# Saving for a Dry Day: Coal, Dams, and the Energy Transition

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# Saving for a *Dry* Day: Coal, Dams, and the Energy Transition*

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**Abstract**

Renewable generation creates a tradeoff between current and future energy production as generators produce energy by releasing previously stored resources. Studying the Colombian market, we find that diversified firms strategically substitute fossil fuels for hydropower before droughts. This substitution mitigates the surge in market prices due to the lower hydropower capacity available during dry periods. Diversification can increase prices, instead, if it results from mergers steepening a firm's residual demand. Thus, integrating production technologies within firms can smooth the clean-energy transition by offsetting higher prices during scarcity periods if the unaffected technologies help store renewables more than exercise market power.

*JEL classifications:* L25, Q21, D47
*Keywords:* energy transition, renewables, hydropower generation, diversified production technologies, energy storage, wholesale electricity markets

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# 1 Introduction

Energy production is responsible for nearly three-quarters of global greenhouse gas emissions, with about half of these emissions coming from electricity generation alone.[1] Stimulated by worldwide policies to revert this trend (e.g., Acemoglu *et al.*, 2016), energy firms are transitioning from fossil fuel to clean energy production by investing in low-carbon renewable energy resources such as dams, solar, and wind. Renewables account for 35% of global energy today (IREA, 2017), but because their volatility, intermittency, and limited storability pose severe challenges for energy markets (Fabra, 2021), fossil fuels are still critical to meet daily energy demands and avoid high consumer prices and blackouts.[2]

Intermittent supply is a severe problem even for storable renewables; hydropower generation, for instance, exposes firms' capacities to weather changes despite using dams to store ample water resources.[3] This problem is exacerbated in the tropics, where extreme droughts and rainfalls are frequent and hydro resources are often closely located, making even regional droughts a threat to the stability of national energy grids (Conway *et al.*, 2017). A potential solution to this risk is to diversify production technologies within firms: A firm expecting future intermittencies may raise its supply of unaffected resources, easing the storage of renewables, while keeping overall supply and thus prices stable without policy intervention.

In this paper, we ask: How do diversified firms – those with fossil and renewable generators – respond to forecasts about the future availability of renewable energy? In turn, how does diversification affect market prices? Leveraging de-

[1]Source: `https://www.climatewatchdata.org/ghg-emissions`. For instance, WHO (2017) estimates that, in 2010, Polish citizens lost 45,854 years of life due to air pollution largely due to the country's reliance on coal power plants despite its abundant hydro resources (Vasev, 2017).

[2]Natural gas, being a clean but depletable resource, is an intermediate step before renewable energy's viability overcomes its technical challenges (Gürsan and de Gooyert, 2020). Like fossil fuels, it can solve renewable intermittency problems (Van Foreest, 2011; Smil, 2015), as, for instance, solar energy is only partially available during cloudy days (Gowrisankaran *et al.*, 2016) and wind farms require strong wind. Hydropower generation offers a solution to this intermittency through dams controlling the storage/release decision.

[3]Developing countries invest heavily in hydropower. For instance, African states aim at providing energy to 60% of their citizens by 2040 by increasing hydropower capacity by 6% a year (Conway *et al.*, 2017). Hydropower generation is also prevalent in many South American countries, such as Argentina, Brazil, and Chile (Moreno *et al.*, 2017). Moreover, Hydropower Europe (2020) suggests that Eastern European countries have exploited only less than half of their economically feasible hydro potential. Hydropower is also a key resource for waterrich developed regions like Canada, New Zeland, and Northern Europe.

tailed data for Colombia,[4] we demonstrate that a diversified firm internalizes future droughts by decreasing its hydro supply and simultaneously raising its fossil fuel supply. Since hydropower becomes expensive ahead of a drought, this substitution effect impacts both current and future prices: it increases current production by currently raising the firm's fossil fuel supply, which, in turn, saves hydro resources for the dry period. However, we also find that diversification through mergers steepens a firm's demand, potentially increasing prices. Therefore, our results suggest that incentivizing diversification can benefit consumers only if it does not substantially increase market power, underscoring the importance of correctly integrating different resources to smooth the clean-energy transition.

Methodologically, we first empirically identify substitution patterns across production technologies, then quantify them through a structural model. We start by documenting that energy prices jump by more than 10 times during droughts,[5] as hydropower production becomes expensive when firms' water stocks are lower.[6] Exploiting exogenous water inflows to diversified firms, we find that they simultaneously raise their fossil fuel supply ahead of an adverse event, which mitigates price hikes. Thus, we conjecture that prices depend on the share of fossil resources owned by the firm expecting a drought; the greater the connected fossil capacity, the lower the price increase.

We asses the impact of these substitution patterns on prices through a dynamic structural model, in which diversified firms compete in hourly auctions. Hydropower generation is storable through dams, so owning a dam creates an intertemporal tradeoff between current and future energy production. As firms maximize intertemporal profits, this tradeoff extends to the other non-hydro generators owned by a diversified firm.[7] We estimate the model on six years characterized by

[4]Hydropower accounts for 70% of the energy supply in Colombia and most large players produce energy through a diverse set of technologies (e.g., dams and combustion of fossil fuels).

[5]The price hikes caused by droughts are a key policy issue in Colombia. The main policies to contain prices include a call option mandating firms to sell a certain amount of energy at a strike price (Cramton and Stoft, 2007) and forward contracts (Ausubel and Cramton, 2010), which, however, often closely mirror spot prices (de Bragança and Daglish, 2016), thus providing few hedging opportunities. Blackouts are frequent when the market fails to clear or clears at high prices (Zapata *et al.*, 2018). The resulting poor electrification can distort incentives to producers (Allcott *et al.*, 2016), and lower both consumer welfare (Westley, 1984) and employment (Vidart, 2020).

[6] The marginal cost of hydro generators is well beyond that of fossil fuels outside of droughts, making fossil energy a marginal resource in regular periods.

[7]In our model, each generator is a bidder whose profits also depend on the other generators within the same firm. Thus, we model a dynamic auction with externalities across bidders. Similar

high price volatility due to extreme weather events such as el Niño and la Niña. For tractability, we examine the fit of the model estimates by simulating the related dynamic Cournot optimization problem (e.g., Reguant, 2014). The model correctly replicates market outcomes over time. We then use it to quantify the price-effect of technology substitution by comparing prices across several scenarios varying the fossil energy capacity of the market-leading firm, EPMG.

Our simulations show three main results. First, increasing EPMG's fossil fuel capacity while holding constant the firm's residual demand lowers market prices one to two quarters ahead of dry spells. Second, this substitution also allows the firm to use more hydropower during droughts. Thus, saving water before droughts effectively curbs price hikes before and during droughts. We then perform a third experiment in which we merge EPMG with all fossil fuel generators owned by other large diversified firms, thereby steepening EPMG's residual demand. Despite easier technological substitution, market prices increase substantially in all seasons because the steeper residual demand increases EPMG's market power even more. Our counterfactuals suggest that diversification can smooth market clearing and that policymakers should balance the objective of diversification with that of containing market power to prevent yet higher prices.

Our first contribution is to empirically document the presence of an intertemporal tradeoff in hydropower generation consistent with previous theoretical works studying the short-run behavior of renewable energy firms in environments where strategic players have access to storage (Bushnell, 2003; Andrés-Cerezo and Fabra, 2020).[8] Our analysis differs from this literature in two main respects. First, we study a long-run tradeoff that arises from firms' expectations about the seasonal availability of renewable resources, rather than the short-run tradeoff arising from the possibility of freely reallocating low-cost renewables from peak to off-peak hours in sequential markets. Second, our results introduce a novel tradeoff between the benefits and costs of diversification when the latter affects market concentration. Thus our results advocate diversification through functioning capacity markets to incentivize firms' capacity investments (e.g., Fabra, 2018; Fabra and Llobet, 2021) rather than mergers and acquisitions. Although the Colombian market

static models include analyses of timber (Kuehn, 2019) and charity auctions (Fioretti, 2020).

[8] Garcia *et al.* (2001, 2005) study strategic behavior across energy producers in hydropower dominated markets. Relatedly, some recent theoretical papers study market power in storage rather than production and its implications for energy supply (e.g., Newbery, 1990; Schmalensee, 2019).

extols the benefits of capacity investments in fossil fuels, our model and results generalize to other resources with different cyclicality than the affected renewable.

A growing theoretical literature studies how to incentivize the efficient combination of fossil and renewable energy sources (e.g., Abrell *et al.*, 2019; Ambec and Crampes, 2019; Schmalensee, 2019) but does not empirically consider the strategic behavior of diversified suppliers. Our analysis fills this gap by extending studies on how different cost structures (e.g., Wolak, 2003; Reguant, 2014) and cost shocks (e.g., Kim, 2017, 2019) affect firms' behaviors and market outcomes (e.g., Hortaçsu and Puller, 2008). In doing so, our paper also relates to previous empirical research on static multi-unit auctions (e.g., Wolak, 2007; Hortaçsu and Puller, 2008; McAdams, 2008; Hortaçsu and McAdams, 2010; Kastl, 2011; Hortaçsu and Kastl, 2012) and dynamic auctions (e.g., Jofre-Bonet and Pesendorfer, 2003).

This work connects with the theoretical and empirical literature studying the impact of horizontal mergers on equilibrium outcomes. The implications of horizontal mergers depend on the tradeoff between the efficiencies from exploiting synergies and the increased market power from internalizing the post-merger competitive externalities (e.g., Williamson, 1968; Farrell and Shapiro, 1990; Nocke and Schutz, 2018).[9] In our context, the merger of two energy firms with different technologies has two opposite effects. Firms internalize future adverse events and react to them with the unaffected production technologies, decreasing market prices, but, simultaneously, their market power increases, which raises market prices.

This paper is structured as follows. Section 2 provides the institutional details and Section 3 describes the data. Evidence of intertemporal technology substitution is in Section 4, while Section 5 presents and estimates the structural dynamic model. Section 6 discusses the counterfactual simulations, and Section 7 concludes.

## 2 Institutional Background

The Colombian energy market, like most national energy markets, consists of generators, transmitters, distributors, and retailers. These agents form the wholesale market, called *Mercado de Energia Mayorista* (MEM). The interconnected national system, *Sistema Interconectado Nacional*, was created in 1994 after the opening of

[9] Asker and Nocke (2021) present a review of the theoretical and empirical literature.

the centralized energy industry to competition through the deregulation of generation and retail activities. Transmission and distribution activities are regulated as natural monopolies. The market is assisted by the *Centro Nacional de Despacho* (CND), whose main task is to determine market prices and equilibrium quantities through a specific body called *XM*. The functioning of the MEM is regulated by the *Comisiòn de Regulaciòn de Energia y Gas*.

Retailers and generators trade energy through the forward and the spot markets. Bilateral contracts among pairs of agents form the forward market. This market allows agents to decide the financial position of each of their power generating units weeks in advance of the actual market. The purpose of these contracts is to hedge the uncertainty in the spot market prices, which is the focus of this paper.[10]

**Bidding in the day-ahead (spot) market.** The day-ahead market, or *despacho central*, sets the output of each generator and the spot market prices. This market takes the form of an auction in which Colombian energy producers compete by submitting quantity- and price-bids to produce energy the following day. Through this bidding process, each generator submits one quantity-bid per hour and one price-bid per day. Quantity-bids state the maximum amount (MWh) a generator is willing to produce in a given hour. Price-bids indicate the minimum price (COP/MW) a generator is willing to accept to produce at each hour of the following day.[11]

**Participation in the spot market.** Participation in the day-ahead market is mandatory for major generating units (i.e., net effective capacity above 20MWh). Smaller generators with a capacity between 10 and 20 MWh can decide to opt out of the market. A generator that posts a bid-price of zero is considered a price-taker and will produce at any market price. Generators with a net effective capacity below 10 MWh can only submit an hourly market schedule detailing how many MWh they are willing to sell at each hour at the prevailing market price. Firms with multiple generators submit bids for each.

**Spot market-clearing.** Before bidding occurs in the day-ahead market, CND provides all generators with the estimated market demand for each hour of the following day. After the bidding, CND collects all bid schedules from the day-ahead

[10]There is a third (intra-day) market, named *Control Automatico de Generacion*, in which real-time differences between demand and supply are balanced.

[11]Divide Colombian Pesos (COP) figures by 3,150 to obtain the U.S. Dollar (US$) equivalent amount, which is the exchange rate at the end of the period we study.

market and ranks them from the least to the most expensive to find the lowest price that satisfies demand in each hour. CND then informs all generators about the auction outcomes, or *despacho economico* (economic dispatch). During the production day, the actual generation can differ from the depacho economico for several reasons (e.g., production constraints or transmission failures). The CND modifies the despacho economico to accommodate these issues during the production day. The new schedule is called *despacho real* (actual dispatch). The day after the production day, XM creates another schedule called *despacho ideal* (ideal dispatch), based on the realized demand and production levels.[12] The spot hourly price is set at the value of the price-bid of the marginal generator. All dispatched units are paid the same price according to this schedule.[13]

**Reliability payment mechanism.** Designed as a mechanism to guarantee the supply of energy during dry periods like el Niño, the reliability payment mechanism, or *Cargo Por Confiabilidad*, consists of financial contracts and capacity payments named *Obligaciones de Energia Firmes* (OEF), or firm energy. The contracts specify a predetermined quantity of energy that each generator must supply at a scarcity price, or *precio de escasez*, whenever the spot market price exceeds this price. The scarcity price is updated monthly and computed as a heat rate times a gas/fuel index plus other (non-fuel) variable costs (Cramton and Stoft, 2007). Scarcity prices do not vary across generators, while scarcity quantities do. Figure 1 shows average prices and the scarcity prices over time. To sell the firm energy at lower prices, firms receive fixed monetary transfers based on their installed capacity. Yearly auctions define these capacity payments, which are constant until the following auction. Thus, these are the two main tools available to the Colombian government to stimulate investment in generation capacity (Cramton *et al.*, 2013).

# 3 Data

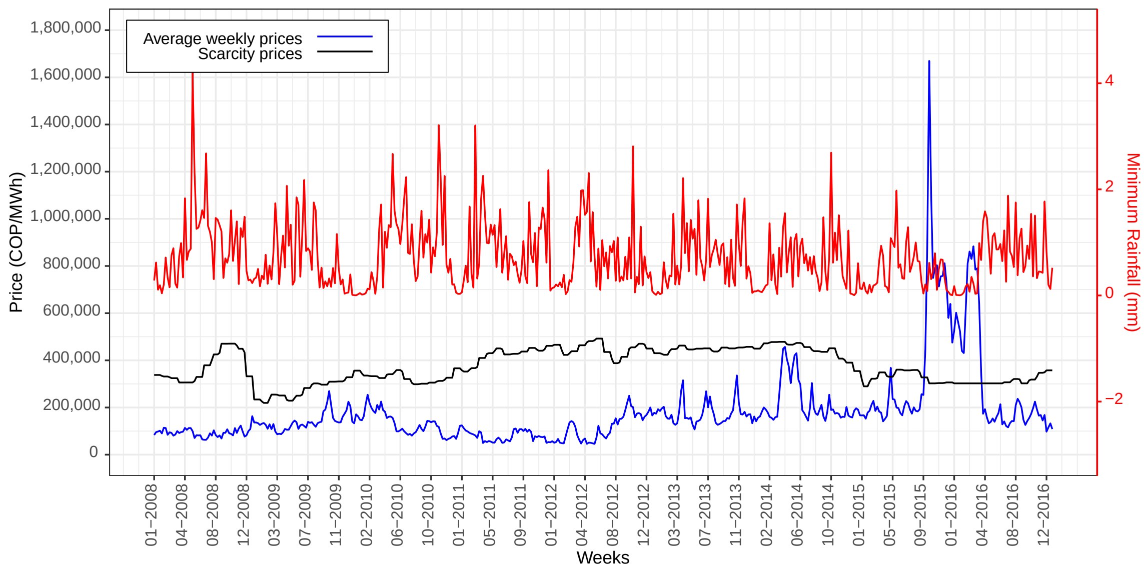
The data come from XM for the period 2006–2017. For all generators, we observe all quantity- and price-bids and forward contract positions. The data also includes the ownership and geolocalization of each generator, and detailed information on

[12]The ideal dispatch takes into account technical characteristics and actual availability of each generator (e.g., technical failures). It does not consider network restrictions.

[13]The actual price paid to different generators may vary because CMD also pays startup costs.

the daily water inflow and stock for hydropower generators with a dam.

Figure 1: Average prices, scarcity prices, and rainfalls




Note: The average weekly price and the scarcity price from Section 2. The red line (right axis) displays the minimum rainfall observed across hydro units (in mm) in each week.

**Data sources.** We source weather information from the *Colombian Institute of Hydrology, Meteorology, and Environmental Studies* (IDEAM). This information contains daily measures of rainfall and temperature from 303 measurement stations. To calculate the daily temperature and rainfall at each generator, we compute a weighted average of the temperatures and rainfalls by all measurement stations within 120 kilometers, weighting each value by the inverse of the distance between that generator and the measurement stations.[14] We also account for the geography of the country – that is, the large mountain chain in Colombia – to compute the distance between generators and weather measure stations, using information from the *Agustin Codazzi Geographic Institute* (IGAC).

To construct the rainfall forecasts, we use monthly summaries of the status of el Niño, la Niña, and the Southern Oscillation, or ENSO, based on the NINO3.4 index, provided by the *International Research Institute* (IRI) of Columbia University.[15]

[14]The 120km radius cover 80% of Colombia's population.

[15]The *El Niño-Southern Oscillation* (ENSO) is one of the most important and longest-studied climate phenomena. It can lead to large-scale changes in sea-level pressures, sea-surface temperatures, precipitation and wind, not only in the tropics but in many other regions of the world. ENSO describes the year-to-year variations in the ocean and atmosphere in the tropical Pacific. Sea-surface

Table 1: Installed capacity and production volumes by technology

| Technology | Installed capacity MWh | Installed capacity % of total | Production MWh | Production % of total |
|---|---|---|---|---|
| Hydro | 9,039 | 61.90 | 5,232 | 75.00 |
| Thermal | 4,639 | 31.80 | 1,348 | 19.30 |
| Run-of-river | 858 | 5.87 | 351 | 5.04 |
| Cogeneration | 54 | 0.37 | 39 | 0.56 |
| Wind | 18 | 0.13 | 6 | 0.08 |
| Total | 14,608 | 1 | 6,976 | 1 |

Note: Average installed capacity and average production volumes by technology over the period from January 2008 through December 2016.

ENSO forecasts are published on the 19th of each month and each issue provides ENSO's probability forecast for the following nine months. The ENSO probability forecasts are a main source for hydropower generators in Colombia. We have monthly information from 2004 to 2017. Finally, we integrate these information with daily prices of oil, gas, coal, liquid fuels, and ethanol. These commodities take part in the production of energy through either thermal (fossil fuel) or cogeneration (sugar manufacturing) generators.

**Production technologies.** Table 1 compares the installed capacity for the five principal production technologies currently used in Colombia: hydropower, thermal (coal and fossil fuel), run-of-river, cogeneration (sugar manufacturing), and wind farms.[16] Hydropower generation accounts for over 60% of the total installed capacity in Colombia between January 2008 and December 2016 and can supply as much as 9,000 MWh. When it comes to production, hydropower generation averages 75% of total energy supply, or above 5,200 MWh.[17] Although thermal units are the second-largest production technology by installed capacity (30% of total capacity), they hardly produce at or close to capacity (less than 20% of total production). The remaining technologies are marginal and their share of installed

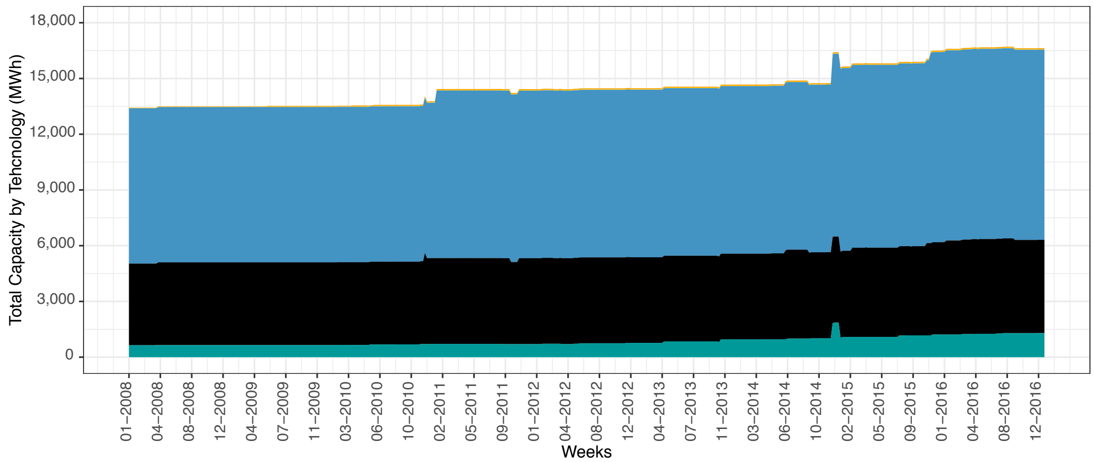
temperatures in the central and eastern equatorial Pacific cycle between above- and below-average. An el Niño state occurs when the central and eastern equatorial Pacific sea-surface temperatures are substantially warmer than usual; la Niña occurs when those waters are cooler than usual. These events typically persist for 9-12 months, though occasionally last up to two years.

[16] Appendix Figure A1 shows examples of generators by technology.

