Risk Asymmetries in Hydrothermal Power Generation Markets

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Outline

Índice

Motivation

Stylized facts of **electricity prices**: mean reversion, spikes, seasonal patterns, long range memory.

On a correct assessment of electricity price dynamics depends accurate decisions about exposition to, and hedging against, market risk $\Rightarrow$ crucial for electricity **producers** and **consumers**.

Literature Gap

- Should risk modeling take into account the idiosyncrasies of the stochastic processes describing the data at different times within a day?
- How to model properly strong seasonally patterns? $\Rightarrow$ weather dependencies.
- Are risks faced by consumers and producers different? $\Rightarrow$ should hedging strategies rely on tail asymmetries?

Proposal

Highlight the asymmetries that characterize electricity prices almost in every level: intraday patterns, seasonal components, spikes, volatility regimes and asymmetric extreme values.

Estimate the effects of such asymmetries on traditional risk measures such as Value at Risk (VaR) and Expected Short Fall (ES).

Proposal

The objective is not forecasting or comparing between different modeling strategies.

We aim to describe several **asymmetries** hidden in the formation of electricity prices, and estimate their consequences in terms of **risk for market agents**.

Application

Power generation prices from the **Colombian electricity market** $\Rightarrow$ opportunity of considering a market with heterogeneous power alternatives and with small capacity in terms of renewable energy providers.

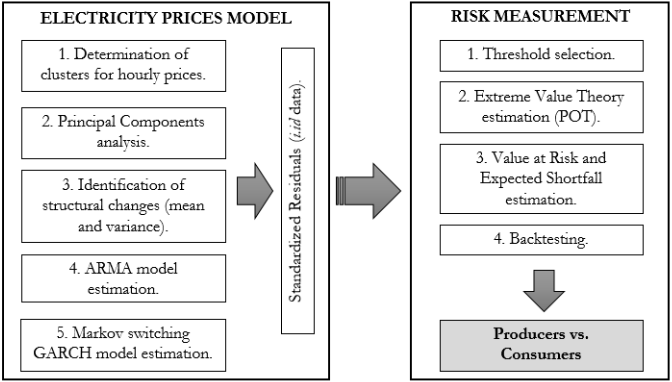
Colombia has an energy system mainly based on **hydropower** (70%) and **thermal plants** generation (19%) $\Rightarrow$ the system is highly weather dependent.

Nevertheless, our empirical results are of general interest.

Índice

Methodology

Table: Flow Diagram of the Proposed Methodology



Índice

The data were obtained from the platform “xm”, operator of the National Interconnected Colombian System and the administrator of the Colombian Energy Market.

The frequency of the data is hourly. January 1^{st}, 2009 - December 31^{st}, 2013.

Índice

Cluster Analysis

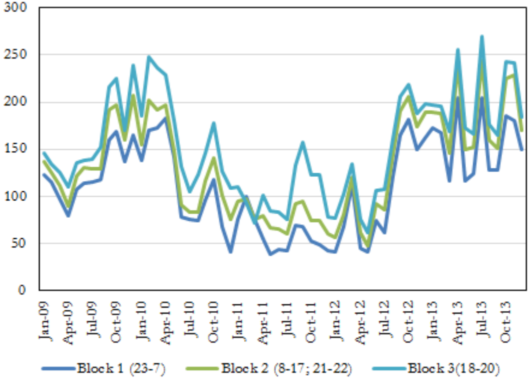
Table: Descriptive Statistics of the Electricity Prices

	Block 1 (23-7)	Block 2 (8-17; 21-22)	Block 3 (18-20)
No. Hours	9	12	3
Mean	110.93	132.54	154.75
Skewness	0.7631	1.0828	1.0258
Kurtosis	4.0853	5.2554	4.9796
Observations	1820	1820	1820

Block 1	23 - 00	00 - 01	01 - 02	02 - 03	03 - 04	04 - 05	05 - 06	06 - 07	07 - 08			
Block 2	08 - 09	09 - 10	10 - 11	11 - 12	12 - 13	13 - 14	14 - 15	15 - 16	16 - 17	17 - 18	21 - 22	22 - 23
Block 3	18 - 19	19 - 20	20 - 21									

Cluster Analysis

Figure: Average Behavior of the Monthly Electricity Prices



Data Aggregation

Each block has a single price return per day $\Rightarrow$ aggregates most of the variability of the original hourly-prices within the block.

The percentage of variation the first principal component explains for Block 1 is 66.63%, for Block 2 is 69.42%, and for Block 3 is 68.89%.

Structural Changes

The sequential test of Bai and Perron (1998) indicates that the series do not present breaks in the first moment of the distribution during the study sample.

The score-based CUSUM test indicates that Block 2 and Block 3 present breaks in the variance.

ARMA and MS-GARCH Estimation

First Moment:

- Block 1: ARMA(1,1) model.
- Block 2 and 3: ARMA(7,7) model $\Rightarrow$ captures seasonality patterns in the prices.

