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Michele Fioretti
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Jorge Tamayo

Harvard Business School

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Michele Fioretti
Bocconi University

Junnan He
Sciences Po

Jorge Tamayo
Harvard Business School

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Prices and Concentration: A U-shape? Theory and Evidence from Renewables*

Michele Fioretti[†] **Junnan He**[‡] **Jorge Tamayo**[§]

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Abstract

We show that when firms compete via supply functions, transferring high-cost capacity to the largest, most efficient firm—thereby diversifying its production technologies while increasing concentration—can lower prices by prompting the leader to expand output and competitors to aggressively defend market shares. However, large transfers prove anticompetitive, as sizable capacity differences discourage price undercutting. Exploiting renewable intermittencies in Colombia's electricity market, where firms are technology-diversified, we consistently find a U-shape relationship between prices and concentration. Counterfactually reallocating 30% of competitors' high-cost capacities to the leader cuts prices 10%, while larger transfers raise them, revealing how capacity and efficiency influence market power.

JEL classifications: L25, D24, Q21
Keywords: diversified production technologies, concentration, market power, supply function equilibrium, renewable energy, hydropower, energy transition

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[†]Bocconi University, Department of Economics, and IGIER. e-mail: fioretti.m@unibocconi.it
[‡]Sciences Po, Department of Economics. e-mail: junnan.he@sciencespo.fr
[§]Harvard University, Harvard Business School, Digital Reskilling Lab. e-mail: jtamayo@hbs.edu

1 Introduction

Technology plays a central role in shaping firms' market power (Sutton, 1991). In some industries, such as automotive manufacturing, rising producer costs—rather than markup expansion—are the primary driver of higher consumer prices (Grieco *et al.*, 2023). As technology advances and firms gain access to multiple production methods for the same outputs, their choices may affect market power and generate misallocation and inefficiencies (Asker *et al.*, 2019). The energy sector provides a natural setting to examine these issues, as firms operate with vastly different technology portfolios, ranging from fossil fuel to renewable plants. Understanding how technology-driven misallocation affects market power in this context is essential for designing policies that promote efficient production and enhance consumer welfare.

How should technologies be allocated across firms, and how do firms with diversified technology portfolios compete? When firms rely on a single technology, competition is limited, as only the most efficient can undercut rivals. In contrast, diversification fosters competition by aligning firms' marginal costs, making it more likely that they face rivals with similar cost structures (Fabra and Llobet, 2024). However, promoting diversification is not straightforward: investments in new technologies typically involve long time horizons and may depend on firms' existing knowledge and expertise (Elliott, 2024, Fioretti *et al.*, 2025). An alternative is for regulators to allow mergers between firms with different technologies—avoiding the need for new capacity. Yet this also raises concentration, which is generally expected to increase prices. This tension raises a central question: Can diversified production offset the anticompetitive effects of concentration? And if so, what is the optimal firm size?

Our contribution is to show that diversifying the market leader's production technologies through capacity transfers from competitors can counteract—or even reverse—the anticompetitive effects of greater concentration. Building on the supply function equilibrium concept (Klemperer and Meyer, 1989), we identify conditions under which a dominant firm may price more aggressively despite increasing its capacity at the expense of rivals, contrary to conventional wisdom. We test these predictions in the Colombian wholesale electricity market, where firms operate both hydropower and fossil fuels. Natural variation in hydropower availability, driven by climatic conditions, provides quasi-experimental shifts in capacity, allowing us to examine how diversification affects pricing. We then use our model to simulate capacity transfers and quantify the separate effects of concentration and diversification on prices. A key advantage of our approach is that it avoids relying on mergers to alter capacity, mitigating endogeneity concerns that typically arise in merger studies.

Examining concentration in markets with technology-diversified firms reveals novel dimensions of competition. Our empirical evidence suggests a more nuanced relationship between concentration and prices than standard models imply, as increasing concentration *can* either raise or lower market prices. For instance, we show that when a drought reduces the capacity of the largest firm—thus decreasing industry concentration—prices rise more than when a smaller firm faces the same shock. Conversely, prices are higher when the largest firm, rather than a smaller rival, benefits from abundance of renewables, consistent with the predictions of standard models where size amplifies market power.

To interpret these patterns, consider a market in which firms operate multiple technologies, each characterized by distinct marginal costs and capacities. To maximize profits, firms utilize their lower-cost technologies first and rely on costlier alternatives only when necessary, as all technologies produce the same homogeneous good. Rather than pricing directly at marginal cost, firms submit supply schedules, committing portions of their capacities at different price points. Because these commitments occur before market demand is realized—a common feature of electricity markets—firms face uncertainty regarding their residual demand.

In this context, the largest firm faces conflicting incentives when it also owns the most efficient technology: in low-demand scenarios, it benefits from undercutting less efficient rivals to capture market share, while in high-demand scenarios, it prefers withholding capacity to raise prices. We find that a "small" transfer of high-cost capacity from rivals to the market leader alters this tradeoff. First, *diversified production* incentivizes the leader to deploy more of its low-cost technology aggressively in low-demand states, securing monopolistic rents by undercutting competitors, while reserving its newly transferred high-cost capacity to capture larger market shares at high prices during periods of high demand.[1] Second, the leader's supply expansion prompts aggressive responses from rivals, who—due to *strategic complementarities*—also increase their supply to defend market share, ultimately pushing down prices.

However, diversification does not always offset the anticompetitive effects of concentration. When the transfer is "large" enough to severely constrain rivals' capacity, they can no longer respond aggressively. In this scenario, the leader can exercise market power by reducing its supply at all prices, raising the market price. As a result, whether market prices rise or fall with concentration depends critically on the magnitude of the capacity transfer. Finally, we show that whether a transfer is "large" or "small" depends on the relative gap in marginal costs and capacities across firms' technology portfolios.

Thus, the impact of concentration on prices hinges on two key factors: the *efficiencies* of technologies and firms' *capacities*. Together, these factors yield U-shaped relationship between prices and concentration when firms operate diverse technologies. This U-shaped pattern disappears if firms specialize in a single technology, even if it varies across firms.

[1] This tradeoff arises whenever a firm faces less efficient rivals, not only when the market leader is the most efficient. We do not examine capacity transfers to smaller firms, which would naturally enhance competition by strengthening their position against the dominant firm.

For example, if a market leader has *abundant* low-cost capacity, it can easily adjust supply across demand scenarios. Transferring capacity from less efficient rivals reduces their supply without meaningfully diversifying the leader, who continues prioritizing its cheaper technology. In this case, competition across technologies does not intensify, and without economies of scale or scope—such as in our setting, where simulated unit transfers lack synergies—prices inevitably rise with concentration.

We bring this model to the data to quantify how diversified production might offset the effects of industry concentration.[2] Our structural model accounts for the intertemporal opportunity cost of hydropower production, which arises because dams can store energy. After estimating marginal and intertemporal opportunity costs for each technology and firm combination, we simulate counterfactual scenarios that reallocate thermal capacity from competitors to the market leader. Quantitatively, doubling the leader's thermal capacity can reduce prices by up to 10%, particularly during drought conditions. However, larger capacity transfers result in substantial price increases, consistent with both our theoretical framework and reduced-form evidence.

Economists have traditionally used the Herfindahl-Hirschman Index (HHI) to measure industry concentration as a proxy for market power, as it correlates with the number of firms, their profits, and consumer welfare in the Cournot model (Tirole, 1988, pages 221-223).[3] In certain contexts, capacity shares may be preferred over market shares in empirical industrial research, as capacity is not dependent on market prices unlike market shares, addressing the simultaneity problem (Miller *et al.*, 2022). However, our findings indicate that HHI-based measures become less informative when firms are technology-diversified. In particular, the traditionally monotonic relationship between HHI and prices—an indicator of consumer welfare in energy markets where demand is typically inelastic—breaks down.

For instance, in standard Cournot games, prices rise with concentration because transferring technology lowers prices only when it increases symmetry—that is, when the recipient is smaller than the sender. Otherwise, the transfer reinforces asymmetries and reduces total supply, leading to higher prices. Alternatively, when symmetric firms with capacity constraints set prices rather than quantities, no pure-strategy equilibrium exists if transfers create asymmetries, as the best response to an undercutting firm may be to raise prices on one's residual demand (Edgeworth, 1925, Beckmann, 1965, Levitan and Shubik, 1972, Cheviakov and Hartwick, 2005).

Our model integrates both the supply reductions typical of Cournot competition and

[2]We model the spot market as a uniform price auction in which firms submit supply schedules for each of its generating units (Ausubel *et al.*, 2014, Reguant, 2014). Because dams allow electricity storage and firms operate multiple units, our structural approach explicitly incorporates dynamic considerations and cross-unit externalities (Jofre-Bonet and Pesendorfer, 2003, Fioretti, 2022).

[3]While prices do not depend on HHI when symmetric firms compete on prices—a phenomenon known as the Bertrand Paradox—higher concentration (fewer firms) is associated with higher prices in markets with differentiated goods, as remaining firms face less competitive pressure (e.g., Alviarez *et al.*, 2025).

the undercutting typical of Bertrand, as the supply function equilibrium allows for vertical (same price for all quantities) and horizontal (same quantity for all prices) supply schedules as limiting cases (Klemperer and Meyer, 1989). We present conditions for prices to rise or fall with concentration, explaining the empirical patterns observed in Colombia while ensuring a unique equilibrium.[4] To capture this, we extend the supply function equilibrium framework to asymmetric firms and non-differentiable marginal costs, as seen in electricity markets where firms operate multiple generating units with step-function cost structures. We show that a system of differentiable equations uniquely characterizes firms' optimal supply schedules.

Early research on diversified production in electricity markets cautioned against integrating renewable and thermal generation. Under Cournot competition, firms with diversified portfolios may strategically withhold capacity to raise market prices—an issue absent under perfect competition, where units are dispatched at marginal cost regardless of ownership (Genc and Reynolds, 2019).[5] As shown by Acemoglu *et al.* (2017), when strategic firms hold more renewable capacity, they reduce thermal output to raise prices, while their low-cost renewable supply is always dispatched in full. More recently, Fabra and Llobet (2024) show that technology diversification can intensify competition relative to specialization. They compare equilibrium prices between two scenarios: one in which each firm specializes in a different technology, and another in which firms are identically diversified, each owning equal capacities of both technologies. Prices are weakly lower under diversification, as firms compete more aggressively across technologies at each price level.

Our findings have implications for the green transition in electricity markets. In Colombia, the legacy of dam ownership from the 1990s privatizations has resulted in geographically clustered hydropower portfolios concentrated within individual firms. Given the country's current energy mix—with limited solar or wind generation—a more geographically diversified ownership of dams would allow firms to hedge drought risks using distant dams rather than relying on their own thermal units, thereby reducing emissions. Such diversification could facilitate the transition to renewable energy by mitigating intermittency without requiring additional policies or investments in battery storage (e.g., Gowrisankaran *et al.*, 2016, Schmalensee, 2019, Butters *et al.*, 2021, Vehviläinen, 2021, Andrés-Cerezo and Fabra, 2023). As Colombia expands renewable generation, a more

[4] As argued by Grossman (1981), firms can commit to supply schedules by specifying the quantity they will produce at each price level in contractual agreements with consumers (see also Wilson, 1979). This framework has been applied extensively in contexts such as energy markets (Green and Newbery, 1992), financial markets (Hortaçsu *et al.*, 2018), government procurement (Delgado and Moreno, 2004), management consulting, airline pricing (Vives, 2011), firm taxation (Ruddell *et al.*, 2017), and transportation networks (Holmberg and Philpott, 2015). It also relates to nonlinear pricing, as it allows for nonlinear supply schedules—unlike standard Cournot or Bertrand models.

[5] Another important contribution is Bushnell (2003), who theoretically shows that diversified firms operating both hydropower and thermal generation allocate more hydro to off-peak periods than they would under perfect competition, resulting in higher prices.

suitable allocation across firms and space could help curb electricity prices, particularly during droughts, by leveraging the lower costs of renewables relative to fossil fuels.

Our analysis complements the literature on competition in electricity markets, which has recently focused on policies favoring the entry of renewable capacities and grid integration to promote competition and keep prices low (e.g., Boffa *et al.*, 2016, De Frutos and Fabra, 2011, Ryan, 2021, Gowrisankaran *et al.*, 2022, Gonzales *et al.*, 2023, Elliott, 2024, Gowrisankaran *et al.*, 2024). However, these analyses often overlook the role of technology ownership—both new and legacy—in shaping market prices. Our findings raise questions about firms' optimal technology structures and the consequences of standard policies aimed at increasing competition such as capacity caps (Alfaro and Chari, 2014). For example, in Colombia, regulations limit firms to no more than 25% of total installed capacity to curb market power. Yet, this cap may inadvertently restrict the potential benefits of diversified production. Although determining the optimal threshold is beyond our scope, neglecting these considerations could result in inefficient firm sizing and suboptimal diversification, particularly in hydropower, where a single dam can significantly exceed the scale of other generation technologies.

Outside the energy literature, several studies empirically examine how capacity constraints influence oligopoly outcomes and market power in single-technology contexts (e.g., Bresnahan and Suslow, 1989, Staiger and Wolak, 1992, Froeb *et al.*, 2003, Genc and Reynolds, 2011). We contribute to this literature by analyzing markets where firms manage asymmetric portfolios of technologies subject to capacity constraints. In contrast, the broader market power literature typically incorporates such constraints indirectly—either through diseconomies of scale or cost-minimization assumptions driven by data limitations that prevent direct microfoundation of technology-specific cost curves.[6]

Building on this perspective, we show that technology diversification generates strategic complementarities both across technologies and across firms. Our results offer two key implications. First, from a research standpoint: standard methods for estimating production functions typically capture only a firm's average costs, not technology-specific marginal costs—especially if technology-level data are unavailable—limiting the feasibility of counterfactual analyses like ours (e.g., Olley and Pakes, 1996). Second, from a policy perspective: our findings indicate that merger-related divestitures may inadvertently raise prices if they reduce firms' technological diversification (Compte *et al.*, 2002, Friberg and Romahn, 2015). This insight complements recent evidence that divestitures can raise prices by affecting negotiations with upstream suppliers (Delaprez, 2024).[7]

More broadly, our framework has implications beyond electricity markets, applying naturally to industries characterized by capacity constraints and uncertain demand. In

[6]In these models, concentration generally raises markups (e.g., De Loecker *et al.*, 2020, Benkard *et al.*, 2021), precluding the mechanism highlighted in our analysis.

[7]Our analysis can be extended to incorporate standard cost synergies between merging firms (Paul, 2001, Verde, 2008, Jeziorski, 2014, Miller *et al.*, 2021, Demirer and Karaduman, 2022, Elliott *et al.*, 2023).

doing so, we revisit early theoretical insights emphasizing how technological heterogeneity shapes firms' supply decisions and market outcomes (Robinson, 1953, Sraffa, 1960). First, the trade-offs identified here extend directly to multi-product settings, since the supply function equilibrium approach we adopt generalizes to differentiated goods (Klemperer and Meyer, 1989, pp. 1267–1270). Second, this equilibrium concept also resonates with recent macroeconomic models in which firms commit to supply schedules prior to resolving uncertainties such as inflation (Flynn *et al.*, 2023). Similar considerations apply to other sectors: for instance, alumina manufacturers operate multiple production technologies (Collard-Wexler and De Loecker, 2015), and firms in labor markets diversify across employee skills and employment levels (e.g., Bonhomme *et al.*, 2019).

The paper is structured as follows. Sections 2 and 3 introduce the Colombian wholesale market, describe the data, and present empirical patterns on the relationship between prices and concentration exploiting occurrences of periods of scarcity and abundance of renewables. Section 4 explains these patterns through a simple theoretical framework, which forms the basis of our empirical analysis developed in Sections 5 and 6. Finally, Section 7 concludes remarking our primary contributions.

2 The Colombian Wholesale Energy Market

2.1 Generation

Colombia's daily energy production is approximately 170 GWh.[8] Between 2011 and 2015, the market featured around 190 units owned by 50 firms. However, it exhibits significant concentration, with six major firms possessing over 50% of all units and approximately 75% of total generation capacities. The majority of firms operate a single unit with limited production capacity.

These major players diversify their portfolios, engaging in *dam* and other generation types, including *thermal* sources such as fossil fuel-based units (coal and gas). Additional sources comprise renewables like wind farms and run-of-river, which utilizes turbines on rivers without water storage capabilities. Figure 1a illustrates the hourly production capacities (MW) for each technology from 2008 to 2016, revealing that hydropower (blue) and thermal capacity (black) constitute 60% and 30% of the industry's capacity, respectively. Run-of-river (green) accounts for less than 6%. Solar, wind, and cogeneration technologies producing energy from other industrial processes are marginal.

Despite the presence of various sources, hydropower dominates production, averaging around 75% of total dispatched units. The remaining energy needs are met by thermal

[8]For regional context, neighboring countries' energy production in 2022 included 227 GWh in Venezuela, 1,863 GWh in Brazil, 165 GWh in Peru, and 91 GWh in Ecuador. Globally, figures were 11,870 GWh in the US, 1,287 GWh in France, and 2,646 GWh in Japan.

generation (approximately 20% of total production) and run-of-river (5%). However, production varies over time, as shown in Panel (b) of the same figure, which contrasts production across technologies with dry seasons proxied by periods of high temperature or low rainfall at dams, which are responsible for evaporation (gray bars). The years 2015 and 2017 were marked by El Niño (a severe dry spell) and, later, La Niña (a severe wet spell), leading to greater variability in hydropower usage. During dry spells, hydropower production decreases, and thermal generation compensates for water scarcity.[9] Similar to dams, run-of-river units also have turbines but lack the ability to store water, so they produce electricity only when sufficient inflows are available.

Thermal generation typically incurs higher marginal costs than hydropower. Consistently, Figure 2 highlights that wholesale energy prices more than double during scarcity periods.[10] Prices experienced a further increase during the sustained dry spell caused by El Niño in 2016 and the annual dry seasons (December to March).

2.2 Institutional Background

The Colombian wholesale energy market is an oligopolistic market with high barriers to entry, as suggested by the fact that the total hourly capacity in Panel (a) of Figure 1 is almost constant over time, and especially so in the period 2010-2015, on which we focus in the following analysis. In this period, only nine units entered the market (out of 190), all belonging to different fringe firms, leading to a mild increase in market capacity (+4%). The market is highly regulated and consists of a spot and a forward market.

The spot market. The spot market, also known as day-ahead market, sets the output of each unit. It takes the form of a multi-unit uniform-price auction in which Colombian energy producers compete by submitting bids to produce energy the following day. Through this bidding process, each firm submits one quantity bid per unit and hour and one price bid per unit every day.[11] Quantity bids state the maximum amount (MWh) a unit is willing to produce in a given hour, while price bids indicate the lowest price (COP/MW) acceptable for production. Each unit bids its own supply schedule, potentially considering the payoffs to the other units owned by the same firm, which we call *siblings* of the focal unit.

Spot market-clearing. Before bidding, the market operator (*XM*) provides all units with estimated market demand for each hour of the following day. After bidding, *XM* ranks bid schedules from least to most expensive to identify the lowest price satisfying demand for each hour. *XM* communicates the auction outcomes or *despacho economico*

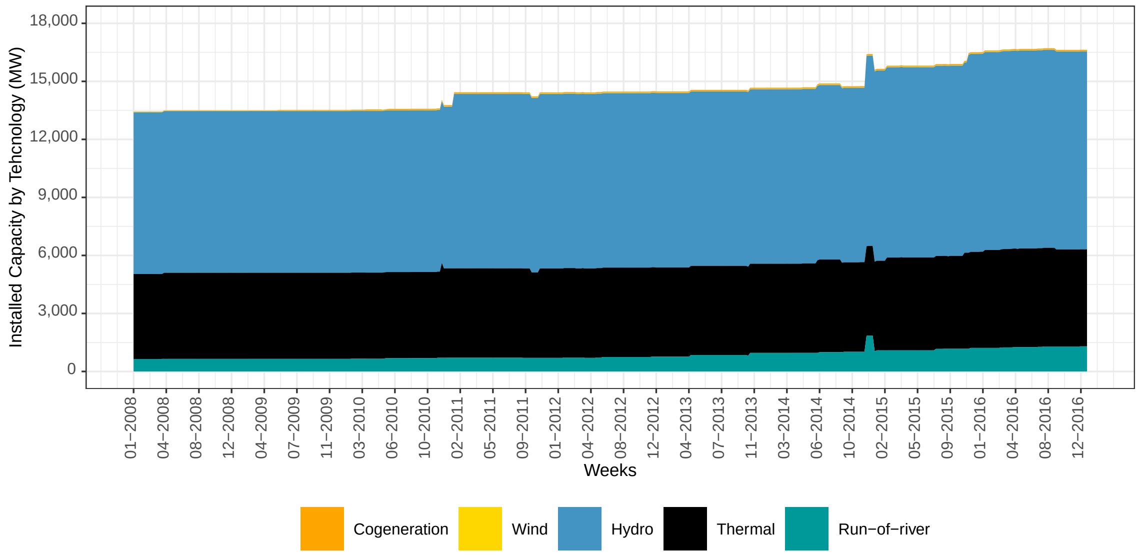
[9]Data reveals a correlation between thermal production and minimum rainfall at Colombian dams of -0.32 (p-value $\leq$ 0.01) and 0.27 (p-value $\leq$ 0.01) for hydropower generation.

[10]The correlation of the average hourly price and rainfall is -0.28 (p-value $\leq$ 0.01). Prices are in Colombian pesos (COP) per MWh and should be divided by 2,900 to get their euro per MWh equivalent.

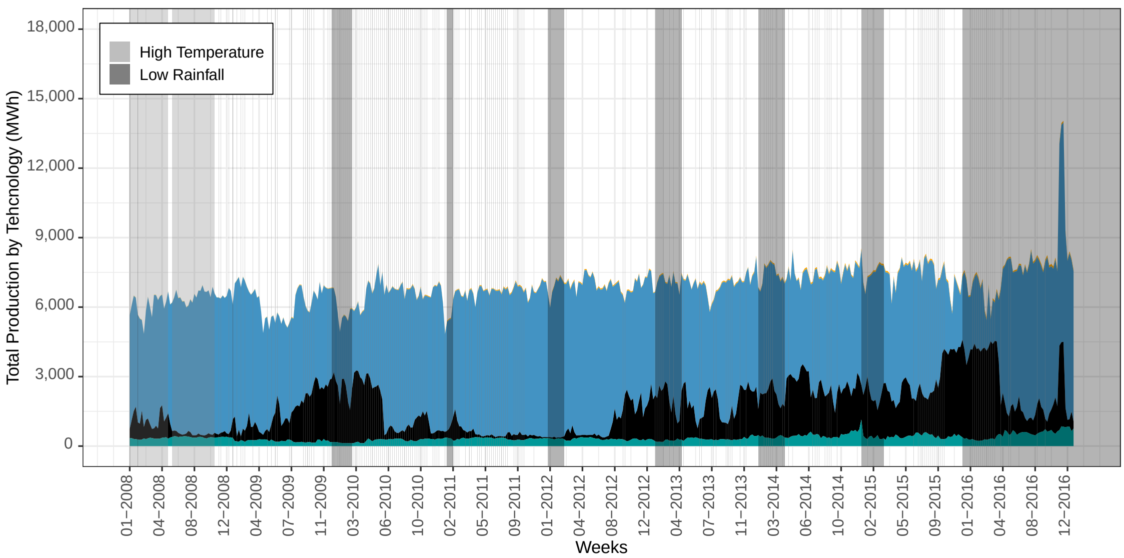
[11]Participation in the spot market is mandatory for large units with capacity over 20MW.