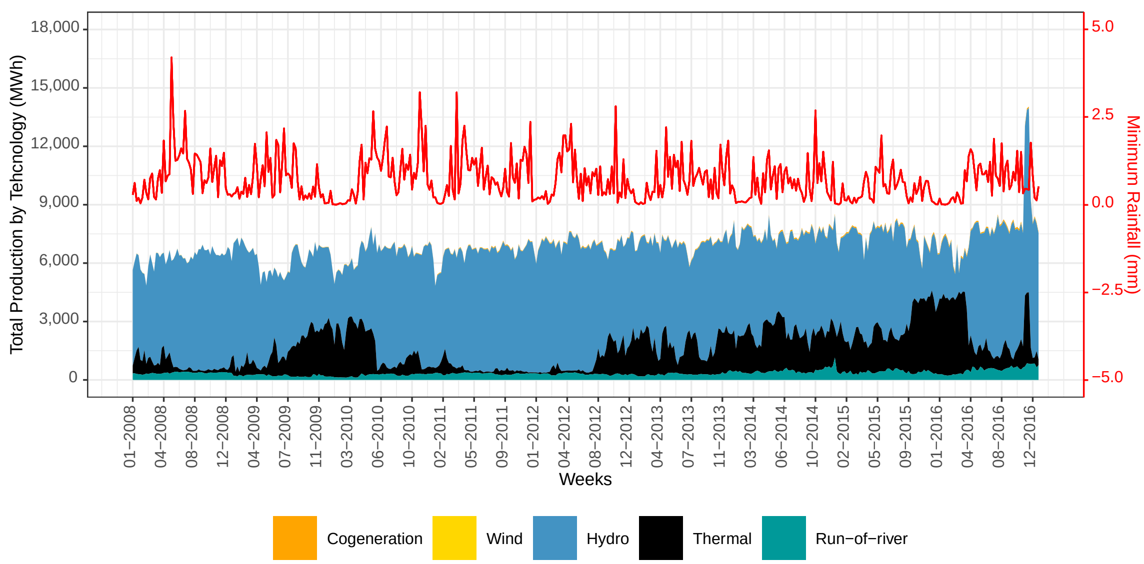
[17] For comparison, the District of Columbia consumes about 73MWh per capita per year. Source: https://www.eia.gov/state/rankings/?sid=DC#series/12

Figure 2: Installed capacity and production volumes by technology over time

(a) Total installed capacity by technology




(b) Total weekly production by technology




Note: Total installed capacity and production volumes by technology. The red line in Panel (b) (right axis) displays the minimum rainfall (in mm) observed across hydro units in each week.

capacity mirrors their production shares.[18]

The discrepancy between output and capacity is evident in Figure 2. Panel (a) shows that each technology's capacity share is constant over time. Hydro (blue

[18] Energy storing makes dams more attractive than run-of-rivers and wind farms in Colombia.

area) and thermal (black area) have most of the available capacity in the period. Panel (b) instead shows considerable variability in the shares of hydro and thermal production. There are periods in which no thermal generator produces and periods in which thermal production reaches 50% of the total.

This variation depends on the timing of the rainy seasons. Panel (b) also plots a proxy for a negative shock to hydropower energy production: the rainfall at the hydro-generator location with the lowest rainfall (red line, right axis). The plot shows a positive relationship between the volume of hydro production (blue area) and the minimum rainfall (red line) (Spearman correlation: 0.27, p-value $\leq 0.01$), meaning that abundant rain is correlated with more hydropower production.[19] At the same time, we observe a negative relation between the production share of thermal units (blue area) and minimum rainfall (Spearman correlation: -0.32, p-value: $\leq 0.01$). Put together, the plot indicates that thermal production substitutes for hydro generators in periods of adverse weather.

Market prices are directly affected by the employed technologies because different technologies have different marginal costs. Figure 1 plots the average weekly market price (blue line) and our simple measure of drought (red line, right axis), suggesting that rainy seasons (abundant water resources) command lower prices (Spearman correlation: -0.28, p-value $\leq 0.01$). In the next sections, we investigate the price-impact of intertemporally substituting production across technologies.

# 4 Intertemporal Substitution

We start by examining how firms respond to production shocks. In particular, we focus on how a firm expecting a future weather shock reallocates production across generators by varying its price- and quantity-bids in advance. We consider both favorable shocks, such as an abundant unexpected rainfall (intense rainy season), and adverse ones, such as a dry season. We focus on the four largest firms (ENDG, EPMG, ESPG, and ISGG); they are diversified, have at least a dam each (15 in total), and cover 60% of total production. We then zoom in on the implications for market prices in Section 4.2. We use weekly data spanning the period between

[19] The effect is particularly visible during the el Niño event at the end of 2016 and during the dry seasons from December to April of each year.

January 2006 to December 2017.[20]

### 4.1 Supply Schedules and Inflow Forecasts: Empirical Strategy

We exploit exogenous changes in the water inflow of hydropower plants to assess the extent of intertemporal substitution within a firm. We estimate the following specification

$$y_{ij,t} = \sum_{l=1}^{4} \beta_l \, \widehat{inflow}_{ij,t+l} + X_{ij,t-1}\,\alpha + \mu_{ij} + \delta_t + \varepsilon_{ij,t}, \tag{4.1}$$

where the outcome variable, $y_{ij,t}$, refers to the average quantity- and price- bids of firm $i$, generator $j$ in week $t$. The variable $\widehat{inflow}_{ij,t+l}$ is the forecast $l$ quarters ahead of the future inflow of water of generator $j$.[21] Although we use weekly data, we aggregate forecasts at the quarter level because weekly and monthly forecasts are highly correlated. The remaining variables include $X_{ij,t-1}$, a set of lagged firm/generator specific-controls such as generator $j$'s water stock and firm $i$'s average net forward contract sales, and market-level controls such as the demand of electricity and the average spot price. We also include firm-generator ($\mu_{ij}$) and month and year ($\delta_t$) fixed effects.

We also investigate nonlinear responses to favorable and adverse expected water inflows to the supply of hydropower by estimating

$$y_{ij,t} = \sum_{l=1}^{4} \left( \beta_l^{low} \mathbb{1}_{\left[\widehat{inflow}_{ij,t+l} \in Q^1_{ij,t+l}\right]} + \beta_l^{high} \mathbb{1}_{\left[\widehat{inflow}_{ij,t+l} \in Q^4_{ij,t+l}\right]} \right) + X_{ij,t-1}\,\alpha + \mu_{ij} + \delta_t + \epsilon_{ij,t}. \tag{4.2}$$

Unlike (4.1), (4.2) studies a generator's differential response to forecasts of extreme weather conditions. The dummy variables $\mathbb{1}_{\left[\widehat{inflow}_{ij,t+l} \in Q^1_{ij,l}\right]}$ and $\mathbb{1}_{\left[\widehat{inflow}_{ij,t+l} \in Q^4_{ij,l}\right]}$ are 1 if the forecasted inflow $l$ quarters ahead falls inside the first ($Q^1_{ij,t+l}$) or fourth ($Q^4_{ij,t+l}$) quartiles of generator $ij$'s distribution of forecasted water inflows for quar-

[20] Appendix B presents robustness of the regressions in this section to varying control variables.

[21] To construct the forecasts, we estimate an ARMA model for each generator's water inflow following the Box-Jenkins selection procedure on quarterly data. The covariates include the ENSO probability forecast for three, six and nine months ahead. For each period, we predict the future water inflows for each future quarter using the estimated ARMA model. The qualitative results do not change if we use moving average forecasts or focus on monthly instead of weekly data.

ter $t + l$, and 0 otherwise.[22] If a hydro generator expects an above-normal dry season, we would expect smaller current quantity-bids (or greater current price-bids) in order to accumulate water to face the adverse expectation. In contrast, if a hydropower generator expects an overly rainy season, it should increase its quantity-bids (or decrease its price-bids) to reap higher profits from current production. The coefficients $\{\beta_l^{low}\}_{l=1}^4$ and $\{\beta_l^{high}\}_{l=1}^4$ in (4.2) capture these mechanisms.

**Sibling generators.** We also inspect potential supply reallocations across technologies owned by the same firm by adjusting equations 4.1 and 4.2 to study the strategy of thermal generators that are siblings of hydropower generators; that is, thermal plants that belong to one of the four firms considered in this section. In this case, the dependent variables become the quantity- and price-bids of each thermal generator, while the forecasts ($\widehat{inflow}_{i,t+l}$) and forecast distributions ($Q^1_{i,t+l}$ and $Q^4_{i,t+l}$) refer to the sum of water inflows to its sibling hydropower generators.

### 4.1.1 Supply Schedules and Inflow Forecasts: Results

This subsection presents the results of the models introduced above. We cluster standard errors either at the generator-quarter-year level or at the firm-quarter-year level.

**Hydropower generators.** Panel (a) of Figure 3 plots the $\beta_l$ coefficients from (4.1) for $l = 1, 2, 3, 4$ periods ahead when quantity-bids are the dependent variable. Figure 3 Panel (b) presents the results for the price-bid as dependent variable. The results indicate that expecting a drought (rainy season) one quarter ahead decreases (increases) quantity-bids by about 378.1 kWh and increases (decreases) price-bids by 2,290 COP/MWh (0.73 US$/MWh). We do not find a significant effect of changes in the expected inflow of water two or more quarters ahead.

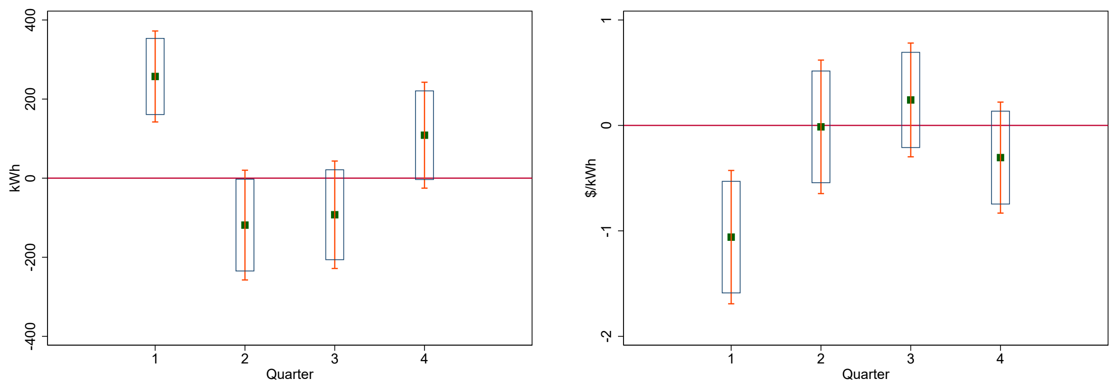
This effect is asymmetric: a future favorable expected shock (fourth quartile) does not affect a plant's current quantity- and price-bids (Appendix Figures A2b and A3b respectively), whereas an adverse shock is statistically significant one quarter ahead for both bid types (Appendix Figures A2a and A3a respectively).[23] An adverse shock to the expected inflow of water a quarter ahead leads a hy-

[22] El Niño and la Niña are examples of such extreme events. They usually develop in April–June and reach their maximum strength in October–February. Thus, around October–November, firms usually have an accurate prediction of whether an extreme event is expected in the next dry season.

[23] Appendix Tables B1 and B2 report the estimates from (4.1) and (4.2), respectively.

Figure 3: Hydropower generators' response to own inflow forecasts

(a) Quantity-bids (b) Price-bids




Note: The estimated $\beta_l$ from equation 4.1 with quantity-bids or price-bids as dependent variables. Appendix Table B1 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

dropower generator to reduce its quantity-bid by 8MWh (1.8% of the average quantity-bid of a hydro generator) and to increase its price-bid by 60 COP/kWh (a 25% change). We conclude that hydropower generators anticipate future adverse shocks by stepping up their supply bids, but do not react to favorable shocks.

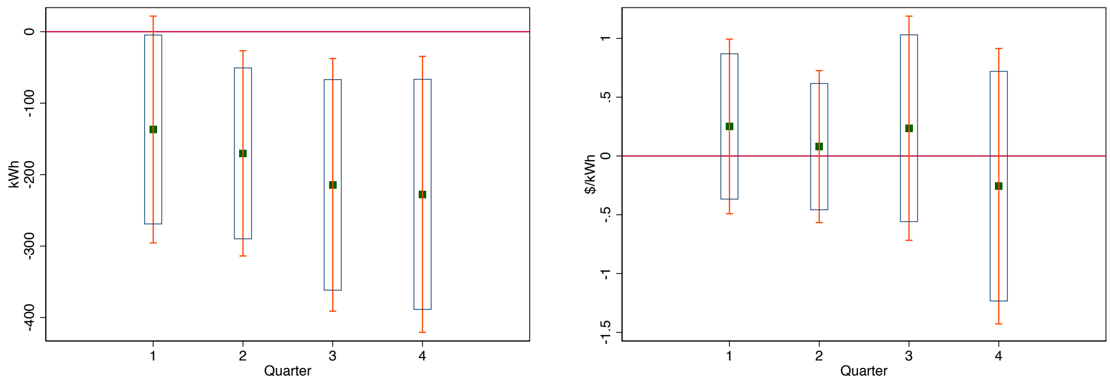
**Sibling generators.** Next, we examine how thermal generators owned by firms with hydropower plants with dams react to inflow forecasts. We use equations 4.1 and 4.2 to regress the bids of thermal generator $j$ of firm $i$ on the forecasted total inflow of water of firm $i$, $l$ quarters ahead. We find the reactions of thermal generators to future shocks are opposite to those of hydro generators.[24] Panel (a) of Figure 4 shows that thermal generators modify their quantity schedule well in advance (between one and four quarters ahead of the shock). However, we detect no change to thermal generators' price-bids, on average (Panel b).[25] The reaction is asymmetric: thermal units mildly decrease their price-bids three quarters ahead of negative shocks (Appendix Figures A4a and A5a) and substantially step up their supply schedules (i.e., decrease their quantity-bids and increase their price-bids) three to nine months before a positive shock (Appendix Figures A4b and A5b).

**Discussion.** Our results detect an asymmetry in the observed intertemporal substi-

[24] The estimates from (4.1) and (4.2) for sibling generators are in Appendix Tables B3 and B4.
[25] Moving average forecasts with monthly updated predicted inflows yield similar results.

Figure 4: Thermal generators' response to sibling generators' forecasts

(a) Quantity-bids (b) Price-bids




Note: The estimated $\beta_l$ from equation 4.1 with quantity-bids or price-bids of sibling thermal generators as dependent variables. Appendix Table B3 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

tution across production technologies: firms react to adverse expected events (dry seasons) but not to favorable ones (rainy seasons) with their hydropower generators. Instead, firms react to favorable expected events by placing high price-bids and lower quantity-bids with their thermal units, decreasing their production.

These results suggest that the intertemporal and technological substitution effect can lower market prices in dry seasons. Since hydropower has a larger share of the total electricity produced, we should expect asymmetric effects on market prices in dry and rainy seasons. The next subsection shows preliminary evidence of these hypotheses and present a structural model to test them in Section 5.

## 4.2 Market Prices: Empirical Strategy

This section examines how moving production across technologies affects market prices. We transform (4.2) to understand how current market prices are affected by the thermal capacity available to firms facing adverse or favorable inflow forecasts in the following four quarters. We focus on the following specification:

$$
\begin{aligned}
price_t = & \sum_{l=1}^{4}\left(\beta_l^{low}\sum_i \mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^1_{i,t+l}\right]} + \beta_l^{high}\sum_i \mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^4_{i,t+l}\right]}\right) \\
& + \sum_{l=1}^{4}\left(\gamma_l^{low}\sum_i\left(\mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^1_{i,t+l}\right]}\sum_{j=1}^{J_i} cap^{Th}_{ijt}\right) + \gamma_l^{high}\sum_i\left(\mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^4_{i,t+l}\right]}\sum_{j=1}^{J_i} cap^{Th}_{ijt}\right)\right) \\
& + \gamma^{cap}\sum_{i,j} cap^{Th}_{ijt} + \prime X_{t-1}\,\alpha + \delta_t + \varepsilon_t,
\end{aligned} \tag{4.3}
$$

where the dependent variable is the average market price in week $t$. The indicator functions $\mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^1_{i,t+l}\right]}$ and $\mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^4_{i,t+l}\right]}$ are 1 if, $l$ quarters ahead of week $t$, firm $i$ expects its total water inflow to be in either the first or fourth quartile of its water inflow distribution.[26] Thus, $\beta_l^{low}$ and $\beta_l^{high}$ measure the market price response due to firms expecting either an adverse or a favorable future expectation. We interact these variables with the amount of thermal capacity available to firm $i$ in each quarter; that is, $\mathbb{1}_{\left[\widehat{inflow}_{i,t+l}\in Q^1_{i,t+l}\right]}\sum_{j=1}^{J_i} cap^{Th}_{ijt}$ for adverse expectations.[27] We then sum these values across all firms, so that the coefficients $\gamma_l^{low}$ and $\gamma_l^{high}$ measure, respectively, how the capacity at sibling thermal generators affects market prices during a negative or a positive weather event. The remaining variables include $X_{t-1}$, a set of lagged specific controls, such as the total net forward contract sales, and lagged market-level controls, such as the average demand for electricity. We also include year and month fixed effects ($\delta_t$). Finally, Newey-West standard errors are computed using four lags.[28]

### 4.2.1 Market Prices: Empirical Evidence

Figure 5 plots the OLS estimates for the coefficients $\gamma_l^{low}$ and $\gamma_l^{high}$ for $l = 1, ..., 4$ in (4.3), which describe the interaction of the quarterly inflow forecasts with the total connected thermal capacity. Focusing first on Panel (b), we find that sibling thermal generators do not affect prices significantly during a favorable future weather event. Moving to Panel (a), we find a significant and negative effect of intertem-

[26]We aggregate plant-level expectations to the firm level; i.e., $\widehat{inflow}_{i,t+l} = \sum_j \widehat{inflow}_{ij,t+l}$.

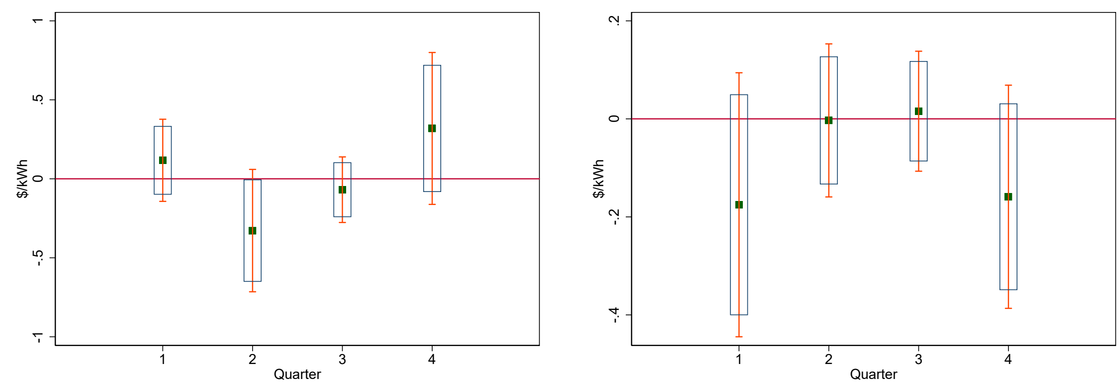
[27]The variable $cap^{Th}_{ijt}$ refers to the maximum quantity (in kWh) produced by the thermal generator $j$ owned by firm $i$ in a year window around week $t$

[28]The results are robust to varying the number of lags and clustering the standard errors at the quarter-by-year level, instead.

poral substitution across hydro and thermal technologies on current market prices two quarters ahead. The coefficient remains negative in the third quarter, but is not significant. Therefore, consistent with the discussion in Section 4.1.1, greater sibling thermal capacities imply lower current prices ahead of an adverse forecast.

Figure 5: The impact of substituting production technologies on market prices

(a) First quartile (b) Fourth quartile




Note: The estimated $\gamma_l^{low}$ (Panel a) and $\gamma_l^{high}$ (Panel b) from equation 4.3. Appendix Table B5 reports the coefficient estimates. The red line and the bar provide 5% and 10% confidence intervals, respectively. Standard errors are clustered using the Newey-West procedure.

To quantify this substitution effect on prices, we compare the price effect through $\hat{\gamma}_2^{low}$ with the average market price observed in case of an adverse forecast two months ahead, which is the sum of the average dependent variable and the price effect described by $\hat{\beta}_2^{low}$. Using the estimates in Columns 1 and 3 of Appendix Table B5, we estimate that the substitution effect accounts for a price reduction between 33% and 35% of the average observed market price, a substantial effect.

In sum, despite their higher production costs, thermal generators have a negligible effect on market prices in expectation of a rainy period, but a negative and significant effect in expectation of a dry season. This analysis has two main limitations. First, moving from (4.2) to (4.3) implies a substantial drop in observations (from 5,441 to 623), even though the number of variables of interest increases. Thus, this analysis may fail to detect important firm-specific variation that is instead averaged out across weekly markets. Second, large Colombian suppliers could trade thermal generators over time to take advantage of this substitution effect. These changes in ownership may overstate the importance of the substitution effect through this reduced-form approach. Therefore, the next section builds a formal model of the Colombian market to examine, through simulations, the price effect of different ownership scenarios of thermal generators.[29]

# 5 Modeling Substitution Across Technologies

The patterns in the bidding data discussed in the previous section underscores the importance of intertemporal substitution across different generators owned by a firm. To examine the underlying mechanism, we model the day-ahead market as a multi-unit auction. There are $N$ firms and each firm $i = 1, ..., N$ owns multiple generators $j = 1, ..., J_i$ of different technology $\tau$ (hydro power, thermal power, run-of-river, wind farms, or cogeneration).

## 5.1 Production Capacities and Costs

Let the set of all technologies available to firm $i$ be denoted by $\mathcal{T}_i$ and its subset of hydro generators by $\mathcal{H}_i$.[30] In the model, we assume that marginal costs vary across technologies and firms, but not across generators of the same technology. A firm's available generation technology limits the amount it can produce in each hour of the day. Each generator has a minimum and a maximum production capacity. Capacities are fixed over time for non-hydro technologies, while the capacity of a hydropower generator varies with the water stock. In particular, a firm's current hydro capacity depends on the water stock at the beginning of the period ($w_{it} \in [\underline{w}_i, \overline{w}_i] \equiv \mathcal{W}_i$), the net water inflow at each dam ($\delta_{ijt} \in \mathbb{R}$), and the energy production according to the water balance equation (Lloyd, 1963):[31]

$$w_{it+1} = w_{it} - \sum_{h=0}^{23} \sum_{j \in \mathcal{H}_i} \mathbb{1}_{[b_{ijt} \leq p_{ht}]}\, q_{ijht} + \sum_{j \in \mathcal{H}_i} \delta_{ijt}, \tag{5.1}$$

where $\mathbb{1}_{[b_{ijt} \leq p_{ht}]}$ indicates that hydro unit $j$'s bid at market hour $h$ is accepted. We denote the transition matrix of the water stock by $f_i(\omega_{it+1}|\Omega_{iht})$, where $\Omega_{iht}$ is a matrix of daily stocks of water and hourly accepted production quantities.

