–response series ($\hat{v}_k$), the obtained series through theoretically predefined processes are compared (see Figure A1). These processes, known as transfer functions, recreate a model based on three components: b, which indicates the number of lags in the series; r, which distinguishes its autoregressive; and s, which identifies its moving average process (8).

$$\hat{Y}_t = \hat{v}_k = \frac{\omega_s(L)}{\delta_r(L)} x_{t-b} \tag{8}$$

2.2.3. Estimated Autoregressive Distributed Lag Models

Once the theoretical IRF function ($\hat{v}_k$) is determined, it is tested via Ordinary Least Squares and Maximum Likelihood (OLS-ML) estimation to verify that the parameters meet the hypothesis of individual significance and the invertibility conditions for $\omega_s L^s$ and the stationarity conditions for $\delta_r L^r$.

After the optimal model is estimated, the model residuals (6) are verified again using the Ljung–Box Test and the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis to confirm if the series is white noise. If it is not white noise, an ARIMA model may be estimated for the residuals to complement possible seasonal effects or nonparameterized components in the transfer model.

2.2.4. Postestimation Review

In this section, we look at the fitting criterion proposal for [22] evaluating the Mean Absolute Percentage Error (MAPE). As observed in (9), a MAPE below 10% is an excellent fit, while a MAPE above 30% indicates a poor fit.

$$MAPE = \frac{1}{T} * \frac{\sum_{t=1}^{n} |e_t^2|}{|Y_t|}; \quad Fitted \begin{cases} \leq 10\% \quad very\ good \\ > 10\%, \leq 20\% \quad good \\ > 20\%, \leq 30\% \quad moderate \\ > 30\% \quad poor \end{cases} \tag{9}$$

3. Results and Discussions

3.1. Data Description

This study includes seven exogenous variables and one endogenous variable (FRP) with information from January 2006 to September 2019 and with 165 observations per variable; the dataset was built in monthly frequency. This information was obtained from the XM the electricity market operator in Colombia.

We work with a monotonically transformed series. In this study, the hydropower generation (HYDRO) series is expressed in GWh after being transformed using the conversion factors of the hydroelectric power plants in the electric grid. Additionally, the transfer of information between this variable and the others is possible using water to generate electricity and not the country's rainfall. Similarly, coal power generation (COAL) expressed in GWh and natural gas power generation (GAS) expressed in GWh are essential to measuring risk because they complement hydropower generation. These types of resources define the energy spot price (SPOT) measured in COP/kWh. For similar reasons, total generation from thermal power stations (SUMTHERM) are expressed in GWh, within which there could be some using liquid fuels. On the other hand,, climate expectation based on the Oceanic Niño Index (ONI) measured in Celsius generates a price expectation that closes with the marginal cost of thermal power stations. However, there exists a high uncertainty regarding the behavior of this variable in future periods, which makes it more interesting for the forward risk analysis. Finally, electricity demand (DEMAND)—also measured in GWh—is the variable that defines the risk because generation ultimately depends on it and, thus, part of the price traded on the electricity market. This variable relies on macro and microeconomic, climate, and time factors, among others.

To understand the previously described procedure, a prior technical analysis of the energy generating series (including FRP) is carried out to contrast the type of information provided; in this case, it is imperative to know the distribution and if the series has statistically normal.

According to the results in Table 1, SPOT, GAS, DEMAND, ONI, and FRP have a dispersion level for the existence of uncertainty events that volatilize prices; for SPOT prices, market conditions change in fact due to the uncertainty regarding climatical phenomena from 2016 to 2018 [13]; the price of GAS has a dependence on the uncertainty of hydrological generation prices; the variation in demand is a reflection of the market and the uncertainty of generators and buyers [23].

Table 1. Descriptive statistics of the exogenous variables considered in the analysis.