Figure 1: Installed capacity and production volumes by technology over time

(a) Total installed capacity by technology



(b) Total weekly production by technology



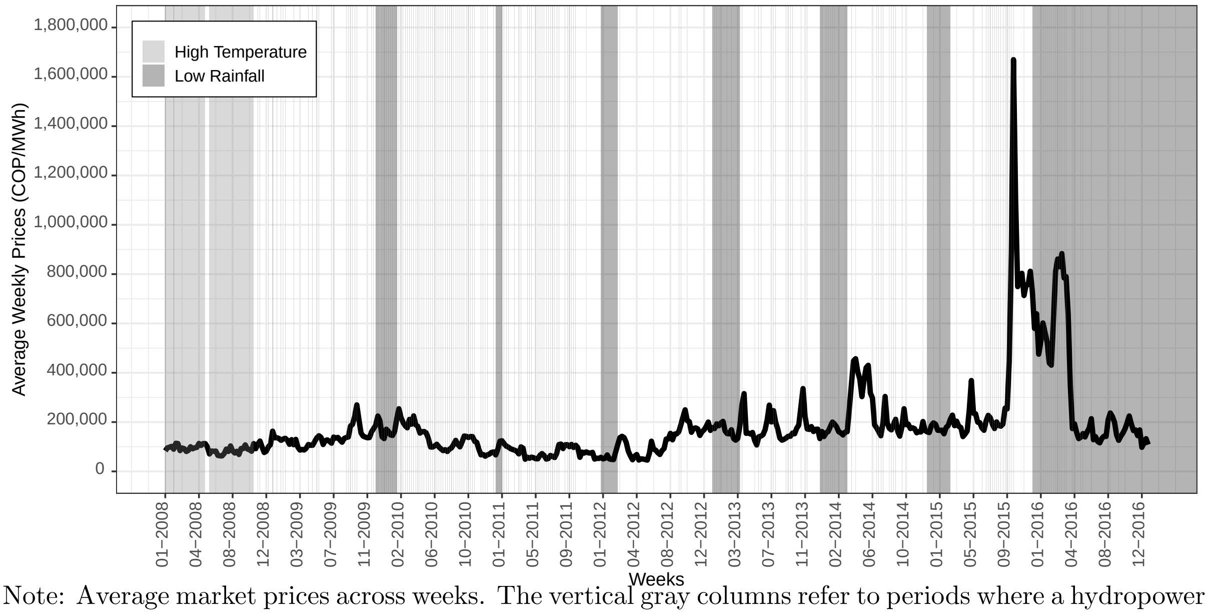
Note: The figure illustrates the total installed capacity (top panel) and production volumes (bottom) by technology. The vertical bars in Panel (b) refer to periods where a hydropower unit experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average.

to all units. During the production day, actual generation may differ due to production constraints or transmission failures. The spot hourly price is set at the value of the price bid of the marginal unit, with all dispatched units paid the same price.[12]

Forward market. The forward market comprises bilateral contracts between pairs of

[12]The price paid to thermal units can vary due to startup costs, which are reimbursed (Balat *et al.*, 2022). Importantly, Bernasconi *et al.* (2023) show evidence of a cartel involving thermal generating units until 2009, when the regulator introduced policies reducing the coordination of cartel members.

Figure 2: Market prices



Note: Average market prices across weeks. The vertical gray columns refer to periods where a hydropower unit experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average. 2,900 COP $\simeq$ 1 US$.

agents. These contracts allow agents to decide the financial position of each unit weeks in advance, serving to hedge against uncertainty in spot market prices. In our dataset, we observe each unit's overall contract position for each hourly market. Note that these contracts are available only with a delay, so market participants have no information about them at the time of bidding.

2.3 Data

The data come from *XM* for the period 2006–2017. We observe all quantity and price bids and forward contract positions. The data also includes the ownership, geolocalization, and capacity for each unit, and daily water inflows and stocks for dams. We complement this dataset with weather information drawn from the *Colombian Institute of Hydrology, Meteorology, and Environmental Studies* (IDEAM). This information contains daily measures of rainfall and temperature from 303 measurement stations.[13]

Rainfall forecasts are constructed using monthly summaries of el Niño, la Niña, and the Southern Oscillation (ENSO), based on the NINO3.4 index from the *International Research Institute* (IRI) of Columbia University.[14] ENSO forecasts, published on the

[13]For each unit, we compute a weighted average of the temperatures and rainfalls by all measurement stations within 120 km, weighting each value by the inverse distance between units and stations. We account for the orography of the country when computing the distance between units and weather measurement stations, using information from the *Agustin Codazzi Geographic Institute.*

[14]ENSO is one of the most studied climate phenomena. It can lead to large-scale changes in pressures, temperatures, precipitation, and wind, not only at the tropics. El Niño occurs when the central and eastern equatorial Pacific sea surface temperatures are substantially warmer than usual; la Niña occurs when they are cooler. These events typically persist for 9-12 months.

19th of each month, provide probability forecasts for the following nine months, aiding dams in predicting inflows. We have monthly information from 2004 to 2017.

This dataset is complemented with (international) daily prices of oil, gas, coal, liquid fuels, and ethanol—commodities integral to energy production through thermal or cogeneration (e.g., sugar manufacturing) units.

3 Diversified Firms: Supplies & Market Prices

We first leverage exogenous variation in forecast inflows to examine how capacity changes affect firms' thermal and hydro supplies. We then examine the implications of our findings for market prices in Section 3.2.

3.1 Firms' Responses to Changes in Water Stocks

We investigate units' reactions to forthcoming inflows through:

$$\begin{aligned} y_{ij,th} = &\sum_{l=1}^{L} \left(\beta_l^{low} \text{adverse}_{ij,t+l} + \beta_l^{high} \text{ favorable}_{ij,t+l} \right) \\ &+ \mathbf{x}_{ij,t-1,h}\alpha + \mu_{jm(t)} + \tau_t + \tau_h + \epsilon_{ij,th}, \end{aligned} \tag{1}$$

where $y_{ij,th}$ is either the quantity or price bid of firm i for unit j. To minimize autocorrelation, we aggregate bids over weeks (t) per hour (h).[15] The definition of the variables "adverse$_{ij,t+l}$" and "favorable$_{ij,t+l}$" varies across analysis. Specifically, when focusing on the supply of hydropower, these variables take the value one if dam j of firm i anticipates its l-month-ahead forecast to deviate by more than one standard deviation (above or below) from its long-run average for that forecast horizon in the same month of the year, based on data from 2008–2016. Otherwise, the variable is set to zero. Conversely, when transitioning the analysis to *sibling* thermal units—those owned by a firm with dams—these indicators are based on the cumulative l-month ahead inflow forecasts associated with all the dams owned by i. The forecasting approach is explained below.[16]

$\mathbf{x}_{ij,t-1,h}$ controls for changes in market conditions. It includes average market demand, water stocks, and forward contract positions (in log) for week $t-1$ and hour h. To account for seasonal variations that may impact units differently, fixed effects are included at the unit-by-month and firm-by-year levels ($\mu_{jm(t)}$). Macro unobservables, such as variations in demand, are captured through fixed effects at the week-by-year (τ_y) and hour levels

[15] We exclude units bidding below the 5th percentile of their technology distribution to exclude unobserved maintenance periods. This truncation does not affect the results qualitatively.

[16] We report results for $l = 1, 3,$ and 5 months to avoid the high correlation across forecasts for adjacent months within units. An alternative approach is to estimate $\{\beta_l^{low}, \beta_l^{high}\}$ in separate regressions similar to (1) for each l. We perform this analysis in Section C.2 and find similar results.

(τ_h). The standard errors are clustered by unit, month, and year.[17]

Forecasting approach. We construct inflow forecasts for each hydropower unit employing a flexible autoregressive distributed-lag (ARDL) model (Pesaran and Shin, 1995). In essence, these forecasts are derived through OLS regressions of a unit's weekly average net water inflow, encompassing evaporation, on the water inflows in past weeks and past temperatures, rainfalls, and el Niño probability forecasts. A two-year moving window is used to generate monthly forecasts up to 5 months ahead for the period between 2010 and 2015, where we observe little entry of new plans and no new dams. Appendix B explains the forecasting technique in details and presents goodness of fit statistics.

Exclusion restriction. Identification of $\{\beta_l^{low}, \beta_l^{high}\}_l$ relies on the assumption that a firm's current supply schedule does not *directly* depend on lagged variables used for forecasting "adverse$_{ij,t+l}$" and "favorable$_{ij,t+l}$." To the extent that the (lagged) water stock accounts for the firm's anticipation of future inflows, the β coefficient vector reports the adjustment in supply schedules in response to different forecasts (i.e., two firms with the same water stocks but different forecasts submit different schedules). Moreover, due to their rural locations, the local weather along the river is unlikely to influence other market level variables, such as energy demand, which is controlled for in the estimation.

The information content of the forecasts. Appendix C.1 examines the information content of our inflow forecasts. In particular, it replaces the inflow forecasts in 1 with the forecast errors, computed as observed minus forecasted inflows. We find that units' responses to forecast errors are small and not statistically different from zero. Therefore, there is no extra information in the error term that we can leverage for our analysis.

Results: hydropower. The top panel of Figure 3 reports estimates of $\{\beta_l^{low}, \beta_l^{high}\}_l$ from (1) for 2010-15. Dams adapt their supplies mainly by changing their quantity bids (Panel b) rather than their price bids (Panel a) because, having low marginal costs, they always produce and the market asks for hourly quantity bids but only daily price bids. Panel (b) show that a dam's supply decreases by 7.1% for one-month adverse forecasts and 1.3% for two-month adverse forecasts (red dots), whereas it only increases by approximately 3.7% one month ahead of a favorable forecast (blue triangles).

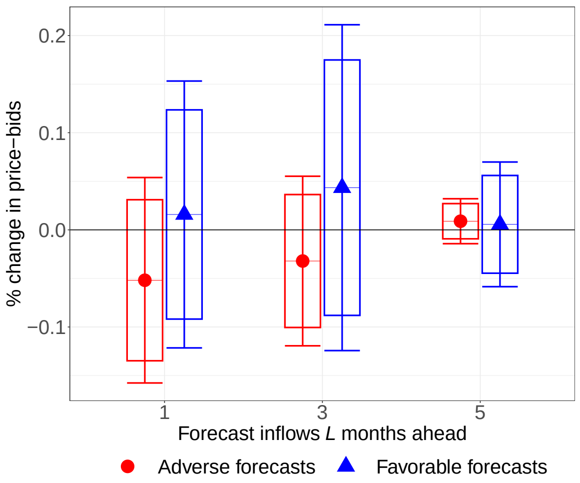
Results: "sibling" thermal units. The bottom panel of Figure 3 shows sibling thermal units increasing supply schedules before favorable events (blue triangles) and decreasing them before adverse ones (red circles). Adjustment happen primarily through price bids because these units are not operational at all times due to high marginal costs and lack the flexibly to vary production across hourly markets. The analysis indicates that they

[17] Spatial clustering the standard errors is an alternative approach. However, hydrology literature suggests that a riverbed acts as a "fixed point" for all neighboring water flows, making shocks at nearby dams independent (Lloyd, 1963). Moreover, spatial distance has no meaning for thermal units. Hence, we do not pursue spatial clustering in this analysis.

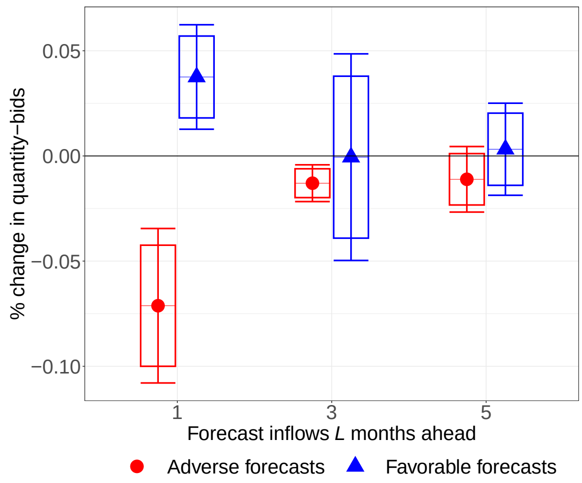
respond to extreme events earlier than hydropower units, likely because this analysis focuses on firm-level forecasts rather than unit-level ones as in the previous paragraph, which may be more severe.

Figure 3: Responses to inflow forecasts

Top panel: Responses of dams to own inflow forecasts

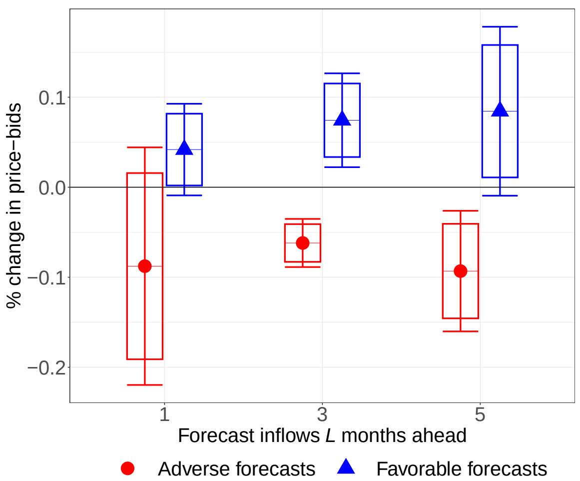


(a) Price bids

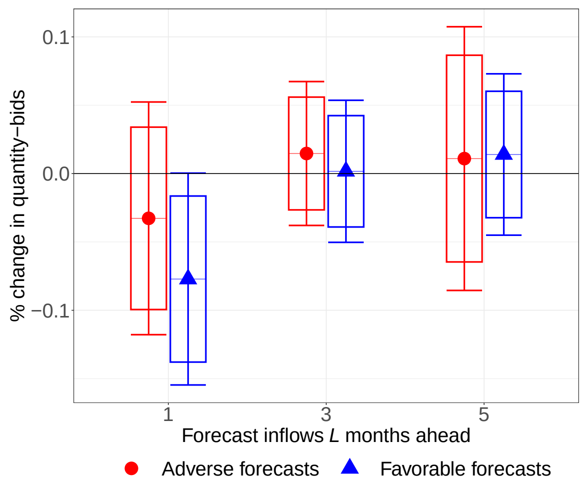


(b) Quantity bids

Bottom panel: Responses of thermal units to the forecasts of their sibling dams



(c) Price bids



(d) Quantity bids

Notes: Each plot reports estimates from (1) of $\{\beta_l^{low}\}$ in red and $\{\beta_l^{high}\}$ in blue for one, three, and five months ahead. Error bars (boxes) report the 95% (90%) CI.

3.2 Implications for Market Prices

The previous section shows that firms increase thermal supply in anticipation of droughts. This raises the question: could expanding firms' thermal capacity help dampen price spikes during scarcity, even at the cost of greater industry concentration? A simple regression of market prices on capacity-level HHI would overlook firms' effective capacity, which depends on expectations about future inflows. To address this, we exploit the exogenous timing of droughts across firms of different sizes as a source of variation. Let

$$\text{net adverse}_{i,t+l} \equiv \text{adverse}_{i,t+l} - \text{favorable}_{i,t+l},$$

where the variables "adverse$_{i,t+l}$" and "favorable$_{i,t+l}$" are indicators equal to 1 if at least one of firm i's dams is expected to experience, respectively, an l-month-ahead inflow forecast that is more than one standard deviation below or above its long-run average. Based on these, "net adverse$_{i,t+l}$" takes a value of 1 if forecasts are adverse, -1 if favorable, and 0 if neither applies.[18] Aggregating across firms, the change in industry concentration due to these forecasts can be measured as:

$$\begin{aligned}&\sum_i (1 - \text{net adverse}_{i,t+l}) \times \text{Firm } i\text{'s capacity share}^2 \\ &= \text{HHI}_t - \sum_i \text{net adverse}_{i,t+l} \times \text{Firm } i\text{'s capacity share}^2 = \text{HHI}_t + \Delta_{t+l}.\end{aligned}$$

The variable Δ_{t+l} measures the expected change in a capacity-based HHI due to the l-month inflow forecasts, weighting each firm's squared capacity share by its net adverse inflow forecast. Firms without dams contribute to the HHI regardless of inflow forecasts, so common adverse forecasts lower the HHI. Larger firms, which contribute more heavily to the HHI, influence Δ_{t+l} disproportionately. For negative Δ_{t+l} values, the HHI is expected to drop as more large firms expect adverse inflows while smaller firms expect favorable inflows, indicating a more competitive and less concentrated market. Conversely, higher Δ_{t+l} values correspond to increasing concentration.

Exploiting time series variation only, we regress market-clearing prices on Δ_{t+l} to capture how inflows targeting firms with larger shares influence pricing:[19]

$$\ln(p_{th}) = \gamma_0 \Big[\sum_i \text{net adverse}_{i,t+3}\Big] + \gamma_1\, \Delta_{t+3} + \alpha_1\, \text{HHI}_{t-1} + \mathbf{x}_{t-1,h}\, \alpha + \tau_{mh,y} + \epsilon_{th}, \qquad (2)$$

where $\ln(p_{th})$ is the logarithm of the market-clearing price in hourly market h at time t, Δ_{t+3} reflects the forecasted concentration effects three months ahead. We set $l = 3$ because it reflects the first time where we detect a response of sibling thermal units to inflow forecasts (Figure 3, Panel c).[20] The remaining terms control for lagged variables at $t-1$ and hour h—namely, HHI, total water stock, hourly forward contracts, demand,

[18] While continuous inflow forecasts at the firm level yield similar results, they raise measurement concerns about the exact information available to firms. Our approach is less sensitive to similar issues as it classifies a firm as facing an adverse forecast only if none of its dams have favorable forecasts.

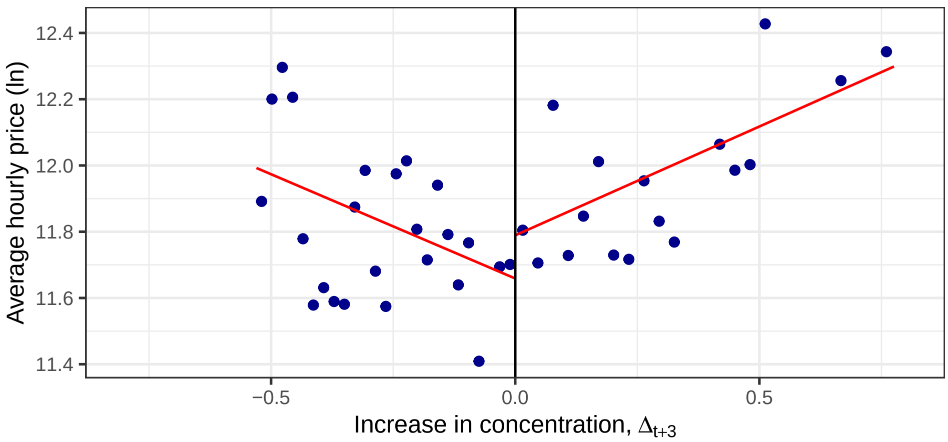
[19] Unlike market-share HHI, capacity-based HHI avoids simultaneity bias as it does not depend on spot prices. Appendix C.3 shows consistent results using thermal capacity only (time invariant) or thermal plus lagged hydro (time varying).

[20] We find qualitatively similar results for forecast horizons $l \neq 3$ (unreported for space considerations).

as well as lagged dependent variable to control for autocorrelation—and month-by-hour and year fixed effects ($\tau_{mh,y}$).[21]

Results ($\hat{\gamma}_1$). Figure 4 presents estimates from a piecewise-linear specification of equation (2), which allows for different slopes (γ_1) and intercepts on either side of $\Delta_{t+3} = 0$. The estimated slope $\hat{\gamma}_1$ on the left side of the plot is -0.629 with a 95% confidence interval of $[-0.692, -0.519]$, while on the right it is 0.657, with a 95% confidence interval of [0.566, 0.699]. Appendix Figure C4 shows a similar U-shape relationship without controlling for $\mathbf{x}_{t-1,h}$ to avoid overfitting the regression. An analogous result holds when studying non-linearities by including a squared Δ_{t+3} term in (2). Appendix C.3 shows that the estimated coefficient for Δ^2_{t+3} is positive and significant, indicating higher prices at the lowest and highest concentration levels. Importantly, controlling for the total water stock in $\mathbf{x}_{t-1,h}$ allows us to isolate the negative portion of the U-shape from mechanical price drops due to changes in the overall hydropower capacity.

Figure 4: Market price and inflow-driven changes in concentration



Notes: Binned scatter plot. The regression slopes are the coefficient estimates of Δ_{t+3} for a version of (2), which allows for different slopes for positive and negative Δ_{t+3}.

Results ($\hat{\gamma}_0$). The estimated $\hat{\gamma}_0$, which captures the direct effect of more firms expecting adverse inflows, is both economically small and statistically insignificant in the analyses presented in Figure 4 (not reported in the plot) and in Appendix C.3. Since changes in capacity, as reflected in "net adverse," should have a first-order effect on costs, holding the markup constant, we would expect γ_0 to be positive and significant. This absence of an effect suggests that, conditional on covariates and fixed effects, inflow forecasts do not directly affect marginal costs but instead shape them indirectly by altering firms' relative capacities and, consequently, their market power. Similar patterns have been

[21]The market-clearing price depends on the difference between demand—which is independent of forecasts and lagged capacities—and the horizontal sum of supply functions in (1). Thus, although our focus is descriptive, a causal interpretation is valid if ε_{th} is uncorrelated with forecasts and capacities, as discussed in Section 3.1.

documented for other intermittent renewables such as wind, where operating costs do not exhibit systematic co-movement with wind capacity (Petersen *et al.*, 2024).

To conclude, our analysis suggests a U-shape relationship between market price and concentration. The next section develops a competition model for technology-diversified firms, shedding light on the underlying mechanism.

4 A Competition Model With Diversified Firms

This section develops a model of competition among technology-diversified firms under random demand. We show that when a dominant firm's market power arises primarily from the *relative efficiency* of its technologies rather than its *overall capacity*, increasing industry concentration by reallocating capacity to the leader from its less-efficient competitors lowers the market price, as illustrated in the left part of Figure 4. This occurs because the leader expands its low-cost supply to further undercut competitors in low-demand scenarios while using the newly acquired higher-cost supply in high-demand ones. However, once firm size becomes the primary driver of market power, greater concentration raises prices, as shown in the right part of Figure 4, aligning with the predictions of standard oligopoly models without technology diversification.

The firm's problem. Consider an oligopolistic market where n firms sell a homogeneous good (electricity). They face an inelastic demand, $D(\epsilon)$, where ϵ is a random shifter moving demand horizontally.[22] A strategy for firm i is a non-decreasing, right-continuous function mapping prices to a maximum level of output for that price so that $S_i(p) : [0, \infty) \to [0, \infty)$. Each firm i chooses such a supply schedule before learning about ϵ. Given each firm's supply schedule, firm i's residual demand is defined as $D^R(p, \epsilon) = D(\varepsilon) - \sum_{j \neq i} S_j(p)$. The market clears at the lowest price such that,

$$p^*(\epsilon) = \min \left\{ p \geq 0 \middle| \sum_{j=1}^{N} S_j(p) \geq D(\epsilon) \right\}. \tag{3}$$

Following the seminal contribution of Klemperer and Meyer (1989), consider a scenario where firm i can delay its supply decision. Given the realized ϵ and the strategy profile of other firms, $S_{-i}(p)$, firm i's optimal "ex post" profit, if the market clears at price p, is

$$\pi_i(p) = p \cdot D_i^R(p, \epsilon) - C_i(D_i^R(p, \epsilon)), \tag{4}$$

where $C_i(q)$ represents firm i's cost of supplying quantity q. Maximizing (4) yields a

[22] In Colombia, electricity demand is uncertain due to firms relying on day-ahead market forecasts, lacking visibility into competitors' bilateral contracts, and submitting daily price bids despite hourly demand fluctuations. For example, the interquartile range of demand typically spans 28% of the median demand, highlighting significant variability.

quantity-price pair $(q(\epsilon), p^*(\epsilon))$, where $p^*(\epsilon)$ is the firm's preferred market-clearing price from (3), and the firm produces $q(\epsilon) = D_i^R(p^*(\epsilon), \epsilon)$. As ϵ varies, the set of such pairs defines an ex post optimal supply schedule, $S_i(p)$. A Supply Function Equilibrium (SFE) is the fixed point where each firm i "ex ante" commits to its ex post optimal supply schedule, given the supply schedules of others. The formal definition follows below.

Definition 4.1 ***Supply Function Equilibrium.*** *An SFE is an N-tuple of supply functions $(S_i)_{i=1}^N$ for strategic firms $i \geq 1$ such that, given S_j for all $j \neq i$, the supply function S_i is chosen by strategic firm i so that at every ϵ, the market clearing price $p^*(\epsilon)$, defined through (3), maximizes i's ex post profit (4).*

The key advantage of SFEs over standard conduct models is that firms maximize the *ex-post* profit (4) for each realization of ϵ, implies maximization of *ex-ante* expected profit before ϵ realizes with no need of specifying firm-level expectations about the random shock ϵ. Moreover, SFEs generalize standard models of conduct as special cases, encompassing Bertrand competition with horizontal supply schedules and Cournot competition with vertical ones.

The best-response markups satisfy the following property.

Proposition 1 ***Markup.*** *If the supply functions are differentiable at p, i's markup is*

$$\frac{p - C_i'(S_i(p))}{p} = \frac{s_i(p)}{\eta} \left(1 - \frac{S_i'(p)}{D_i^{R\prime}(p)}\right), \tag{5}$$

where $s_i(p)$ is firm i's market share, and η is its price elasticity of demand. Given S_{-i}'', the best response S_i' is a strategic complement to S_{-i}'.