[29] Appendix D shows that technology substitution decreases prices also during adverse events.

[30] $\mathcal{T}_i$ is the partition of the set of generators $\{1, \ldots, J_i\}$ by production technology.

[31] All these variables are measured in energy metrics (e.g., kWh or MWh). Water inflows are net of precipitation and natural outflows such as evaporation. We disregard a firm's decision to spill water when one of its dam is flooded for tractability (less than 5% of the observations).

## 5.2 Market-clearing

The auction rules in Section 2 determine the hourly equilibrium price and quantities produced. At the bidding stage, each firm $i$ submits a vector of daily price-bids, $\mathbf{b}_{it} = \{b_{i1t}, ..., b_{iJ_it}\}$, and hourly quantity-bids, $\mathbf{q}_{iht} = \{q_{i1ht}, ..., q_{iJ_iht}\}$, which define how much each of its $J_i$ generators is willing to produce and its minimum acceptable price. As in Klemperer and Mayer (1989) and Wolak (2007), bidders face uncertainty in terms of the demand in hour $h$ of the following day, which is known only up to a noise parameter $\epsilon_{ht}$ with mean zero and full support. Although we assume $\epsilon_{ht}$ to be i.i.d. for simplicity, we allow for arbitrary correlations across hours and time at the estimation stage. The market demand $D_{ht}(\epsilon_{ht})$ is perfectly inelastic and bidders take it as given. The system operator crosses the supply schedules submitted by each firm $S_{iht}(p_{ht}) = \sum_{j=1}^{J_i} \mathbb{1}_{[b_{ijt} \leq p_{ht}]} q_{ijht}$ against $D_{ht}$ to determine the lowest price-bid so that demand equals supply:

$$D_{ht}(\epsilon_{ht}) = \sum_{i=1}^{N} S_{iht}(p_{ht}), \quad \text{for all } h = \{0, ..., 23\} \text{ and } t. \tag{5.2}$$

The market price, $p_{ht}$, is the lowest price at which (5.2) holds. At this price, firm $i$'s residual demand is $D_{ht}(\epsilon_{ht}) - \sum_{l \neq i}^{N} S_{lht}(p_{ht}) = D^R_{iht}(p_{ht}, \epsilon_{ht})$, or just $D^R_{iht}$.[32]

## 5.3 Profit Maximization

In each day $t$, firm $i$ chooses a combination of price- and quantity-bids to maximize the following objective function:

$$\begin{aligned} V_i(w_{it}) = \mathbb{E}_\epsilon \Bigg[ \sum_{h=0}^{23} \Big( & D^R_{iht} p_{ht} - C_{iht}(\mathbf{q}_{iht}) - (p_{ht} - PC_{iht}) QC_{iht} - \mathbb{1}_{[p_{ht} > \overline{p}_t]} (p_{ht} - \overline{p}_t) \overline{q}_{it} \Big) \\ & + \beta \int_{\mathcal{W}} V_i(u) f_i(u|\Omega_{iht}) \, \mathrm{d}u \Bigg], \end{aligned} \tag{5.3}$$

where the first line describes the expected profits in the day-ahead market at each of the 24 hourly auctions held on the following day. Current profits include the operating revenues, $D^R_{iht} \cdot p_{ht}$, minus production costs $C_{iht}(\mathbf{q})$ for each accepted

[32] At the equilibrium price, a firm's supply equals its residual demand, which is the portion of demand not satisfied by its competitors at the market price.

unit. Colombian rules also allow for financial returns through long-term contracts to hedge production. In the data, we observe both the average size and the price of a firm's net contract position: $QC_{iht}$ and $PC_{iht}$, respectively. The difference between $PC_{iht}$ and $p_{ht}$ determines the financial profit or loss from selling $QC_{iht}$ units of energy in the forward market. Firms are also subject to the *Cargo Por Confiabilidad* rule, which forces them to sell a fixed amount of energy, $\overline{q}_{it}$, if the market price exceeds the scarcity price, $\overline{p}_t$.[33]

The second line of (5.3) links current and future payoffs according to (5.1), which updates a firm's water stock, $w_{it+1}$, based on $\Omega_{it}$, which includes the current hydropower production, water stock, and weather conditions. This transition probability is described by the conditional density $f_i(\cdot|\Omega_{it})$. The latter variable is zero for all firms that do not have access to hydropower technology, as they do not face any intertemporal tradeoff related to the water cycle. These firms solve a static optimization problem instead. $\beta \in (0,1)$ is the discount factor.

The model 5.3 assumes that a firm's current water stock is the sole state variable. Thus, the expectation is over the vector of residual demand shocks, $\epsilon_{ht}$.[34] To back this assumption empirically, Appendix C extends the reduced-form approach from Section 4 to include water forecasts for a firm's competitors. We do not find evidence of any correlation between a firm's price- and quantity-bids and competitors' expected inflows and water stocks after controlling for future weather changes such as the season, the forecasted rain and temperatures, and the future probabilities of el Niño.[35] Consistent with these findings, today's water

[33]Market participants cannot affect $PC$, $QC$, $\overline{p}$ and $\overline{q}$ in the daily wholesale markets.

[34]An alternative approach would assume that firms form expectations about their competitors' supply schedules. The empirical way to recreate this uncertainty for day $t$ consists of considering the resampled firm's residual demand from a sample of "similar markets" instead of the realized demand at $t$, as our formulation supposes. For instance, Reguant (2014) bases her resampling procedure on demand similarity by resampling a firm's residual demand for its day $t$ moment conditions on days with similar demand (e.g., if $t$ is a Monday, she resamples $D^R_{iht}$ across the $D^R_{iht}$ observed on Mondays). However, supply similarity is equally central in the Colombian wholesale energy market, as markets are similar also if a firm's water stock intertemporal value – that is, its realized value function – is similar across comparable days. Since the value function is the very object of the estimation, this operation is unfeasible. Therefore, we follow the best-response bidding approach of Wolak (2003), in which bidders form only expectations of the random residual demand shocks, which provides more precise estimates if its assumptions are respected. We believe that this is the case because past bids are an excellent predictor of current bids in the Colombian energy market ($\rho > 0.96$). All bids (and forward contract positions) are public knowledge with a day lag, reducing the uncertainty with respect to competitors' future supply functions.

[35]Industry experts confirmed that Colombian firms use similar statistical methods and data to

consumption affects tomorrow's profits directly through changes in firms' water stocks, but not indirectly through potential changes in future equilibrium prices due to changes in competitors' future water stocks. An explanation is that weather changes might be correlated across firms, so accounting for the current market conditions and a firm's forecasted inflows is enough to control for competitors' future strategies. Thus, the assumption we make retains the central empirical features discussed in Section 4 while allowing us to reduce a firm's state space considerably, thus keeping the empirical analyses tractable even when considering several years of daily auction data.[36]

**Optimal bidding.** This section derives necessary conditions for optimal bidding in the day-ahead market. In this framework, a marginal increase in the quantity-bid of generator $j$ affects firm $i$'s marginal cost in two possible ways. First, it affects the supply schedule of the production technology used by generator $j$. Denote the set of generators with this technology by $\tau_i \in \mathcal{T}_i$. Then the supply function for firm $i$ technology $\tau$ is $S^{\tau}_{iht} = \sum_{j\in\tau_i} \mathbb{1}_{\{b_{ijt}\leq p_{ht}\}} q_{ijht}$. Second, a marginal change in $q_{ijht}$ also implies a change in the market outcomes through the market-clearing condition 5.2 and can thus affect also the costs sustained by technologies different than $\tau$ through this price channel. To capture these two channels, we smooth the supply function following the seminal contribution of Wolak (2003), which ensures that the value function 5.3 is continuous and differentiable. Therefore, the derivative of the cost function for a technology $\tau$ with respect to $q_{ijht}$ is

$$\Big(\frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\tau}_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\Big)\frac{\partial C_{it}}{\partial q_{ijht}} + \sum_{\kappa\in\mathcal{T}_i,\, \kappa\neq\tau} \frac{\partial S^{\kappa}_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\frac{\partial C_{it}}{\partial q_{ijht}}, \tag{5.4}$$

where $q^{\tau}_{iht}$ indicates the overall production of firm $i$'s generator with technology $\tau$. The first term accounts for the direct effect and the second term accounts for the indirect effect. Similarly, a change in $q_{ijht}$ affects the value function directly

forecast future water inflows. This information further corroborates our conclusion that accounting for weather variables is enough to control adequately for competitors' future water stocks.

[36]The oblivious equilibrium (e.g., Weintraub *et al.*, 2008) is a common modeling assumption to reduce the dimensionality of dynamic games because it maintains that a firm's decisions depend only on its state variable (e.g., $w_{it}$) and the long-run average firm state that will prevail in equilibrium, while ignoring the current industry states. However, Colombian generators do not seem to react to the average long-run industry state, as their current decisions do not correlate with the total water stock of competitors but only to their own.

through the transition probability, $f_i(u|\Omega_{iht})$, and indirectly through the price, as

$$\frac{\partial \int_{\underline{w}}^{\overline{w}} V_i(u) f_i(u|\cdot)\mathrm{d}u}{\partial q_{ijht}} = \int_{\underline{w}}^{\overline{w}} V_i(u) \frac{\partial f_i(u|\cdot)}{\partial q_{ijht}} \mathrm{d}u = \left( \frac{\partial S^{\mathcal{H}}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\mathcal{H}}_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \right) \int_{\underline{w}}^{\overline{w}} V_i(u) \frac{\partial f_i(u|\cdot)}{\partial q^{\mathcal{H}}_{iht}} \mathrm{d}u,$$

with the superscript $\mathcal{H}$ indicating a hydro technology. Optimal quantity-bids solve

$$\mathbb{E}_{\epsilon}\Big[ p_{ht} \frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} + (D^R_{iht} - QC_{iht}) \frac{\partial p_{ht}}{\partial q_{ijht}} + \beta \Big( \frac{\partial S^y_{iht}}{\partial q_{ijht}} + \frac{\partial S^y_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \Big) \int_{\underline{w}}^{\overline{w}} V_i(u) \frac{\partial f_i(u|\Omega_{iht})}{\partial q^{\mathcal{H}}_{iht}} \mathrm{d}u$$
$$- \sum_{\tau \in \mathcal{T}_i} \Big( \frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\tau}_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \Big) \frac{\partial C_{it}}{\partial q_{ijht}} - \mathbb{1}_{[p_{ht} > \overline{p}_t]} \frac{\partial p_{ht}}{\partial q_{ijht}} \overline{q}_{it} \Big] = 0, \qquad (5.5)$$

The first-order conditions suggest two observations in line with the reduced-form results in Section 4. First, firms that do not have hydro units do not face any intertemporal technological substitution. Their bids reflect only their marginal cost – which, according to engineer estimates, is higher than that of hydro units – plus a markup related to the elasticity of their residual demand. Second, the indirect effect of changing $q_{ijht}$ on the value function has a negative sign for both thermal and hydro units. However, the direct effect is switched off for thermal generators (i.e., $\frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} = 0$ s.t. $\tau_i \cap \mathcal{H}_i = \varnothing$) but positive for hydro generators (i.e., $\frac{\partial S^y_{iht}}{\partial q_{ijht}} \geq 0$).[37]

We can examine how the direct and indirect effects impact bids through a change in the intertemporal marginal cost; that is, the marginal cost minus the marginal value function in (5.5). Consider the bidding problem of a hydro generator that expects a future drought. Everything else equal, producing $q_{ijht}$ units reduces the availability of future water, which is reflected in a drop in the probability mass allocated to high future water stocks in $f_i(\cdot|\Omega)$. This translates to a higher intertemporal marginal cost if the direct (positive) effect on the firm's hydropower supply is larger than the indirect (negative) effect.

For example, consider a firm with a hydropower generator and a thermal generator. The thermal generator internalizes the future drought only through the indirect effect, as producing $q_{ikht}$ thermal units reduces its intertemporal marginal cost by taking away a portion of the residual demand curve from its sibling hydro generator. Therefore, we expect bids of sibling hydro and thermal generators to

[37] McRae and Wolak (2017) and Wolak (2019) discuss the market power implications that residual demand and $\overline{q}$ have in the Colombian market (see also de Frutos and Fabra, 2012).

move in opposite directions. This misalignment will be stronger during or before a drought rather than a rainy season because thermal generators are more likely to be price-setters in the former than in the latter period, when their higher marginal costs make them residual claimants (Figure 2b).[38]

Consistent with the analysis in Section 4, market prices will drop as a result of intertemporal substitution across production technologies. Therefore, a diversified technology mix may be an effective tool to reduce price hikes due to droughts. Surprisingly, this effect is accentuated when a small supply change affects prices substantially due to market power, which is necessary for a stronger indirect effect.[39] However, market power also affects the marginal revenue portion of (5.5), thus the net effect is ambiguous. We address this question in the next section by first estimating the model and then performing counterfactual exercises.

## 5.4 Identification

Marginal costs and the value function are identified from the first-order conditions 5.5 and from variation in bids, market prices, water inflows and water stocks across generators and time. Note that the first-order condition with respect to the quantity-bid of generator $j$ of firm $i$ at time $t-h$ can be written as

$$\mathcal{MR}_{ijht} = \sum_{\tau \in \mathcal{T}_i} X^{\tau}_{ijht} \frac{\partial C_{it}}{\partial q_{ijht}} - \beta X^{y}_{ijht} \int_{\underline{w}}^{\overline{w}} V_i(u) \frac{\partial f_i(u|\Omega_{it})}{\partial q^{y}_{iht}} \mathrm{d}u, \tag{5.6}$$

where $\mathcal{MR}_{ijht} \equiv \left(p_{ht}\frac{\partial D^R_{iht}}{\partial p_{ht}} + D^R_{iht} - QC_i - \mathbf{1}_{[p_{ht} > \overline{p}_t]}\overline{q}_i\right)\frac{\partial p_{ht}}{\partial q_{ijht}}$ and $X^{\tau} \equiv \frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\tau}_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}$ are the marginal revenue and the total derivative of the supply schedule of the generators with technology $\tau$ with respect to the quantity-bid, $q_{ijht}$, respectively. Because we smoothed the supply function, all the terms in $\mathcal{MR}_{ijht}$ and $X^{\tau}$ are known and can be computed directly from observables. The firm-level transition density and its derivative are also nonparametrically identified for each firm from variation in the terms included in the water balance (5.1).

The only unknowns in (5.6) are the value function, $V_i(w_{it})$, and the technology-specific marginal cost, $\partial C_{it}/\partial q_{ijht}$. Given our assumption that firms do not track the

[38] In these cases, the indirect effect is zero for dams but negative for thermal generators.

[39] Decomposing $\frac{\partial p_{ht}}{\partial q_{ijht}}$ as in Wolak (2007), yields $\frac{\partial p_{ht}}{\partial q_{ijht}} = \frac{\partial S_{iht}}{\partial q_{ijht}} / \left(\frac{\partial D^R}{\partial p_{ht}} - \frac{\partial S_{iht}}{\partial p_{ht}}\right) \leq 0$, which is highest when both the firm's residual demand and its total supply are inelastic.

water stocks of their competitors beyond tracking exogenous weather forecasts, the value function depends only on the future realization of the water stock of firm $i$ at day $t$. Therefore, we model the value function as a polynomial expansion of the water stock $\beta \cdot V_i(w) = \sum_{r=1}^{R} \gamma_r \cdot w^r$, where the vector $\{\gamma_r\}_{r=1}^{R}$ describes a firm's discounted future cash-flows given the current water stock.[40]

Following the previous section, we assume that production costs are linear in the equilibrium quantity supplied; that is, $C_{iht} = \sum_{\tau}^{\mathcal{T}_i} \psi^\tau S_{iht}^\tau$. In principle, we could adopt a more flexible functional form for costs. However, the linear assumption requires a small number of parameters to be estimated, reducing the number of instruments in the estimation routine.[41] Since $S_{iht}^\tau$ is smooth, costs are differentiable both in the quantity-bids and in the market price. Rewriting (5.6) in terms of the unknown parameters, $\{\psi^\tau\}_{\tau}^{|\mathcal{T}_i|}$, $\{\gamma_r\}_{r=1}^{R}$, yields the estimating equation

$$\mathcal{MR}_{ijht} = \sum_{\tau \in \mathcal{T}_i} \psi^\tau X_{ijht}^\tau - X_{ijht}^y \sum_{r=1}^{R} \gamma_r \int_{\underline{w}}^{\overline{w}} u^r \frac{\partial f_i(u|\Omega_{it})}{\partial q_{ilht}^y} \mathrm{d}u + \varepsilon_{ijht}, \tag{5.7}$$

which is linear in the parameters of interest that are identified by the standard full-rank condition of the matrix of regressors.

Due to the way we model costs, (5.7) is isomorphic to an environment where each firm $i$ owns a generator per technology, or $\mathcal{T}_i$ generators, and that submits multiple bids with each generator. In that situation, $S_{iht}^\tau$ would be the smooth supply function that links all quantity-bids submitted by the generator $\tau$, whereas, in our setting, we smooth all quantity-bids across all $i$'s generators with a specific technology $\tau$. As a result, we assume that all units within a technology share the same primitives, $\psi^\tau$, and also $\gamma_r$ for hydro.[42] However, we allow for firm-specific value function parameters and control for firm (and time fixed) effects at the estimation stage, enabling these primitives to vary within technologies across firms.

[40] We do not estimate $\beta$ separately from $\{\gamma_r\}_{r=1}^{R}$ because it is not needed for simulating the model.

[41] Although we do not consider startup costs (e.g., Reguant, 2014), the dynamic cost savings from keeping a started thermal generator operational would further increase the benefits from intertemporal substitution across technologies.

[42] This modeling device results from calculating the water-balance equation (5.1) at the firm rather than at the generator level. The modest correlation observed across water inflows within firms (e.g., 11.6% for EPMG) supports this simplifying assumption.

## 5.5 Estimation

The best environment in which to estimate the primitives of the model is a period with stable demand and supply conditions; for example, with no merger and acquisition activity and no fuel price shocks. Therefore, a short period would be ideal for estimating the model while avoiding peak hours. However, a short period would not capture dynamic substitution patterns between thermal and hydro units, which necessarily require a long horizon due to the length of the weather cycle in a tropical country like Colombia.[43] We therefore estimate the model using six years of data from January 1, 2010 through December 31, 2015, which includes twelve dry and rainy seasons and only a few mergers and acquisitions. The estimation of the model closely follows the identification and consists of three steps. The next subsections describe the estimation routine in detail.

### 5.5.1 First Step: Smoothing Supply and Demand

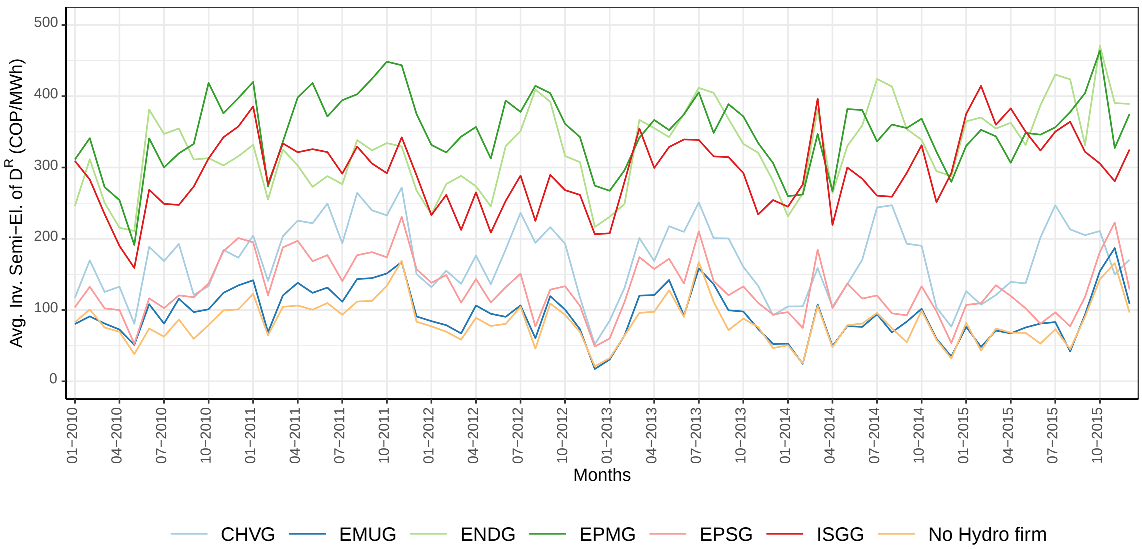
First, we smooth each firm's supply function and residual demand for each hour $h$ and day $t$. Similarly, we smooth the technology-specific supply functions, which include all the quantity- and price-bid schedules placed by the generators with the same production technology. We exclude wind farms because their overall capacity is negligible. Following Ryan (2021), we smooth these supply schedules using a normal kernel with bandwidth equal to 10% of the average price.[44]

Using these smoothed variables, Figure 6 shows the evolution of markups, defined by the inverse semi-elasticities of the residual demand. The inverse semi-elasticity tells the COP/MWh increase in the market-clearing price that would result from a 1% reduction of a firm's energy supply. Figure 6 shows two main results. First, markups are greater for the firms with more capacity and lower for those with less capacity. Firms with no hydro generators are residual claimants and charge the smallest markup. In particular, EPMG and ENDG (dark and light green lines, respectively) consistently charge the top markup over the whole sample, suggesting a dominant position over competitors. Second, the Colombian dry seasons (from July to Agust, and from December to January) are accompanied by greater exercise of market power.

[43] A typical year has two rainy seasons: from the end of March to the beginning of June and from September through November.

[44] Details on the smoothing approach are in Appendix E.

Figure 6: Monthly average inverse semi-elasticities by firm




Note: The mean inverse elasticity for the six firms with hydro units and the average across all firms with no hydro generators (orange). The semi-elasticity is equal to the COP/MWh increase in the market-clearing price that would result from a supplier reducing the amount of energy it sells in the short-term market during hour $h$ by one percent.