	Series in Levels (X_t)							
	Min	**1st Q**	**Median**	**Mean**	**3rd Q**	**Max**	**Std.Dev**	**CV**
SPOT	46.88	83.25	122.33	157.39	181.81	1107.40	139.58	0.89
HYDRO	73.65	112.60	135.33	136.54	166.43	205.44	36.70	0.27
COAL	20.98	35.75	38.87	39.15	42.02	52.14	5.95	0.15
GAS	2.70	5.35	6.65	7.64	9.49	18.22	3.22	0.42
DEMAND	0.46	1.81	3.00	3.21	4.39	9.50	1.78	0.55
SUMTHERM	38.81	45.77	50.33	50.36	55.14	62.57	5.50	0.11
ONI	3.55	7.51	9.35	11.28	14.35	28.49	5.12	0.45
FRP	−3.80	11.12	21.31	20.84	20.85	38.08	11.63	0.55

3.2. Initial Analysis of the Variables

Using the tests indicated in process "ii" of Section 2.2, in Table 2, the results show the statistical acceptance of the non-stationarity hypothesis by performing first-order differentiation for all. Only the COAL and ONI series in the ADF test and GAS in the KPSS test have a significance of 10% of the evaluation, and those do not impact the decision of differentiate the series because these series must present stationarity in first difference to be able to perform the ADL model.

Table 2. ADF, KPPS, PP seasonality tests results in p-values contrasted at a significance level of 5%.

Test	**SPOT**	**HYDRO**	**COAL**	**GAS**	**DEMAND**	**SUMTHERM**	**ONI**	**FRP**
ADF	0.000	0.000	0.096	0.010	0.010	0.010	0.062	0.039
KPSS	0.000	0.000	0.010	0.098	0.047	0.010	0.010	0.085
PP	0.002	0.002	0.014	0.010	0.049	0.010	0.010	0.078

Once verified the stationarity condition, verify the Granger causality test for statistical causality between the exogenous series (x_t) and the endogenous series (y_t). As seen in Table 3, there is no evidence of Granger causality between the exogenous variables and the endogenous variable at twelve lags, following the results of the tests proposed by [19–21]. In the variables evaluated relationships, a contagion effect is visible, except for the SPOT variable on the endogenous variable, present p-values higher than a 5% significance level, this meaning the relationship between SPOT and FRP variables is impossible, as proposed by [19–21]. Regarding the (optimal) AIC* values, it shows all series present lags at 12 months and they are optimal values fitting an optimal (ADL) model.

Table 3. Granger causality test for the series differentiated at twelve lags.

FRP vs. Variable	***p*-Value**	**AIC ***
	Y~X	
SPOT	0.032	687.5
HYDRO	0.437	699.5
COAL	0.472	699.9
GAS	0.680	702.7
DEMAND	0.077	691.0
SUMTHERM	0.313	697.5
ONI	0.863	705.4

*: is the number of optimal lags assessed with AIC.

3.3. Prewhitened Models

Once the stationarity condition and non-Granger causality test are working, the ARIMA models for each exogenous series are estimated to establish the prewhitened series (α_t and β_t). The results are presented in Table 4.

Table 4. Results of the prewhitened series (α_t and β_t).

Variable	ARIMA	Parameter	Coeff.	$Pvalue_{x_t}$	σ_{α_t}	σ_{β_t}
SPOT	(1,1,1)	ar1 ma1	0.793 −0.979	0.000 0.000	83.29	8.77
HYDRO	(1,1,1)	ar1 ma1	0.838 −0.968	0.000 0.000	2.86	7.17
GAS	(0,1,0)	—	—-	—-	—-	—-
COAL	(1,1,1)	ar1 ma1	0.779 −0.975	0.000 0.000	1.08	8.71
DEMAND	(2,1,0)	ar1 ar2	−0.816 −0.256	0.000 0.001	1.54	14.64
SUMTHERM	(0,1,0)	—	—-	—-	—-	—-
ONI	(2,1,1)	ar1 ar2 ma1	1.787 −0.852 −0.963	0.000 0.000 0.000	0.11	53.07

According to Table 4, Using the evaluation results of Sections 3.2 and 3.3, the pre-whitened models, α_t and β_t from Equation (3), standard deviations (σ_{α_t}) and (σ_{β_t}) work as input for the impulse response function plots, with ARIMA components not greater than two information lags for both autoregressions and moving averages evaluated in a *p*-value for 5% individual significance. This behavior is usual in commodities with some degree of storability [24]. Regarding the GAS and SUMTHERM series, they only exist when there is a risk of shortage of the main variables (e.g., hydropower or coal power generation). In addition, those variables are not helpful to identify the FRP risk valuation in situ. Both differentiated series show a white noise effect that does not enable making progress in the ADL construction methodology ruling out.