Second Moment:

- Block 1: standard GARCH(1,1) model with residuals distributing **Gaussian** and Student t.
- Block 2 and 3: MS-GARCH(1,1) model $\Rightarrow$ one, **two** and three regimes, with residuals distributing Gaussian and **Student t.**

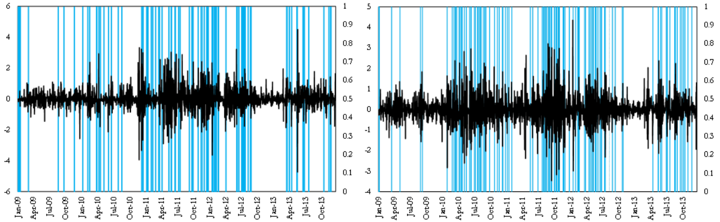
GARCH Models

Table: Parameter Estimates for Selected GARCH models

Regime	$\alpha_{s1} + \beta_s$	$\alpha_{s1}/(1-\beta_s)$	% time in k
Block 1			
	0.6929	0.5910	100%
Block 2			
Low Volatility	0.9809	0.9528	73%
High Volatility	1.0051	1.1750	27%
Block 3			
Low Volatility	0.8429	0.6098	53%
High Volatility	1.0144	1.3812	47%

GARCH Models

Figure: High Volatility Regime Probabilities and Price Returns: Block 2 and 3



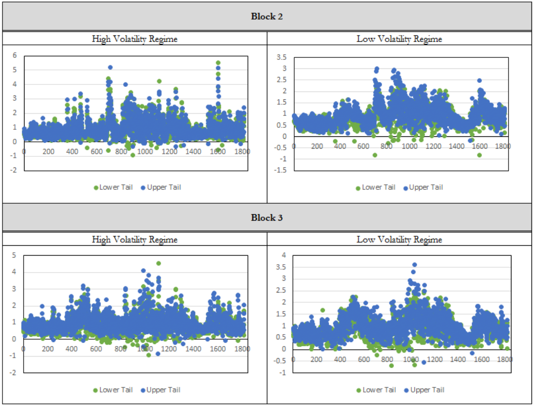
EVT

Table: Mean Difference Tests for Shape Parameter Estimates

	Upper Tail	*Lower Tail*	*Lower Tail - Upper Tail*	
	Mean (Shape)	**Mean (Shape)**	**Mean Difference**	**t Statistic**
Block 1	0.1560	0.2056	0.0496	2.4098**
Block 2				
High Volatility Regime	0.1798	0.2411	0.0613	3.782***
Low Volatility Regime	0.0892	0.2686	0.1795	10.65***
Block 3				
High Volatility Regime	0.1691	0.0389	-0.1301	-4.50***
Low Volatility Regime	0.0916	0.0909	-0.0006	-0.0236

VaR and ES

Figure: Block 2 and 3 Value at Risk Estimations, 95% Confidence Level



VaR and ES

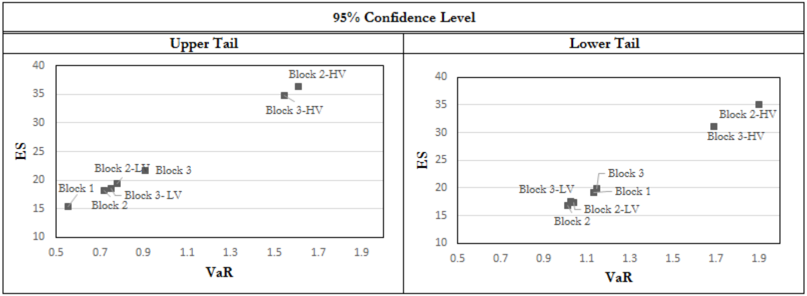
- *Block 1:* risk faced by **producers** (lower tail) tends to be higher than the risk that consumers face (upper tail).
- *Blocks 2 and 3*: the risk faced by **buyers** tend to be higher than the risk faced by sellers.

The risk faced by the agents measured with the VaR and ES, not only depends on the concentration of extreme events in the tails (kurtosis), it also depends on the threshold (bias).

VaR and ES

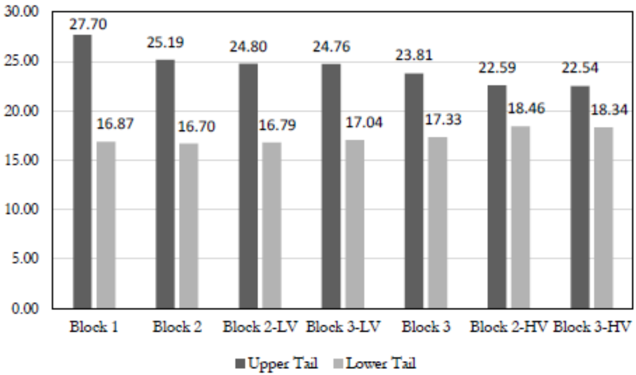
The methodology considers risk measurements for producers and consumers separately, taking into account different volatility regimes, in different blocks that depend on demand charges.

Figure: Example Value at Risk vs. Expected Shortfall



VaR and ES

Figure: Example ES/VaR – 95% Confidence Level



Índice

In the case of electricity markets, an accurately modeling of the main features presented by price and return distributions has proved to be a challenging task.

We propose to blend some recent advances in the financial econometrics field, to model electricity prices in a coherent and relatively complete fashion.

Our modeling strategy allows us to highlight important asymmetries in terms of block-prices, market variances and extreme demand and supply shocks to the market.

Clustering and volatility regimes help to improve risk measuring and enrich the information available to make educated decisions by electricity firms, traders and consumers.

We compare the tails of the modeled returns distribution for electricity prices. Here, we take distance from the common approach in the literature, which mainly ignored possible asymmetries in the tails, focusing only on one tail (generally the positive tail).

These asymmetries are not conclusive in the sense that one could ensure that the risk is greater at one or another side of the spectrum, all the time $\Rightarrow$ Risk asymmetries are important and significant, but changing.

We document a complex interplay between conditional skewness and conditional kurtosis of the returns distribution.

By highlighting the asymmetries in electricity markets risk, we aim to send a message about the importance of considering complete models when measuring risk and pricing derivatives in electricity markets.

New starting point for pricing and quantifying complex risks, associated to electricity commodities, particularly for those depending on hydrothermal based generation systems.