Proof. By definition, $D_i^R \equiv D(\epsilon) - S_{-i}(p)$. The FOC of (4) implies that $(p - C_i') \cdot S_{-i}'(p) = S_i(p)\ \forall p$. The markup follows from rewriting the FOCs by defining $\eta \equiv \frac{p}{D} / \frac{dp}{dD} = \frac{p}{\sum_l S_l(p)} \frac{d}{dp} \sum_l S_l(p)$ because, in equilibrium, $D(\epsilon) = \sum_l S_l(p)$ at the market clearing p. Strategic complementarities follow from totally differentiating the FOCs w.r.t. p. □

The following heuristic argument intuitively explains how Proposition 1 aligns with the results from Section 3.2—Section 4.1 provides a detailed numerical illustration.

Consider firm i as the market leader due to its larger capacity and superior technology. Suppose there exists a price p^0 at which firm i's supply is constrained. This constraint may arise for two reasons. First, the firm may be directly capacity-constrained at p^0. Second, since supply schedules are increasing in price, the constraint may instead bind at a higher price $p^1 > p^0$, where the firm would like to supply more than its capacity allows if residual demand $D^R(p^1)$ is sufficiently high—effectively limiting its output at all lower prices as well. How would a "small" capacity transfer from competitors to firm i, increasing industry concentration, affect competition? The first-order effect is to relax firm i's constraint, allowing it to expand supply in a neighborhood around p^0. As a result, the residual demand faced by its competitors contracts.

If $C'(\cdot)$ is constant in a neighborhood of p^0, the left-hand side of (5) remains unchanged after the transfer. When i expands production at p^0, all else equal, its market share, $s_i(p^0)$, increases. For (5) to hold, $(1 - S'_i/D_i^{R'})$ must decrease since η does not depend on firm i. Thus, S'_{-i} must increase as $S'_{-i} = -D_i^{R'}$ from the definition of the residual demand. In other words, i's competitors will raise their supplies at p^0 to undercut firm i and prevent losing market share after the transfer.

Heuristically, *strategic complementarity* implies that both i and its competitors will increase their supplies near p^0. As all firms expand supply, the market price falls, explaining the price drop observed in the left half of Figure 4, despite increasing concentration.

However, if the capacity transfer is "large," i's competitors must decrease their supply as they might not have any extra capacity left at p^0 after the transfer. Firm i can take advantage of this situation by similarly decreasing its production level at p^0. As total supply drops but market demand stays unchanged, prices will increase, consistent with the upward slope in Figure 4.

This explanation provides intuition but is not a proof, as it does not account for the overall equilibrium effects of capacity changes on each firm's supply curve. Section 4.1 examines this mechanism in more detail through a parametrization that allows for a closed-form solution. The proofs and derivations are in Appendix A.

4.1 Analytical Solution and Comparative Statics

To illustrate the specifics in our context, assume that there are three production technologies: a low-, a high-, and a fringe-cost technology, with constant marginal costs c^l, c^h, and c^f, respectively, with $0 \leq c^l < c^h < c^f < \infty$. A *technology portfolio*, $K_i = (K_i^l, K_i^h, K_i^f)$, summarises firm i's capacity for each technology. Its cost, $C_i = \sum_{\tau \in \{l,h,f\}} c^\tau \cdot S_i^\tau(p)$, depends on its non-decreasing, right-continuous technology-specific supplies, $S_i^\tau(p)$, at price p with $0 \leq S_i^\tau(p) \leq K_i^\tau$. The firm's total supply is $S_i(p) = \sum_{\tau \in \{l,h,f\}} S_i^\tau(p)$.

We consider a market with two strategic firms, Firm 1 and Firm 2, who have access to low- and high-cost technologies. The remaining $N - 2$ firms belong to the *non-strategic fringe* and only possess the fringe-cost capacity. Their portfolios are $K_j = (0, 0, K_j^f)$ for each $j \geq 3$, and their supplies do not depend on the strategies of others, i.e. $S_j(p) = 0$ for $p < c^f$ and $S_j(p) = K_j^f$ otherwise. We assume that there are enough fringe firms, or the highest possible demand is bounded so that the market always clears.[23] Without loss of generality, ties are broken by prioritizing the supply of strategic firms, with fringe

[23]Fringe firms ensure that the residual demands for each strategic firms decerases in p. A price cap can serve the same role and is common in the energy literature. An alternative assumption maintains that the market demand decreases in p, as in Klemperer and Meyer (1989).

firms serving any remaining demand at any p.[24]

Baseline scenario. None of the $N \geq 1$ firms is diversified at baseline. The technology portfolios are $K_1 = (K_1^l, 0, 0)$ for Firm 1 and $K_2 = (0, K_2^h, 0)$ for Firm 2, with $K_1^l > K_2^h > 0$, making Firm 1 the *market leader*.[25] We focus on two numerical illustrations in Panels (a) and (c) of Figure 5, corresponding to the cases of abundance and scarcity of the low-cost technology K_1^l, respectively. In each panel, the red (blue) dotted line represents Firm 1's (Firm 2's) cost curve. All the model primitives are constant across panels—i.e., $c^l = 0$, $c^h = 1$, $c^f = 2$, and $K_2^h = 4$—besides Firm 1's low-cost capacity: $K_1^l = 9$ under abundance (Panel a) but only $K_1^l = 5$ under scarcity (Panel c). In each panel, the solid red line is Firm 1's supply, $S_1(p)$, while its residual demand, $D_1^R(p) = D - S_{-1}(p)$, is in black. Although firms do not observe the realization of ϵ ex-ante, we fix the realized demand, $D(\epsilon)$, at 6 (gray line) to facilitate comparisons across scenarios. A different value for D would simply shift D^R horizontally, without affecting the underlying mechanism.

Unsurprisingly, the market price is larger in Panel (c) than (a) as Firm 1 is smaller under scarcity. $S_1(p)$ has the same shape in both plots: the firm does not produce for prices below c^h, perfectly undercutting its competitor for small quantities (4 in Panel a and 2.5 in Panel c). For greater quantities, it lets Firm 2 have a positive market share by raising markups according to (5) for $p \in [c^h, c^f]$. Although both firms exhaust all their capacity at $p = c^f$, as keeping extra capacity for $p > c^f$ is not profitable due to the entry of the fringe firms, there is a key difference in Panels (a) and (c), which defines the constraint at p^0 in the heuristic argument made above.

In (a), Firm 1 has extra capacity in a neighborhood of $p \to c^f$, as illustrated by the fact that $S_1(c^f)$ is flat, so that, if $D^R(c^f)$ were to be between 8 and 9 at price $p = c^f$, Firm 1 could still ensure the highest profit margin $(c^f - c^l)$. In (c), instead, Firm 1 exhausts all its capacity as $p \to c^f$, which, in equilibrium, forces Firm 1 to produce less $\forall\, p \in [c^h, c^f]$, than in Panel (a) since, in equilibrium, at least one firm must fully utilize its capacity in the limit; otherwise, a firm could freely capture market shares from its competitor by producing more at lower prices. This illustration provides a rationale for why, despite being largest, Firm 1 is "constrained" at p^0 according to the heuristic argument in the previous section.

Because of strategic complementarities, Firm 2's supply is less aggressive in (c) than in (a), as shown in Appendix Figure A1, which plots Firm 2's supply across both scenarios. Therefore, since both firms supply more in (a) than in (c), but market demand is constant, the market clearing price is strictly higher in (c).

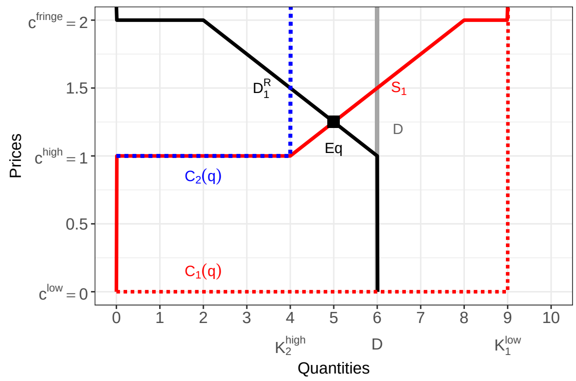
Scenario with diversified firms. Panels (b) and (d) reallocate $\delta = 0.5$ units of high cost capacity from Firm 2 to 1, so that $\tilde{K}_1 = (K_1^l, 0.5, 0)$ and $\tilde{K}_2 = (0, 3.5, 0)$. Panel

[24] That is, a strategic firm can, in principle, undercut fringe firms by an infinitesimal price reduction.

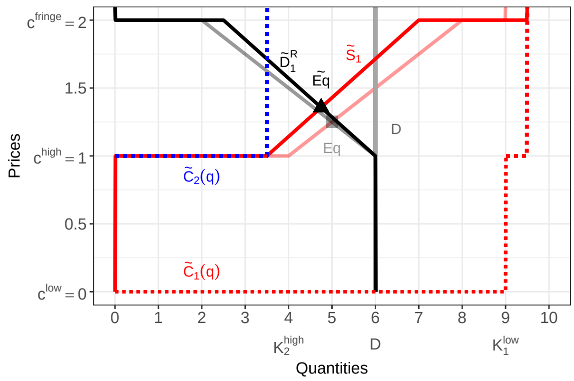
[25] At baseline Firms 1 and 2 can be viewed as owning a dam and a fossil-fuel plant, respectively.

Figure 5: Equilibrium before and after diversifying Firm 1

Top panel: Abundance of low-cost technology

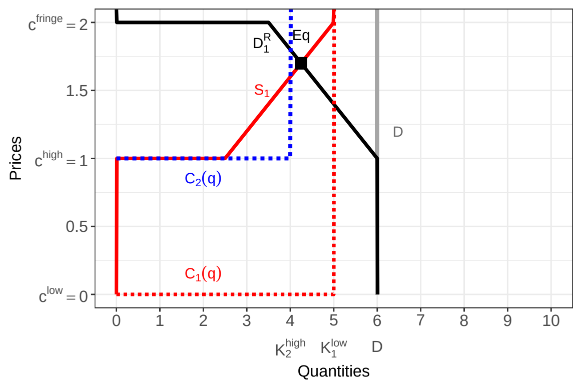


(a) Before the transfer
$K_1 = (9, 0, 0)$ & $K_2 = (0, 4, 0)$

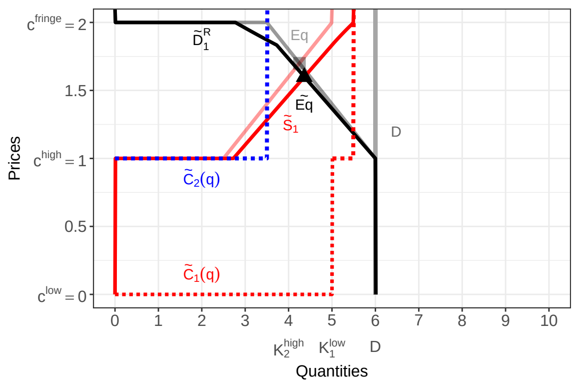


(b) After the transfer
$\tilde{K}_1 = (9, 0.5, 0)$ & $\tilde{K}_2 = (0, 3.5, 0)$

Bottom panel: Scarcity of low-cost technology



(c) Before the transfer
$K_1 = (5, 0, 0)$ & $K_2 = (0, 4, 0)$



(d) After the transfer
$\tilde{K}_1 = (5, 0.5, 0)$ & $\tilde{K}_2 = (0, 3.5, 0)$

Notes: Each panel illustrates equilibrium outcomes from the perspective of Firm 1. Solid lines represent equilibrium outcomes, while dotted lines depict marginal cost curves for Firm 1 (red) and Firm 2 (blue). In each panel, the left plot shows outcomes before a capacity transfer, and the right plot shows outcomes after transferring 0.5 units of high-cost capacity from Firm 2 to Firm 1. The shaded square (Eq) and curves in the right plot represent the pre-transfer equilibrium, and superscript $\sim$ denotes post-transfer variables. Each subcaption details the technology profile of each firm as $K_i = (K_i^l, K_i^h, K_i^f)$. Ex-post market demand is constant at 6 (gray solid line) and the cost parameters are $c^l = 0$, $c^h = 1$, and $c^f = 2$.

(b) replicates with diversified firms the standard effect of concentration. Because of the merit order, Firm 1 produces first with its low-cost capacity, leaving the newly received δ units for demand realizations such that $D^R(c^f) \geq 9$. Being smaller, Firm 2 must now produce less at every price. As a result, the equilibrium price increases, consistent with the apward slope in Figure 4. In contrast, the market price drops after the transfer under scarcity (Panel d). Here, the transferred δ capacity helps Firm 1 to undercut further its competitors for all $p \in [c^h, c^f]$, as $\tilde{S}_1$ expands in the direction of S_1 in Panel (c), where it was not constrained. Firm 2 responds aggressively to maintain market shares according to (5), leading to a drop in prices despite greater capacity concentration.[26]

Return to scale. It is worth noting that across all panels of Figure 5, Firm 1 exclusively utilizes its low-cost technology at the equilibrium p, highlighting the *absence of economies of scale* because the average cost stays unchanged, which is consistent with the finding that $\hat{\gamma}_0 = 0$ in (2).

Generalization. Appendix A extends the results to richer technology portfolios for strategic Firms 1 and 2, while firms $j \geq 3$ remain non-strategic as follows:

Proposition 2 ***Existence, uniqueness, and comparative statics.*** *Suppose* $0 \leq c^l < c^h < c^f < \infty$*, and the capacity portfolios are* $K_1 = (K_1^l, K_1^h+\delta, 0)$*,* $K_2 = (0, K_2^h-\delta, 0)$*, and* $K_j = (0, 0, K_j^f)$ *for fringe* $j \geq 3$*. Then, assuming* $K_2^h \geq \delta$*,*

1. *there exists a unique SFE for every* $\delta \geq 0$*;*
2. *denote by* $S^\delta(p) = \sum_i^N S_i^\delta(p)$ *the equilibrium market supply for the SFE* $(S_i^\delta)_{i=1}^N$ *at* δ*, then for* $\delta_1 > \delta_2 > 0$*:*
   a. $S^{\delta_1} < S^{\delta_2}$ *for* $K_1^l > \frac{c^f - c^l}{c^f - c^h} K_2^h$ *(i.e., abundance scenario);*
   b. $S^{\delta_1} > S^{\delta_2}$ *for* $K_1^l < \frac{c^f - c^l}{c^f - c^h} K_2^h$ *and* $K_1^h + \delta_1$ *small enough (i.e., scarcity scenario).*

Proof. See Appendix A.2.□

We assume $K_2^h \geq \delta$ only to avoid cases of negative capacities after a transfer. The first part of the proposition establishes the existence and uniqueness of an SFE, extending the seminal approach of Klemperer and Meyer (1989) to an industry with step-function marginal costs, as in Figure 5. The proof shows that for $p \geq c^h$, the supply functions of Firms 1 and 2 satisfy a system of differential equations derived from the FOCs of (4). The boundary conditions are determined by firms reaching their capacity constraints at $p = c^f$, ensuring a well-posed initial value problem. For $p < c^h$, Firm 2 ceases production due to its higher marginal cost, and Firm 1 best responds by producing nothing.

The second part performs comparative statics, defining abundance and scarcity from Figure 5 in terms of capacity and marginal costs. When Firm 1's low-cost capacity exceeds (falls short of) Firm 2's high-cost capacity, normalized by a productivity factor reflecting the maximum returns from either technology ($\frac{c^f - c^l}{c^f - c^h}$), a δ-transfer from Firm 2 to Firm 1 always increases (decreases) prices, corresponding to the abundance (scarcity) scenario in the top (bottom) panels of Figure 5. Under scarcity, point 2.b requires also that after the transfer, $K_1^h + \delta$ is small enough for the market price to decrease in δ—e.g., $K_1^h = 0$ and $\delta = 0.5$ in Figure 5.[27] Naturally, if Firm 1 had ample high-cost capacity at baseline,

[26] In Panel (d), the kink in the residual demand curve reflects the price at which Firm 1 exhausts its low-cost capacity. At that price, both firms adjust their supply slopes to account for the increase in Firm 1's marginal cost, although the change in $\tilde{S}_1$'s slope is less apparent in the plot.

[27] This restriction holds in Colombia, as firms with dams have very little thermal capacity. For instance, only $\approx 20\%$ of the market leader firm's capacity is thermal.

the transfer would only strengthen its size-leadership position vis-á-vis its competitors, incentivizing it to reduce its supply. These illustrations highlight the distinct incentives that *capacity* and *efficiency* considerations create for diversified firms, as Firm 1's market power arises from its greater capacity in Proposition 2.2.a and from its superior efficiency in Proposition 2.2.b relative to its competitors.

Concentration & market power. Now, consider a "large" increase in δ rather than the "small" ones analyzed so far. For instance, what would the price be if Firm 1 acquired all of Firm 2's capacity? The newly consolidated firm would price all its units at c^f, undercutting fringe firms. Thus, while small transfers lower prices, larger ones raise them, leading to the *U-shaped* relationship between concentration and prices in Figure 4.

A natural question to ask is, then, what is the optimal distribution of technology ownership across firms for consumer welfare? Our theory shows that competition is highest when strategic firms have symmetric technology portfolios ($K_1 = K_2$):

Proposition 3 ***Symmetric firms.*** *Without loss of generality, let $\delta \geq 0$, $K_1 = (K^l, K^h + \delta, 0)$ and $K_2 = (K^l, K^h - \delta, 0)$. Then, if $K^h - \delta \geq 0$ there exists a unique SFE for every δ. The equilibrium market supply at the δ transfer, S^δ, is monotonically decreasing in δ.*

Proof. See Appendix A.3. □

Note that the constraint on δ is imposed solely to prevent transfers that would leave Firm 2 with negative capacities, and that S^δ was defined in Proposition 2.2. Before the transfer ($\delta = 0$), the proof shows that both firms submit identical supplies. After the transfer ($\delta > 0$), however, the transferring Firm 2 cuts its low-cost supply at low prices to offset its expected capacity mismatch against the receiving Firm 1 at high prices for high-demand scenarios. Firm 1 best responds by lowering its supply to leverage its larger size. Thus, any deviation from symmetry raises market prices by reducing competition within technologies across firms.

Next, we test this model in the data to quantify the *capacity* and *efficiency* channels.

5 Application to the Colombian Energy Market

We extend the model in Section 4 to account for the main institutional and competitive aspects of the Colombian energy market, namely, the structure of the spot market and responses to the expectation of future water availability.

Generation. Each firm i is equipped with $J_i \geq 1$ units indexed by j. For simplicity, as illustrated in Figure 1, we focus on two technologies: hydro and thermal with marginal costs c^H and c^T, respectively. Let $\mathcal{H}_i$ ($\mathcal{T}_i$) represent the set of hydro (thermal) units owned by firm i. Firm i is diversified if both sets $\mathcal{H}_i$ and $\mathcal{T}_i$ are not empty. Hence, firm i's hydro capacity on day t is $K_{it}^H = w_{it} = \sum_{j\in\mathcal{H}_i} w_{ijt}$, the sum of the water stocks of firm i's dams, w_{ijt}. Similarly, firm i's (time-invariant) total thermal capacity is $K_i^T = \sum_{j\in\mathcal{T}_i} K_{ij}^T$.

Institutions. As in the previous section, the system operator crosses the supply schedules, $S_{iht}(p_{ht}) = \sum_{j=1}^{J_i} \mathbb{1}_{[b_{ijt}\le p_{ht}]} q_{ijht}$—where b_{ijt} and q_{ijht} are the daily price and hourly quantity bid of unit j of firm i—against the realized demand $D_{ht}(\hat{\epsilon})$ to ascertain the lowest price, $p_{ht}(\hat{\epsilon})$, such that demand equals supply:

$$D_{ht}(\epsilon_{ht}) = \sum_{i=1}^{N} S_{iht}(p_{ht}(\epsilon_{ht})), \quad \text{for all } h = \{0, ..., 23\} \text{ and } t. \tag{6}$$

Firm i's profits in hour h of day t hinge on the demand shock ϵ_{ht} through $p_{ht}(\epsilon)$,

$$\pi_{iht} = \underbrace{D_{iht}^R(p_{ht}, \epsilon_{ht}) \cdot p_{ht} - C_{iht}}_{\text{Spot market}} + \underbrace{(PC_{iht} - p_{ht}) \cdot QC_{iht}}_{\text{Forward market}} + \underbrace{\mathbb{1}_{[p_{ht} > \overline{p}_t]}(\overline{p}_t - p_{ht}) \cdot \overline{q}_{ijt}}_{\text{Reliability charge}}. \tag{7}$$

The first term is i's spot market profits as in (4). Additionally, firm i's profits are influenced by its forward contract position, resulting in an economic loss (profits) if it sells QC_{iht} MWh at PC_{iht} below (above) p_{ht}. The last term is the reliability charge mechanism, known as *cargo por confiabilidad*, which mandates units to produce $\overline{q}_{ijt}$ whenever the spot price exceeds a scarcity price, $\overline{p}_t$.[28]

Water balance equation. Drawing from the hydrology literature (e.g., Lloyd, 1963, Garcia *et al.*, 2001), a dam's water stock depends on the past water stock, the water inflow net of evaporation and other outflows, and the water used in production. At the firm level, this law of motion can be summarised through as,

$$w_{it+1} = w_{it} - \underbrace{\sum_{h=0}^{23} S_{iht}^H(p_{ht}^*)}_{\text{Water used in production}} + \underbrace{\sum_{j\in\mathcal{H}_i} \delta_{ijt}}_{\text{Water inflows}}, \tag{8}$$

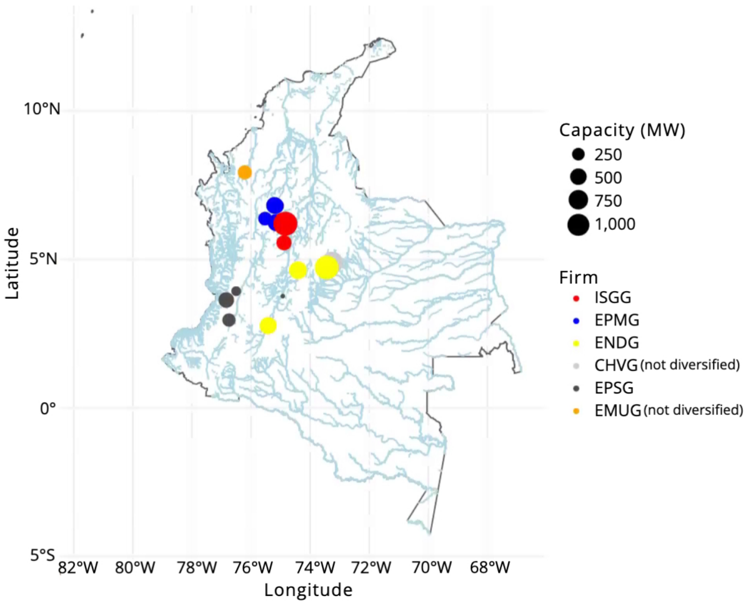
where $w_{it}\,(\in [\underline{w}_i, \overline{w}_i] \equiv \mathcal{W}_i)$ denotes the observed water stock of firm i in period t in MWh, $S_{iht}^H(p_{ht}^*) = \sum_{j\in\mathcal{H}_i} \mathbb{1}_{[b_{ijt}\le p_{ht}^*]}\, q_{ijht}$ is hydropower supplied by firm i's units at the market price p_{ht}^*, and δ_{ijt} denotes water inflows at dam j.

We focus on variation in water stocks at the firm rather than the unit level. First, our findings indicate that the units of the same technology that a firm owns respond to forecasts accruing to the whole firm, suggesting that the locus of control is the firm itself. Second, dams belonging to the same firm tend to be on nearby rivers (Figure 6), meaning dependence on the water inflow of dams owned by the same firm. In contrast, the inflow

[28] Scarcity prices, $\overline{p}_{ijt}$, are updated monthly and calculated as a heat rate times a gas/fuel index, plus other variable costs. Firm energy obligations, $\overline{q}_{ijt}$, are set through auctions held at varying intervals (Cramton and Stoft, 2007, McRae and Wolak, 2024). We treat both variables as given in the spot market.

correlation across firms' water stocks – after accounting for seasons and lagged inflows – is less than 0.2.

Figure 6: Dam locations



Notes: The location of Colombia dams by firm (color) and capacity (size). Colombia's West border is with the Pacific Ocean while rivers streaming East continue through Brazil and Venezuela. To give a sense of the extension of Colombia, its size is approximately that of Texas and New Mexico combined.