### 5.5.2 Second Step: Transition Matrix

River inflows are conventionally modeled using autoregressive integrated moving average ($ARIMA$) models (e.g., Montanari *et al.*, 1997, 2000; Lei *et al.*, 2018). Since every moving average ($MA$) model can be rewritten in terms of an autoregressive ($AR$) model with more lags, we focus instead on the more flexible family of autoregressive distributed-lag ($ARDL$) models (Pesaran and Shin, 1998), with $p$ lags of the dependent variable and $q$ lags of the independent variables. To study each firm $i$'s average weekly inflow, $\delta_{it}$, as an $ARDL(P,Q)$ process, we perform the following regressions:

$$\delta_{it} = \alpha_0 + \sum_{p=1}^{P} \gamma_p \delta_{it-p} + \beta x_{it} + \sum_{q=1}^{Q} \beta_q x_{it-q} + v_{it}, \, \forall\, i = (ENDG, EPMG, EPSG, ISGG),$$

which include the following controls (and their lags) in $x_{it}$: the average rainfall and temperature in the previous month and three and six months earlier, the monthly average of the ENSO probability for the next month and the next nine months, and year fixed effects. $v_{it} \sim \mathcal{N}(0, \sigma_i)$ is a serially uncorrelated disturbance with zero means and constant variance-covariances. All these variables are stationary according to the ADF test, and do not display unit roots after differencing. For each firm, the optimal $ARDL(P,Q)$ is the one with the smallest Schwartz Bayesian Criterion (BIC). We report autocorrelation tests and goodness of fit for the four largest firms in Appendix Figures A6 and A7.

Given the water inflow, we proceed by estimating the transition matrix as $Pr(w_{it+1} \leq u) = Pr(w_{it} + \delta_{it} - S_{it} \leq u) = Pr(\hat{v} \leq u - w_{it} + S_{it} - \hat{\delta}_{it})$, where $\hat{\delta}_{it}$ is the fitted value and $\hat{v}_{it}$ is its residual from the $ARDL(P,Q)$ model of firm $i$. Therefore, we get that $Pr(\hat{v} \leq u - w_{it} + S_{it} - \hat{\delta}_{it}) = F_i(u - w_{it} + S_{it} - \hat{\delta}_{it})$ where $F_i(\cdot)$ is the distribution of the firm-specific error term, $\hat{v}_i$. Although we can estimate $\hat{F}_i(\cdot)$ nonparametrically, we opt for a distribution from the Pearson family, as is common in the hydrology literature (e.g., Abdullah *et al.*, 2017; Lorenzo-Lacruz *et al.*, 2010). Since $\delta_{it}$ takes values on the whole real line, we adopt the Pearson Type IV distribution, which, being asymmetric, fits well our purpose of modeling rainy and dry seasons. We fit the distribution to the data by maxmimum likelihood and compare the Pearson-distributed $\hat{F}(\cdot)$ with other commonly used parametric (normal and logistic) distributions and nonparameatric distributions in Appendix Figure A8. The figure indicates a satisfactory fit of the Pearson distribution.

Finally, we exploit the polynomial approximation to the value function to compute the expected value function in the next period up to the vector of primitives $\{\gamma_r\}_{r=1}^{R}$, as shown in (5.7). Given the estimated density and $r$, since

$$\int_{\underline{w}}^{\overline{w}} V_i(u) \frac{\partial f_i(u - w_{iht} + \sum_{h,j} q_{ijht}^{y} | \Omega_{it})}{\partial q_{ilht}^{y}} \mathrm{d}u = \sum_{r=1}^{R} \gamma_r \int_{\underline{w}}^{\overline{w}} u^r \frac{\partial f_i(u - \omega_{it} + \sum_{h,j} q_{ijht}^{y} - \delta)}{\partial q_{ilht}^{y}} \mathrm{d}u,$$

we first compute each of the $R$ integrals by parts and then estimate the vector $\{\gamma_r\}_{r=1}^{R}$ in the third step of the estimation routine, which we describe next.

### 5.5.3 Third Step: Marginal Cost and Value Function Parameters

In the last step, we plug all the terms estimated in Sections 5.5.1 and 5.5.2 into (5.7) and estimate the marginal cost and value function parameters for the four largest firms – ENDG, EPMG, ESPG and ISGG.[45] Since bids and market prices are equilibrium objects the presence of unobserved variables correlated with supply and demand will result in biased estimates. For instance, an unobserved demand

[45]Section 4 focuses on the same firms.

shock due to high air conditioning usage on an especially dry day may result in a positive correlation between the supplied schedules and the error term of (5.7). Without properly accounting for such endogeneity, we could mistakenly relate a firm's more aggressive bidding to the expectation of future water availability. The long estimation horizon (six years) needed to uncover the dynamic switch across production technologies exacerbates this problem.

To avoid this bias, we instrument $X^{\tau}_{ijht}$ with a set of instruments and add a set of fixed effects. In particular, we include as instruments the temperature and the linear, squared, and cubic terms of rainfall at the location of each hydropower generator. We also include, as cost shifters, the price of coal, gas, oil, and ethanol in levels and interacted with the lagged demand of the previous week for each hour. As demand shifters, we include the temperature in Colombia's seven largest cities in levels and interacted with the hourly lagged demand of the previous week as a proxy for each hour's expected demand.

We consider two sets of estimations. First, we estimate the model using the full dataset (3,704,578 observations); that is, at the day-hour level. In this case, we include week-year, day-of-the-week, hour, and firm fixed effects. Second, we collapse the data by week-hour and estimate (5.7) for all the week-hours of the day and include month-year, hour, and firm fixed effects. This dataset covers 528,141 week-hour-generator observations.

Table 2 presents the parameter estimates. The first two columns report the weekly estimates; the second two report the daily estimates. Odd columns display estimation using only linear and quadratic polynomials for the value function ($R = 2$), and even columns add a cubic term ($R = 3$). The bottom panel reports the F-test for all instrumented $X^{\tau}_{ijht}$, indicating a strong first stage.

The top panel of Table 2 reports the estimated marginal costs. Across columns, we find that hydropower generation is consistently the cheapest production technology at about 25 US$/MWh. The second-cheapest production technologies are run-of-river and cogeneration at about 44 US$/MWh. As expected, a thermal generator's marginal cost exceeds that of a hydro generator, costing a firm over 56 US$/MWh on average.[46] Our results are in line with engineers' cost estimates

[46]To compare marginal costs with market prices, the average market price in the whole sample is 180,859 COP/MWh (s.d. 172,944 COP/MWh). The estimated thermal marginal cost of 181,321 COP/MWh shows the residual claimant role played by thermal generators.

Table 2: Estimated primitives of the structural model

| | | Weekly | | Daily | |
|---|---|---|---|---|---|
| | | Quadratic | Cubic | Quadratic | Cubic |
| Marginal costs (COP/MWh) | | | | | |
| Cogeneration | | 141,101*** | 144,373*** | 152,383*** | 156,340*** |
| | | (2,244) | (2,893) | (1,268) | (2,915) |
| Hydropower | | 106,609*** | 78,366*** | 117,054*** | 71,678*** |
| | | (4,371) | (11,092) | (3,720) | (7,621) |
| Run-of-river | | 140,711*** | 140,132*** | 160,213*** | 165,051*** |
| | | (1,663) | (2,121) | (1,019) | (1,563) |
| Thermal | | 181,321*** | 175,608*** | 218,839*** | 224,379*** |
| | | (3,735) | (6,311) | (2,492) | (4,207) |
| Firm-specific value function parameters (COP/MWh) | | | | | |
| ENDG: | - Linear term | –40,666*** | 346,354*** | –14,279*** | –258,253*** |
| | | (7,665) | (62,088) | (4,407) | (36,012) |
| | - Quadratic term | 0.00766*** | –0.157*** | 0.00474*** | 0.107*** |
| | | (0.00125) | (0.0264) | (0.000792) | (0.0151) |
| | - Cubic term | | 1.69e-08*** | | –1.01e-08*** |
| | | | (2.72e-09) | | (1.54e-09) |
| EPMG: | - Linear term | 9,283** | 167,721*** | 35,002*** | –10,837 |
| | | (4,628) | (28,845) | (3,049) | (14,865) |
| | - Quadratic term | –0.00369*** | –0.0528*** | -0.00825*** | 0.0122 |
| | | (0.000924) | (0.0149) | (0.000641) | (0.00785) |
| | - Cubic term | | 3.12e-09* | | –1.94e-09* |
| | | | (1.83e-09) | | (1.02e-09) |
| EPSG: | - Linear term | –72,046*** | –358,862*** | 103,252*** | –560,839*** |
| | | (19,772) | (108,459) | (12,454) | (101,224) |
| | - Quadratic term | 0.111** | 1.467** | –0.230*** | 3.629*** |
| | | (0.0531) | (0.668) | (0.0306) | (0.571) |
| | - Cubic term | | –1.40e-06 | | –5.27e-06*** |
| | | | (9.98e-07) | | (7.97e-07) |
| ISGG: | - Linear term | 81,098*** | 406,119*** | 138,575*** | 920,211*** |
| | | (16,830) | (77,491) | (10,862) | (67,240) |
| | - Quadratic term | –0.0610*** | –0.712*** | –0.133*** | –2.653*** |
| | | (0.0182) | (0.235) | (0.0125) | (0.208) |
| | - Cubic term | | 3.94e-07** | | 1.82e-06*** |
| | | | (1.68e-07) | | (1.54e-07) |
| Observations | | 528,141 | 528,141 | 3,704,578 | 3,704,578 |
| F-test cogeneration | | 24,855 | 19,903 | 106,106 | 106,106 |
| F-test hydropower | | 1,954 | 1,451 | 5,991 | 5,991 |
| F-test run-of-river | | 15,432 | 10,638 | 56,358 | 56,358 |
| F-test thermal | | 2,512 | 1,979 | 11,765 | 11,765 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: Two-stage least squares estimates of equation 5.7 assuming firm-specific value function parameters. We estimate the model using data at the at the week-hour and day-hour level. For the first case, we include month-year, hour, as well as, firm fixed effects, and standard errors are clustered at the firm-week level. For the second case, we include week-year, day-of-the-week, hour, as well as, firm fixed effects and standard errors are clustered at the firm-day level. The instruments are the temperature in Colombia's seven largest cities interacted with the hourly lagged demand of the previous week (demand shifters), the price of coal, gas, oil, ethanol, and sugar interacted with the lagged-demand for each hour (cost shifters), and the rainfall for each hydro-power plant in levels, squared and cubic terms. Columns 1 and 3 have the lowest BIC. 1 US$ is worth 3,150 COP.

for Colombia (e.g., Camelo *et al.*, 2018). In the second panel of Table 2 we report the estimates of the value function parameters for each firm, $\gamma_{i,r}$. The quadratic daily estimates are slightly larger than the weekly ones, but are consistent across columns. Guided by the engineers' cost estimates for Colombia, our favorite specification is the weekly regression in the first column, which we use in the simulations presented in the next section.[47]

# 6 Benefits and Limitations of Diversifying Suppliers

The estimation of the dynamic model depends on the necessary conditions for optimal behavior, but these are not sufficient to characterize a firm's full optimal strategy. Following the standard approach in the literature (e.g., Bushnell, 2003; Reguant, 2014), Section 6.1 develops a tractable simulation model that validates the fit of the structural estimates and Section 6.2 performs policy experiments to assess the economic advantage of diversified production technologies.

## 6.1 The Simulation Model

We model the day-ahead market as a (dynamic) Cournot oligopoly in which a firm chooses how much energy to sell in each hourly market to maximize its intertemporal profits.[48] The computational model solves for a firm's best response given the other firms' strategies, using a mixed-linear integer programming problem that determines the global optimum (Reguant, 2014).[49] For tractability, we focus on the firm with the largest semi-elasticity of demand in the time period under analysis, EPMG (see Figure 6). Since the computational solver works with discrete optimization problems, these technology-specific supplies are step functions with $K$ steps each. On each day $t$, the firm chooses the $K$- dimensional vector of hourly

[47] Appendix Table B6 estimates the model assuming that the value function parameters are homogeneous across firms (i.e., $\gamma_{i,r} = \gamma_r$ for all firms and $r$), and find that imposing symmetry in the value function does not substantially affect the marginal cost estimates from Table 2. Appendix Table B7 finds similar results focusing on data for markets on weekdays at 9:00 AM.

[48] Willems *et al.* (2009) compare the two approaches used in this paper, supply function equilibrium and Cournot oligopoly, and find that they perform similarly.

[49] We use the `Rcplex` package in `R` and the `IBM ILOG CPLEX` software to solve this mixed-linear integer problem; these softwares are freely available for academic research at https://cran.r-project.org/web/packages/Rcplex/index.html, and https://www.ibm.com/it-it/products/ilog-cplex-optimization-studio, respectively.

quantities $\{\mathbf{q}^{\tau}_{ht,k}\}_{h=0}^{23}$ for each technology $\tau$ to solve

$$\max_{\left\{q^{\tau}_{ht,k}\right\}_{k=1,h=0,\tau}^{K,23,\mathcal{T}}} \quad \sum_{h=0}^{23}\left[GR(D^R_{ht}) - \sum_{\tau=1}^{\mathcal{T}}\sum_{k=1}^{K}\hat{\psi}^{\tau} q^{\tau}_{ht,k}\right] + \beta\sum_{m=1}^{M}\mathbb{E}V_{t,m}\left(w_t \middle| w_{t-1}, \sum_{k=1}^{K}\sum_{h=1}^{23} q^{y}_{ht,k}\right),$$

$$s.t.$$

$$\text{[Market-clearing:]} \; D^R_{ht} = \sum_{\tau=1}^{\mathcal{T}}\sum_{k=1}^{K} q^{\tau}_{ht,k}, \;\; \forall\, h, \tag{6.1}$$

$$\text{[Constraints on residual demand steps:]} \; 0 \leq D^R_{ht,z} \leq \sum_{\tau}^{\mathcal{T}} cap^{\tau}_{ht/Z}, \;\; \forall\, h, z,$$

$$\text{[Constraints on supply steps:]} \; 0 \leq q^{\tau}_{ht,k} \leq cap^{\tau}_{ht/K}, \;\; \forall\, h, \tau, k,$$

$$\text{[Constraints on value function steps:]} \; 0 \leq \mathbb{E}V_{t,m} \leq cap^{y}_{ht/M}, \;\; \forall\, h, \tau, m,$$

where we dropped the subscript $i$ because the focus is on EPMG. The gross revenue function, $GR(D^R_{ht})$, is the discretized version of the static revenues in (5.3). It depends on $D^R_{ht}(p_{ht}) = \sum_{z=1}^{Z}\mathbb{1}_{[p_{ht,z}\leq p_{ht}]}D^R_{ht,z}$, a step function composed of $Z$ steps that describes EPMG's residual demand at $p_{ht}$. The cost function is equal to the cost of producing $\sum_{\tau,k} q^{\tau}_{ht,k}$ MWh of energy using the technology-specific marginal costs estimated in the first column of Table 2, $\{\hat{\psi}^{\tau}\}_{\tau}^{|\mathcal{T}|}$. The remaining term of (6.1) is the expected value function, which depends on the water stock at $t-1$, the total MW of hydrogeneration produced at $t$, and the transition matrix estimated in Section 5.5.2. We discretize this term over $M$ steps.

The first optimization constraint requires the hourly equilibrium price to be such that EPMG's supply (increasing) equals the residual demand (decreasing). We also constrain each step function to be nonnegative, and include upper bounds for each step, so that all steps have equal size; we denote as $cap^{\tau}_{ht/Y}$ the total hourly MW available of technology $\tau$ divided by the number of steps $Y$.[50] To simulate the model, we set the parameters to $Z=20, K=5, M=5$. Changing these parameters does not qualitatively affect the results presented below.

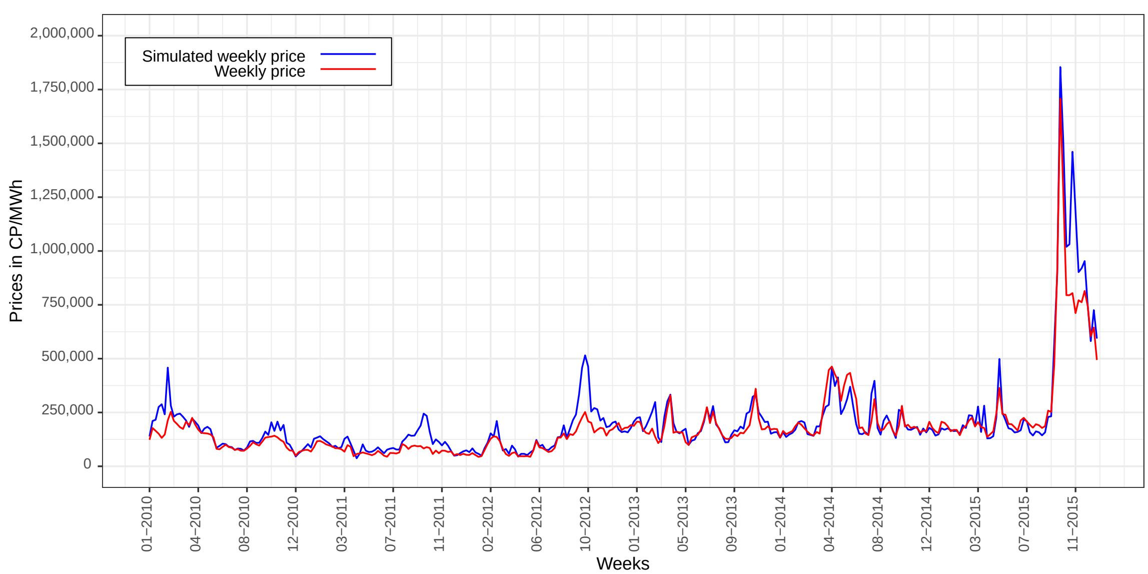
Because the main focus of this paper is on intertemporal allocation of supply over seasons, we do not attempt to simulate each daily market over the six-year period under consideration. We instead average the state space – hourly demand,

[50] For all three variables, we also include constraints to ensure that the algorithm fully exhausts the quantity available in step $x-1$ before allocating units to step $x$.

hourly competitor's supplies, and hourly net contract position – across weeks and solve for EPMG's best response using (6.1) for each hour-week pair. This approach reduces computation time substantially without sacrificing precision.

**Model fit.** We assess the fit of the model by computing the market price in each period given the estimated marginal costs and value function parameters, the reliability payment mechanism, the observed net forward position, the observed water stock, and the observed strategy of EPMG's competitors at time $t$. Figure 7 compares the observed average weekly prices (red line) with the simulated ones (blue line).[51] The model correctly reproduces price hikes, which are the focus of the counterfactual analyses in the next section.[52] Moreover, the simulation exercise well replicates the volatility of prices and quantities across hours, as reported in Table 3, which summarizes the average hourly difference (and its standard error) between simulated and observed hourly prices and quantities. The simulated hourly prices are within 5% of the actual price for all hours and the average daily price. Average hourly quantity produced show a similarly satisfactory fit.

Figure 7: Simulated and actual average weekly prices




Note: The actual average weekly price (red line) and the simulated average daily price (blue line).

[51]We compare the average simulated price across the 24 hourly markets (blue line) with the corresponding average weekly price (red line). Prices are in Colombian pesos per MWh.

[52]Appendix Figure A10 replicates the analysis by approximating the value function with 20 steps instead of five and finds similar results.

Table 3: Change in observed and simulated equilibrium prices and quantities

| Hour | Δ Market price Avg. diff. (COP/MWh) | Avg. diff. (%) | St. err. of diff. (COP/MWh) | Δ EPMG's quantity-bid Avg. diff. (MWh) | Avg. diff. (%) | St. err. of diff. (MWh) |
|---|---|---|---|---|---|---|
| 1:00 AM | -5,744.21 | 5.21 | 2,453.39 | -114.44 | 5.68 | 77.31 |
| 5:00 AM | -7,900.62 | 3.00 | 2,428.64 | -106.53 | 5.07 | 76.12 |
| 9:00 AM | 569.51 | 1.37 | 4,903.08 | 59.72 | 6.48 | 60.44 |
| 1:00 PM | 13,357.65 | 5.98 | 5,653.45 | -24.70 | 3.88 | 61.44 |
| 5:00 PM | 12,373.29 | 5.88 | 6,501.49 | 38.32 | 6.00 | 61.16 |
| 9:00 PM | 13,822.49 | 8.55 | 5,761.78 | 4.76 | 3.64 | 55.73 |
| All | 4,413.02 | 5.00 | 2,004.24 | -23.81 | 5.13 | 26.91 |

Note: Average difference between simulated and observed market prices and EPMG's accepted quantity-bids for different market hours.

## 6.2 Counterfactual Simulations

Our main hypothesis is that a diversified product mix can limit price hikes before a dry season, but plays no role in a normal or rainy season. To test this hypothesis, we artificially modify EPMG's thermal capacity and examine the resulting change in the simulated prices.

EPMG is one of the most diversified producers in Colombia, with hydropower, thermal, cogeneration, run-of-river generators, and wind farms. Panel (a) of Appendix Figure A9 reports the evolution of the firm's installed capacity by technology over time. Compared to the total industry (Figure 2a), a greater share of EPMG's production comes from hydropower generation and this share has increased over time. Panel (b) shows that, until the second half of 2010, EPMG's hydropower capacity was 80% of the sum of the two largest production technologies it employs, hydropower and thermal. Since then, the share of hydropower has increased further to about 85% as of the end of 2015.

**Policy scenarios.** In the simulations below, we modify the share of thermal capacity between 0%, 25%, and 50% of the sum of thermal and hydro capacity to examine how prices would react if (a) EPMG had divested from its thermal plans, (b) EPMG had invested in thermal instead of hydropower, or (c) EPMG had brought thermal and hydropower to equal footing. To isolate the role of production synergies from market power, these policy exercises do not reallocate the capacity removed from

EPMG to other firms, nor do they move energy capacity from other firms to EPMG. Lastly, Section 6.2.3 allows for changes in market power by merging EPMG with the thermal powerplants owned by its competitors.