3.4. Impulse–Response Function Series (IRF)

The pre-whitened series (α_t and β_t) and their valued standard deviations (σ_{α_t} and σ_{β_t}) can produce the IRF plots depicted in Figure 2. In the figure, it is shown that the only relationship that does not have a statistically significant information correlation is that between FRP and SPOT (PB), considering that Table 4 shows statistical evidence that this process intervenes with the assumption of noncorrelation for the Granger causality test, which hinders the development of the transfer function model. The rest of the relationships exhibit a cross-correlation, which is the transfer function of each contrasted series.

Having identified the cross functions, now it is possible to search the optimal ADL model for each series

3.5. Transfer Function Models

By broadening the theoretical parameter identification method proposed by [13] and taking the optimization of the Granger causality test, we make 12-lag iterations to identify the components of these ω_s and δ_r that meet the conditions of statistical significance, invertibility, and stationarity. The estimated optimal models that satisfy the mentioned conditions are in Table 4.

Therefore, FRP identifies in advance the time of the energy transaction with a few months of lag. Thus, the HYDRO variable explains the behavior of the FRP after three months of information lag (δ_3) and is affected by stochastic behaviors two months before trading the risk Premia (ω_2). Still, the behaviors of the FRP are traded for terms of one to two years, prior to market events. Therefore, FRP identifies in advance the time of the energy transaction with a few months of lag.

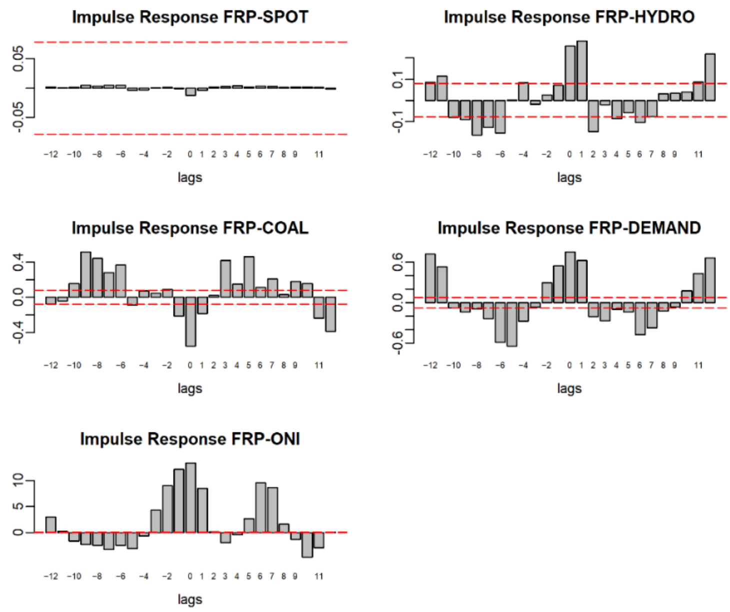

Figure 2. Impulse–response function between the FRP series and the energy variables—testing procedure. Note: From top to bottom, spot price (SPOT), total hydropower generation (HYDRO), coal power generation (COAL), electricity demand (DEMAND), and Oceanic Niño Index (ONI).

After identifying the optimal transfer functions for each series, the residuals of each model (η_t) are analyzed to verify and confirm the white noise condition in them. According to Table 5, there is a marked seasonal component at twelve periods, $(P,\ D,\ Q)_{12}$, for each series of residuals, showing an annual market behavior on the prices of the FRP.

Table 5. Results of the transfer function models for the FRP.