Objective function. Since diversified firms take into account future inflows, its supply schedule will maximize the sum of its current and future profits (given capacities),

$$\Pi_{it} = \mathbb{E}_{\epsilon}\left[\sum_{l=t}^{\infty} \beta^{l-t} \sum_{h=0}^{23} \pi_{ihl}(\epsilon_{hl})\right],$$

where the expectation is over the vector of market demand uncertainties, ϵ, and $\beta \in (0,1)$ is the discount factor. Using a recursive formulation, the objective function becomes,

$$V(\mathbf{w}_t) = \mathbb{E}_{\epsilon}\left[\sum_{h=0}^{23} \pi_{iht} + \beta \int_{\mathbb{W}} V(\mathbf{u})\, f\left(\mathbf{u}\middle|\mathbf{\Omega}_t\right)\, \mathrm{d}\mathbf{u}\right], \quad (9)$$

where vectors are in bold font. The state variable is the vector of water stocks, $\mathbf{w}_t$ with domain $\mathbb{W} \equiv \{\mathcal{W}_i\}_i^N$, and transition matrix $f(\cdot|\mathbf{\Omega}_t)$, which defines the probability of observing water stocks $\mathbf{w}_{t+1}$ given the current $\mathbf{w}_t$ and the vector of hydro supplies according to (8)—i.e., $\Pr(\vec{\delta}_t = \mathbf{u} - \mathbf{w}_t + \mathbf{S^H}_t|\mathbf{Z}_t)$, where $\mathbf{Z}_t$ are exogenous factors influencing the joint inflow distribution (e.g., el Niño probabilities) so that $\mathbf{\Omega}_t = \{\mathbf{w}_t, \mathbf{S^H}_t, \mathbf{Z}_t\}$.

5.1 Equilibrium Supply

Firms have greater flexibility in selecting quantity than price bids because they submit hourly quantity bids but only daily price bids for each unit. Thus, we focus on the optimal quantity bid submitted for unit j of firm i. We examine a smoothed version of the first-order conditions because the step-function nature of supply schedules poses challenges for analytical characterization and estimation (Wolak, 2007, Kastl, 2011, Reguant, 2014). The smoothing procedure is explained in Appendix E.

For clarity, we omit the expectation over ϵ and simplify the notation by writing a unit's technology as τ instead of τ_{ij} when no ambiguity arises, where $\tau_{ij} = H$ for dams and $\tau_{ij} = T$ for thermal units. The first-order conditions are then given by:

$$\begin{aligned} \frac{\partial V(\mathbf{w}_t)}{\partial q_{ijht}} = 0 : \; & \underbrace{\left(p_{ht}\frac{\partial D^R_{iht}}{\partial p_{ht}} + D^R_{iht}\right)\frac{\partial p_{ht}}{\partial q_{ijht}} - \left(QC_{iht} + \mathbb{1}_{\{p_{ht}>\overline{p}\}}\overline{q}_{ijt}\right)\frac{\partial p_{ht}}{\partial q_{ijht}}}_{\text{Marginal revenue}} \\ & - \underbrace{\sum_{\tau\in\{H,T\}}\left(\frac{\partial S^\tau_{iht}}{\partial q_{ijht}} + \frac{\partial S^\tau_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\right)c^\tau}_{\text{Marginal cost}} \\ & + \underbrace{\left(\frac{\partial S^H_{iht}}{\partial q_{ijht}} + \frac{\partial S^H_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\right)\int_{\mathbb{W}}\beta V(\mathbf{u})\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}}d\mathbf{u}}_{\text{Marginal value of holding water}} \\ & + \underbrace{\frac{\partial p_{ht}}{\partial q_{ijht}}\sum_{l\neq i}^{N}\frac{\partial S^H_{lht}}{\partial p_{ht}}\int_{\mathbb{W}}\beta V(\mathbf{u})\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{lht}}d\mathbf{u}}_{\text{Marginal value from competitor } l\text{'s holding water}} \quad = \quad 0. \end{aligned} \tag{10}$$

Although equation (10) cannot be rewritten to express the markup as a function of elasticities, as in Proposition 1, it reflects the same underlying trade-off between *capacity* and *efficiency* discussed in Section 4. We highlight these two channels in turn by describing the terms in (10).

***Capacity* channel.** We begin with the first row. The first term in parentheses represents the marginal revenue from unit j in the spot market. When the slope of the price with respect to unit j's output is negative, $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$, marginal revenue lies below the market price. Conversely, if firm i is a price taker ($\frac{\partial p_{ht}}{\partial q_{ijht}} = 0$), it receives exactly p_{ht} on its marginal unit. As $\left|\frac{\partial p_{ht}}{\partial q_{ijht}}\right|$ increases, firm i reduces q_{ijht}, illustrating the *capacity channel* described in Proposition 2: the firm cuts supply to raise the marginal revenue earned on inframarginal units. This mechanism applies uniformly across technologies, affecting the behavior of all units regardless of their type. The second term in this row captures the influence of forward contracts and reliability payments on the unit's supply decision.

***Efficiency* channel.** Market power also operates through an *efficiency channel*, which depends on the unit's marginal cost. Firm i's marginal cost includes its technology-specific operating cost, $\{c^\tau\}_{\tau=T,H}$, in the second row, and an intertemporal opportunity cost in the third and fourth rows. This opportunity cost arises from the ability of hydropower to store energy across periods and reflects the effect of current output on future water availability. The integral in the third row of (10) is weakly negative, as the transition matrix decreases in firm i's hydro supply S^H_{iht} under the law of motion in (8). This intertemporal term shifts the effective cost of hydro production based on the state $\mathbf{\Omega}_t$, placing the firm under scarcity when $\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}} < 0$ and under abundance when this derivative is close to zero.

Unit j's response to this intertemporal cost depends on $\frac{\partial p_{ht}}{\partial q_{ijht}}$. When $\frac{\partial p_{ht}}{\partial q_{ijht}} = 0$, a marginal increase in q_{ijht} reduces expected future profits by depleting the water stock: this loss is given by $\frac{\partial S^H_{iht}}{\partial q_{ijht}}(> 0)$ times the expected marginal value of water (the integral). When $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$, the firm partially offsets this loss because a marginal increase in q_{ijht} lowers p_{ht}, reducing the share of its hydro supply that clears in equilibrium ($\frac{\partial S^H_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} < 0$). Thus, the two terms in the third row of (11) may pull j's supply in opposite directions.

Thermal units cannot directly affect the firm's water stock ($\frac{\partial S^H_{iht}}{\partial q_{ijht}} = 0$ as unit $j \notin \mathcal{H}_i$), so the third row of (10) is always non-negative for thermal units. As a result, diversified firms increase thermal output in anticipation of droughts to preserve hydro capacity—unlike independent thermal units, which we assume as static profit maximizers. This mechanism explains the patterns in Figure 3, where thermal units expand (contract) supply ahead of drought (abundance) forecasts that affect a sibling dam.

The last line in (10) captures how a change in unit j's output affects the hydro supply of competitors through changes in the market price. Specifically, $\frac{\partial p_{ht}}{\partial q_{ijht}} \frac{\partial S^H_{lht}}{\partial p_{ht}}$ for each firm $l \neq i$ reflects the response of competitors' hydro units. However, since this channel operates only through the market clearing, $\frac{\partial p_{ht}}{\partial q_{ijht}}$, as $\frac{\partial S^H_{lht}}{\partial q_{ijht}} = 0$, this term does not affect firm i's thermal and hydro units differently. That is, a change in competitors' water stocks impacts a unit's bid only through $\frac{\partial p_{ht}}{\partial q_{ijht}}$, which can be factored out from the FOC if the bid is accepted—otherwise, the whole FOC equals zero for unit j. As our focus is on differences in hydro and thermal behavior, we do not emphasize this channel further.

Discussion. The mechanism outlined in Section 4 is reflected in the FOC (10). When a firm has abundant water stock, its thermal units reduces production, as they do not internalize changes in the water stock ($\frac{\partial f(\cdot|\mathbf{\Omega}t)}{\partial Siht^H} \simeq 0$). As a result, the firm responds mainly to changes in residual demand (see the first row of Figure 5). In contrast, under scarcity ($\frac{\partial f(\cdot|\mathbf{\Omega}t)}{\partial Siht^H} < 0$), thermal units internalize the value of stored water, allowing the firm to undercut competitors and preserve market share. As a result, the firm's total supply expands relative to a scenario where it lacks thermal units, potentially lowering prices.

Consider now the polar case where firm i owns the entire market capacity. In this fully concentrated setting, residual demand coincides with market demand, and the firm behaves as a monopolist. Prices are highest, as the firm cannot lose market shares.

Since the FOCs here are simply a discretized version of those in Section 4, defined at the generator-unit level, this discussion illustrates how the same *capacity-efficiency* mechanism operates in the Colombian market. We now turn to estimating the primitives in equation (10) to assess this mechanism empirically through counterfactual analysis.

5.2 Identification and Estimation

The extensive state space outlined in (10) presents a dimensionality challenge in estimating the relevant primitives. The existing literature offers two primary strategies. The first method involves leveraging terminal actions (Arcidiacono and Miller, 2011), which eliminate the need to compute the value function during estimation. This approach is not applicable to our study since no exit occurred in our sample.

We approximate the value function using a low-dimensional representation of the state space: $V(w) \simeq \sum_{r=1}^{R} \gamma_r \cdot B_r(w_r)$, where $B_r(w_r)$ are basis functions (e.g., polynomials or neural networks, as in Bodéré (2023)). This approach follows Sweeting (2013), who introduced a nested iterative procedure. Starting from an initial policy function σ, the algorithm (i) simulates static profits π_{iht} in (9) for $\rho > 1$ days across initial water stock values w, given a discount factor β; (ii) regresses the discounted sum of profits on w to estimate the γ_r parameters of $V(w)$; and (iii) estimates the cost parameters in (9) using the approximated value function $V(w; \hat{\gamma}, B)$. The iteration stops when the updated policy σ' from maximizing $V(w; \hat{\gamma}, B)$ is sufficiently close to the previous one.

While this procedure works in settings where all components of profits are observed, we cannot simulate the contribution of forward markets to current profits π_{ijht} in step (i), since forward contract prices PC_{iht} in equation (7) are unobserved. As a result, the regression in step (ii) using forward static profits cannot identify the γ_r coefficients: the left-hand side is a poor proxy for discounted cumulative profits. Specifically, the term being regressed is $\sum_{t=1}^{\rho} \beta^t \sum_h \pi_{ijht}(w) - PC_{iht}(w) \cdot QC_{iht}(w)$, where both PC_{iht+l} and QC_{iht+l} depend on w. Since the firm re-optimizes its forward position as w varies, this endogeneity breaks the identification of γ_r in the approximation $\sum_{r=1}^{R} \gamma_r \cdot B_r(w_r)$.

To overcome these challenges, we base our analysis on the FOCs with respect to a firm's quantity bids, which do not require knowledge of PC_{iht}, by rearranging (10) as:

$$mr_{ijht} = \sum_{\tau \in \{H,T\}} X^{\tau}_{ijht} c^{\tau} - X^{H}_{ijht} \int_{\mathbb{W}} \beta V(\mathbf{u}) \frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^{H}_{iht}} \mathrm{d}\mathbf{u} - \sum_{k \neq i}^{N} \tilde{X}^{H}_{ijht} \int_{\mathbb{W}} \beta V(\mathbf{u}) \frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^{H}_{kht}} \mathrm{d}\mathbf{u}, \qquad (11)$$

where we grouped known terms into the following variables. The left-hand side, mr, is the marginal revenue which appears explicitly in the first row of (10). On the right-hand side, the direct effect of a change in q_{ijht} on the technology specific supply of unit j, S^{τ}_{ijht} plus its indirect effect on S^{τ}_{ijht} through the market clearing—i.e., $\frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\tau}_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$—is denoted by X^τ. In the last term, $\tilde{X}^H = \frac{\partial S^H_{kht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, which is the indirect effect on the hydro supplies of i's rivals in the last row of (10).

The only unknowns are c^H, c^T, and $\beta V(\cdot)$, while all the other terms can be estimated separately. Since the FOCs are linear, variation in the Xs and $\mathbf{\Omega}_t$ identifies these primitives. We postpone the analysis of the policy function to Section 6.3.

5.2.1 Estimation

Estimation requires specifying the number of coefficients R and the basis functions B_r used to approximate $V(\cdot)$. A standard spline approximation of a univariate function typically uses five basis functions or knots (e.g., Stone and Koo, 1985, Durrleman and Simon, 1989), meaning five parameters are needed per dimension. With four firms, fully interacting the bases would require estimating 5^4 parameters—an infeasible task, especially since these coefficients must be instrumented.

Our working assumption for estimation is that firms consider only their own future water stock when bidding.[29] Under this assumption, the transition matrix $f(\mathbf{w}|\mathbf{\Omega}_t)$ simplifies to $f(w|\mathbf{\Omega}_{it})$, and future profits, β, $V(w)$, depend on the firm's own water stock and the law of motion (8) via the state vector $\mathbf{\Omega}_{it} = \{w_{it}, \mathbf{S}^H_{ijt}, \mathbf{Z}_{it}\}$. Competitors' water stocks enter only indirectly, through the residual demand curve $D^R_{iht}(p_{ht})$.

We allow the transition matrix to vary across firms, denoted $f_i(\cdot|\mathbf{\Omega}_{it})$. Firm-level water inflows are modeled using an ARDL specification, consistent with the forecast estimation in Section 3. The model residual—the unexplained component—captures the probability that firm i will hold a given water stock tomorrow, conditional on today's stock and net inflows. We fit this residual distribution using a Type IV Pearson distribution, commonly employed in hydrology due to its asymmetric tails, which help capture firm behavior under both drought and surplus conditions. Appendix B details the estimation and assesses the transition matrix's fit.

Under these assumptions, the moment condition becomes:

$$mr_{ijht} = \sum_{\tau \in \{H,T\}} c^\tau X^\tau_{ijht} - X^H_{ijht} \sum_{r=1}^{5} \gamma_r \int_{\underline{w}_i}^{\overline{w}_i} B_r(u) \frac{\partial f_i(u|\mathbf{\Omega}_{it})}{\partial S^H_{iht}} \mathrm{d}u + FE + \varepsilon_{ijht}, \qquad (12)$$

where we approximate the value function as $\beta \cdot V(w) \simeq \sum_{r=1}^{5} \gamma_r \cdot B_r(w_r)$, so no assumption about the discount factor is required. We allow for a non-deterministic i.i.d. component in operating costs, which gives rise to the error term ε_{ijht}. Our assumption about the state space removes the last row in (10) from the moment condition as $\frac{\partial f_i(\cdot|\mathbf{\Omega}_i)}{\partial S^H_l} = 0$. However, since changes in competitors' supply affect firm i's hydro and thermal units similarly,

[29] This assumption is required for estimation, but not for identification. Nonetheless, Appendix C.4 supports it with several exercises showing that, after controlling for time fixed effects, a firm's supply is primarily driven by its own forecasts, while competitors' forecasts have only second-order effects.

omitting this term does not distort substitution across units, which is our focus.

Estimating c^H, c^T, and $\gamma_r{}_{r=1}^5$ requires instruments, as unobserved shocks to supply and demand (e.g., unusually hot days) may be correlated with X^τ.

We use temperature at dam locations and global gas price fluctuations as instruments, as they affect hydro capacity and the marginal cost of thermal units, respectively. To capture seasonality, these variables are interacted with month dummies. Although domestic fuel prices are regulated and energy firms have access to subsidized reserves, global energy prices partially pass through, since the government's pricing formulas depend on international fuel benchmarks (Abdallah *et al.*, 2019). In our data, the elasticity of electricity prices to global gas prices is 0.8 (s.e. = 0.02), with an R^2 of 53% in a regression including month and year fixed effects. We also instrument for start-up costs of thermal units using the ratio of competitors' lagged thermal generation to lagged demand, which reflects regulatory incentives to prioritize already-active thermal plants. We interact this proxy with lagged gas prices to account for variation in marginal start-up costs.

We include fixed effects (FE) to account for persistent differences across firms and units—since operating costs may vary even within hydro and thermal categories—as well as time-varying factors that affect all units of a given technology, such as changes in national gas prices faced by electricity firms.

5.2.2 Results

We estimate equation (12) using daily data from January 1, 2010, to December 31, 2015, via two-stage least squares. Results are reported in Table 1. Columns (1) and (2) include week fixed effects, while Columns (3) and (4) use daily fixed effects. Columns (2) and (4) additionally control for month-by-technology fixed effects, alongside firm, unit, and time fixed effects. These specifications allow us to flexibly account for seasonal patterns that may differentially affect hydro and thermal units.

The table includes four panels. The first two report estimates of marginal costs for thermal (c^T) and hydro (c^H) units, along with the five value function parameters (γ_r). The third panel summarizes the fixed effects used in each specification, and the fourth presents test statistics for the instrumental variables.

Focusing on Columns (2) and (4), which control for seasonal variation by technology, we find that thermal marginal costs are approximately 140,000 COP) per MWh—roughly equal to the average market price between 2008 and 2016 (Figure 2). This confirms that thermal units are typically dispatched only during scarcity periods, as shown in Panel (b) of Figure 1. In contrast, hydropower has substantially lower operating costs, making it the inframarginal technology. Due to the spline approximation, the γ_r coefficients lack a direct economic interpretation.

While direct comparisons with engineering studies on hydropower are not possi-

Table 1: Estimated model primitives

	(1)	(2)	(3)	(4)
Marginal Costs (COP/MWh)				
Thermal (c^T)	203,677.62***	141,668.46***	221,304.18***	144,744.21***
	(1,711.10)	(1,875.29)	(1,665.82)	(1,561.62)
Hydropower (c^H)	64,258.02***	20,123.07***	29,187.79***	52,755.37***
	(6,692.81)	(5,309.73)	(3,931.92)	(3,731.31)
Intertemporal Value of Water (COP/MWh)				
Spline 1 (γ_1)	–2,950.20***	–6,812.77***	–11664.64***	–3,812.18***
	(908.25)	(528.12)	(526.66)	(385.60)
Spline 2 (γ_2)	–2.301e-03***	–1.546e-04	6.286e-04***	–8.402e-04***
	(3.213e-04)	(1.456e-04)	(1.819e-04)	(1.036e-04)
Spline 3 (γ_3)	–3.527e-09***	1.919e-08***	–1.932e-08***	1.712e-08***
	(1.282e-09)	(1.041e-09)	(1.174e-09)	(8.106e-10)
Spline 4 (γ_4)	3.246e-08***	–3.119e-08***	4.536e-08***	–2.729e-08***
	(2.422e-09)	(1.894e-09)	(2.057e-09)	(1.492e-09)
Spline 5 (γ_5)	–1.414e-08***	9.357e-08***	5.167e-08***	8.566e-08***
	(3.053e-09)	(2.950e-09)	(2.480e-09)	(2.568e-09)
Fixed Effects				
Firm	✓	✓	✓	✓
Unit	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
Date			✓	✓
SW F (c^T)	3,300.46	1,170.68	2,889.26	1,000.69
SW F (c^H)	458.72	267.20	877.47	360.16
SW F (c^{γ_1})	272.15	201.92	274.58	214.83
SW F (c^{γ_2})	220.24	266.10	266.58	292.22
SW F (c^{γ_3})	466.55	494.96	291.98	491.58
SW F (c^{γ_4})	570.57	577.42	292.40	566.81
SW F (c^{γ_5})	419.44	1,156.74	432.57	920.39
Anderson Rubin F	1,213.31	1,395.05	1,527.77	1,539.08
KP Wald	143.70	142.85	138.91	147.23
N	1,451,592	1,451,592	1,451,592	1,451,592

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

Notes: This table presents the coefficients obtained estimating (12) by two-stage least squares on daily data between January 1, 2010, and December 31, 2015. The top panels separate the marginal cost estimates and the value function parameters from the fixed effects used in estimation, which vary across columns. Our favorite specification is in Column (4), which includes day and month-by-technology fixed effects. The bottom panel provides diagnostic tests for the first stage. 2,900 COP ≃ 1 US$.

ble—since those typically report levelized costs that include both investment and operational expenses over a dam's lifetime—we can benchmark our thermal marginal cost estimates against findings from other sources. Our estimates, ranging from \$45.57 to \$70.44 per MWh (USD), reflect peso-to-dollar exchange rate fluctuations during the sample period. These values are consistent with prior studies and engineering assessments, which place coal-fired plant operating costs between 20–40 per MWh and gas-fired plants between 40–80 per MWh (e.g., Blumsack, 2023).[30]

We present several robustness checks in the appendix. First, we show that changing the number of knots used to approximate $\beta, V(\cdot)$ has little effect: Appendix Table D1 reports similar results using four knots instead of five. Second, we find consistent estimates when modeling the transition matrix with a normal distribution rather than a Pearson Type IV distribution (Appendix Tables D2 and D3).

6 Quantifying the Benefits of Diversification

This section first explains our simulation framework (Section 6.1) and investigates its goodness of fit (Section 6.2). Then, Section 6.3 performs counterfactual analyses by reallocating thermal capacity in the spirit of Section 4. Section 6.4 discusses our findings.

6.1 Simulations

We base our simulation exercises on the firm's objective function (9) because the first-order conditions (10) alone are necessary but not sufficient for optimality. However, solving the equilibrium supply functions of the entire game for each firm across every hourly market during the six-year sample period is computationally infeasible. Thus, following the approach in Reguant (2014), we construct a computational model grounded in the intertemporal profits in (9). This model numerically computes a firm's optimal response given competitors' strategies in each hourly market, using a mixed-integer linear programming solver.[31]

Specifically, we simulate bids for the market's leading firm (EPMG), holding competitors' bids constant. We focus on EPMG because it holds the largest water stock in over 90% of the markets between 2010 and 2015. Among the firms with dams, it also has the largest thermal capacity, and approximately 80% of its total capacity comes from hydropower. As a result, EPMG exhibits the highest demand semi-elasticity, a common proxy for market power (Appendix Figure F2).

The computational model discretizes (9) to ensure a global optimum when solving for EPMG's supply for each hour and technology (τ)—discretized in G steps, $\{\mathbf{q}^{\tau}_{ht,g}\}_{h=0}^{23}$—given its hourly realized residual demand $D^R(p_{ht})$. In particular, the firm solves:

$$\max_{\{q^{\tau}_{ht,k}\}^{G,23,\mathcal{T}}_{g,h,\tau}} \sum_{h=0}^{23}\left[GR(\bar{D}^R_{ht}) - \sum_{\tau\in\{H,T\}}\sum_{g=1}^{G}\hat{c}^{\tau} q^{\tau}_{ht,g}\right] + \beta\sum_{m=1}^{M}\mathbb{E}\hat{V}_{t+1,m}(w_{t+1}|w_t, \sum_{g=1}^{G}\sum_{h=1}^{23} q^{H}_{ht,g}),$$
$$s.t. \tag{13}$$

[30] As an illustration, Reguant (2014) estimates thermal production costs in Spain at €30–€36 per MWh in 2007, a period with significantly lower oil and gas prices. The average oil price that year was $72 per barrel, compared to an average of $84.70 between 2010 and 2015, with peaks above $100.

[31] Since the FOCs (10) do not depend PC_{ht}, not observing this variable does not pose an issue.

$$\begin{aligned}
\text{[Market-clearing:]}\ & \bar{D}^R_{ht}(p_{ht}) = \sum_{\tau\in\{H,T\}} \sum_{g=1}^{G} q^{\tau}_{ht,g}, \ \ \forall\, h, \\
\text{[Constraints on residual demand steps:]}\ & 0 \leq D^R_{ht,z}(p_{ht}) \leq \sum_{\tau\in\{H,T\}} K^{\tau}_t/Z, \ \ \forall\, h, z, \\
\text{[Constraints on supply steps:]}\ & 0 \leq q^{\tau}_{ht,g} \leq K^{\tau}_t/G, \ \ \forall\, h, \tau, g, \\
\text{[Constraints on value function steps:]}\ & 0 \leq \mathbb{E}\hat{V}_{t+1,m} \leq w_{ht}/M, \ \ \forall\, h, \tau, m
\end{aligned}$$

where we dropped the subscript i because the focus is on EPMG. The gross revenue function, $GR(\bar{D}^R_{ht})$, is a discretized version of the static revenues in (7). It depends on $\bar{D}^R_{ht}(p_{ht}) = \sum_{z=1}^{Z} \mathbb{1}_{[p_{ht}\leq p_z]} D^R(p_{ht})$, a step function composed of Z steps of equal size describing how EPMG's residual demand varies with p_{ht}. The cost function is equal to the cost of producing $\sum_g q^{\tau}_{ht,g}$ MWh of energy using the technology-specific marginal costs estimated in Column (4) of Table 1. The last term of (13) is the expected value function, which depends on the water stock at t, the total MW of hydro generation produced in the 24 hourly markets of day t, the transition matrix, and the value function parameters $\hat{\gamma}_r$ estimated in Column (4) of Table 1. We discretize the value function over M steps.[32]

Instead of simulating each daily market from 2010 to 2015, we simplify the problem by aggregating the hourly markets across weeks and hours. We then determine EPMG's optimal response using (13) for each hour-week combination. This strategy significantly reduces computation time while maintaining precision, as we show next.