**Policy exercises.** We perform two main sets of exercises. First, Section 6.2.1 focuses on anticipation responses and simulate the computational model conditional on EPMG's observed water stock. This allows us to detect the time of the price impact in isolation from the reallocation of resources across technology and time. Then, Section 6.2.2 extends this analysis to take into account the dynamic implications of saving water before dry periods. These simulations identify the full extent of the price benefit of intertemporal substitution.

### 6.2.1 Simulations without Reservoir Updates

Figure 8 examines the impact of reallocating energy capacity across thermal and hydro generation. Each black dot shows the difference between the simulated price under standard market condition minus the simulated price when we bring EPMG's thermal capacity to $x \in \{0\%, 25\%, 50\%\}$ of the sum of its thermal and hydro capacity. Therefore, dots above (below) 0 indicate that the reallocation exercise led to lower (higher) prices. The red error bars are the 95% confidence interval for the realized price difference in week $t$. The plots also provide information on dry periods through light and dark gray vertical bars, indicating periods of exceptional heat and rainfall, respectively, at EPMG's hydro locations.[53]

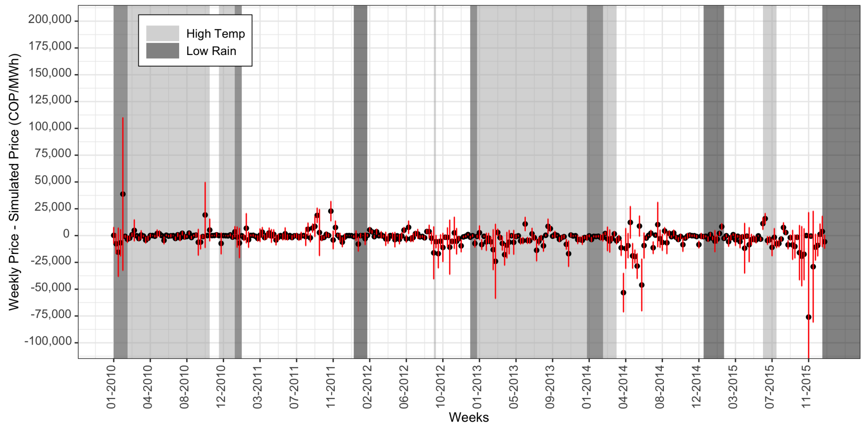
Comparing the three panels leads to two main results. First, greater thermal capacity results in lower market prices, on average. In particular, removing thermal capacity increases prices (Panel a), whereas adding it substantially decreases prices (Panel c). Second, consistent with our empirical analysis (cf. Figure 5), the impact is particularly visible three to six months before an especially dry period (gray bars), with no consequences in rainy or normal periods.

Next, we turn to the magnitude of the impact. Panel (a) removes EPMG's thermal energy. Out of the 312 weeks under study, we find that reallocation has a significant price impact at the 10% (5%) level for 129 (96) weeks. Prices would increase on average by 1.69% (1.97%) in these weeks, with peaks of 25.4%. Increasing

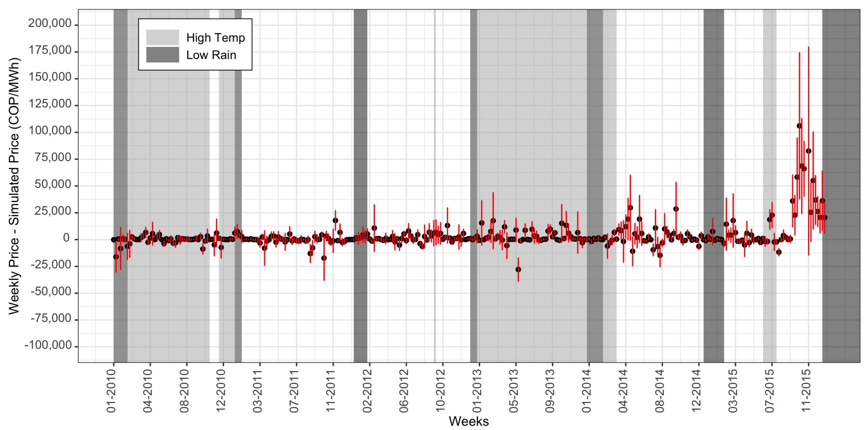
[53] Dark (light) gray bars mark periods with at least one hydro unit owned by EPMG records rainfalls (temperatures) 1 standard deviation below (above) its long-run average.

Figure 8: Counterfactual prices: Changing EPMG's thermal capacity to

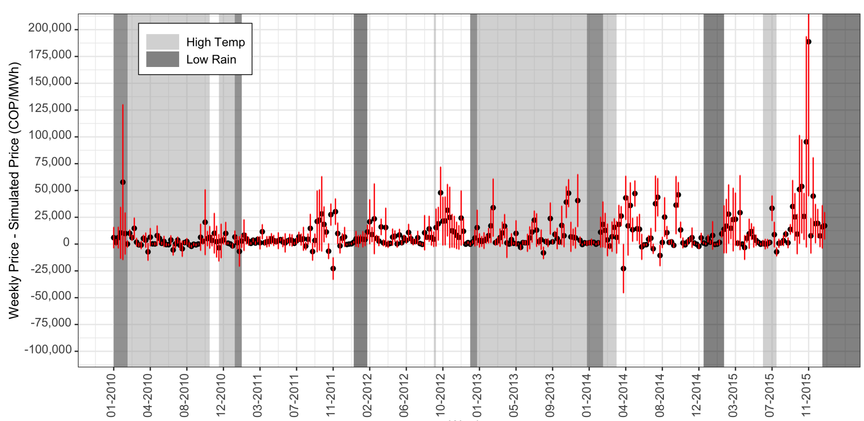
(a) 0% of its combined hydro and thermal capacity




(b) 25% of its combined hydro and thermal capacity




(c) 50% of its combined hydro and thermal capacity




Note: Comparison of weekly average prices simulated with simulated prices from three scenarios. In each scenario, EPMG's water stock in week $t$ is that observed in the data. Dark (light) gray bars mark periods with at least one hydro unit owned by EPMG records rainfall (temperature) 1 standard deviation below (above) its long-run average. 95% C.I. in red.

thermal production to 25% of the the sum of hydro and thermal capacities (Panel b) has a signficant price effect at the 10% (5%) level in 109 (79) weeks. The average price decreases by 1.56% (1.59%) in these weeks, with peaks of 22.4%. Panel (c) shows even larger estimates, with average price drops of 4.5%. Thus, these simulations support the conclusions drawn from the reduced-form exercises in Section 4.2 and show a sizable impact of synergies on market prices, even though only the policy change affects only one firm. Although this analysis offer some insights, it does not reveal the full price implication of diversification because it does not allow for the feedback in a firm's water stock due to a different intensity of hydropower usage in previous weeks. We extend our analysis to account for this dynamics in the next subsection.

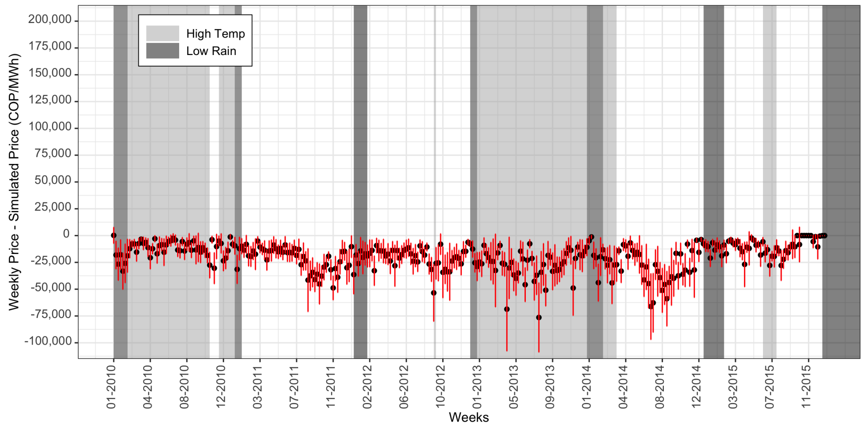
#### 6.2.2 Simulations with Reservoir Updates

This section amends the computational model 6.1 by allowing EPMG's production decision in week $t$ to affect the size of the reservoir in week $t+1$. We perform the same counterfactual exercise by varying EPMG's thermal capacity between $x \in \{0\%, 25\%, 50\%\}$ of EPMG's combined installed thermal and hydro capacity in each period. Figure 9 reports the output of the simulation in a format similar to that of Figure 8; across panels, increasing thermal capacity decreases prices. Unlike Figure 8, the price changes are not limited to the months before a dry period, but persist during negative shocks. This is especially evident after 2012.[54] Forcing EPMG to dispose of its thermal generators would significantly affect prices at the 10% (5%) level in 292 (282) weeks out of 312. In such a scenario, prices will increase by 12.1% (12.4%) in these weeks, with peaks of 50%. Moving to Panel (b), increasing EPMG's thermal capacity to 25% of its combined hydro and thermal capacity would affect market prices in 249 (218) weeks. Average prices will drop by 6.1% (6.6%) in these weeks, with price savings up to 24.7%. Finally, a considerable increase in EPMG's capacity, as that in Panel (c), would lower prices by 10.3% (11.1%) on average, with price savings up to 34.1%. Thus, these simulation exercises support our empirical finding that greater diversification can reduce market prices in the Colombian wholesale energy market.

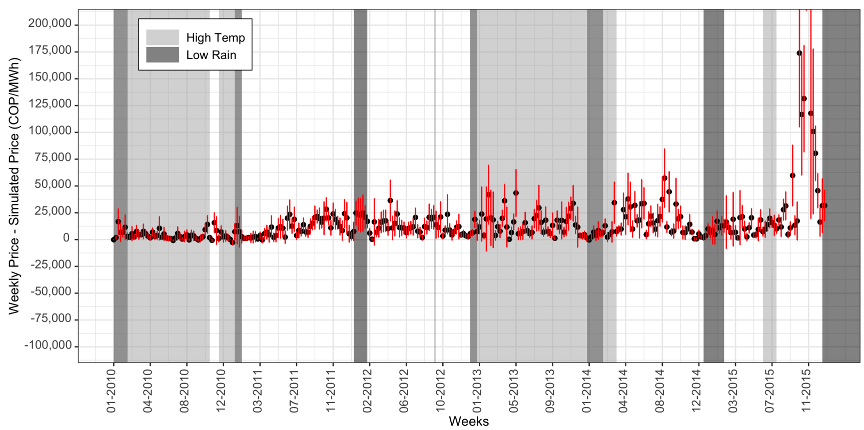
[54] Since 2010 had an especially dry el Niño period, the counterfactual EPMG did not have enough time to reallocate energy away from hydro, implying small synergies in 2010 and 2011.

Figure 9: Dynamic counterfactual prices: Changing EPMG's thermal capacity to

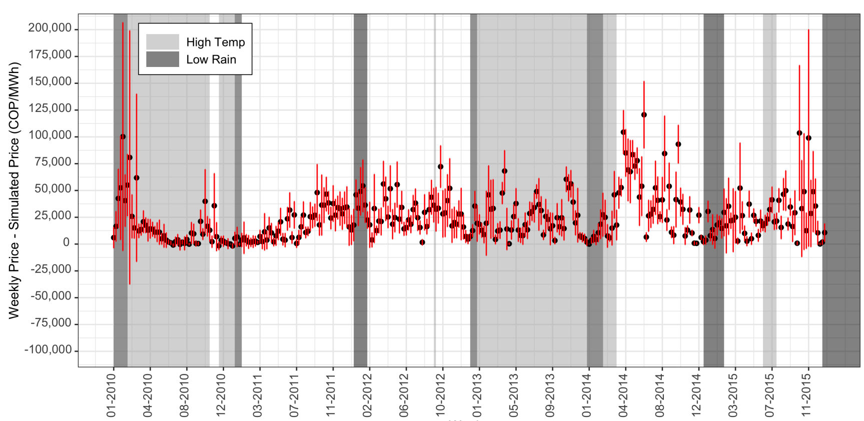
(a) 0% of its combined hydro and thermal capacity




(b) 25% of its combined hydro and thermal capacity




(c) 50% of its combined hydro and thermal capacity

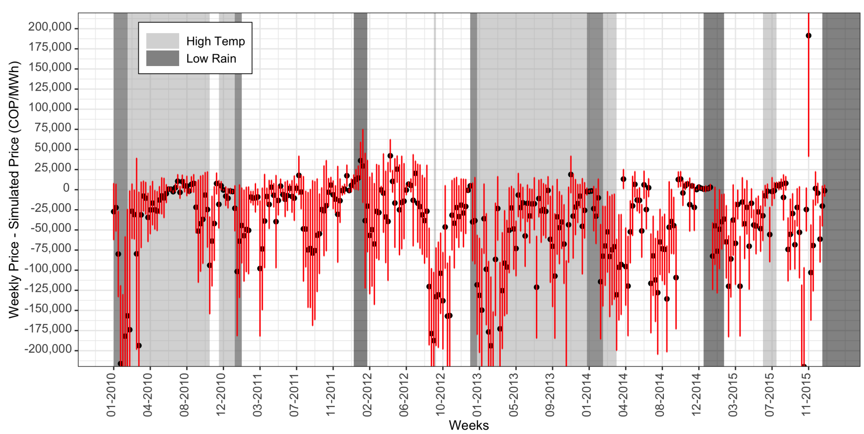



Note: Comparison of weekly average prices simulated with simulated prices from three scenarios. In each scenario, EPMG's production decision in week $t$ affects its reservoir level in week $t+1$. Dark (light) gray bars mark periods with at least one hydro unit owned by EPMG records rainfall (temperature) 1 standard deviation below (above) its long-run average. 95% C.I. in red.

#### 6.2.3 Mergers and Market Power

All the previous simulations artificially modified EPMG's capacity without affecting that of its competitors. Whether EPMG acquires a generator from another firm or expands an existing one has consequences for competition. In particular, acquiring a new generator would make EPMG's residual demand steeper, further increasing its ability to affect prices by changing quantity unilaterally. In addition, if the new thermal generator comes from a competing firm with hydro production, that competitor would be more constrained in its ability to intertemporally substitute production across technologies, which, according to our findings, would increase prices. Focusing on the first channel, Figure 10 shows (provocatively) what would come of reallocating all thermal generators owned by the other large companies to EPMG. As a result, the artificial EPMG will increase prices substantially in all periods, dry or not. Therefore, Figure 10 provides a cautionary tale for policymakers: incentivizing suppliers to hold a diversified technology mix helps curb price hikes, but it backfires if market power simultaneously rises.

Figure 10: Counterfactual prices: A merger with competitors' thermal generators




Note: Comparison of the weekly average price simulated with the simulated prices if all thermal generators of CHVG, EMUG, ENDG, EPSG, and ISGG are merged with EPMG. EPMG's production decision in week $t$ affects its reservoir level in week $t+1$. Dark (light) gray bars mark periods with at least one hydro unit owned by EPMG records rainfall (temperature) 1 standard deviation below (above) its long-run average. 95% C.I. in red.

**A final note.** The simulations focus on thermal capacity because of its importance in Colombia (Table 1). However, our results extend to similar, potentially greener energy sources displaying a different cyclicality than hydropower.

# 7 Discussion and Conclusion

This paper describes a new mechanism in the energy sector to lower market prices in times of scarcity – a major problem for the clean-energy transition and for energy systems heavily reliant on renewables. Leveraging detailed data on the Colombian market, in which hydropower is prevalent, we exploit exogenous weather variations to show that firms with diverse technology portfolios raise their fossil fuel supply – and simultaneous lower their hydropower supply – in expectation of an adverse inflow forecast. This intertemporal substitution across production technologies helps dams store water, allowing market prices to increase less than they would otherwise during scarcity events. We build, estimate, and simulate a dynamic structural model suggesting that an increase in the non-hydro capacity of Colombia's market-leading firm would lower prices, on average, between 6% and 10%.

The model also finds that the benefits of diversifying a firm's production portfolio reverse if diversification takes place through mergers raising the firm's market power. Because energy markets are characterized by oligopolistic competition, aggregating many generators within the same firm reduces the number of competitors, increasing the firm's residual demand. Despite the substitution channel, mergers can exacerbate a preexisting dominance position (see Figure 10), implying higher, rather than lower, market prices. For this reason, government incentives to diversify production technologies – for example, through functioning capacity markets to incentivize investments (Fabra, 2018; Fabra and Llobet, 2021) – should go hand-in-hand with policy attention to abuses of market power.

One advantage of the substitution channel that we identify is that it requires no specific policies targeting the behavior of market participants. The standard way to counteract scarcity periods relies on reliability payment systems which, like call options, force all generators to sell a given amount of energy at a predetermined price anytime the market price goes above a strike price. These systems have various shortcomings as, in particular, generators with market power can create the conditions for scarcity themselves to raise their profits (McRae and Wolak, 2019). Favoring intertemporal substitution across technologies avoids such shortcomings because it relies on sibling generators internalizing future hydropower marginal-cost changes by reacting accordingly. If firms had only one generator each instead, a hydro supply drop due to scarcity would not be automatically rebalanced by non-hydro supply as generators do not internalize adverse events of competitors.

Our results might extend to other markets dominated by intermittent renewables if adequate storing facilities exist. Also, our results are of particular interest for the transition to clean energy, especially for developing countries in tropical Latin America and Africa that have abundant water supplies and ongoing plans to increase their hydropower capacities. Abandoning nonrenewable generation altogether would expose national energy systems to the intermittency of renewables, increasing energy prices and blackouts under scarcity. More generally, our paper relates to the literature on the anticompetitive behaviors of horizontal mergers for homogeneous good markets originally developed by Williamson (1968) and Farrell and Shapiro (1990). The tradeoff between market power and diversification that we quantify in this paper may apply to other industries in which different production processes result in the same homogeneous outputs and marginal costs are volatile (e.g., Collard-Wexler and De Loecker, 2015).

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# Online Appendix

## A Additional Figures

Figure A1: Energy production technologies available in Colombia

(a) Hydropower (b) Run-of-river (c) Thermal

(d) Wind Farm (e) Cogeneration

Note: Each panel displays an example of a generator of the technology specified in the subtitle.

Panel (a) Chivor. This is one of the largest dams in Colombia, with an installed capacity of 1,000MW. It is located 160km away from the capital, Bogota.

Panel (b) San Miguel. This Run-of-river generator has a capacity of 44MW and it is located in the Antioquia region. These generators generally have no water storage and produce energy as water enters penstock pipes that lead to the turbines.

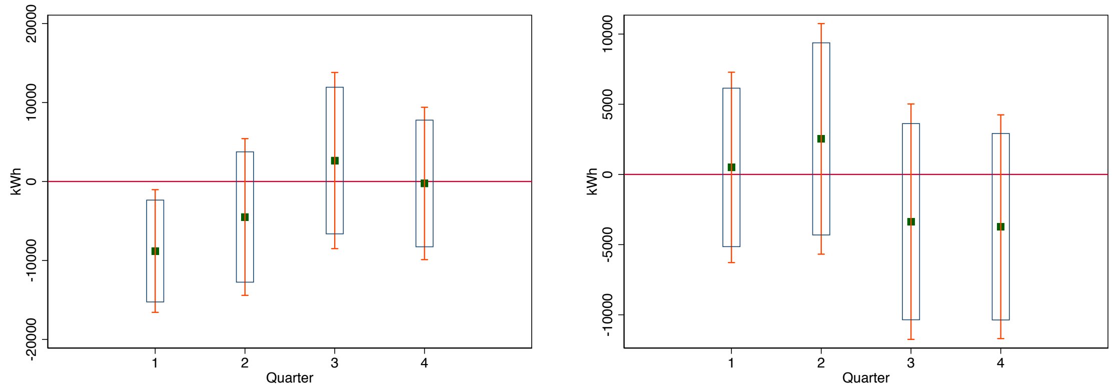
Panel (c) Tebsa. This is the largest thermal energy generator in Colombia, with an installed capacity of almost 800MW. The organization is located close to Barranquilla, in the Caribbean Sea area. The plant has a combination of gas an steam turbines.

Panel (d) Jepirachi. This wind power generation facility has a capacity of about 19MW. It is located in the Wayuu indigenous territory, within the municipality of Uribia in the Department of Guajira, in the northwest region of the Atlantic coast of Colombia. The name Jepirachi means ”northeast wind” in the Wayuu language.

Panel (e) Ingenio Providencia. This cogeneration generator is part of a sugarcane mill. During the combustion process, the osmotized water is heated to produce high pressure steam, which generates energy. This generator has an installed capactiy of 14MW.