Variables	($\hat{\nu}_t$) ADL	Coeff.	*p*-Value	($\hat{\eta}_t$) *SARIMA*	Coeff.	*p*-Value	ARIMA+$\hat{\nu}_t$+ $\hat{\eta}_t$	MAPE
HYDRO	T1-AR1	1.512	0.000	sar1	0.854	0.000	$(1,1,1)(0,3,2)(1,0,1)_{12}$	6.74%
	T1-AR2	−1.502	0.000	sma1	−0.628	0.080		
	T1-AR3	0.503	0.000					
	T1-MA0	0.176	0.005					
	T1-MA1	−0.206	0.002					
	T1-MA2	0.228	0.000					
COAL	T1-AR1	−0.899	0.000	sar1	0.833	0.000	$(1,1,1)(0,1,1)(1,0,1)_{12}$	6.88%
	T1-MA0	−0.488	0.003	sma1	−0.535	0.018		
	T1-MA1	−0.553	0.001					
DEMAND	T1-AR1	−0.657	0.000	sar1	0.285	0.000	$(2,1,0)(0,4,1)(2,0,0)_{12}$	6.25%
	T1-AR2	−0.255	0.000	sar2	0.198	0.013		
	T1-AR3	−0.731	0.000					
	T1-AR4	−0.903	0.000					
	T1-MA0	−0.063	0.021					
	T1-MA1	−0.072	0.009					
ONI	T1-AR1	−0.478	0.000	sar1	−0.394	0.001	$(2,1,1)(0,2,0)(2,0,1)_{12}$	7.29%
	T1-AR2	−0.931	0.000	sar2	0.507	0.000		
	T1-MA0	−1.988	0.064	sma1	0.799	0.000		

These prices explain the FRP movement with one seasonal autoregressive (SAR) and one seasonal moving average component (SMA) at least, except for the DEMAND variable that is explained by two autoregressive seasonal parameters (SAR). These latter components are described by the inertia of volatile systematic elements of the market (such as rain), except for month 12, which has its own marked behavior.

In the case of the ONI variable, the fitting with the FRP market explains the behavior concerning the expectations of the climate analysis of one El Niño or La Niña phenomenon with at least two periods of information lag.

The MAPE values for each model were below 10%, showing an adjusted projection with soft noise residuals according to the criteria considered [22]. The estimated ADL models can be rewritten in equation form (Table 6).

Table 6. ADL models in equation form.

Model	Equation
HYDRO	$(1-L)Y_t = \frac{0.17+0.20L-0.22L^2}{1+1.51L-1.50L^2-0.50L^3}(1-L)X_t + \frac{(1-0.85L^{12})}{(1+0.62L^{12})}a_t$
COAL	$(1-L)Y_t = \frac{-0{,}48+0.55L}{1+0.89L}(1-L)X_t + \frac{(1-0.83L^{12})}{(1+0.53L^{12})}a_t$
DEMAND	$(1-L)Y_t = \frac{-0.06+0.07L}{1+0.65L+0.25L^2+0.73L^3+0.90L^4}(1-L)X_t + (1-0.28L^{12}-0.19L^{24})a_t$
ONI	$(1-L)Y_t = \frac{-1.98}{1+0.47L+0.93L^2}(1-L)X_t + \frac{1+0.39L^{12}-0.50L^{24}}{(1-0.79L^{12})}a_t$

Figure 3 illustrates the behavior of the FRP and the estimated variable FRP_{ADL} explained by each market variable; the fit shows a slight residual in the downward peaks marked by El Niño events registered in 2009 and 2016. Only the ONI variable presents a better fit in these periods of structural change.