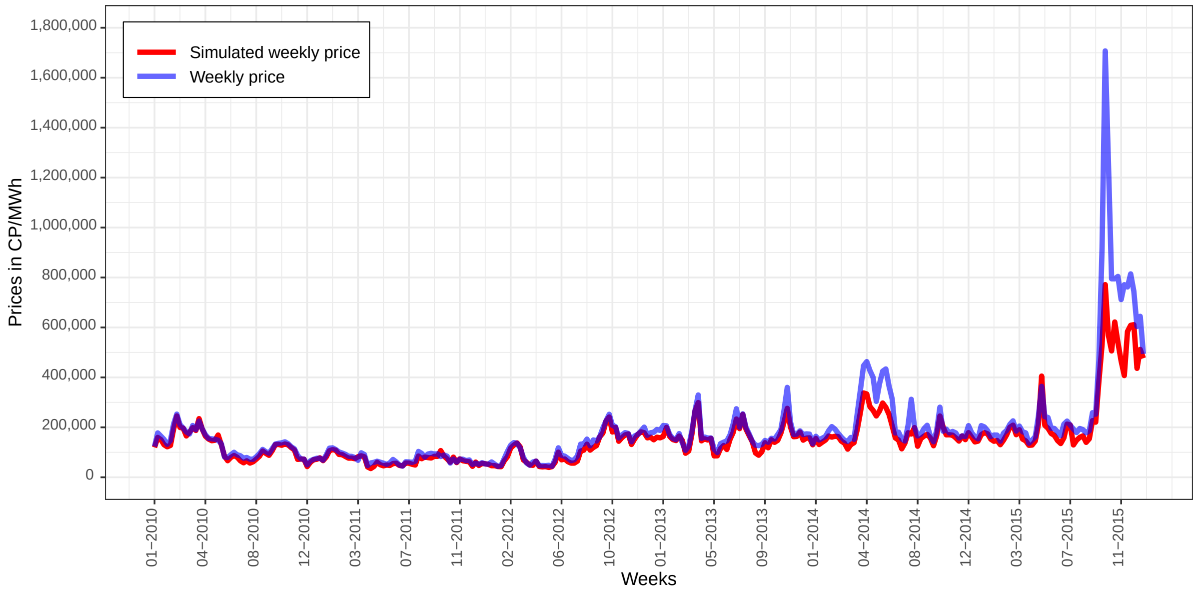
6.2 Model Fit

In Figure 7, we compare observed average weekly prices (blue line) with simulated prices (red line). The model captures price volatility well, particularly during the first four years. However, the El Niño event in 2016, an unprecedented drought, likely affected the transition matrix in late 2015, causing discrepancies between simulated and actual prices. Although the model underestimates the extreme price spike in late 2015—where prices increased more than tenfold—it does predict an increase between five- to seven-fold. Appendix Table F1 further evaluates hourly price variations, generally within 10% of actual prices, underscoring the model's robust performance.[33] Overall, despite its parsimony (only seven parameters), the model effectively reproduces Colombia's price volatility over an extended period.

[32] The optimization is subject to constraints. The first ensures EPMG's hourly supply matches its residual demand at the market price. Subsequent constraints keep EPMG's residual demand, supply, and value function within their capacity K^{τ}, with supply functions being weekly increasing (not reported). Since $K^H_t = w_t$, the third constraint also prevents a water deficit. Deficits are not a real concern, as extreme droughts are rare in the data: a dam exhaust its water stock in only four days in six years, and the 1st percentile of the water stock is over ten times larger than the median hydro-quantity bid.

[33] The simulation uses ten discretization steps for demand, supply, and the value function ($M = G = Z = 10$). Increasing the number of steps does not significantly improve fit (Appendix Figure F1).

Figure 7: Model fit: simulated (red) vs. observed prices (blue)



Note: Comparison between observed (blue) and fitted (red) prices from solving EPMG's profit maximization problem (13). The solver employs ten steps to discretize the residual demand, the supply, and the value function ($M = G = Z = 10$). 2,900 COP $\simeq$ 1 US$.

6.3 Counterfactual Exercises

The counterfactual exercises relax EPMG's thermal capacity constraint by reallocating capacity from its competitors (see Section 4). Note that the estimated value function parameters ($\{\gamma_r\}_{r=1}^{R}$) may differ across industry configurations. However, re-estimating these parameters would require observing counterfactual submitted quantities—a practically infeasible task.

If we could compute the new equilibrium parameters ($\{\gamma_r'\}_{r=1}^{R}$), the first-order effect would be a reduction in the marginal benefit of holding water as EPMG's thermal capacity increases. This intuition is formalized in the following proposition (where $K^H = w_t$).

Proposition 4 ***Decreasing marginal benefits of holding water.*** *If the gross revenues are strictly concave and twice differentiable for all $D^R(p(\epsilon))$, then $\frac{\partial^2 V(\cdot)}{\partial K^H \partial K^T} < 0$.*

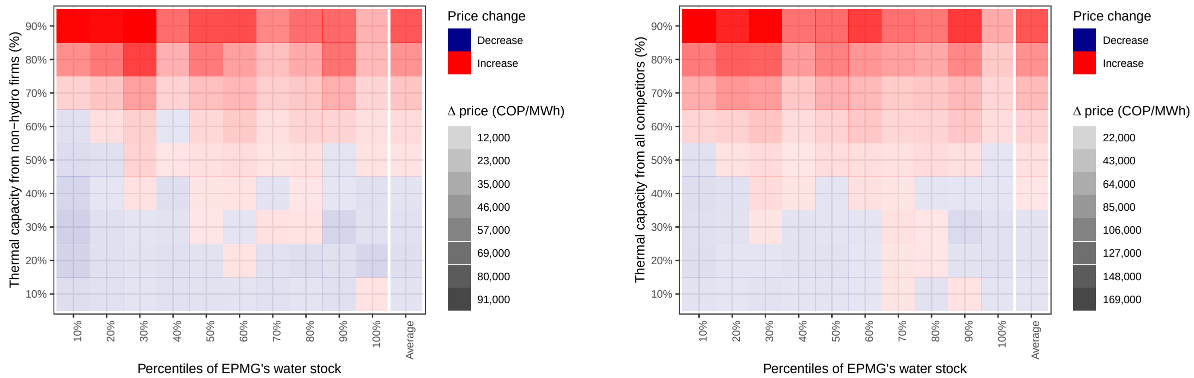
Proof. See Appendix A.4. □

Thus, Proposition 4 suggests that, keeping competitors' supplies constant, EPMG would release more water than our counterfactual predicts as its own thermal capacity increases, leading to even lower average prices relative to the fixed $\{\gamma_r\}_r$ scenario.

Updating the bids of EPMG's competitors per (13) after each capacity reallocation is also computationally prohibitive, for the same reason we explained in Section 6.1 and that led us to focus on EPMG's bids. Instead, we exploit the strategic complementarities identified in Proposition 1 to approximate adjustments in competitor supplies. Specifically, when transferring κ% of capacity from unit k, we leave its supply unchanged if unused capacity is sufficient; otherwise, we proportionally reduce its quantity bid.[34] The resulting price changes should be viewed as lower bounds on the true price changes because of strategic complementarities.

Figure 8 summarizes the counterfactual results. Panel (a) shows the effects of reallocating capacity from firms without dams, while Panel (b) presents the results of transferring thermal capacity from all of EPMG's competitors.[35] In each heatmap, the x-axis ranks markets by drought severity—grouped into deciles based on EPMG's water stocks—and the y-axis shows the magnitude of the capacity transfer (expressed as a fraction of competitors' thermal capacity). Each cell displays the average difference between counterfactual and status quo market prices, with darker blue (red) shades indicating lower (higher) prices. Note that water stocks are used as a basic measure of drought, without accounting for future inflows—we find similar results for inflows. Because this metric only partially capture drought conditions, smooth color transitions across cells are not to be expected.

Figure 8: The price effect of a capacity transfer to the market leader



(a) Transferring κ% from non-hydro firms (b) Transferring κ% from all firms

Notes: The figure compare baseline prices with counterfactual market prices as we endow the market leading firm with greater fractions of its competitors' thermal capacities (y-axis) for varying scarcity levels (x-axis). We proxy scarcity by grouping markets based on the deciles of the leader's water inflow (stock): each cell reports the average price difference between the simulated market and the simulated baseline price with different shades of red and blue colors based on the sign and magnitude of the change. The left (right) panels transfers capacity to EPMG from non-hydro (all) competitors. The average market price is approximately 150,000 COP/MWh. 2,900 COP $\simeq$ 1 US$.

Absolute price changes. In Panel (a), the first row corresponds to EPMG being endowed with 10% of the non-hydro firms' thermal capacity. On average, energy market prices are lower in nearly all periods except the highest decile, despite the firm has the

[34]We define a unit's capacity as its maximum observed quantity bid, although results are qualitatively similar when using technical capacity. Units that do not submit bids in a market are excluded from the simulations, as their absence may be due to technical constraints, which would otherwise inflate the total capacity in the counterfactual compared to the data, mechanically decreasing the counterfactual prices.

[35]Transfers from firms with dams only are omitted, as Proposition 3 indicates that such transfers would reduce symmetry among diversified firms, potentially undermining competition.

largest market power in the industry across periods, as proxied by the inverse price semi-elasticity (Appendix Figure F2). Focusing on transfers below 50%, Appendix Figure G1 reveals that most price gains occur during dry periods (the southwest portion of the plot). In these cases, price gains can be substantial—ranging from 8,000 to 13,000 COP/MWh (just under 10% of the average energy price) when 20% to 30% of fringe firms' capacity is transferred. Notably, such a transfer would effectively double EPMG's thermal capacity.

For larger transfers, counterfactual prices mostly increase, particularly in the driest periods. Under these conditions, EPMG behaves as a standard non-diversified firm facing an increasingly vertical residual demand: it reduces output, thereby driving prices higher. Consequently, on average (right-most column), prices first decline at low transfer levels, reach a minimum, and then rise as transfers increase—exhibiting a U-shaped pattern similar to that in Figure 4 and discussed in Section 4.

We also observe that within a given transfer decile the cells gradually become less blue or red as we move rightward across columns. This indicates that the gains from capacity transfers are generally larger when EPMG faces dry spells than abundance, mirroring our theoretical findings.

Percentage price changes. A 10,000 COP price change has different implications during droughts compared to periods of abundance. To facilitate cross-column comparisons, Appendix Figure G2 normalizes the difference between counterfactual and baseline prices by the baseline price, reporting the average in each cell (i.e., $\frac{1}{H \cdot T}\sum_{h,t}^{H,T} \frac{p_{ht}^{\kappa\%} - p_{ht}^{base}}{p_{ht}^{base}}$ where the superscripts $\kappa\%$ and *base* denote counterfactual and baseline prices, respectively). The results indicate that transferring thermal capacity does not yield gains when EPMG's water stock is large. This observation aligns with Figure 5, which shows that transfers increasing concentration raise prices under conditions of abundance (Panel b), whereas under scarcity, 20%-30% capacity reallocations produce price drops of roughly 10% of the average price in the cell at baseline, meaning a much larger absolute price change during dry periods.

Transfers from all firms. Finally, Panel (b) of Figure 8 examines the case where thermal capacity transfers are made from all firms, including diversified ones. In this scenario, the magnitude of price increases (or gains) is more pronounced compared to Panel (a), as EPMG's residual demand steepens. This result is consistent with Proposition 3, which shows that transferring high-cost capacity among symmetrically diversified firms leads to higher market prices because the effects of increased concentration dominate efficiency gains. In sum, transfers from firms of similar size to EPMG reduce available capacity more substantially, thereby diminishing market competition more than transfers solely from fringe firms.

Only markets dominated by EPMG. Appendix Figures G4 and G3, which focus on absolute and percentage price changes respectively, show that our main findings also hold when restricting the exposition to markets where EPMG holds the largest water stock (91% of total). By excluding markets where EPMG is not the dominant water holder, we rule out transfers that reduce industry concentration rather than increase it.

6.4 Discussion

The transition to greener energy systems, particularly in developing economies like Colombia, introduces new challenges. Although renewable sources are increasingly cost-competitive, their intermittent nature can lead to price spikes during periods of scarcity, disproportionately affecting lower-income consumers. Our findings show that a diversified ownership structure—leveraging both renewable and non-renewable generation—can help mitigate such spikes, as firms internalize scarcity effects more efficiently.

However, Colombia's current regulatory environment may limit these benefits. The legacy of dam ownership from the 1990s privatizations has led to geographic concentration, limiting firms' ability to hedge inflow risk. In addition, the 25% capacity cap restricts firms from holding sufficiently diversified portfolios—particularly in a market where a single large unit, such as a dam, can represent a substantial share of a firm's total capacity. As a result, current policies may prevent efficient allocations of technology and production risk. Looking ahead, solar and wind projects are expected to make up as much as 38% of Colombia's installed capacity by 2027 (Arias-Gaviria *et al.*, 2019, Rueda-Bayona *et al.*, 2019, Moreno Rocha *et al.*, 2022). To fully capture the benefits of this transition, Colombia should not only expand renewable capacity but also promote firm-level diversification to reduce dependence on fossil fuels for backup. As storage technologies improve and battery costs decline, the combination of diversification and renewables will yield both environmental and economic gains.

These insights also have broader implications for antitrust policy. Traditional merger evaluations focus on market concentration and cost synergies (Nocke and Whinston, 2022), but our results show that synergies in diversified firms arise from managing supply across technologies—not just from economies of scale or scope. Regulators should assess a firm's technological diversity (i.e., its marginal cost and capacity mix) when evaluating mergers or concentration thresholds, rather than relying solely on aggregate size.

Despite these synergies, market outcomes still deviate from the perfect competition benchmark, as firms' supply schedules diverge from marginal cost (see the solid and dotted red lines in Figure 5). Our model shows that the most competitive outcome arises when firms are symmetrically diversified (Proposition 3), and our counterfactual exercises support this conclusion. This provides a novel benchmark for designing industrial policy in markets where production technologies differ.

A key advantage of electricity markets is that firm-level bids and capacities are directly observable—unlike in most industries. Yet the framework we develop applies more broadly. Similar mechanisms arise in sectors where firms manage portfolios of inputs with differing costs under demand uncertainty: aluminum production, where firms operate multiple technologies (e.g., Collard-Wexler and De Loecker, 2015); in automobile manufacturing, where producers manage portfolios of car platforms (e.g., Reynolds, 2015); and in labor markets, where firms have workers with heterogeneous skills (e.g., Bonhomme *et al.*, 2019). In all these settings, firms manage portfolios of inputs with different costs and uncertain demand (e.g., Asker *et al.*, 2014). The supply function approach we adopt is also flexible. As shown by Klemperer and Meyer (1989), it extends naturally to multi-product firms and differentiated goods. Future work could explore how product cannibalization with multi-product firms interact with technology differentiation. These parallels suggest that technology diversification—and both its distribution *within* and *across* firms—can be a central factor of market power in a wide range of industries.

7 Conclusion

This paper shows that technology diversification can offset the anticompetitive effects of concentration when firms face demand uncertainty. Giving the dominant firm access to more diverse production technologies—by reallocating high-cost capacity from rivals—changes how it competes: it uses its low-cost units to undercut competitors in low-demand periods and relies on the transferred capacity to expand output in high-demand states. This aggressive strategy pushes others to defend market shares, increasing total supply and lowering prices. But this mechanism breaks down when the transfer is large enough to constrain rivals' capacity: competition weakens, and prices rise. As a result, the relationship between prices and concentration is U-shaped, depending on how diversification interacts with capacity asymmetries.

We document this mechanism using data from Colombia's wholesale electricity market, where hydropower availability fluctuates with rainfall. These natural variations provide exogenous changes in firm-level capacity that we use to estimate causal reduced-form effects. We then bring a structural supply function model to the data to quantify the U-shape and identify the conditions under which diversification lowers or raises prices.

These findings have clear implications for market design in Colombia, where regulatory limits on firm size may unintentionally prevent beneficial diversification. More broadly, the mechanism extends to other sectors where firms manage multiple technologies or inputs under uncertainty. For instance, cement manufacturers may switch between kilns powered by gas or coal depending on energy prices; aluminum producers operate smelters with varying energy intensity; and large employers may diversify across worker types—such as full-time and temporary staff—to adapt to fluctuating demand. In each case, the allocation of production capacity across firms shapes how aggressively they compete, with consequences for prices, efficiency, and welfare.

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Part

Online Appendix

Table of Contents

A Theoretical Appendix

A.1 Preliminaries and Lemmas

Notation. For notation brevity, the indices $i, -i \in \{1,2\}$ are reserved for the strategic firms and not for fringe firms. In the general setting of Section 4.1 with many non-strategic fringes, the market clearing condition, the residual demands, and the profits have the following characterization.

Market clearing. With many non-strategic firms supplying at c^f, the market always clears at some price $p \leq c^f$.Hence, for any realization D of $D(\epsilon)$, given the supply schedules $S_i(p)$, it follows that the market clears at

$$p^* = \min\Big\{c^f, \min\{p| \sum_i^2 S_i(p) \geq D\}\Big\}. \tag{A1}$$

Residual demand. Since the strategic firms have priority in production over the fringe firms at price $p = c^f$,for $i, -i \in \{1,2\}$, Firm i's residual demand function is derived as

$$D_i^R(p,\epsilon) = \begin{cases} D(\epsilon) - S_{-i}(p), & \text{for } p \in [0, c^f), \\ \min\{D(\epsilon) - S_{-i}(p), \sum_\tau K_i^\tau\}, & \text{for } p = c^f, \\ 0, & \text{for } p > c^f. \end{cases} \tag{A2}$$

Profits and best responses. Given the marginal costs in Section 4.1, the profit (4) of firm i given the opponent's strategy, when the market clears at price p is

$$\pi_i(p) = D_i^R(p,\epsilon) \cdot p - \sum_{\tau \in \mathcal{T}} c^\tau S_i^\tau(p). \tag{A3}$$

It follows from Definition (4.1) that an SFE is then a pair of supply functions (S_1, S_2), so that for $i \in \{1,2\}$ $S_i(p) = \sum_\tau S_i^\tau(p)$, the market clearing $p^*(\epsilon)$ in (A1) maximizes i's ex post profit (A3) at every $D(\epsilon)$.

The propositions in Appendices A.2 and A.3 rely on the following lemmas.

Lemma A.1 *Suppose (S_1, S_2) is an SFE. Then for $i \in \{1,2\}$, $S_i(p) < \sum_\tau K_i^\tau$ for every $p < c^f$. Moreover, $p < c^f$ and $S_i(p) > 0$ implies $S_i(p') > S_i(p)$ whenever $p' > p$.*

Proof. To prove the first part, suppose for contradiction that at some $p < c^f$, firm i exhausts all its capacity, $S_i(p) = \sum_\tau K_i^\tau$. By right-continuity of S_i, there is $\underline{p} = \min\{p|S_i(p) = \sum_\tau K_i^\tau\}$. In this case, one can check that the best response to S_i by $-i$ satisfies $S_{-i}(p) = S_{-i}(\underline{p})$ for all $p \in (\underline{p}, c^f)$.

Now that $S_i(p) = S_i(\underline{p})$ on $p \in (\underline{p}, c^f)$ for both $i \in \{1,2\}$, this contradicts ex post optimality. In the event that $D = S_1(\underline{p}) + S_2(\underline{p})$ realizes so that $p^* = \underline{p}$ in (A1) clears the market, Firm i can reduce production by ϵ to $\min\{0, S_i(p) - \epsilon\}$, so that $D > S_i(p) - \epsilon + S_2(p)$ for all $p \in (\underline{p}, c^f)$, causing the clearing price to jump up to c^f, a profitably deviation. Hence, it is not ex post optimal to exhaust capacity at $p < c^f$.

To see the second part, suppose for contradiction, there exist two prices $p < p' < c^f$ such that $0 < S_i(p) = S_i(p') < K_i$. Suppose $\underline{p} = \min\{r|S_i(r) = S_i(p') > 0\}$. One can similarly check that the best response to S_i by $-i$ satisfies $S_{-i}(\underline{p}) = S_{-i}(p')$. Similarly, consider the demand D such that $\underline{p}$ clears the market, Firm i can slightly reduce production to cause the clearing price to jump up to at least p', a profitable deviation. This completes the proof. □

Lemma A.2 *In SFE, there exists* $i \in \{1, 2\}$ *such that* $\lim_{p \to c^f-} S_i(p) = \sum_\tau K_i^\tau$.

Proof. Since fringe firms enter and there will be no residual demand for $p > c^f$, any remaining capacity of i will be produced at c^f, so $S_i(c^f) = \sum_\tau K_i^\tau$ for $i = 1, 2$. Suppose for contradiction $\lim_{p \to c^f-} S_i(p) < \sum_\tau K_i^\tau$ for both $i = 1, 2$, then both supply schedules jump discretely at c^f. In the event that market clears at c^f but with realized demand $D < \sum_{i,\tau} K_i^\tau$, firm i can deviate by supplying all its capacity at $c^f - \epsilon$. This increases i's ex post profit by capturing additional demand with a unit price arbitrarily close to c^f. □

Lemma A.3 *In SFE, the production cost for firm* $i \in \{1, 2\}$ *at different market-clearing prices satisfies*

$$C_i = \begin{cases} c^l S_i^l(p) & \textit{iff } S_i^l(p) < K_i^l; \\ c^l K_i^l + c^h S_i^h(p) & \textit{iff } S_i^l(p) = K_i^l. \end{cases}$$

Proof. Since C_i is the minimal cost function for producing a given quantity, and because $c^l < c^h$, Firm i will necessarily first produce with $\tau = l$ and only start $\tau = h$ production when K_i^l is exhausted. □

Lemma A.4 *In SFE, for* $i \in \{1, 2\}$

1. *both* S_i*'s are continuous on* (c^h, c^f);
2. *if* $S_i(p) \neq K_i^l$ *for both* $i \in \{1, 2\}$, *then both* S_i*'s are continuous at* p;
3. *if* $S_i(p) > 0$ *and* $S_i(p) \neq K_i^l$ *for both* $i \in \{1, 2\}$, *then both* S_i*'s are continuously differentiable at* p.

Proof. We begin with Part 2. first. Suppose there exists $\hat{p} \in (\underline{p}, c^h)$ at which at least one of S_i for $i = 1, 2$ is discontinuous. Denote by $\hat{q}_i$ the left limit $\hat{q}_i = \lim_{p \to \hat{p}-} S_i(p)$ for $i = 1, 2$. When the realized demand equals the sum of limits $\hat{D} = \hat{q}_1 + \hat{q}_2$, the market clears at $\hat{p}$ by (A1).

Case 1. Suppose for contradiction, let $S_i(\hat{p}) < K_i^l$ for both $i \in \{1, 2\}$. Then $C_i'(\hat{q}_i) = c^l < \hat{p}$ by Lemma A.3. Consider $\delta > 0$ small enough so that we have

$$\begin{cases} \delta < \max_i \{S_i(\hat{p}) - \hat{q}_i\}; \\ C_i'(\hat{q}_i + \delta) = c^l < \hat{p} \quad \text{holds for both} \quad i \in \{1, 2\}. \end{cases}$$

In the event the realized demand is $\hat{D} + \delta$, the market still clears at $\hat{p}$ due to the first inequality above, with i supplying $\hat{q}_i + \delta_i$ and $-i$ supplying $\hat{q}_{-i} + \delta_{-i}$ where $\delta_i + \delta_{-i} = \delta$ for some non-negative δ_i and δ_{-i}. WLOG, let $\delta_i < \delta$. At the realization of demand $\hat{D} + \delta$, i can locally increase supply to $S_i + \delta$ to under cut $-i$ and capture the entire demand of δ at the clearing price $\hat{p}$ with the same marginal cost c^l, a profitable deviation. This proves the first part of the Lemma.

Case 2. Suppose $S_i(\hat{p}) > K_i^l \geq 0$ for one of $i \in \{1, 2\}$. Optimality of S_i implies $\hat{p} > c^h$. Continuity follows from an analogous argument as above. Since if there is a discontinuity at $\hat{p}$, one of the firms will benefit from locally increasing supply by δ to undercut the opponent, at the marginal profit of at least $\hat{p} - c^h$.

Part 1 follows from an analogous argument as above since any price $\hat{p} \in (c^h, c^f)$ are above the marginal costs. It follows that if there is a discontinuity on this interval, one of the firms will benefit from locally increasing supply by δ to undercut the opponent.