Figure A2: Hydropower generators' asymmetric quantity-bids response

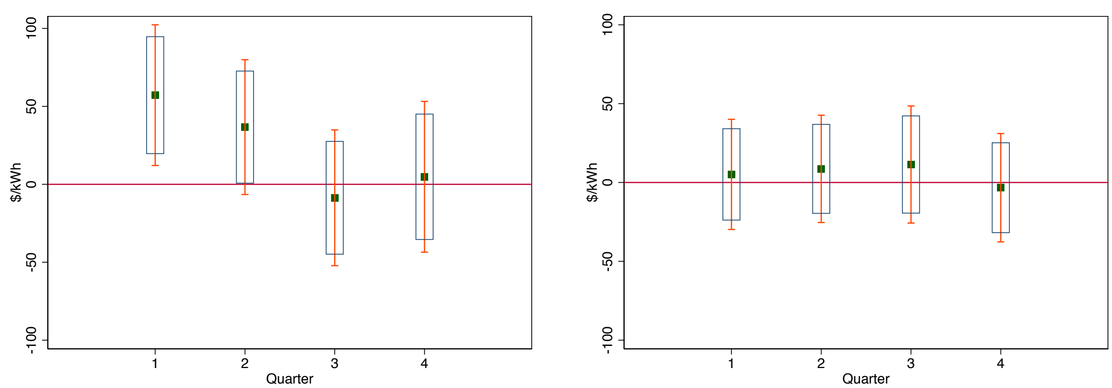
(a) First quartile (b) Fourth quartile




Note: The estimated $\beta_{l,low}$ (Panel a) and $\beta_{l,high}$ (Panel b) from equation 4.2 with quantity-bids as dependent variable. Appendix Table B2 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

Figure A3: Hydropower generators' asymmetric price-bids response

(a) First quartile (b) Fourth quartile

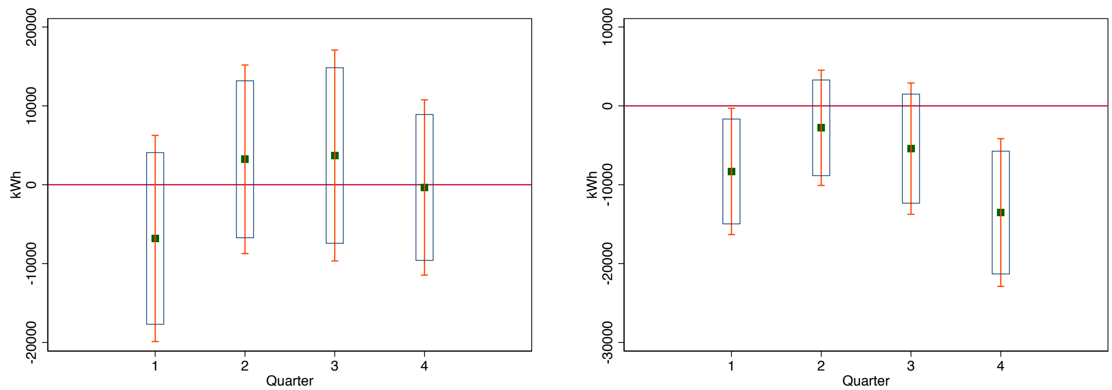



Note: The estimated $\beta_{l,low}$ (Panel a) and $\beta_{l,high}$ (Panel b) from equation 4.2 with price-bids as dependent variable. Appendix Table B2 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

Figure A4: Sibling thermal generators' asymmetric quantity-bids response

(a) First quartile

(b) Fourth quartile

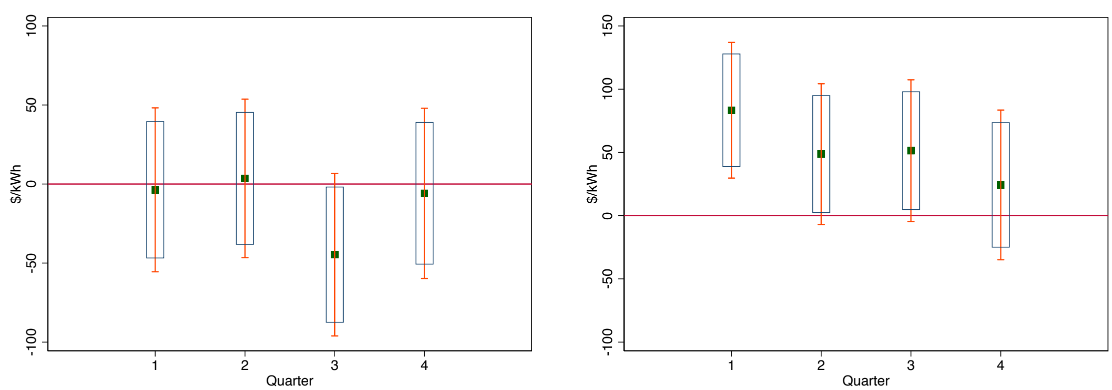



Note: The estimated $\beta_{l,low}$ (Panel a) and $\beta_{l,high}$ (Panel b) from equation 4.2 with quantity-bids of thermal generators and inflow expectations accruing to the whole firm as dependent and independent variables, respectively. Appendix Table B4 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

Figure A5: Sibling thermal generators' asymmetric price-bids response

(a) First quartile

(b) Fourth quartile

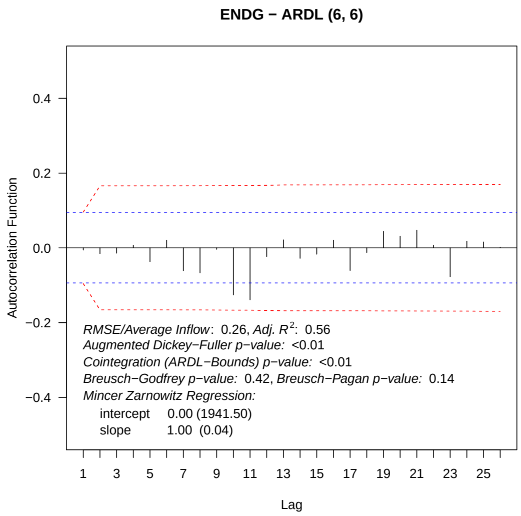



Note: The estimated $\beta_{l,low}$ (Panel a) and $\beta_{l,high}$ (Panel b) from equation 4.2 with price-bids of thermal generators and inflow expectations accruing to the whole firm as dependent and independent variables, respectively. Appendix Table B4 reports the coefficient estimates. The red line and the bar tell the 95% and 90% C.I.s, respectively. Standard errors are clustered at the generator-quarter-year level.

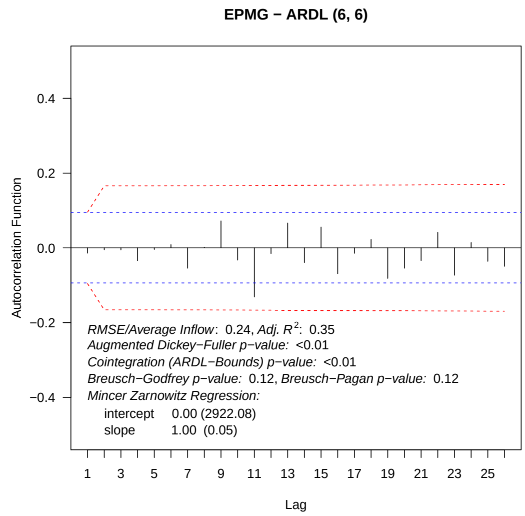
## A.1 Estimation of the Transition Matrix

Figure A6: Autocorrelation plots from the ARDL models

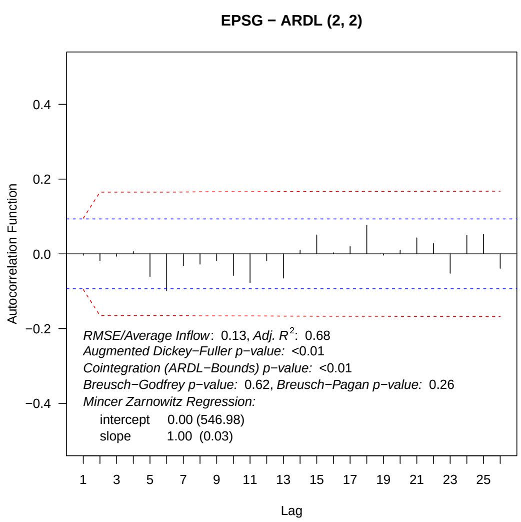
(a) ENDG



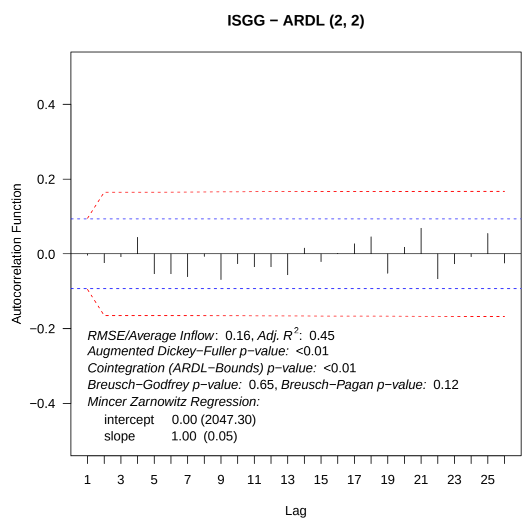

(b) EPMG




(c) EPSG



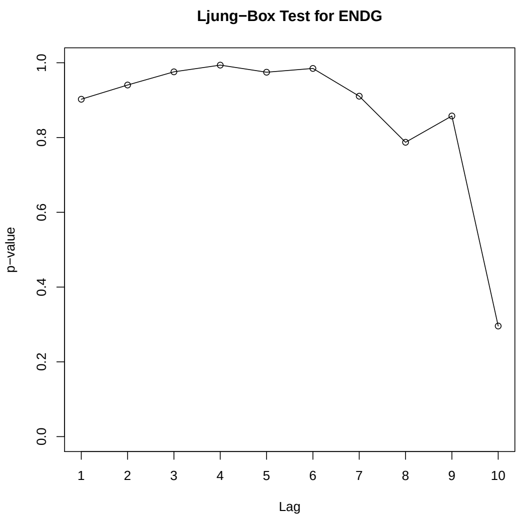

(d) ISGG



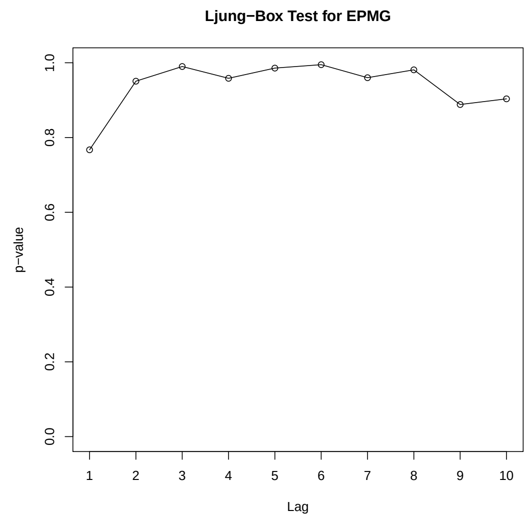

Note: Autocorrelation plots of Colombia's four largest energy suppliers. Each plot titles report the selected $ARDL(p, q)$ model. The blue and red dotted lines show the standard 95% and the Bartlett's 95% critical values respectively. The bottom of each plot reports goodness of fit statistics.

Figure A7: Autocorrelation diagnostics: Ljung-Box statistic p-values

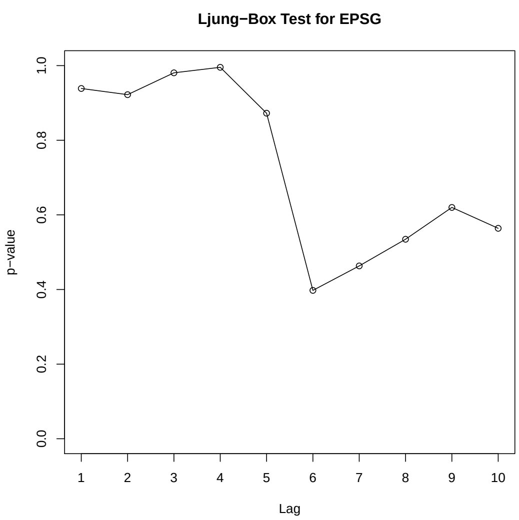
(a) ENDG



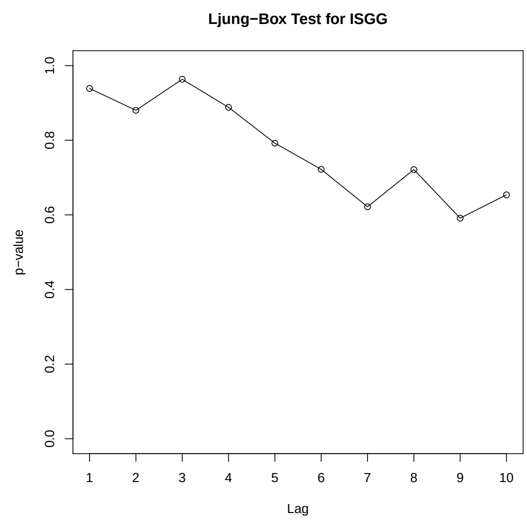

(b) EPMG




(c) EPSG



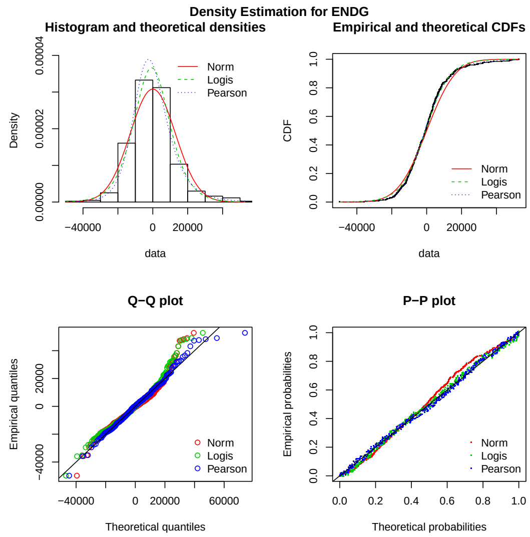

(d) ISGG



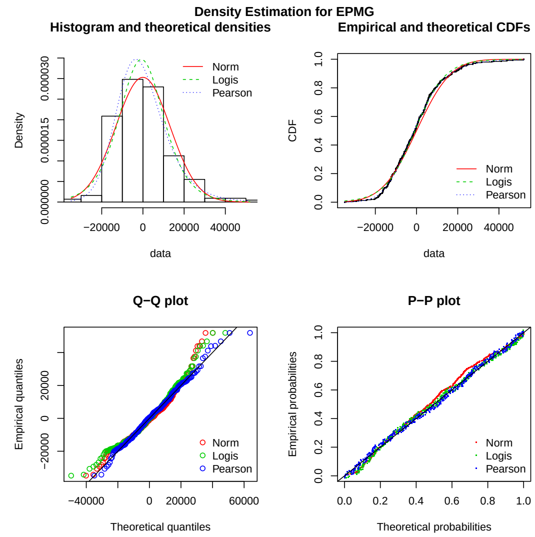

Note: The p-values from the Ljung-Box Test for Colombia's four largest energy suppliers. The null hypothesis states that the data are independently distributed (i.e., the correlations in the population from which the sample is taken are 0, so that any observed correlations in the data result from randomness of the sampling process).

Figure A8: Goodness of fit of the Pearson distribution

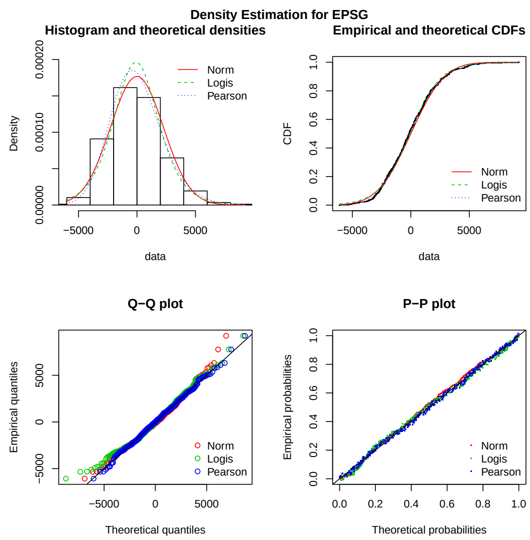
(a) ENDG



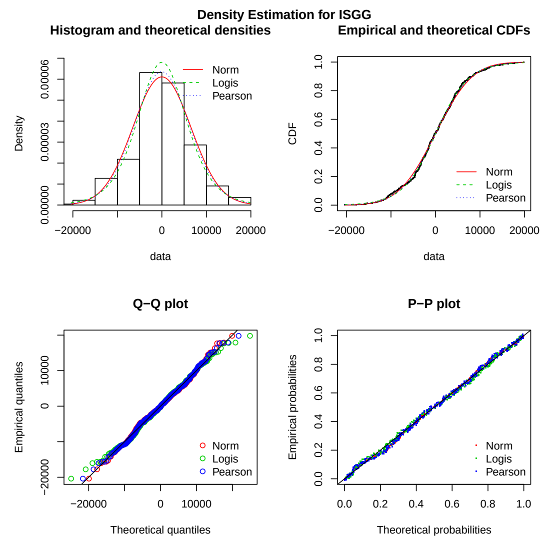

(b) EPMG




(c) EPSG




(d) ISGG

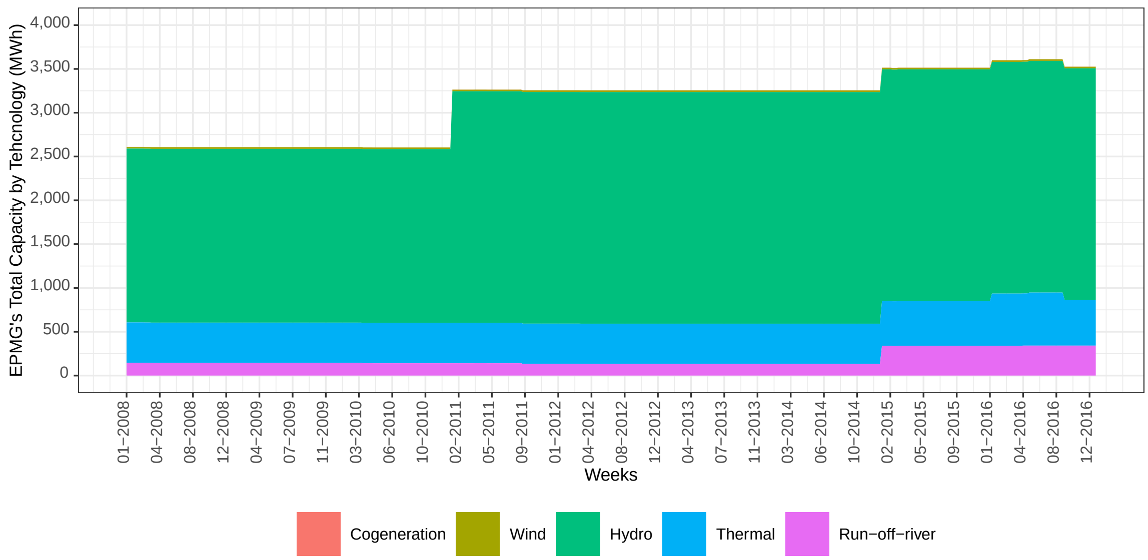



Note: Goodness of fit of the Pearson Type IV distrubtion. Each subplot reports (clockwise) the comparisons of pdfs, cdfs, the quantile-quantile plot and the probability-probability plot across the selected parametric distributions and the data. The Pearson distribution is in blue, the logistic distribution is in green, and the normal distribution is in red. The Kolmorov-Smirnov test never rejets the null that the Pearson Type IV distribution and the nonparametric distribution are equal at the 5% level.

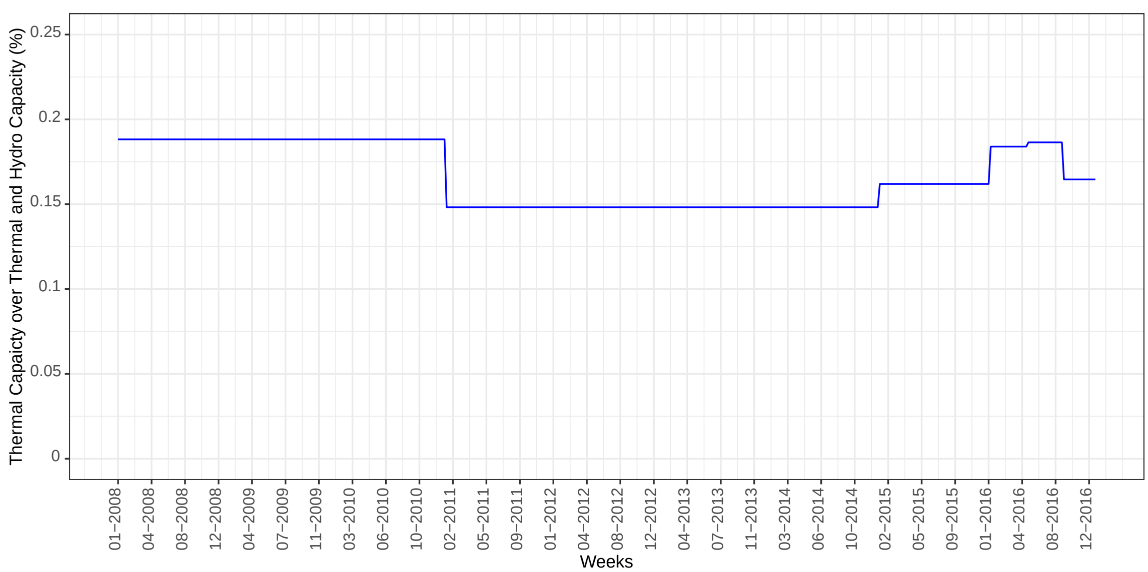
## A.2 Additional Figures from the Structural Model

Figure A9: EPMG's installed capacity over time

(a) Total installed capacity by technology

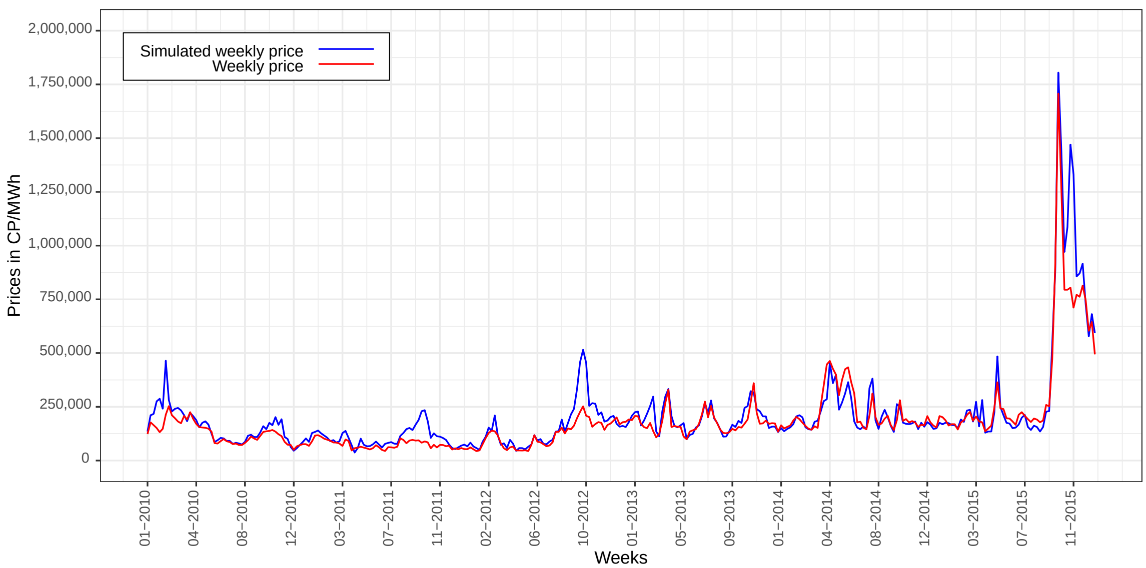



(b) Thermal capacity as a percentage of EPMG's thermal and hydro capacity




Note: The relative contribution of different technologies to EPMG's installed capacity over time.