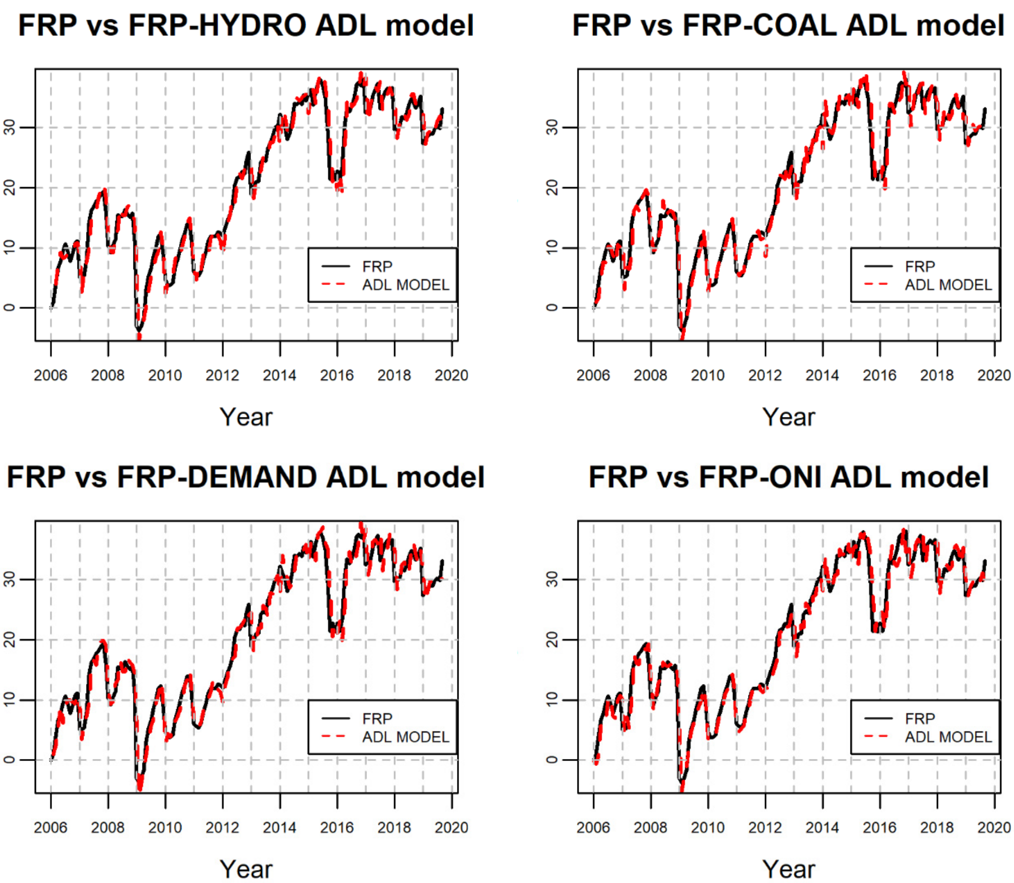

Figure 3. Estimated ADL models versus the original FRP series.

4. Conclusions

This study analyzes the transfer of uncertainty from electricity market variables to the forward risk Premia in long-term contracts. For this purpose, we evaluate the construction of ADL contagion models for the FRP using information regarding electricity demand, spot price, power generation via various technologies, and the Oceanic Niño Index.

In the initial analysis for the construction of the ADL models, no evidence of Granger causality was found between the FRP and hydropower generation (HYDRO), coal power generation (COAL), electricity demand (DEMAND), and the ONI (Oceanic Niño Index). For these variables, the valuation made by the market at each moment in time does not depend on the instantaneous value of the total thermal generation movements. Furthermore, this process suggests that markets react intuitively to weather forecasts regarding the ONI variable, although not directly on this variable. Consequently, these variables allow the creation of univariate transfer models, except for the SUMTHERM and GAS variables, which are white noise series with jumps in the market, occur spontaneously, and are managed through a regime relationship; hence, the ADL model cannot be directly applied to find a relationship. Moreover, the SPOT variable was found not to have applicability because it showed Granger causality.

The transfer models can identify the FRP series with the hydrological generation series, coal generation, the ONI index, and energy demand with a minimum of two lags toward the time of contract agreement, showing evidence of prior fundamental analysis by market agents; the ADL models show that an analytical procedure focused on uncertainty and fundamental analysis would not be necessary.

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Data Availability Statement: The data presented in this study are openly available in [25,26] recalculated in a monthly dataset.