Part 3. When $S_i(p) > 0$, then $p > c^l$. By Lemma A.3, it holds that and $S_i(p) \neq K_i^l$ for $i \in \{1, 2\}$, for any small enough interval $U \ni p$, we have $C_i'(S_i(p)) = c_i^\tau \geq c_i^l$ is constant on U. So for all p' on U

$$C_i(S_i(p)) - C_i\left(S_i(p) + S_{-i}(p) - S_{-i}(p')\right) = -c_i^\tau\left(S_{-i}(p) - S_{-i}(p')\right). \tag{A4}$$

since S_{-i} is continuous at p from Part 2.

Now consider the demand $D(\epsilon) = S_1(p) + S_2(p)$ such that p clears the market, firm i maximizes by producing $S_i(p)$. Therefore, any $p' \in U$ satisfies

$$S_i(p) \cdot p - C_i(S_i(p)) \geq [D(\epsilon) - S_{-i}(p')] \cdot p' - C_i\left(D(\epsilon) - S_{-i}(p')\right).$$

Substitute in $D(\epsilon)$ and apply (A4), we have

$$\frac{S_i(p)}{p' - c_i^\tau}(p - p') \geq S_{-i}(p) - S_{-i}(p').$$

Similarly, consider market clearing at p' gives

$$\frac{S_i(p')}{p - c_i^\tau}(p' - p) \geq S_{-i}(p') - S_{-i}(p).$$

Therefore, for any $p, p' \in U$ we have

$$\frac{S_i(p)}{p' - c_i^\tau} \geq \frac{S_{-i}(p) - S_{-i}(p')}{p - p'} \geq \frac{S_i(p')}{p - c_i^\tau}.$$

Since this holds for all $p, p' \in U$, continuity of S_i from Part 2 implies S_{-i} is continuously differentiable. The exception is when $S_i(p) = K_i^l$, then c_i^τ changes discontinuously to another constant as $S_i(p') \to K_i^l$. □

Lemma A.5 *Using c_3, c_4 solved in c_1 as in (A13), whenever $c_1 \geq \frac{K_1^l}{c^f - c^l}$ we have*

1. *$c_3(c^f - c^h) - c_4/(c^f - c^h) \geq c_1(c^f - c^h)$ where the equality holds iff $c_1 = \frac{K_1^l}{c^f - c^l}$;*
2. *$c_3(c^f - c^h) + c_4/(c^f - c^h) \geq c_1(c^f - c^l)$ where the equality holds iff $c_1 = \frac{K_1^l}{c^f - c^l}$;*
3. *$c_3(c^f - c^h) - c_4/(c^f - c^h)$ and $c_3(c^f - c^h) + c_4/(c^f - c^h)$, as functions in c_1, are continuous and strictly increasing to ∞.*

Proof. *Item 1*: Using the above notations, we have

$$c_3(c^f - c^h) - c_4/(c^f - c^h) - c_1(c^f - c^h) = \frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h},$$

which is an increasing function in c_1. Its minimum is at $c_1 = \frac{K_1^l}{c^f - c^l}$, for which we have

$$\frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} = \frac{c_1}{2}(c^h - c^l) - \frac{(c^h - c^l)}{2}\frac{K_1^l}{c^f - c^l} = 0.$$

Item 3: The first part of Item 3 is straightforward. To see the second part, we have

$$c_3(c^f - c^h) + c_4/(c^f - c^h) = \frac{c_1}{2}\left(2 + \frac{c_1}{\alpha - c_1}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h},$$

Differentiate with respect to c_1 gives

$$c^f - c^h + \frac{2c_1(c^f - c^h)}{2(\alpha - c_1)} + \frac{c_1^2(c^f - c^h)}{2(\alpha - c_1)^2} - \frac{(c^h - c^l)^2}{2(c^f - c^h)},$$

which is increasing in c_1. Substitute in $c_1 = \frac{K_1^l}{c^f - c^l}$ to obtain its lower bound as

$$\left(c^f - c^h + \frac{2c_1(c^f - c^h)}{2(\alpha - c_1)}\right) + \frac{\left(\frac{K_1^l}{c^f - c^l}\right)^2 (c^f - c^h)}{2(\alpha - c_1)^2} - \frac{(c^h - c^l)^2}{2(c^f - c^h)} = c^f - c^h + \frac{2c_1(c^f - c^h)}{2(\alpha - c_1)}.$$

To finish the proof for Item 3, it is easy to see as $c_1 \to \alpha$, both expressions in Item 3 go to ∞.

Item 2: we have that

$$c_3(c^f - c^h) + \frac{c_4}{c^f - c^h} - c_1(c^f - c^l) = \frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^h - c^l).$$

Its derivative is increasing in c_1 and hence

$$\frac{2c_1(c^f - c^h)}{2(\alpha - c_1)} + \frac{c_1^2(c^f - c^h)}{2(\alpha - c_1)^2} - \frac{(c^h - c^l)^2}{2(c^f - c^h)} - (c^h - c^l) \geq \frac{c_1(c^f - c^h)}{(\alpha - c_1)} - (c^h - c^l) = 0.$$

Therefore $c_3(c^f - c^h) + c_4/(c^f - c^h) - c_1(c^f - c^l)$ is increasing in c_1, and its minimum is at $c_1 = \frac{K_1^l}{c^f - c^l}$ which is

$$\frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^h - c^l) = 0.$$

□

A.2 Proof of Proposition 2

First, we prove part *1.* in Section A.2.1 and then *2.a* and *2.b* in Sections A.2.2 and A.2.3, respectively. The proofs rely on the Lemmas and definitions listed in Appendix A.1.

A.2.1 Proof of Proposition 2.1 *(Existence and Uniqueness of the SFE)*

Proof. Firm $i \in \{1, 2\}$'s profits are as follows,

$$\max_p \pi_i(p) := p \cdot D_i^R(p, \epsilon) - C_i(D_i^R(p, \epsilon)). \tag{A5}$$

This maximization can be solved by the following FOCs almost everywhere due to differentiability (Lemma A.4),

$$p\frac{\partial D_i^R(p, \epsilon)}{\partial p} + D_i^R(p, \epsilon) - C_i' \cdot \frac{\partial D_i^R(p, \epsilon)}{\partial p} = 0. \tag{A6}$$

Since $C_i' = c_i^\tau$ for the appropriate $\tau \in \{l, h\}$ and $S_i(p) = D_i^R(p)$ when market clears at p, firm i's best response to $-i$ satisfies

$$S_i(p) = (p - c_i^\tau) S_{-i}'(p) \tag{A7}$$

for both $i \in \{1, 2\}$. To better determine the appropriate c_i^τ, we analyze the supply functions by partitioning the domain into four intervals: 1. $p < c^h$; 2. $p \in [c^h, c^f)$ and $S_1^l(p) < K_1^l$; 3. $p \in [c^h, c^f)$ and $S_1^l(p) = K_1^l$;[1] and 4. $p \geq c^f$. By Lemma A.4, $S_i(p)$ must be smooth in these intervals, and thus we proceed to characterize $S_i(p)$ in each interval separately.

1. *Interval:* $p < c^h$. Firm 2 does not produce using the c^h technology for prices $p < c^h$, hence $S_2(p) = 0$ and S_1 best response with $S_1(p) = 0$ as can be solved from (A7) with $S_2' = 0$. The equilibrium supply functions in this interval are:

$$\begin{cases} S_1(p) = 0, & \text{if } p < c^h, \\ S_2(p) = 0, & \text{if } p < c^h. \end{cases} \tag{A8}$$

2. *Interval:* $p \geq c^h$ and $S_1^l(p) < K_1^l$. From the FOCs (A6), Firm 1 solves:

$$S_1(p) = S_1^l(p) = S_2'(p) \cdot (p - c^l),$$

as Firm 1 will spend only its low-cost capacity before moving to the high-cost one (Lemma A.3). Firm 2's supply solves:

$$S_2(p) = {S_1^l}'(p) \cdot (p - c^h).$$

Solving these two partial differential equations gives

$$\begin{cases} S_1^l(p) & = c_2 \frac{(p-c^l)\log(p-c^h)+(c^l-p)\log(p-c^l)-c^l+c^h}{(c^l-c^h)^2} + c_1(p - c^l), \\ S_2(p) & = c_2 \frac{(p-c^h)\left(\ln(p-c^h)-\ln(p-c^l)\right)+c^h-c^l}{(c^l-c^h)^2} + c_1(p - c^h), \end{cases}$$

where c_1 and c_2 are the two undetermined coefficients. Since the supply functions are non-negative and non-decreasing, we have $c_2 = 0$. Therefore, the supply schedules

[1] The difference between intervals 2. and 3. is whether Firm 1 has exhausted its low-cost capacity.

in this interval are,

$$\begin{cases} S_1^l(p) = c_1(p - c^l) \\ S_2(p) = c_1(p - c^h) \end{cases} \quad \text{when } p \geq c^h \,\&\, S_1^l(p) < K_1^l, \tag{A9}$$

where both $S_1^l(p)$ and $S_2(p)$ are non-negative and non-decreasing for an undetermined coefficient c_1 to be solved for later.

3. *Interval:* $p \geq c^h$ and $S_1^l(p) = K_1^l$. Firm 1 exhausted its low-cost technology, so that $S_1^l(p) = K_1^l$ in this interval. It follows from (A7) that

$$S_1(p) = S_1^l(p) + S_1^h(p) = K_1^l + S_1^h(p) = S_2'(p) \cdot (p - c^h).$$

At the same time, Firm 2's supply solves

$$S_2(p) = S_1^{h\prime}(p) \cdot (p - c^h).$$

Solving this system of differential equations obtains the following solutions with undetermined coefficients c_3 and c_4 (we solve for c_3 and c_4 later):

$$\begin{cases} S_1(p) = c_3\left(p - c^h\right) + c_4 \frac{1}{p - c^h} \\ S_2(p) = c_3\left(p - c^h\right) - c_4 \frac{1}{p - c^h} \end{cases} \quad \text{when } p \geq c^h \,\&\, S_1^l(p) = K_1^l. \tag{A10}$$

4. *Interval*: $p \geq c^f$. To prevent the entry of fringes, it is optimal to exhaust capacity at $p = c^f$,

$$\begin{cases} S_1(p) = \sum_\tau K_i^\tau, & \text{if } p \geq c^f, \\ S_2(p) = \sum_\tau K_i^\tau, & \text{if } p \geq c^f. \end{cases} \tag{A11}$$

To solve for $\{c_1, c_3, c_4\}$. By continuity of Lemma A.4.1, the boundary condition at $\hat{p}$, defined implicitly by $S_1(\hat{p}) = K_1^l$, together with (A9) and (A10) yield the following system of equations at the price $\hat{p}$

$$\begin{cases} K_1^l & = c_1(\hat{p} - c^l), \\ c_1(\hat{p} - c^l) & = c_3(\hat{p} - c^h) + c_4 \frac{1}{\hat{p} - c^h}, \\ c_1(\hat{p} - c^h) & = c_3(\hat{p} - c^h) - c_4 \frac{1}{\hat{p} - c^h}, \end{cases}$$

which we can simplify as Subtract the third line from the second line and rearrange to obtain

$$\hat{p} = \frac{2c_4}{c_1(c^h - c^l)} + c^h. \tag{A12}$$

Then, substitute this equation in the first and third line to obtain

$$\begin{cases} c_4 & = \frac{(c^h - c^l)^2}{2}\left(\alpha - c_1\right), \\ c_3 & = \frac{c_1}{2}\left(1 + \frac{\alpha}{\alpha - c_1}\right), \\ \hat{p} - c^h & = \frac{(c^h - c^l)}{c_1}\left(\alpha - c_1\right), \end{cases} \tag{A13}$$

where we defined $\alpha \equiv \frac{K_1^l}{c^h - c^l}$.

The solution in (A9) implies $c_1 > 0$, or else the supply function will not be strictly increasing, violating Lemma A.1. On the other hand, if $c_1 > \alpha$, substitute in the price $p = c^h$ into (A9) to see that

$$S_1^l(c^h) = c_1(c^h - c^l) > K_1^l.$$

This exceeds the capacity, implying when $c_1 > \alpha$, Firm 1 will exhaust its low-cost capacity at some $p < c^h$. This contradicts Lemma A.1, since Firm 1 will not produce with high-cost capacity at prices below c^h, and hence its supply function cannot be strictly increasing.

Consider the values of the (left) limits $\lim_{p\to c^f-} S_1(p)$ and $\lim_{p\to c^f-} S_2(p)$ as functions of $c_1 \in (0, \alpha)$. When $c_1 < \frac{K_1^l}{c^f - c^l} < \alpha$, we have by substituting c_4 into(A12) that

$$\hat{p} = \frac{K_1^l}{c_1} + c^l > c^f.$$

With this value of c_1, Firm 1 does not exhaust its low-cost capacity when $p \to c^f$ from below. In this case both left limits $\lim_{p\to c^f-} S_1(p)$ and $\lim_{p\to c^f-} S_2(p)$ are defined by the solution in (A9). It is clear that both limits are increasing in c_1 on the interval $(0, \frac{K_1^l}{c^f - c^l})$.

On the other hand, when $c_1 \in (\frac{K_1^l}{c^f - c^l}, \alpha)$, we have $\hat{p} < c^f$, and so Firm 1 exhausts low-cost capacity when $p \leq c^f$. In this case both left limits $\lim_{p\to c^f-} S_1(p)$ and $\lim_{p\to c^f-} S_2(p)$ equals the left limits of the expressions in (A10). It follows from Lemma A.5 that these left limits are monotonically increasing for $c_1 \in (0, \alpha)$.

By Lemma A.2, now the equilibrium can be pinned down by monotonically increasing $c_1 \in (0, \alpha)$ until the first c_1 that satisfies the boundary condition $\lim_{p\to c^f-} S_i(p) = \sum_\tau K_i^\tau$ is found for some $i \in \{1, 2\}$. Such an equilibrium always exists due to Lemma A.5.3. Moreover, any larger c_1 will imply that S_i exceeds i's capacity as $p \to c^f$ from below due to the monotonicity. Therefore the equilibrium exists and is unique. □

A.2.2 Proof of Proposition 2.2.a *(Under Abundance)*

Proof. It can be verified that in this case Firm 2 exhausts its capacity before Firm 1 exhausts low-cost capacity. From (A9), we have that $S_2^l(p) = c_1 \cdot (p - c^h)$. In the limit $p \to c^{f-}$, $S_2^l(p) \to K_2^h$, pinpointing $c_1 = \frac{K_2^h}{c^f - c^h}$. Since Firm 1 still has low-cost capacity, from the first equation in (A9), we have that $S_1(p) = S_1^l(p) = \frac{K_2^h}{c^f - c^h} \cdot (p - c^l)$. Hence as $p \to c^{f-}$, $K_1^l > \frac{p - c^l}{c^f - c^h}\big|_{p=c^f} \cdot K_2^h = S_1^l(c^f)$.Given this value for c_1 we can compute c_3 and c_4 from (A13), thereby constructing $S_i(p)$ for $i = \{1, 2\}$. Joining the systems (A8), (A9), and (A11) yields

$$S_1 = \begin{cases} 0, & \text{when } p < c^h, \\ c_1(p - c^l), & \text{when } p \in [c^h, c^f), \\ K_1^l + K_1^h, & \text{when } p = c^f, \end{cases} \text{ and } S_2 = \begin{cases} 0, & \text{when } p < c^h, \\ c_1(p - c^h), & \text{when } p \in [c^h, c^f]. \end{cases}$$

If we reduce K_2^h to $K_2^h - \delta$ and increase K_1^h to $K_1^h + \delta$ for a $\delta < K_2^h$, it will still hold that Firm 2 just exhausts its capacity at $p \to c^f$ and hence $c_1 = \frac{K_2^h - \delta}{c^f - c^h}$ still holds.

Therefore, c_1 decreases and the market-wide production

$$S_1(p) + S_2(p) = \begin{cases} 0 & \text{when } p < c^h \\ \frac{K_2^h - \delta}{c^f - c^h}(2p - c^l - c^h) & \text{when } p \in [c^h, c^f) \\ K_1^l + K_1^h + K_2^h & \text{when } p = c^f \end{cases}$$

decreases at every price level as δ increases. Hence the market clearing price increases. □

A.2.3 Proof of Proposition 2.2.b *(Under Scarcity)*

Proof. It can be verified that for K_1^h small enough (to be specified later), the SFE permits a switching price $\hat{p}$ such that, for $p \in [\hat{p}, c^f]$, $S_1^h(p) > 0$ and $S_1^l(p) = K_1^l$ as Firm 1 exhausts its low-cost capacity at $p = \hat{p}$, and in addition, Firm 1 also exhausts its high-cost capacity in the limit as $p \to c^{f-}$.

Suppose for contradiction, that for any K_1^h, Firm 2 exhausts its capacity as $p \to c^{f-}$. From (A10), Firm 2's production schedule at $p = c^f$ is

$$S_2(c^f) = c_3(c^f - c^h) - \frac{c_4}{c^f - c^h}.$$

By Lemma A.5, $S_2(c^f)$ is increasing in c_1 and so there is a unique $\tilde{c}_1$ such that $S_2(c^f) = K_2^h$. Since in this scenario Firm 1 produces also with high-cost capacity, and that $S_1^l(\hat{p}) = K_1^l$ for some switching price $\hat{p} < c^f$. At this price $K_1^l = S_1^l(\hat{p}) = \tilde{c}_1(\hat{p} - c^l)$, which means that $\tilde{c}_1 = \frac{K_1^l}{\hat{p} - c^l} \geq \frac{K_1^l}{c^f - c^l}$ since $c^f \geq \hat{p}$. Denote by

$$\tilde{S}_1(c^f) = \tilde{c}_3(c^f - c^h) + \frac{\tilde{c}_4}{c^f - c^h},$$

where $\tilde{c}_3$ and $\tilde{c}_4$ are the corresponding coefficients evaluated at $\tilde{c}_1$. Since Firm 1 is producing with the high-cost technology at high prices, $\tilde{S}_1(c^f) - K_1^l > 0$. To support this supply of $\tilde{S}_1(c^f)$, it has to hold that $\tilde{S}_1(c^f) - K_1^l \leq K_1^h$, where the left-hand side is a function of the primitives $\{K_2^h, K_1^l, c^h, c^l, c^f\}$ but not of K_1^h. Therefore, let K_1^h be small enough so that $\tilde{S}_1(c^f) - K_1^l > K_1^h$ then $\tilde{S}_1(c^f) > K_1^l + K_1^h$ as $p \to c^{f-}$ is infeasible. Hence Firm 2 does not exhaust its capacity for small enough K_1^h.

Therefore by Lemma A.2, we must have an alternative coefficient c_1' such that Firm 1 just exhausts its capacity as $p \to c^{f-}$. Lemma A.5 then implies $c_1' < \tilde{c}_1$: Firm 2 has extra capacity in the limit $p \to c^f$. Hence the equilibrium parameter c_1' is uniquely solved for using $\lim_{p \to c^{f-}} S_1(p) = K_1^h + K_1^l$, which gives

$$\frac{c_1'}{2}\left(2 + \frac{c_1'}{\alpha - c_1'}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{c^f - c^h} = K_1^h + K_1^l,$$

by plugging in c_3 and c_4 from (A13). This unique c_1' can be found numerically.

Joining the systems of equations (A8), (A9), (A10), and (A11) and expliciting c_3 and

c_4 in terms of this c_1', the equilibrium solution is found by :

$$S_1 = \begin{cases} 0, & \text{if } p < c^h, \\ c_1'(p - c^l), & \text{if } p \in [c^h, \hat{p}), \\ \frac{c_1'}{2}\frac{2\alpha - c_1'}{\alpha - c_1'}(p - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{p - c^h}, & \text{if } p \in [\hat{p}, c^f], \end{cases}$$

and

$$S_2 = \begin{cases} 0, & \text{if } p < c^h, \\ c_1'(p - c^h), & \text{if } p \in [c^h, \hat{p}), \\ \frac{c_1'}{2}\frac{2\alpha - c_1'}{\alpha - c_1'}(p - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{p - c^h}, & \text{if } p \in [\hat{p}, c^f), \\ K_2^h & \text{if } p = c^f, \end{cases}$$

where $\hat{p}$ is the price at which $S_1^l(\hat{p}) = K_1^l$. At this price, due to Lemma A.4 $\lim_{p \to \hat{p}^-} S_2(p) = \lim_{p \to \hat{p}^+} S_2(p)$. Hence $\hat{p}$ is solved by expressing the c_3 a and c_4 in as a function of c_1', then equate the second line of (A10) to (A9) and simplify gives

$$\hat{p} = c^h + \frac{\alpha - c_1'}{c_1'} \cdot \left(c^h - c^l\right).$$

Now if we reduce K_2^h to $K_2^h - \delta$ and increase K_1^h by $\delta > 0$ small enough, it will still hold that Firm 1 just exhausts its capacity at $p \to c^f$. Hence,

$$\frac{c_1'}{2}\left(2 + \frac{c_1'}{\alpha - c_1'}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{c^f - c^h} = K_1^h + K_1^l + \delta.$$

By Lemma A.5 we have c_1' is increasing in δ. Therefore the market-wide production

$$S_1 + S_2 = \begin{cases} 0, & \text{if } p < c^h, \\ c_1'(2p - c^h - c^l), & \text{if } p \in [c^h, \hat{p}), \\ c_1'\left(1 + \frac{\alpha}{\alpha - c_1'}\right)(p - c^h), & \text{if } p \in [\hat{p}, c^f), \\ K_2^h + K_1^h + K_1^l, & \text{if } p = c^f, \end{cases}$$

is increasing at every price level as δ increases. Hence the market clearing price decreases. □

A.3 Proof of Proposition 3 (*Symmetric Case*)

The proofs rely on the Lemmas and definitions listed in Appendix A.1.

Proof. Since $S_i(p) = 0$ for all $p < c^l$, it follows from Lemma A.4.3 that supply functions are differentiable except at the price that one of the firms exhausts low-cost capacity or at $p = c^l$. By Lemma A.2, at least one of the firms exhausts all capacities as $p \to c^f$, and $S_i(p) = K^h + K^l$ for $p \geq c^f$. By the FOCs in (A6) and (A7):

$$S_i(p) = S_{-i}'(p) \cdot (p - c^\tau). \tag{A14}$$

Lemma A.3 implies $\tau = h$ is used only when the capacity for $\tau = l$ is exhausted. Denote by $\hat{p}$ the lowest price at which one of the firms exhausts low-cost capacity, i.e. $\hat{p} := \min\{p | S_i(p) \geq K^l \text{ for some } i = 1, 2\}$. On the interval for $p \in [c^l, \hat{p})$ both firms compete using only $\tau = l$, so that $c^\tau = c^l$. Above this price $\hat{p}$, some firm compete using $\tau = h$ with $c^\tau = c^h$.

Solving for the system of equations (A14) for $p \in [c^l, \hat{p})$ gives

$$\begin{cases} S_1(p) &= \frac{c_8}{p-c^l} + c_7 \cdot (p - c^l), \text{if } p \in [c^l, \hat{p}), \\ S_2(p) &= -\frac{c_8}{p-c^l} + c_7 \cdot (p - c^l), \text{if } p \in [c^l, \hat{p}). \end{cases} \tag{A15}$$

Since supply functions are non-decreasing, we have $c_8 = 0$,. Therefore $K_1^l = K_2^l = K^l > 0$ implies both firms exhausts capacity at the same $\hat{p}$ and $c_7 > 0$.