Figure A10: Simulated and actual average weekly prices, different number of steps




Note: The actual average weekly price (red line) and the simulated average daily price (blue line). The plot approximates residual demand with $Z = 20$ steps, each technology-specific supply function with $K = 5$ steps and the value function with $M = 20$ steps (instead of 5 as in the main text).

# B Additional Tables

## B.1 Hydropower generation

Table B1: Hydropower generators' response to own inflow forecasts

| | Quantity-bid (kWh) | | | Price-bid (COP/kWh) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 1st quarter | 327.3*** | 312.1*** | 257.1*** | -1.570*** | –1.506*** | –1.059*** |
| | (65.86) | (64.93) | (58.68) | (0.357) | (0.352) | (0.323) |
| 2nd quarter | –127.4 | –111.9 | –118.7* | –0.534 | –0.598 | –0.0135 |
| | (77.68) | (78.22) | (70.80) | (0.372) | (0.375) | (0.323) |
| 3rd quarter | –132.4* | –122.8* | –92.56 | –0.00291 | –0.0405 | 0.242 |
| | (70.82) | (70.95) | (69.30) | (0.287) | (0.288) | (0.275) |
| 4th quarter | 75.18 | 56.41 | 108.6 | 0.254 | 0.330 | –0.305 |
| | (76.89) | (76.46) | (68.33) | (0.287) | (0.291) | (0.269) |
| Month and year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | | ✓ | ✓ | | ✓ | ✓ |
| Lagged water stock | | ✓ | ✓ | | ✓ | ✓ |
| Lagged contracts | | ✓ | ✓ | | | ✓ |
| Lagged spot price | | | ✓ | | | ✓ |
| Clustered s.e. | GQY | GQY | GQY | GQY | GQY | GQY |
| Mean of dep. var. | 420,569 | 420,500 | 420,500 | 229.2 | 229.3 | 229.3 |
| Observations | 9,020 | 9,005 | 9,005 | 9,005 | 9,005 | 9,005 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimated $\beta_l$ from equation 4.1 with either quantity-bids (Columns 1-3) or price-bids (Columns 4-6) as dependent variables. The second panel specifies the covariates included in each regression. Standard errors are clustered at the generator-quarter-year level. 1 US$ is worth 3,150 COP.

Table B2: Hydropower generators' asymmetric response to own forecasts

| | Quantity-bid (kWh) | | | Price-bid (COP/kWh) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Favorable expectations ($\beta_{l,low}$) | | | | | | |
| 1st quarter | 2,241 | 501.3 | –855.9 | –1.764 | 3.536 | 5.143 |
| | (3,455) | (3,460) | (3,432) | (18.11) | (18.09) | (17.82) |
| 2nd quarter | 3,058 | 2,534 | 2,437 | 13.89 | 14.77 | 8.631 |
| | (4,197) | (4,191) | (4,169) | (18.02) | (18.18) | (17.36) |
| 3rd quarter | –2,648 | –3,366 | –3,791 | 7.876 | 9.535 | 11.40 |
| | (4,338) | (4,279) | (4,249) | (19.96) | (19.99) | (18.95) |
| 4th quarter | –2,632 | –3,725 | –4,030 | –15.35 | –12.53 | –3.301 |
| | (4,111) | (4,067) | (4,034) | (18.28) | (18.43) | (17.53) |
| Adverse expectations ($\beta_{l,high}$) | | | | | | |
| 1st quarter | –8,810** | –8,804** | –5,038 | 107.6*** | 107.1*** | 57.20** |
| | (3,998) | (3,964) | (3,701) | (24.66) | (24.65) | (23.03) |
| 2nd quarter | –4,173 | -4,498 | -2,153 | 69.46*** | 70.21*** | 36.69* |
| | (5,068) | (5,064) | (4,833) | (23.89) | (23.82) | (22.07) |
| 3rd quarter | 3,036 | 2,654 | 2,239 | –11.40 | –9.657 | –8.654 |
| | (5,679) | (5,692) | (5,458) | (23.29) | (23.28) | (22.22) |
| 4th quarter | –714.0 | –248.9 | –6,222 | –53.29** | –55.23** | 4.830 |
| | (4,948) | (4,922) | (4,720) | (25.54) | (25.67) | (24.68) |
| Month and year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged water stock | | ✓ | ✓ | | ✓ | ✓ |
| Lagged contracts | | | ✓ | | ✓ | ✓ |
| Lagged spot price | | | ✓ | | | ✓ |
| Clustered s.e. | GQY | GQY | GQY | GQY | GQY | GQY |
| Mean of Dv | 431,882 | 431,852 | 431,852 | 228 | 228 | 228 |
| Observations | 9,544 | 9,527 | 9,527 | 9,544 | 9,527 | 9,527 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimated $\beta_{l,low}$ (top panel) and $\beta_{l,high}$ (middle panel) from equation 4.2 with either quantity-bids (Columns 1-3) or price-bids (Columns 4-6) as dependent variables. Standard errors are clustered at the firm/generator-quarter-year level. 1 US$ is worth 3,150 COP.

## B.2 Thermal generation

Table B3: Sibling thermal generators' response to same firm's inflow forecasts

| | Quantity-bid (kWh) | | | Price-bid (COP/kWh) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| 1st quarter | –138.1$^{*}$ | –136.8$^{*}$ | –117.8 | 0.248 | 0.251 | 0.193 |
| | (80.98) | (80.95) | (76.60) | (0.377) | (0.379) | (0.390) |
| 2nd quater | –171.0$^{**}$ | –170.2$^{**}$ | –54.83 | 0.088 | 0.0800 | 0.055 |
| | (73.25) | (73.27) | (74.81) | (0.325) | (0.330) | (0.397) |
| 3rd quater | –211.9$^{**}$ | –214.3$^{**}$ | –100.1 | 0.230 | 0.236 | 0.253 |
| | (90.17) | (90.18) | (85.01) | (0.484) | (0.486) | (0.457) |
| 4th quater | –226.3$^{**}$ | –227.6$^{**}$ | –192.1$^{**}$ | –0.259 | –0.257 | –0.218 |
| | (98.70) | (98.50) | (96.73) | (0.597) | (0.598) | (0.600) |
| Month and year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | | ✓ | ✓ | | ✓ | ✓ |
| Lagged contracts | | | ✓ | | | ✓ |
| Lagged spot price | | | ✓ | | | ✓ |
| Clustered s.e. | FQY | FQY | FQY | FQY | FQY | FQY |
| Mean of dep. var. | 104,179 | 104,265 | 104,265 | 421.8 | 422.1 | 422.1 |
| Observations | 5,441 | 5,419 | 5,419 | 5,441 | 5,419 | 5,419 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimated $\beta_l$ from equation 4.1 with quantity-bids or price-bids of sibling thermal generators as dependent variables. Standard errors are clustered at the firm-quarter-year level. 1 US$ is worth 3,150 COP.

Table B4: Sibling thermal generators' asymmetric response to same firm's inflow forecasts

| | Quantity-bid (kWh) | | | Price-bid (COP/kWh) | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Favorable expectations ($\beta_{l,low}$) | | | | | | |
| 1st quarter | –8,393** | –8,318** | –6,735* | 82.94*** | 82.95*** | 83.33*** |
| | (4,093) | (4,084) | (3,982) | (26.66) | (26.74) | (27.35) |
| 2nd quarter | –2,846 | –2,782 | 1,940 | 41.55 | 40.93 | 48.62* |
| | (3,728) | (3,728) | (3,925) | (27.54) | (27.52) | (28.40) |
| 3rd quarter | –5,517 | –5,425 | –1,379 | 43.51* | 43.47 | 51.38* |
| | (4,263) | (4,248) | (3,993) | (26.24) | (26.28) | (28.59) |
| 4th quarter | –13,582*** | –13,527*** | –10,564** | 18.42 | 18.01 | 24.29 |
| | (4,789) | (4,778) | (4,739) | (29.54) | (29.71) | (30.20) |
| Adverse expectations ($\beta_{l,high}$) | | | | | | |
| 1st quarter | –7,204 | –6,811 | –13,528** | 2.105 | 1.633 | –3.665 |
| | (6,701) | (6,670) | (6,229) | (24.72) | (24.96) | (26.45) |
| 2nd quarter | 2,893 | 3,228 | –109.2 | 8.999 | 8.516 | 3.574 |
| | (6,000) | (6,101) | (5,793) | (25.60) | (25.74) | (25.58) |
| 3rd quarter | 3,281 | 3,708 | 1,446 | –39.95 | –41.01 | –44.66* |
| | (6,847) | (6,820) | (6,253) | (25.13) | (25.48) | (26.24) |
| 4th quarter | –761.7 | –346.4 | 94.76 | 1.277 | 0.254 | -5.871 |
| | (5,542) | (5,671) | (5,392) | (24.69) | (25.27) | (27.47) |
| Month and year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | | ✓ | ✓ | | ✓ | ✓ |
| Lagged contracts | | | ✓ | | | ✓ |
| Lagged spot price | | | ✓ | | | ✓ |
| Clustered s.e. | FQY | FQY | FQY | FQY | FQY | FQY |
| Mean of dep. var. | 104,179 | 104,265 | 104,265 | 421.8 | 422.1 | 422.1 |
| Observations | 5,441 | 5,419 | 5,419 | 5,441 | 5,419 | 5,419 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimated $\beta_{l,low}$ (top panel) and $\beta_{l,high}$ (middle panel) from equation 4.2 with either quantity-bids (Columns 1-3) or price-bids (Columns 4-6) of sibling generators and inflow expectations accruing to the whole firm as dependent and independent variables, respectively. Standard errors are clustered at the firm/generator-quarter-year level. 1 US$ is worth 3,150 COP.

Table B5: Intertemporal technological substitution and weekly market prices

| | Market prices (COP/kWh) | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Thermal Capacity ($\gamma^{cap}$) | –0.227** | –0.144* | –0.176** | –0.112* | –0.274*** |
| | (0.0910) | (0.0835) | (0.0845) | (0.0638) | (0.0774) |
| Favorable expectations ($\beta_l^{high}$) | | | | | |
| 1st quarter | 48.81 | 30.68 | | | |
| | (42.00) | (24.15) | | | |
| 2nd quarter | 19.60 | | 28.44 | | |
| | (23.87) | | (20.25) | | |
| 3rd quarter | –5.308 | | | 6.843 | |
| | (20.06) | | | (23.12) | |
| 4th quarter | 30.41 | | | | –43.93** |
| | (35.16) | | | | (18.39) |
| Adverse expectations ($\beta_l^{low}$) | | | | | |
| 1st quarter | –4.302 | 67.25 | | | |
| | (39.95) | (52.78) | | | |
| 2nd quarter | 150.3** | | 167.9** | | |
| | (61.84) | | (69.50) | | |
| 3rd quarter | 16.36 | | | –6.768 | |
| | (33.27) | | | (51.06) | |
| 4th quarter | –138.5** | | | | –116.3* |
| | (60.96) | | | | (61.83) |
| Interactions of favorable expectations with thermal capacity ($\gamma_l^{high}$) | | | | | |
| 1st quarter | –0.175 | –0.110 | | | |
| | (0.137) | (0.0847) | | | |
| 2nd quarter | –0.00317 | | –0.0568 | | |
| | (0.0797) | | (0.0717) | | |
| 3rd quarter | 0.0156 | | | –0.0642 | |
| | (0.0625) | | | (0.0756) | |
| 4th quarter | –0.159 | | | | 0.0821 |
| | (0.116) | | | | (0.0610) |
| Interactions of adverse expectations with thermal capacity ($\gamma_l^{low}$) | | | | | |
| 1st quarter | 0.117 | –0.0799 | | | |
| | (0.133) | (0.183) | | | |
| 2nd quarter | –0.328* | | –0.365* | | |
| | (0.198) | | (0.221) | | |
| 3rd quarter | –0.0690 | | | –0.0474 | |
| | (0.106) | | | (0.175) | |
| 4th quarter | 0.319 | | | | 0.148 |
| | (0.245) | | | | (0.229) |
| Month FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged Demand | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged Contract | ✓ | ✓ | ✓ | ✓ | ✓ |
| Clustered s.e. | Newey | Newey | Newey | Newey | Newey |
| Mean of dep. var. | 154.398 | 154.398 | 154.398 | 154.398 | 154.398 |
| Observations | 623 | 623 | 623 | 623 | 623 |

$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

Note: The estimated coefficients from equation 4.3. All regressions include month fixed effects, and lagged demand and average net forward contract position. Columns 2 to 5 replicate the analysis in column 1 adding each expectation indicator quarter by quarter. Newey-West standard errors are computed using four lags. 1 US$ is worth 3,150 COP.

Table B6: Estimated primitives of the structural model, homogeneous value function across firms

| | Weekly | | Daily | |
|---|---|---|---|---|
| | Quadratic | Cubic | Quadratic | Cubic |
| Marginal costs (COP/MWh) | | | | |
| Cogeneration | 143,563*** | 144,539*** | 136,419*** | 134,594*** |
| | (1,836) | (1,194) | (847.3) | (1,204) |
| Hydropower | 122,150*** | 116,837*** | 88,419*** | 66,508*** |
| | (5,197) | (2,797) | (2,282) | (3,448) |
| Run-of-river | 141,096*** | 142,661*** | 139,516*** | 142,173*** |
| | (1,314) | (1,200) | (701.9) | (894.1) |
| Thermal | 183,465*** | 185,528*** | 172,183*** | 177,079*** |
| | (3,100) | (2,542) | (1,621) | (2,101) |
| Value function parameters (COP/MWh) | | | | |
| Linear term | –26,586*** | –2,098 | –11,784*** | 33,123*** |
| | (1,824) | (2,865) | (868.9) | (3,355) |
| Quadratic term | 0.00425*** | –0.00938*** | 0.00223*** | –0.0254*** |
| | (0.000361) | (0.00147) | (0.000190) | (0.00164) |
| Cubic term | | 1.66e-09*** | | 3.65e-09*** |
| | | (1.80e-10) | | (1.95e-10) |
| Observations | 528,141 | 528,141 | 3,704,578 | 3,704,578 |
| F-test cogeneration | 24855 | 24,855 | 102583 | 106,112 |
| F-test hydropower | 1,954 | 1,954 | 5,802 | 5,989 |
| F-test run-of-river | 15,432 | 15,432 | 54,598 | 56,354 |
| F-test thermal | 2,512 | 2,512 | 11,368 | 11,759 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: Two-stage least squares estimates of equation 5.7 assuming same value function parameters for all firms. The instruments are the temperature in Colombia's seven largest cities interacted with the hourly lagged demand of the previous week (demand shifters), the price of coal, gas, oil, ethanol, and sugar interacted with the lagged-demand for each hour (cost shifters), and the rainfall for each hydro-power plant in levels, squared and cubic terms. Each column includes week-of-the-year, firm and hour fixed effects. Standard errors are clustered at the firm-day level. 1 US$ is worth 3,150 COP.

Table B7: Estimated primitives of the structural model, homogeneous value function across firms

| | 9:00 AM | | Weekdays | |
|---|---|---|---|---|
| | Quadratic | Cubic | Quadratic | Cubic |
| Marginal costs (COP/MWh) | | | | |
| Cogeneration | 157,081*** | 157,410*** | 137,607*** | 140,927*** |
| | (9,670) | (6,555) | (2,098) | (1,521) |
| Hydropower | 129,126*** | 137,912*** | 103,391*** | 104,772*** |
| | (28,782) | (17,703) | (5,530) | (3,465) |
| Run-of-river | 151,679*** | 150,588*** | 137,682*** | 141,766*** |
| | (5,064) | (4,738) | (1,517) | (1,421) |
| Thermal | 189,663*** | 186,928*** | 170,895*** | 179,465*** |
| | (13,934) | (11,335) | (3,531) | (3,023) |
| Value Function parameters (COP/MWh) | | | | |
| Linear term | 27,499** | 701.7 | –35,852*** | –10,892*** |
| | (11,094) | (14,906) | (1,956) | (3,261) |
| Quadratic term | –0.00438** | 0.0125* | 0.00642*** | –0.00783*** |
| | (0.00186) | (0.00712) | (0.000392) | (0.00174) |
| Cubic term | | –2.12e-09** | | 1.77e-09*** |
| | | (8.89e-10) | | (2.21e-10) |
| Observations | 22,006 | 22,006 | 528,081 | 528,081 |
| F-test cogeneration | 1006 | 1006 | 26597 | 26597 |
| F-test hydropower | 87.31 | 87.31 | 1868 | 1868 |
| F-test run-of-river | 612.6 | 612.6 | 14637 | 14637 |
| F-test thermal | 101.7 | 101.7 | 2530 | 2530 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: Two-stage least squares estimates of equation 5.7 assuming same value function parameters for all firms and subsetting the data to either 9:00 AM markets or markets on weekdays. The instruments are the temperature in Colombia's seven largest cities interacted with the hourly lagged demand of the previous week (demand shifters), the price of coal, gas, oil, ethanol, and sugar interacted with the lagged-demand for each hour (cost shifters), and the rainfall for each hydro-power plant in levels, squared and cubic terms. Each column includes week-of-the-year, firm and hour fixed effects. Standard errors are clustered at the firm-day level. 1 US$ is worth 3,150 COP.

# C Supply Schedules and Inflows to Competitors

**Forecasted inflows to competitors.** To study whether a generator reacts to the expected inflow of its competitors, we extend equation 4.2 as follows:

$$
\begin{aligned}
y_{ij,t} = &\sum_{l=1}^{4}\left(\gamma_l^{low}\mathbb{1}_{\left[\widehat{inflow}_{-i,t+l}\in Q^1_{-i,t+l}\right]} + \gamma_l^{high}\mathbb{1}_{\left[\widehat{inflow}_{-i,t+l}\in Q^4_{-i,t+l}\right]}\right) \\
&+\sum_{l=1}^{4}\left(\beta_l^{low}\mathbb{1}_{\left[\widehat{inflow}_{ij,t+l}\in Q^1_{ij,t+l}\right]} + \beta_l^{high}\mathbb{1}_{\left[\widehat{inflow}_{ij,t+l}\in Q^4_{ij,t+l}\right]}\right) + X_{ij,t-1}\,\alpha + \mu_{ij} + \delta_t + \varepsilon_{ij,t},
\end{aligned}
\tag{C.1}
$$

where $\widehat{inflow}_{-i,t+l} = \sum_{k\neq i}\sum_{j=1}^{J_k}\widehat{inflow}_{k,j,t+l}$ is the sum of the expected inflows to the competitors of firm $i$, $l$ quarters ahead. Both the indicator function and the second line of (C.1) are defined as in (4.2). This setting is particularly convenient because it allows testing the hypothesis that a firm's strategy depends also on future expected events to its competitors through simple F-tests of joint significance of the four sets of coefficients $\{\gamma_l^{low}\}_{l=1}^4$, $\{\gamma_l^{high}\}_{l=1}^4$, $\{\beta_l^{low}\}_{l=1}^4$ and $\{\beta_l^{high}\}_{l=1}^4$.

The top panel of Appendix Table C1 reports the coefficient estimates for both quantity- and price-bid regressions.[55] First, we confirm that a firm reacts to its expectations of adverse events, but not to its own favorable ones as the estimates relating to a generator's own shocks ($\beta^{low}$ and $\beta^{high}$ in equation C.1) are similar in magnitude to those already presented in Appendix Table B2. The F-test results in the bottom panel further validate this conclusion.

Across columns, we also see that generators do no react to favorable expectations to competitors. The reaction to adverse expectations is incoherent. For instance, we observe a rise in a generator's quantity-bid if the adverse shock happens in two or four quarters ahead, but not three quarters ahead (column 3), suggesting that these estimates capture noise rather than actual strategies. The F-test results in the bottom panel support this interpretation.

**Future water stocks of competitors.** However, a firm could react to the water stock rather than the inflow accruing to its competitors because the water stock determines the available supply of a hydropower generator. Thus, we extend the

[55] The correlations between the dummy variables in equation C.1 are an order of magnitude lower than those across the actual forecasted inflows. Looking at the Spearman correlation matrix of the 16 dummies, its average absolute value is 0.22, its minimum (maximum) is -0.35 (0.70), and 90% of the correlations are below 0.36, which indicates no multicollinearity problem.

analysis above to consider whether a firm's supply schedule correlate with the observed future water stock of competitors by regressing,

$$\begin{aligned} y_{ijt} = \beta_0 + \beta^{self} \log\left(\sum_{l=1}^{|\mathcal{H}_i|} w_{ilt+q}\right) + \beta^{comp} \log\left(\sum_{k\neq i}\sum_{l=1}^{|\mathcal{H}_i|} w_{ikt+q}\right) \\ + X_{ij,t-1}\,\alpha + \mu_{ij} + \delta_t + \varepsilon_{ijt}, \end{aligned} \tag{C.2}$$

where the dependent variable refers to generator $i-j$ quantity- or price-bid, and $\beta^{self}$ and $\beta^{comp}$ multiply by firm $i$'s total water stock and firm $i$'s competitors water stock $q$-quarters ahead, respectively. Appendix Tables C2 and C3 inspect these correlations – that is, $\beta^{self}$ and $\beta^{comp}$ – quarter-by-quarter by either focusing on all generators, or only on generators of firms with dams – that is, the largest Colombian firms. Across tables, we find that generators' decisions correlate substantially with the water stock of the firm, but that they do not correlate with those of their competitors, supporting our findings from appendix Table C1.

**Discussion.** In conclusion, when forecasting future events, a generator is concerned about the outcomes to itself and its sibling generators. We do not find evidence that generators update their price- or quantity-bids due to competitors' future expected inflows.