Conflicts of Interest: The authors report no conflict of interest. The authors alone are responsible for the content and writing of the paper.

Appendix A

ADL Theoretical transfer Function.

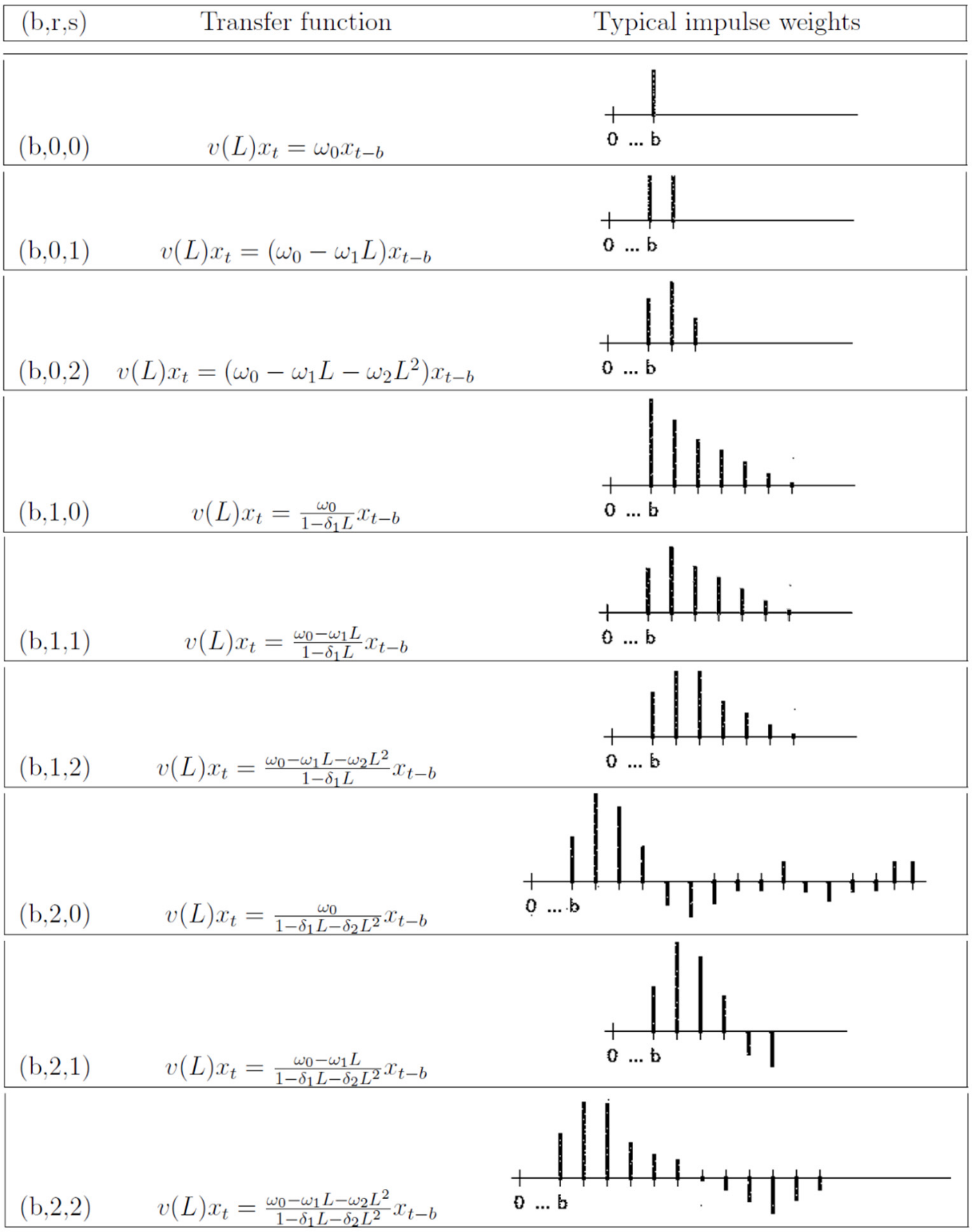

Figure A1. Resource: Galeano (2015).

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