Now solve the system of equations (A14) for $p \in [\hat{p}, c^f)$. The solution is similarly,

$$\begin{cases} S_1(p) &= \frac{c_5}{p-c^h} + c_6 \cdot (p - c^h), \text{if } p \in [\hat{p}, c^f), \\ S_2(p) &= -\frac{c_5}{p-c^h} + c_6 \cdot (p - c^h), \text{if } p \in [\hat{p}, c^f). \end{cases} \tag{A16}$$

Due to profit maximization, we have $\hat{p} \geq c^h$. If $\hat{p} = c^h$, then $c_5 = 0$ by monotonicity of S_i. However this violates monotonicity of S_i since $\lim_{p \to c^h+} S_i(p) = 0 < \lim_{p \to c^h-} S_i(p) = K^l$. Therefore $\hat{p} > c^h$, and hence Lemma A.4.1 implies S_i's are continuous at $\hat{p}$ with $K^l = \lim_{p \to \hat{p}} S_i(p)$ for both i, and so $c_5 = 0$. To pin down c_6, note that if Firm i has a weakly smaller K^h, it exhausts $K^l + K^h$ exactly at limit $p \to c^f-$. Hence, $K^l + K^h = c_6 \cdot (c^f - c^h)$, meaning that $c_6 = \frac{K^l+K^h}{c^f-c^h}$. We can then determine $\hat{p}$ as the solution of:

$$K^l = \lim_{p \to \hat{p}^+} S_i(p) \Rightarrow \hat{p} = \frac{c^h K^h + c^f K^l}{K^l + K^h}.$$

Therefore, the optimal response in this interval is:

$$S_i(p) = \frac{K^l + K^h}{c^f - c^h} \cdot (p - c^h), \quad \text{if } p \in \left[\frac{c^h K^h + c^f K^l}{K^l + K^h}, c^f\right). \tag{A17}$$

Turning back to the interval $p \in [c^l, \frac{c^h K^h + c^f K^l}{K^l + K^h})$, consider the system (A15) with $c_8 = 0$. To pin down c_7, notice that $S_i(p) = K^l$ as $p \to \frac{c^h K^h + c^f K^l}{K^l + K^h}$. Therefore,

$$K^l = \lim_{p \to \hat{p}^-} S_i(p) \Rightarrow c_7 = \frac{K^l(K^l + K^h)}{(c^h - c^l)K^h + (c^f - c^l)K^l}.$$

Therefore, the optimal supply in this interval is:

$$S_i(p) = \frac{K^l(K^l + K^h)}{(c^h - c^l)K^h + (c^f - c^l)K^l} \cdot (p - c^l), \text{if } p \in \left[c^l, \frac{c^h K^h + c^f K^l}{K^l + K^h}\right). \tag{A18}$$

Joining all the intervals, we find that i supplies:

$$S_i(p) = \begin{cases} 0 & p \in [0, c^l), \\ \frac{K^l(K^l+K^h)}{(c^h-c^l)K^h+(c^f-c^l)K^l}(p - c^l) & p \in [c^l, \frac{c^h K^h + c^f K^l}{K^l+K^h}), \\ \frac{K^l+K^h}{c^f-c^h}(p - c^h), & p \in [\frac{K^h c^h + K^l c^f}{K^l+K^h}, c^f), \\ K^l + K^h, & p \in [c^f, \infty). \end{cases}$$

Reallocation. We move δ units of high-cost capacity from Firm 2 to Firm 1, the above solution holds with K^h replaced by $K^h - \delta$ on $[0, c^f)$. When $p \geq c^f$ the supply of firm 1 jump to $K^l + K^h + \delta$ but Firm 2 remains at $K^l + K^h - \delta$. The new supply functions are:

$$S_1(p) = \begin{cases} 0, & p \in [0, c^l), \\ \frac{K^l(K^l+K^h-\delta)}{(c^h-c^l)(K^h-\delta)+(c^f-c^l)K^l}(p - c^3), & p \in [c^l, \frac{c^h(K^h-\delta)+c^f K^l}{K^l+K^h-\delta}), \\ \frac{K^l+K^h-\delta}{c^f-c^h}(p - c^h), & p \in [\frac{(K^h-\delta)c^h+K^l c^f}{K^l+K^h-\delta}, c^f), \\ K^l + K^h + \delta, & p \in [c^f, \infty), \end{cases}$$

and

$$S_2(p) = \begin{cases} 0, & p \in [0, c^l), \\ \frac{K^l(K^l+K^h-\delta)}{(c^h-c^l)(K^h-\delta)+(c^f-c^l)K^l}(p - c^3), & p \in [c^l, \frac{c^h(K^h-\delta)+c^f K^l}{K^l+K^h-\delta}), \\ \frac{K^l+K^h-\delta}{c^f-c^h}(p - c^h), & p \in [\frac{(K^h-\delta)c^h+K^l c^f}{K^l+K^h-\delta}, c^f), \\ K^l + K^h - \delta, & p \in [c^f, \infty). \end{cases}$$

It is clear that the solution is unique, and the supplies decrease at every price level when δ increase. This concludes the proof. □

A.4 Proof of Proposition 4 (*Decreasing Marginal Returns*)

This section shows that that the marginal benefit of holding water decreases as thermal capacity increases in the following typical dynamic problem of the firm.

We start by rewriting the profits (6) as follows. Let the Gross Revenue function at each time t be $GR_{\epsilon_t}(w_t + \delta_t - w_{t+1} + q_t)$, in which the quantity $w_t + \delta_t - w_{t+1} + q_t$ is the total output during period t, $w_t + \delta_t - w_{t+1}$ is the hydro output, q_t is the thermal output, and ϵ_t is the demand shock. Let δ_t and ϵ_t be Markovian in the context. Denote by c^T and c^H the marginal costs for thermal and hydro respectively, then we have the profit function for each period t,

$$\Pi_{\epsilon_t}(w_t + \delta_t - w_{t+1}, q_t) := GR_{\epsilon_t}(w_t + \delta_t - w_{t+1} + q_t) - c^T q_t - c^H(w_t + \delta_t - w_{t+1}).$$

Therefore, the value function for the firm's dynamic optimization problem is given as

$$V(w_0, K) := \mathbb{E}_{\delta,\epsilon}\left[\max_{\phi_w,\phi_q} \sum_{t=0}^{\infty} \beta^t \Pi_{\epsilon_t}(w_t + \delta_t - w_{t+1}, q_t)\right], \tag{A19}$$

where we denote the policy functions for the water stock and thermal production as $w_{t+1} = \phi_w(w_t + \delta_t, K)$ and $q_t = \phi_q(w_t + \delta_t, K)$, respectively, where we denoted by K the firms' thermal capacity and we suppressed the notation of V's possible dependency on the previous realized history of δ_t and ϵ_t. The maximum is taken over policy functions satisfying $w_{t+1} \in [0, w_t + \delta_t]$ and $q_t \in [0, K]$ where K is the thermal capacity.

Typically for our context, the gross revenue GR_ϵ is strictly concave (see Appendix Figure A2). Proposition 4 in the main text shows this concavity is sufficient to imply that the marginal benefit of holding water decreases as thermal capacity increases. We present the proof below.

Proof. First, observe that standard arguments show that when δ_t and ϵ_t are Markovian, the value function satisfies the functional equation

$$V(w_0, K) = \mathbb{E}_{\delta_0,\epsilon_0}\left[\max_{\substack{w_1 \le w_0+\delta_0 \\ q_0 \le K}} \{\Pi_{\epsilon_0}(w_0 + \delta_0 - w_1, q_0) + \beta V(w_1, K)\}\right]. \tag{A20}$$

Second, we show that V is concave if GR_ϵ is concave for all ϵ. To see so, fix a sequence of δ and ϵ. For two possible initial values (w_0, K) and (w_0', K'), let the optimal policy adopted be (w_{t+1}, q_t) and (w_{t+1}', q_t') respectively for all $t \ge 0$. Consider a convex combination of the initial conditions $\lambda(w_0, K) + (1-\lambda)(w_0', K')$, the same convex combination of the policy is feasible because

$$(\lambda w_t + (1-\lambda)w_t') + \delta_t = \lambda(w_t + \delta_t) + (1-\lambda)(w_t' + \delta_t) > \lambda w_{t+1} + (1-\lambda)w_{t+1}'$$

for all t, and $\lambda q_t + (1-\lambda)q_t'$ is also feasible by a similar argument. Since this holds for all sequences of δ and ϵ, it follows from the concavity of GR_ϵ that

$$\begin{aligned}&\Pi_{\epsilon_t}((\lambda w_t + (1-\lambda)w_t') + \delta_t - \left(\lambda w_{t+1} + (1-\lambda)w_{t+1}'\right), (\lambda q_t + (1-\lambda)q_t'))\\ \ge&\lambda \Pi_{\epsilon_t}(w_t + \delta_t - w_{t+1}, q_t) + (1-\lambda)\Pi_{\epsilon_t}(w_t' + \delta_t - w_{t+1}', q_t').\end{aligned}$$

By the defining equation (A19) we have V concave.

With the above two observations, consider formulation (A20) at time t, given $\delta_t, \epsilon_t, w_t$, the future water stock w_{t+1} is determined by FOC:

$$\frac{\partial}{\partial w_{t+1}}\Pi_{\epsilon_t}(w_t + \delta_t - w_{t+1}, q_t) + \beta V_1(w_{t+1}, K) = 0$$

which can be equivalently expressed as

$$-GR_{\epsilon_t}'(w_t + \delta_t - w_{t+1} + q_t) + c^H + \beta V_1(w_{t+1}, K) = 0.$$

Differentiating this FOC with respect to w_t gives

$$-\left(1 - \frac{\partial w_{t+1}}{\partial w_t}\right) GR_{\epsilon_t}''(w_t + \delta_t - w_{t+1} + q_t) + \frac{\partial w_{t+1}}{\partial w_t}\beta V_{11}(w_{t+1}, K) = 0.$$

Rearranging the equation gives

$$\frac{\partial w_{t+1}}{\partial w_t} = \frac{GR_{\epsilon_t}''(w_t + \delta_t - w_{t+1} + q_t)}{GR_{\epsilon_t}''(w_t + \delta_t - w_{t+1} + q_t) + \beta V_{11}(w_{t+1}, K)}$$

where it follows from concavity of GR_{ϵ_t} and V that $\frac{\partial w_{t+1}}{\partial w_t} \in (0, 1)$.

Now consider formulation (A19). Denote the optimized control variables by w_{t+1} and q_t for all t. Partially differentiate the value function with respect to K gives

$$\begin{aligned}\frac{\partial}{\partial K}V(w_0, K) &= \mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty} \beta^t \frac{\partial}{\partial K}\Pi_{\epsilon_t}(w_t + \delta_t - w_{t+1}, q_t)\right]\\ &= \mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty} \beta^t \left[GR_{\epsilon_t}'(w_t + \delta_t - w_{t+1} + q_t) - c^T\right] \frac{\partial q_t}{\partial K}\right]\end{aligned}$$

$$= \mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty}\beta^t\left[GR'_{\epsilon_t}(w_t+\delta_t-w_{t+1}+K)-c^T\right]\mathbf{1}\{q_t=K\}\right]$$

where the second and third equality follows from the Envelope Theorem and the fact that K only affects the boundary of q_t, and the corner solution satisfies $\frac{\partial q_t}{\partial K}=1$ and $GR'_{\epsilon_t}(w_t+\delta_t-w_{t+1}+K)-c^T>0$ when the optimal $q_t=K$.

Therefore, we have

$$\begin{aligned}
V_{21}(w_0,K)=&\frac{\partial}{\partial w_0}\frac{\partial}{\partial K}V(w_0,K)\\
=&\mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty}\beta^t\frac{\partial}{\partial w_0}\left[GR'_{\epsilon_t}(w_t+\delta_t-w_{t+1}+K)-c^T\right]\mathbf{1}\{q_t=K\}\right]\\
=&\mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty}\beta^t\left[\frac{\partial}{\partial w_0}GR'_{\epsilon_t}(w_t+\delta_t-w_{t+1}+K)\right]\mathbf{1}\{q_t=K\}\right]\\
=&\mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty}\beta^t\left[\left(\prod_{i=0}^{t-1}\frac{\partial w_{i+1}}{\partial w_i}\right)\frac{\partial}{\partial w_t}GR'_{\epsilon_t}(w_t+\delta_t-w_{t+1}+K)\right]\mathbf{1}\{q_t=K\}\right]\\
=&\mathbb{E}_{\delta,\epsilon}\left[\sum_{t=0}^{\infty}\beta^t\left[\left(\prod_{i=0}^{t-1}\frac{\partial w_{i+1}}{\partial w_i}\right)\left(1-\frac{\partial w_{t+1}}{\partial w_t}\right)GR''_{\epsilon_t}\right]\mathbf{1}\{q_t=K\}\right]
\end{aligned}$$

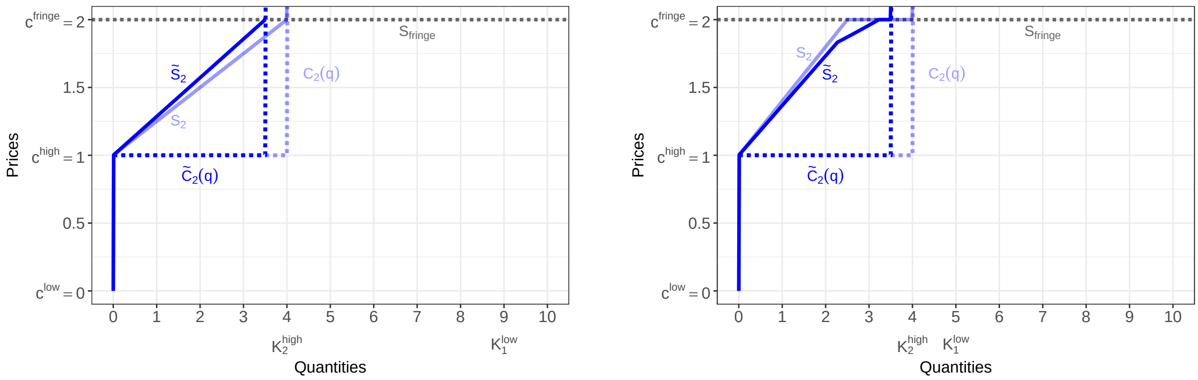
Recall that we have shown $\frac{\partial w_{t+1}}{\partial w_t}\in(0,1)$ for all $t\geq 0$, therefore for all t,

$$\left(\prod_{i=0}^{t-1}\frac{\partial w_{i+1}}{\partial w_i}\right)\left(1-\frac{\partial w_{t+1}}{\partial w_t}\right)>0.$$

Since $GR''_{\epsilon_t}<0$, it follows that $V_{21}<0$. This completes the proof. □

A.5 Figures Pertaining to the Theoretical Framework

Figure A1: Supplies of Firm 2 and fringe firms before and after the transfer

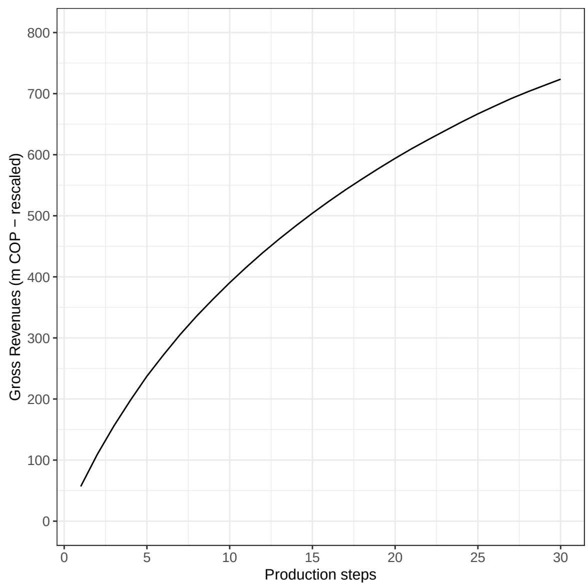


(a) Abundance scenario
$K_1 = (9, 0, 0)$ & $K_2 = (0, 4, 0)$

(b) Scarcity scenario
$K_1 = (5, 0, 0)$ & $K_2 = (0, 4, 0)$

Notes: Each panel illustrates the equilibrium supply of Firm 2 and the supply of fringe firms (gray dotted lines) under abundance in Panel (a) and scarcity in Panel (b) using the parameters as in Figure 5. The cost of Firm 2 is the dotted blue line. Solid (shaded) lines refer to Firm 2's costs and supply after (before) the capacity transfer of 0.5 units from Firm 2 to Firm 1.

Figure A2: Concavity of the expected gross revenue function



Notes: Average gross revenues for EPMG.

B Inflow Forecasts

First, we run the following ARDL model using the weekly inflows of each unit j as dependent variable,

$$\delta_{j,t} = \mu_0 + \sum_{1 \le p \le t} \alpha_p \delta_{j,t-p} + \sum_{1 \le q \le t} \beta_q \mathbf{x}_{j,t-q} + \epsilon_{j,t} \ \forall j \tag{B1}$$

We denote by $\delta_{j,t}$ the inflow to the focal dam in week t. $\mathbf{x}_{j,t}$ is a vector that includes the average maximum temperature and rainfalls in the past week at dam j, and information about the future probabilities of el niño. We average the data at the weekly level to reduce the extent of autocorrelation in the error term. Importantly for forecasting, the model does not include the contemporaneous effect of the explanatory variables.

Forecasting. For forecasting, we first determine the optimal number of lags for P and Q for each dam j using the BIC criterion. Given the potential space of these two variables, we set $Q = P$ in (B1) to reduce the computation burden. For an h-ahead week forecast, we then run the following regression:

$$\delta_{j,t+h} = \hat{\mu}_0 + \hat{\alpha}_1 \delta_t + \cdots + \hat{\alpha}_P \delta_{j,t-P+1} + \sum_{k=1}^{K} \hat{\beta}_{1,k} x_{j,t,k} + \cdots + \hat{\beta}_{q,k} x_{j,t-Q+1,k} + \epsilon_t, \tag{B2}$$

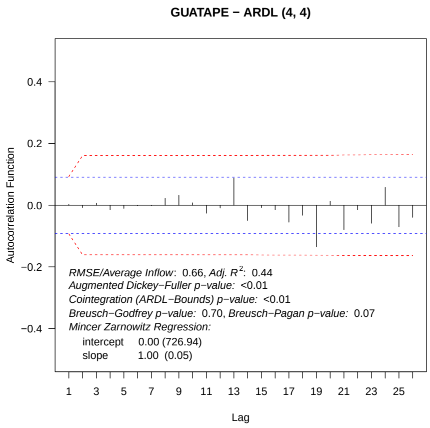
where K denotes the number of control variables in $\mathbf{x}_{j,t-q}$.

Forecasting algorithm. For each week t of time series of dam j, we estimate (B2) for $h \in \{4, 8, 12, 16, 20\}$ weeks ahead (i.e., for each month up to five months ahead) using only data for the 104 weeks (2 years) before week t. In the analysis, we only keep dams for which we have at least 2 years of data to perform the forecast. Dropping this requirement does not affect the results.

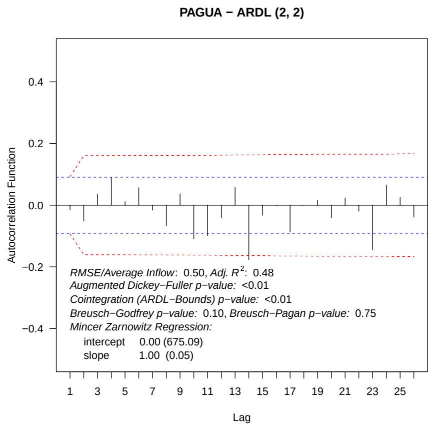
Quality of the fit. Figures B1 and B2 report the autocorrelation function and the Ljung-box test for the error term ϵ_t in (B2) for the largest dams in Colombia in the period we consider. The p-values of Ljung-box test never reject the null of autocorrelation.

Analysis at the firm level. In the structural model, we estimate a transition matrix by using an ARLD model similar to that in (B1), with the only difference that the explanatory variables are averaged over months rather than weeks to better capture heterogeneity across seasons. We also control for long-term time variation like el niño. We present the autocorrelation function and Ljung-box tests in Appendix Figures B3 and B4. For estimation, we model the error term $\epsilon_{j,t}$ in (B1) through a Pearson Type IV distribution as commonly done in the hydrology literature. This distribution feats our purposes because it is not symmetric, meaning different probabilities at the tails (dry vs wet seasons). We show that this distribution fits well the data for the largest four diversified firms (ENDG, EPMG, EPSG, and ISGG) in Figures B3a, B3b, B3c, and B3d.

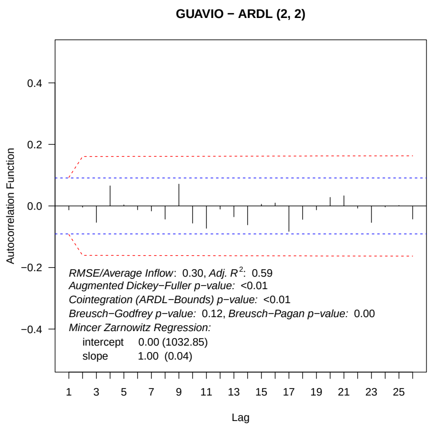
Figure B1: ARDL model diagnostics for some of the largest dams in Colombia in our sample period



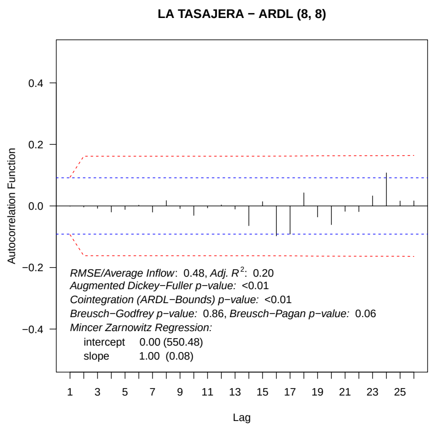
(a) Guatape



(b) Pagua



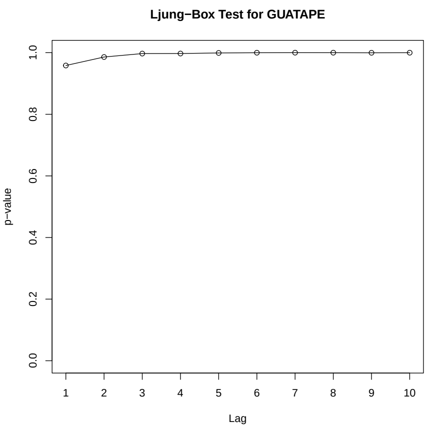
(c) Guavio



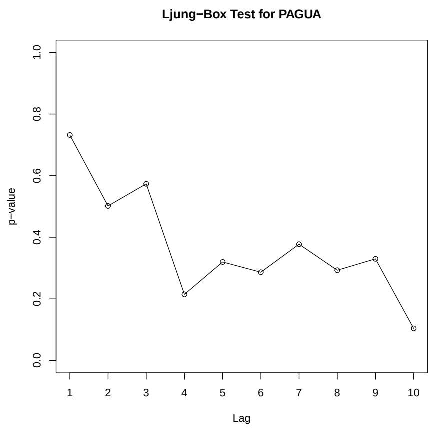
(d) La Tasajera

Notes: The plot shows the autocorrelation plots for the residuals of the ARDL model used to forecast future inflows. The title indicates the number of lagged dependent variables and explanatory variables selected by the algorithm. The test indicates the extent of autocorrelation and heteroskedasticity in the error terms.

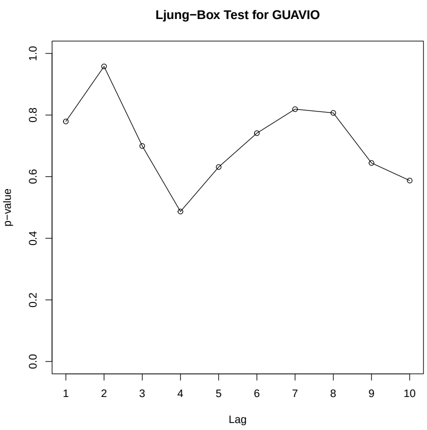
Figure B2: Ljung boxes for some of the largest dams in Colombia



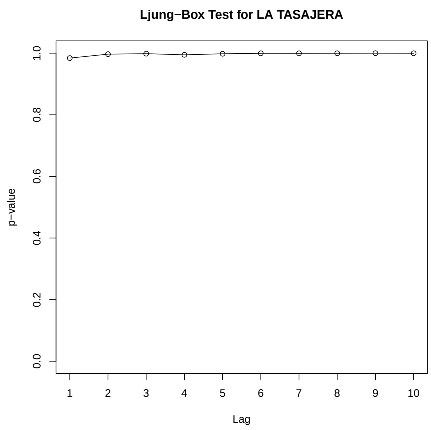
(a) Guatape



(b) Pagua



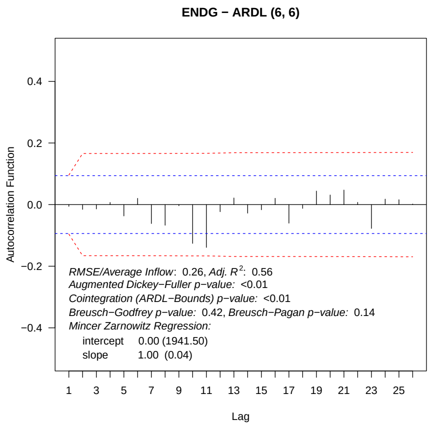
(c) Guavio



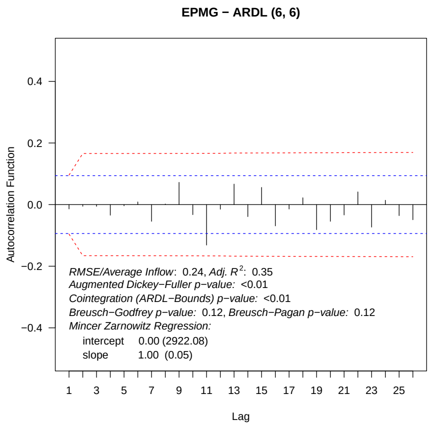
(d) La Tasajera

Notes: The plot shows the p-values of Ljung-box tests of whether any of a group of autocorrelations of a time series are different from zero.