Table C1: Supply schedule reactions to extreme inflow expectations of competitors

| | Quantity-bid (kWh) | | | | Price-bid (COP/kWh) | | | |
|---|---|---|---|---|---|---|---|---|
| | coef. | s.e. | coef. | s.e. | coef. | s.e | coef. | s.e |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Favorable expectations for competitors ($\gamma_l^{high}$) | | | | | | | | |
| 1st quarter | 1,412 | (1,166) | 1,412 | (1,083) | 3.856 | (6.812) | 3.856 | (6.812) |
| 2nd quarter | 1,304 | (1,333) | 1,304 | (1,137) | 0.235 | (6.925) | 0.235 | (6.925) |
| 3rd quarter | 1,289 | (1,045) | 1,289 | (1,024) | -6.619 | (7.149) | -6.619 | (7.149) |
| 4th quarter | 329.4 | (1,173) | 329.4 | (1,032) | -12.13* | (6.412) | -12.13* | (6.412) |
| Adverse expectations for competitors ($\gamma_l^{low}$) | | | | | | | | |
| 1st quarter | 286.0 | (1,264) | 286.0 | (1,299) | -8.500 | (5.459) | -8.500 | (5.459) |
| 2nd quarter | 1,815 | (1,292) | 1,815* | (1,089) | -1.958 | (4.940) | -1.958 | (4.940) |
| 3rd quarter | -373.0 | (1,310) | -373.0 | (1,159) | 6.199 | (6.045) | 6.199 | (6.045) |
| 4th quarter | 2,134 | (1,312) | 2,134* | (1,271) | -3.918 | (5.582) | -3.918 | (5.582) |
| Favorable expectations for self ($\beta_l^{high}$) | | | | | | | | |
| 1st quarter | 2,859 | (3,191) | 2,859 | (3,128) | -2.054 | (17.49) | -2.054 | (17.49) |
| 2nd quarter | 2,487 | (3,491) | 2,487 | (3,486) | -4.399 | (16.90) | -4.399 | (16.90) |
| 3rd quarter | -3,663 | (3,717) | -3,663 | (3,704) | -19.67 | (18.65) | -19.67 | (18.65) |
| 4th quarter | -2,150 | (3,922) | -2,150 | (3,866) | -44.49** | (17.84) | -44.49** | (17.84) |
| Adverse expectations for self ($\beta_l^{low}$) | | | | | | | | |
| 1st quarter | -9,431** | (4,142) | -9,431** | (4,258) | 114.2*** | (24.22) | 114.2*** | (24.22) |
| 2nd quarter | -5,456 | (4,951) | -5,456 | (5,301) | 65.23*** | (23.07) | 65.23*** | (23.07) |
| 3rd quarter | -2.934 | (5,123) | -2.934 | (5,482) | 11.60 | (25.58) | 11.60 | (25.58) |
| 4th quarter | -4,111 | (4,401) | -4,111 | (4,304) | -28.94 | (24.30) | -28.94 | (24.30) |
| Month-year FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Generator FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Lagged demand | ✓ | | ✓ | | ✓ | | ✓ | |
| Lagged contracts | ✓ | | ✓ | | ✓ | | ✓ | |
| Lagged spot price | ✓ | | ✓ | | ✓ | | ✓ | |
| Clustered s.e. | GQY | | FQY | | GQY | | FQY | |
| Observations | 42,454 | | 42,454 | | 42,454 | | 42,454 | |

*Tests of Joint Significance of Quarter-Specific Coefficients*

| | F-test | p-value | F-test | p-value | F-test | p-value | F-test | p-value |
|---|---|---|---|---|---|---|---|---|
| Fav. expect. for comp. | 0.819 | 0.513 | 1.192 | 0.316 | 1.342 | 0.252 | 1.342 | 0.252 |
| Adv. expect. for comp. | 1.384 | 0.237 | 1.514 | 0.200 | 0.886 | 0.472 | 0.886 | 0.472 |
| Fav. expect. for self | 0.652 | 0.626 | 0.653 | 0.625 | 2.022 | 0.089 | 2.022 | 0.089 |
| Adv. expect. for self | 2.795 | 0.025 | 2.794 | 0.028 | 9.583 | 0.000 | 9.583 | 0.000 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimates from equation C.1. Columns 1 to 4 (5 to 8) report the coefficient from OLS regressions for quantity-bids (price-bids). The drop in the number of observations between quantity- and price-bids regressions depend on several non-hydro generators bidding only quantity-bids (i.e., they accept any price). Even columns report the standard errors which are clustered either at the generator-quarter-year (GQY) level or at the firm-quarter-tear (FQY) level. The bottom panel test shows test results of joint significance of the quarter-level coefficients in the top panel. The analysis includes all generators. 1 US$ is worth 3,150 COP.

Table C2: Correlation between a firm's generator schedule and the total future water stock at the firm level, all generators

| | Quantity-bid (kWh) | | | | Price-bid (COP/kWh) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Firm $i$'s future water stock ($\beta^{self}$): | | | | | | | | |
| 1st quarter | 3,305 | | | | -11.86 | | | |
| | (4,538) | | | | (21.48) | | | |
| 2nd quarter | | 244.6 | | | | 26.22 | | |
| | | (4,256) | | | | (21.04) | | |
| 3rd quarter | | | 4,107 | | | | 61.16*** | |
| | | | (4,430) | | | | (22.06) | |
| 4th quarter | | | | 9,893** | | | | 53.87** |
| | | | | (4,877) | | | | (22.67) |
| Competitors' future water stock ($\beta^{comp}$): | | | | | | | | |
| 1st quarter | -1,095 | | | | -11.23 | | | |
| | (4,535) | | | | (16.67) | | | |
| 2nd quarter | | -327.6 | | | | -6.902 | | |
| | | (4,534) | | | | (17.26) | | |
| 3rd quarter | | | 811.4 | | | | -14.28 | |
| | | | (4,929) | | | | (17.43) | |
| 4th quarter | | | | 1,780 | | | | -42.77** |
| | | | | (5,212) | | | | (18.60) |
| Week counter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged water stock | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged spot price | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged contracts | ✓ | ✓ | ✓ | Y | Y | Y | Y | Y |
| Clustered s.e. | GQY | GQY | GQY | GQY | GQY | GQY | GQY | GQY |
| Observations | 42,078 | 41,782 | 41,499 | 41,235 | 42,080 | 41,784 | 41,501 | 41,237 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimates from equation C.2 where the dependent variable refers to generator $i - j$ quantity- (Columns 1 to 4) or price-bid (Columns 5 to 8). Each column refers to different values of $q$ (1 to 4 quarter). We run separate regressions for each quarter instead of pooling all regressors together because the realizations of future water stocks are highly correlated. Standard errors are clustered at the generator-quarter-year (GQY) level. Controls are defined in the bottom panel. 1 US$ is worth 3,150 COP.

Table C3: Correlation between a firm's generator schedule and the total future water stock at the firm level, only hydropower generators

| | Quantity-bid (kWh) | | | | Price-bid (COP/kWh) | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Firm $i$'s future water stock ($\beta^{self}$): | | | | | | | | |
| 1st Quarter Ahead | 16,374 | | | | 107.0*** | | | |
| | (10,002) | | | | (35.87) | | | |
| 2nd quarter | | 5,097 | | | | 186.5*** | | |
| | | (9,206) | | | | (35.42) | | |
| 3rd quarter | | | 15,119 | | | | 248.2*** | |
| | | | (9,574) | | | | (38.71) | |
| 4th quarter | | | | 32,211*** | | | | 181.2*** |
| | | | | (10,507) | | | | (36.80) |
| Competitors' future water stock ($\beta^{comp}$): | | | | | | | | |
| 1st quarter | -11,074 | | | | 40.45 | | | |
| | (9,961) | | | | (34.50) | | | |
| 2nd quarter | | -10,669 | | | | 56.90* | | |
| | | (9,851) | | | | (34.18) | | |
| 3rd quarter | | | -6,115 | | | | 56.15 | |
| | | | (10,358) | | | | (36.74) | |
| 4th quarter | | | | -2,112 | | | | 4.381 |
| | | | | (11,010) | | | | (40.69) |
| Week counter FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Generator FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged demand | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged water stock | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged spot price | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Lagged contracts | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Clustered s.e. | GQY | GQY | GQY | GQY | GQY | GQY | GQY | GQY |
| Observations | 9,527 | 9,527 | 9,527 | 9,527 | 9,527 | 9,527 | 9,527 | 9,527 |

* – $p < 0.1$; ** – $p < 0.05$; *** – $p < 0.01$.

Note: The estimates from equation C.2 where the dependent variable refers to generator $i-j$ quantity- (Columns 1 to 4) or price-bid (Columns 5 to 8). Each column refers to different values of $q$ (1 to 4 quarter). We run separate regressions for each quarter instead of pooling all regressors together because the realizations of future water stocks are highly correlated. We subset the data to include only hydropower generators. Standard errors are clustered at the generator-quarter-year (GQY) level. Controls are defined in the bottom panel. 1 US$ is worth 3,150 COP.

# D Market Prices During Extreme Weather Events

This section studies the impact of intertemporal substitution across production technologies *during* weather shocks. We consider asymmetric behavior across positive and negative shocks using the following specification:

$$\begin{aligned} p_{ht} = {} & \beta^{low} \sum_{lk} \mathbb{1}_{[lk\text{: adverse}]} cap_{lkt} + \beta^{high} \sum_{lk} \mathbb{1}_{[lk\text{: favorable}]} cap_{lkt} \\ & + \psi \sum_{lk} cap_{lkt} + \gamma^{low} \mathbb{1}_{[\sum_{lk} \mathbb{1}_{[lk\text{: adverse}]} > 0]} + \gamma^{high} \mathbb{1}_{[\sum_{lk} \mathbb{1}_{[lk\text{: favorable}]} > 0]} + X_{ht}\,\alpha + \varepsilon_{ij,t}, \end{aligned} \tag{D.1}$$

where the left-hand side is the average market price at hour $h$ of week $t$ in COP/MWh, and the first line includes coefficients for the total thermal capacity connected to firms that are adversely and favorably shocked ($\beta^{low}$ and $\beta^{high}$), while the second line includes the direct effect of the shocks through indicators for whether these shocks take place ($\gamma^{low}$ and $\gamma^{high}$, respectively) and for the total thermal capacity available ($\psi$), and $X_{ht}$ includes control variables.

We estimate equation D.1 on a subset of the data which includes only firms with hydro units. Appendix Table D1 reports the results for morning hours (columns 1-3) and evening hours (columns 4-6) separately. Across all columns, we find that the average hourly price decreases between 255 and 309 COP per MW of thermal capacity connected with a negatively shocked hydro unit. Taking a conservative approach, since on average there are 538MW of connected thermal capacity, the price impact of synergies is about 137,259 COP/MW (about 37 USD/MW), and this value increases with the connected thermal capacity. On the other hand, prices increase with the size of the total thermal capacity in the market. This suggests that thermal units with no hydro siblings contribute negatively to prices because they do not internalize the intertemporal shocks of other firms.

For positive shocks, we estimate coefficients between 6 and 12 times smaller than those for negative shocks, and not significantly different from zero after including controls for demand, forward contracts (Columns 2 and 3), and weather (Columns 5 and 6).[56] Thus, the possibility of switching production from hydro to thermal units lowers market prices also during an adverse weather event, extending the results presented in Section 4.2.

[56] Appendix Table D2 shows similar results including month fixed effects and instrumenting the average water stock with its lagged value.

Table D1: Price impact of substituting hydro and thermal production during extreme events

| | Market price (COP/MWh) | | | | | |
|---|---|---|---|---|---|---|
| | Hours 7 AM – 1 PM | | | Hours 5 PM – 9 PM | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Adversely shocked cap. ($\beta^{low}$) | $-308.993^{***}$ | $-289.358^{***}$ | $-255.415^{***}$ | $-303.112^{***}$ | $-286.662^{***}$ | $-256.082^{***}$ |
| | (22.875) | (22.556) | (22.411) | (27.805) | (27.204) | (27.129) |
| Favorably shocked cap. ($\beta^{high}$) | $56.304^{**}$ | $48.030^{*}$ | 39.410 | 46.240 | 27.932 | 20.671 |
| | (25.647) | (25.346) | (24.947) | (31.175) | (30.744) | (30.364) |
| Total thermal capacity (MW) | $331.525^{***}$ | $237.229^{***}$ | $196.869^{***}$ | $329.861^{***}$ | $249.924^{***}$ | $215.297^{***}$ |
| | (15.210) | (18.396) | (18.675) | (18.488) | (21.485) | (21.874) |
| Indicator for adv. shock ($\gamma^{low}$) | $133,565.500^{***}$ | $135,129.800^{***}$ | $124,143.000^{***}$ | $132,758.600^{***}$ | $133,235.200^{***}$ | $124,219.400^{***}$ |
| | (7,889.021) | (7,758.074) | (7,709.313) | (9,589.359) | (9,365.906) | (9,330.556) |
| Indicator for adv. shock ($\gamma^{high}$) | −10,869.370 | −7,821.529 | 5,714.682 | −5,548.333 | −1,731.293 | 10,702.290 |
| | (7,659.088) | (7,527.685) | (7,520.256) | (9,309.870) | (9,097.170) | (9,117.074) |
| Avg. weekly water stock | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Avg. weekly market demand | | ✓ | ✓ | | ✓ | ✓ |
| Forward contracts | | ✓ | ✓ | | ✓ | ✓ |
| Avg. weekly temperature | | | ✓ | | | ✓ |
| Avg. weekly rainfall | | | ✓ | | | ✓ |
| Adjusted $R^2$ | 0.318 | 0.342 | 0.364 | 0.300 | 0.332 | 0.350 |
| Observations | 3,276 | 3,276 | 3,276 | 2,340 | 2,340 | 2,340 |

$^{*}$ – $p < 0.1$; $^{**}$ – $p < 0.05$; $^{***}$ – $p < 0.01$.

Note: The estimates from equation D.1 for two different hourly periods. Columns 1 to 3 refer to the hours between 7 AM and 1 PM and Column 2 refers to the hours between 5 PM and 9 PM. An adverse (favorable) shock is defined by a drop (surge) of the water stock by two standard deviations. The total thermal capacity is defined in MW (instead of GW), which inflates the coefficients of the indicator variable. 1 US$ is worth 3,150 COP.

Table D2: Price impact of substituting hydro and thermal production during extreme events, FE and 2SLS regressions

| | Market price (COP/MWh) | | | | | |
|---|---|---|---|---|---|---|
| | Hours 7 AM – 1 PM | | | Hours 5 PM – 9 PM | | |
| | OLS | 2SLS | 2SLS | OLS | 2SLS | 2SLS |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Adversely shocked cap. ($\beta^{low}$) | $-257.387^{***}$ | $-253.317^{***}$ | $-257.422^{***}$ | $-255.674^{***}$ | $-254.275^{***}$ | $-255.859^{***}$ |
| | (21.724) | (34.384) | (31.243) | (26.226) | (41.781) | (37.811) |
| Favorably shocked cap. ($\beta^{high}$) | 34.445 | 35.823 | 32.868 | 16.342 | 17.536 | 15.306 |
| | (24.384) | (22.289) | (21.757) | (29.555) | (26.734) | (25.985) |
| Total thermal capacity(MW) | $207.644^{***}$ | $199.764^{***}$ | $209.584^{***}$ | $223.767^{***}$ | $218.182^{***}$ | $225.711^{***}$ |
| | (18.221) | (21.685) | (21.662) | (21.484) | (25.052) | (25.377) |
| Indicator for adv. shock ($\gamma^{low}$) | $119,609.300^{***}$ | $125,202.100^{***}$ | $120,424.000^{***}$ | $119,236.600^{***}$ | $125,020.800^{***}$ | $119,818.400^{***}$ |
| | (7,415.948) | (13,005.170) | (11,421.650) | (8,942.061) | (15,675.250) | (13,734.290) |
| Indicator for fav. shock ($\gamma^{high}$) | 5,138.690 | 5,187.892 | 5,098.261 | 11,546.630 | 10,218.500 | 11,531.040 |
| | (7,349.802) | (7,351.475) | (7,318.955) | (8,882.394) | (9,093.546) | (8,999.696) |
| Avg. weekly water stock | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Avg. weekly market demand | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Forward contracts | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Avg. weekly temperature | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Avg. weekly rainfall | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Month FE | | | ✓ | | | ✓ |
| F-test | | 74,042.418 | 69,241.192 | | 56,076.098 | 51,916.649 |
| Adjusted $R^2$ | 0.433 | 0.364 | 0.434 | 0.424 | 0.349 | 0.424 |
| Observations | 3,276 | 3,269 | 3,269 | 2,340 | 2,335 | 2,335 |

$^{*} - p < 0.1$; $^{**} - p < 0.05$; $^{***} - p < 0.01$.

Note: The estimates from equation D.1 for two different hourly periods. Columns 1 to 3 refer to the hours between 7 AM and 1 PM and Column 2 refers to the hours between 5 PM and 9 PM. An adverse (favorable) shock is defined by a drop (surge) of the water stock by two standard deviations. Columns 1 and 4 present the OLS estimates, while columns 2 and 3 and columns 5 and 6 presents instruments the averaged stock of water with its lagged value. The total thermal capacity is defined in MW (instead of GW), which inflates the coefficients of the indicator variable. 1 US$ is worth 3,150 COP.

# E Smooth Supply and Demand Functions

This appendix section shows how to smooth the Bellman equation to make it differentiable. This approach is based on the seminal work of Wolak (2007) and relies on smoothing the indicator defining the supply function with a kernel. For example, we replace the indicators in $S_{iht}(p) = \sum_{j=1}^{J_i} q_{ijht}\mathbb{1}_{[p\leq b_{ijt}]}$ with a smoothing kernel to account how far a price bid $b_{ijt}$ is from the realized market price $p$. This transformation effectively allows interchanging differentiation and expectation after taking the first-order conditions of the value function 5.3 – that is, $\frac{\partial \int_{\varepsilon} V(w,p(\epsilon))f_{\epsilon}(\epsilon)\mathrm{d}\epsilon}{\partial p} = \int_{\epsilon} \frac{\partial V(w,p(\epsilon))}{\partial p} f_{\epsilon}(\epsilon)\mathrm{d}\epsilon$ – simplifying the identification of the primitives of the model presented in Section 5.

**Residual demand of firm $i$.** Following the notation in Section 5, the residual demand to firm $i$ is $\tilde{D}^R_{iht}(p,\epsilon) = D_{ht}(\epsilon) - \tilde{S}_{-iht}(p)$, where the notation $\tilde{x}$ means that variable $x$ is smoothed.[57] Smoothing the residual demand follows from smoothing the supply of the competitors of firm $i$, $\tilde{S}_{-iht}(p) = \sum_{m\neq i}^{N}\sum_{j=1}^{J_m} q_{mjht}\mathcal{K}\left(\frac{p-b_{mjt}}{bw}\right)$, where $J_m$ is the number of generation units owned by firm $m$. Let $\mathcal{K}(\cdot)$ denote the smoothing kernel, which we choose to be the standard normal distribution in the estimation (Wolak, 2007). We follow Ryan (2021) and set $bw$ equal to 10% of the expected price in MWh. The derivative of $D^R_{iht}(p,\varepsilon)$ with respect to the market price in hour $h$ and day $t$ is $\frac{\partial \tilde{D}^R_{iht}(p,\varepsilon)}{\partial p_{ht}} = -\sum_{m\neq i}^{N}\sum_{k=1}^{K_m} q_{mkht}\frac{\partial \mathcal{K}\left(\frac{p-b_{mkt}}{bw}\right)}{\partial p_{ht}}$.

**Supply of firm $i$.** The supply of firm $i$ becomes, $\tilde{S}_{iht}(p_{ht}) = \sum_{j=1}^{J_i} q_{ijht}\mathcal{K}\left(\frac{p-b_{ijt}}{bw}\right)$, leading to the following smoothed derivatives,

$$\frac{\partial \tilde{S}_{iht}}{\partial p_{ht}} = \sum_{j=1}^{J_i} q_{ijht}\frac{\partial \mathcal{K}\left(\frac{p-b_{mkt}}{bw}\right)}{\partial p_{ht}},$$

$$\frac{\partial \tilde{S}_{iht}}{\partial q_{ijht}} = \mathcal{K}\left(\frac{p-b_{ijt}}{bw}\right),$$

$$\frac{\partial \tilde{S}_{iht}}{\partial b_{ijt}} = -q_{ijht}\frac{\partial \mathcal{K}\left(\frac{p-b_{ijt}}{bw}\right)}{\partial b_{ijt}}.$$

The derivatives of the smoothed supply functions by technology $\tau$ are found anal-

[57] We drop the tilde in the main text for smoothed variables to simplify the notation.

ogously:

$$\frac{\partial \tilde{S}^{\tau}_{iht}}{\partial p_{ht}} = \sum_{k\in\tau} q_{ikht} \frac{\partial \mathcal{K}\left(\frac{p-b_{ikt}}{bw}\right)}{\partial p_{ht}},$$

$$\frac{\partial \tilde{S}^{\tau}_{iht}}{\partial q_{ijht}} = \begin{cases} \mathcal{K}\left(\frac{p-b_{ijt}}{bw}\right) & \text{if } j \text{ has technology } \tau, \\ 0 & \text{otherwise,} \end{cases}$$

$$\frac{\partial \tilde{S}^{\tau}_{iht}}{\partial b_{ijt}} = \begin{cases} -q_{ijht} \frac{\partial \mathcal{K}\left(\frac{p-b_{ijt}}{bw}\right)}{\partial b_{ijt}} & \text{if } j \text{ has technology } \tau, \\ 0 & \text{otherwise.} \end{cases}$$

**Market price.** The derivatives of the market price with respect to price- and quantity-bids in (5.3) are computed using the envelop theorem. Their smoothed versions are $\frac{\partial p_{ht}}{\partial b_{ijt}} = \frac{\frac{\partial \tilde{S}_{iht}}{\partial b_{ijt}}}{\frac{\partial \tilde{D}^R_{iht}}{\partial p_{ht}} - \frac{\partial \tilde{S}_{iht}}{\partial p_{ht}}}$ and $\frac{\partial p_{ht}}{\partial q_{ijht}} = \frac{\frac{\partial \tilde{S}_{iht}}{\partial q_{ijht}}}{\frac{\partial \tilde{D}^R_{iht}}{\partial p_{ht}} - \frac{\partial \tilde{S}_{iht}}{\partial p_{ht}}}$, respectively.

# References in the Online Appendix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