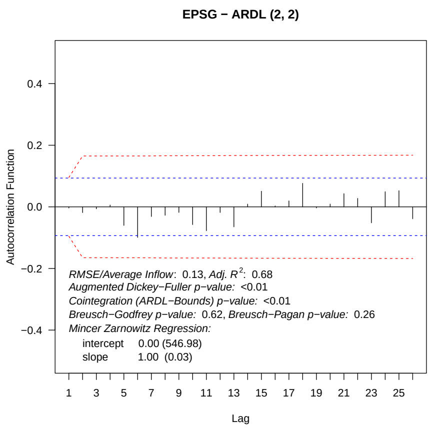
Figure B3: ARDL model diagnostics at firm level



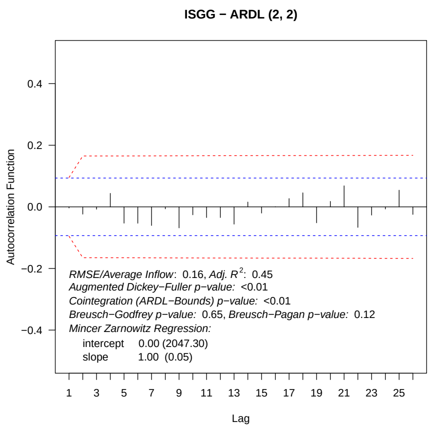
(a) ENDG



(b) EPMG



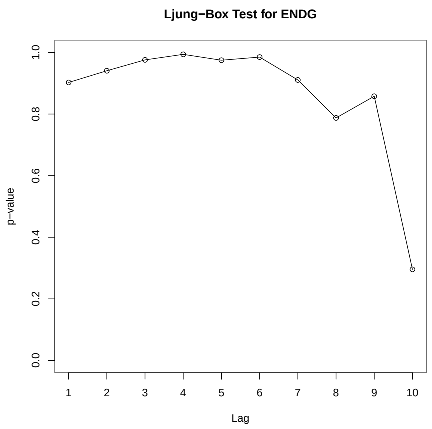
(c) EPSG



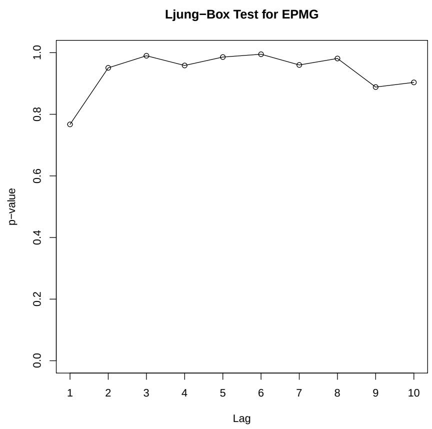
(d) ISGG

Notes: The plot shows the autocorrelation plots for the residuals of the ARDL model used to forecast future inflows at the firm level. The title indicates the number of lagged dependent variables and explanatory variables selected by the algorithm. The test indicates the extent of autocorrelation and heteroskedasticity in the error terms.

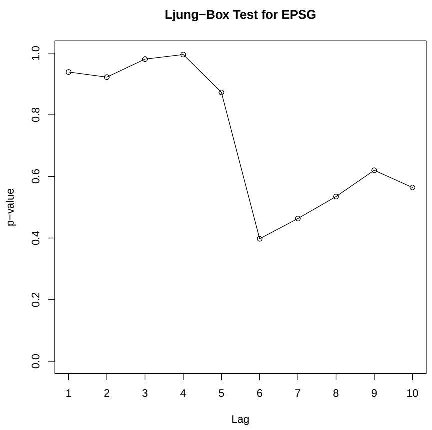
Figure B4: Ljung boxes at the firm level



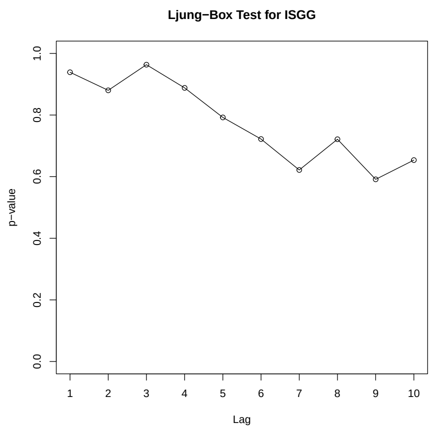
(a) ENDG



(b) Pagua



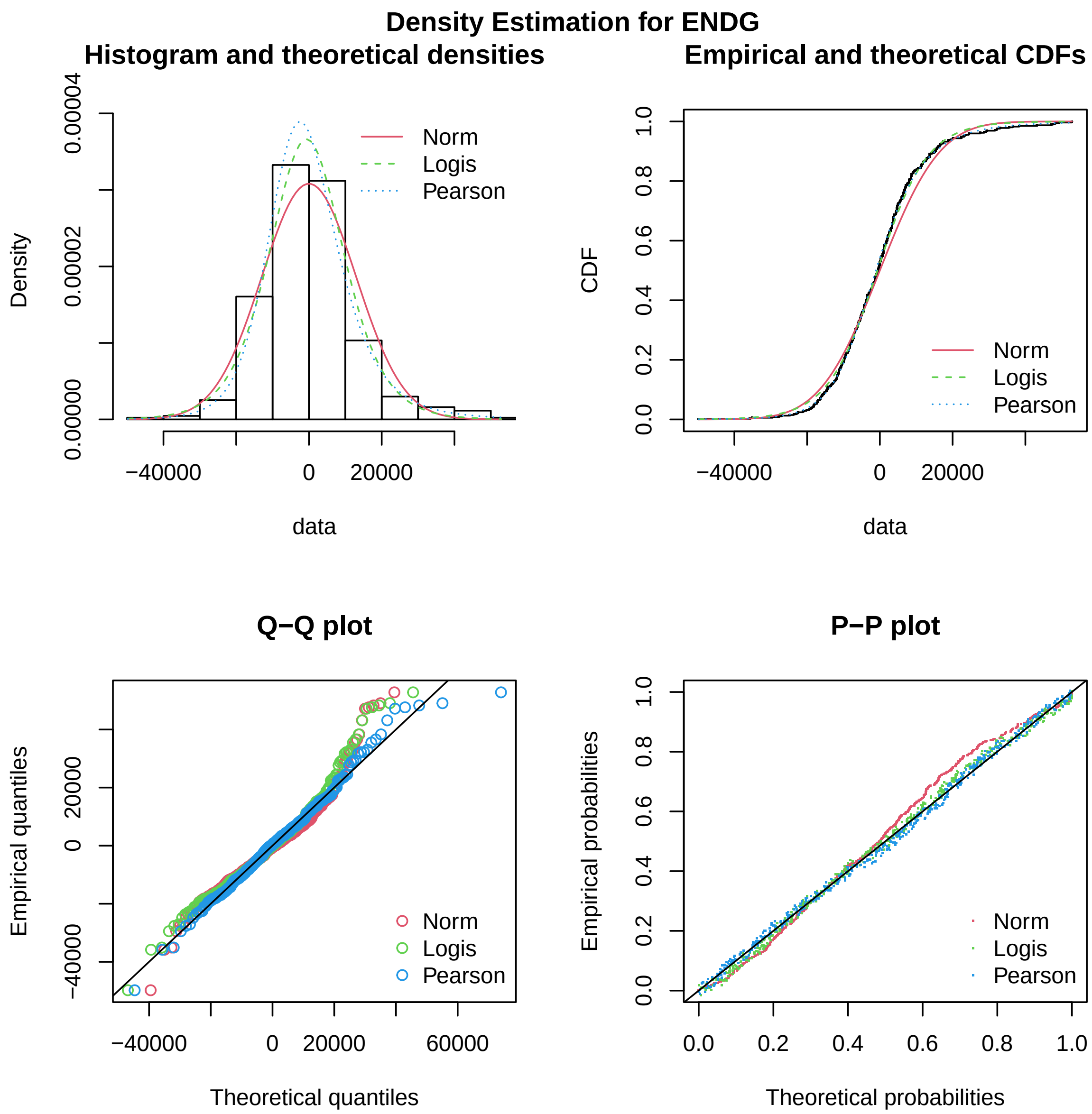
(c) EPSG



(d) ISGG

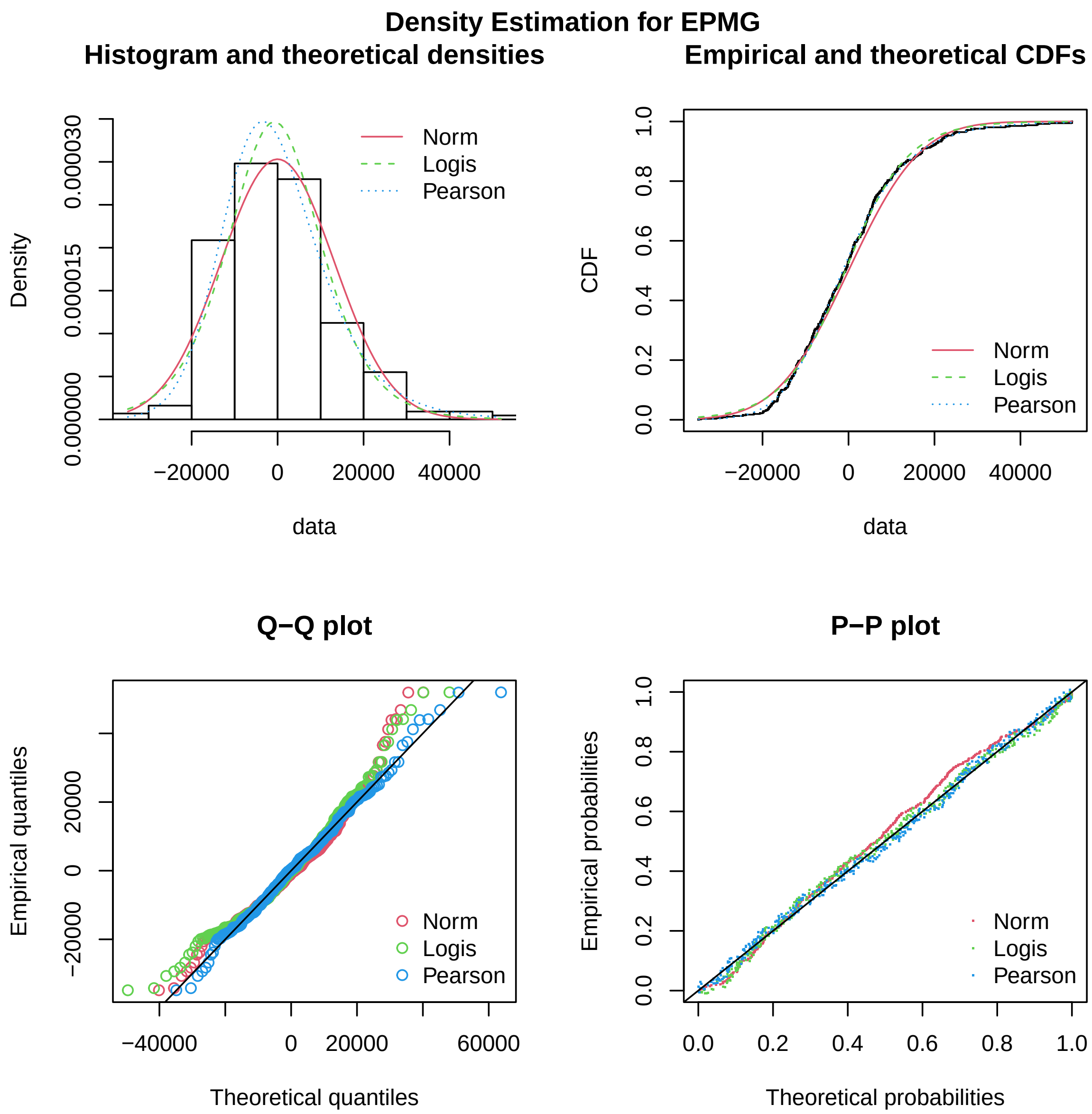
Notes: The plot shows the p-values of Ljung-box tests of whether any of a group of autocorrelations of a time series are different from zero.

Figure B5: Transition matrix for ENDG



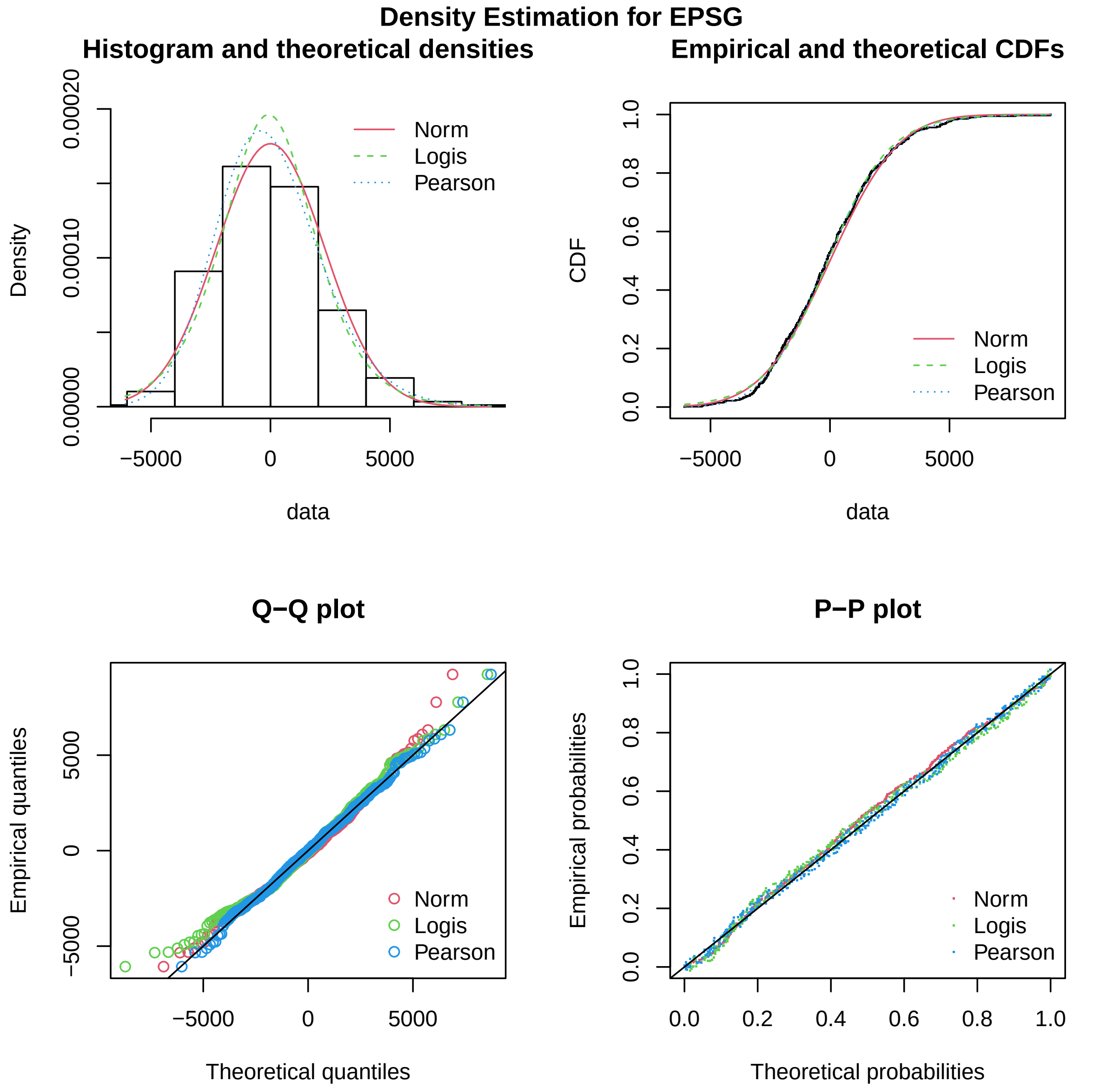
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B6: Transition matrix for EPMG



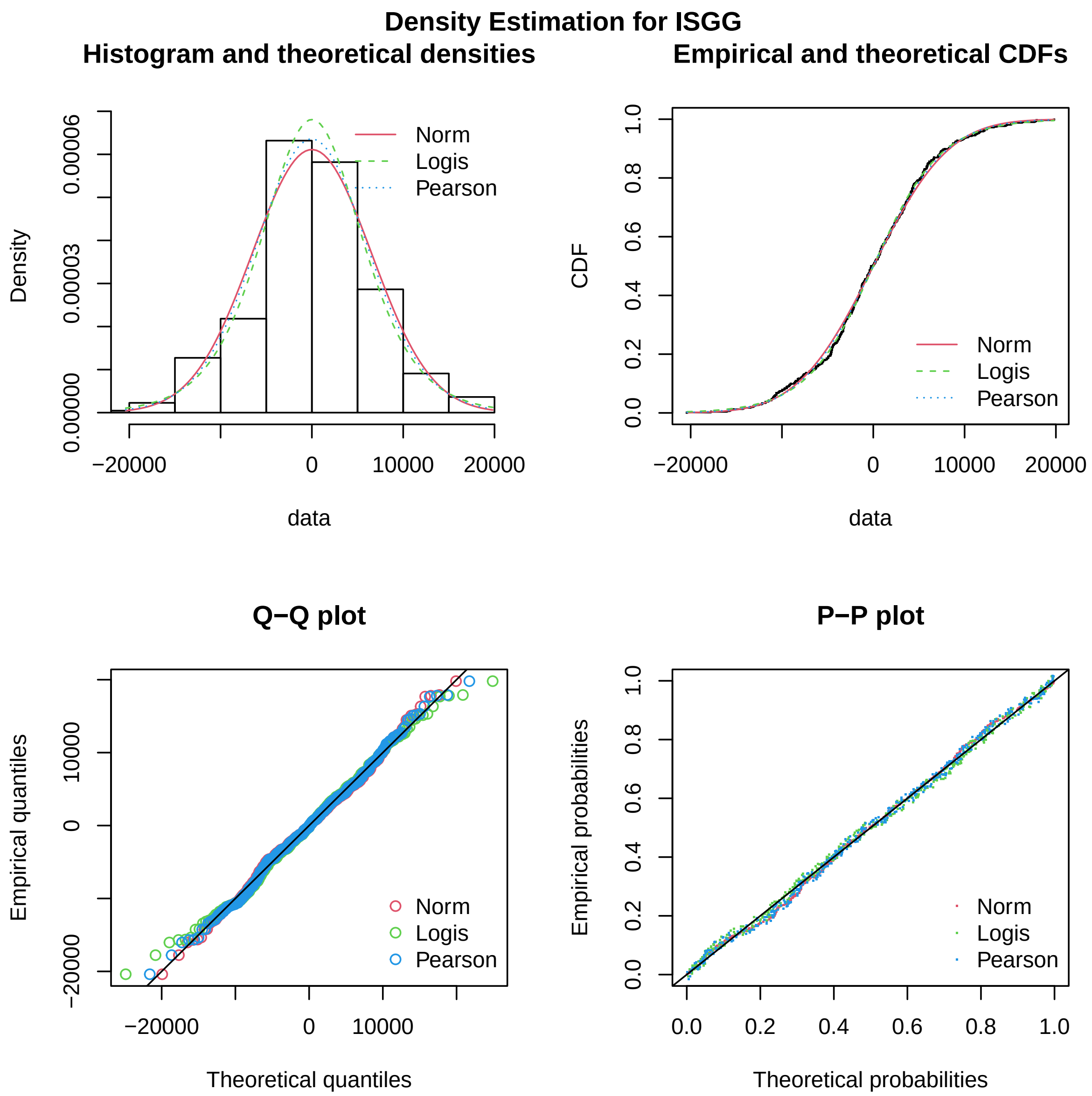
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B7: Transition matrix for EPSG



Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B8: Transition matrix for ISGG



Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

C More on Responses to Inflow Forecasts

C.1 Symmetric Responses to Forecasts

The main text focuses on units' responses to extreme forecasts. This section shows consistent results with a less flexible specification that forces firms to respond equally to favorable and adverse shocks. We employ the following specification:

$$y_{ij,th} = \sum_{l=1}^{L} \beta_3 \, \widehat{inflow}_{ij,t+l} + \mathbf{x}_{ij,t-1,h} \, \alpha + \mu_{j,m(t)} + \tau_t + \tau_h + \varepsilon_{ij,th}, \tag{C1}$$

where the sole departure from (1) is that $\{\widehat{inflow}_{ij,t+l}\}_l$ is a vector of forecasted inflows l months ahead. We also allow the slope of j's lagged water stock to vary across units to control for the relative size of reservoirs across firms.

Zooming in on sibling thermal units, we define $\{\widehat{inflow}_{ij,t+l}\}_l$ as the sum of the l-forecast inflows accruing to firm i, and by controlling for lagged total water stock by firms as in Section 3. In this case, we let the slope of this variable vary across firms.

The response of dams. The top panel of Figure C1 plots the main coefficient of interest, β_l, for inflow forecasts one, three, and five months ahead. Panel (a) finds that dams are willing to produce approximately 5 % more per standard deviation increase in inflow forecast. The effect fades away for later forecasts. Units respond mostly through quantity bids (black bars) rather than price bids (gray bars).[2]

Information content of inflow forecasts. To show that our forecasts indeed capture variation that is material for firms, Panel (b) performs the same analysis as in (C1) using the forecast residuals (i.e., $inflow_{ij,t+l} - \widehat{inflow}_{ij,t+l}$), instead of the forecast. Reassuringly, we find that bids do not react to "unexpected inflows," pointing to no additional information in the forecast residuals.

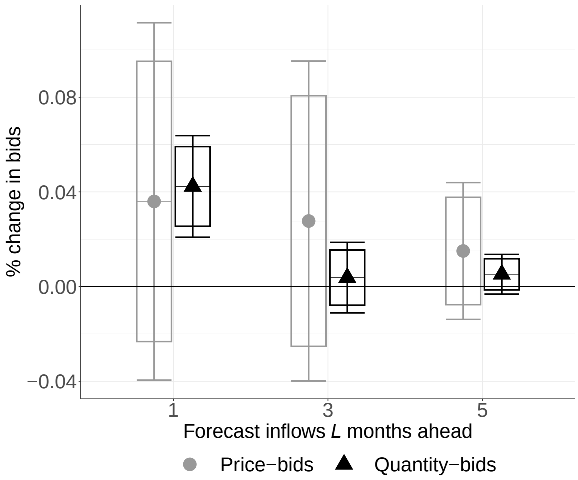
Correlation across monthly forecasts. To break the extent of correlation across monthly forecasts, the bottom panels plot the estimate from five separate regressions as in (C1) with each regression allowing for l being either 1, 2, 3, 4, or 5. This approach break the autocorrelation across monthly inflows within units. Panel (c) shows a smooth decay in quantity bids, while price bids are highly volatile but always insignificant, consistent with the results in the top panel. Panel (d) shows that firms do not respond to unexpected inflows.

The response of "sibling" thermal plants. The coefficient estimates are in Figure C2. As in Section 3, sibling thermal units respond mostly with their price-bids. The effect is particularly evident in Panel (b), which runs separate regressions for each monthly forecast in (C1) and shows that current thermal units reflect inflow forecasts that are two to four months ahead.

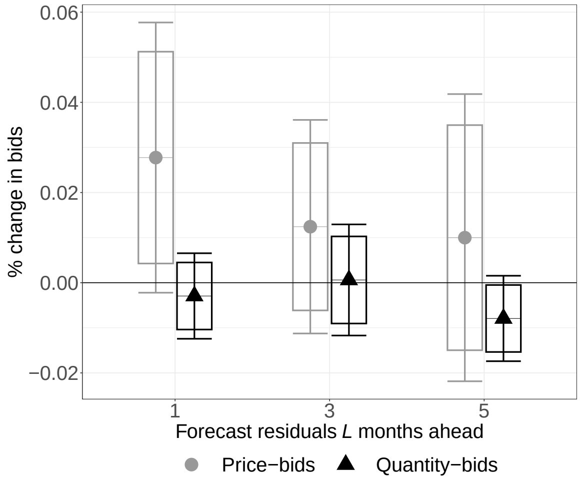
[2] Some price-bid coefficients are positive in Panel (a). However, this result is rather noisy, as suggested by the slightly higher response of price bids to the unexpected one-month forecast in Panel (b). The rationale is that units submit only one price bid per day but multiple quantity bids; thus, there is less variation in price bids. Reassuringly, if we were to control for lagged quantities (in logs) in the price-bids regressions of Figure C1, $\hat{\beta}_{l=1}$ would collapse to zero. Instead, controlling for lagged price bids in the quantity-bid regressions would not change the results.

Figure C1: Symmetric responses to inflow forecasts by dams

Top Panel. All l-forecasts in the same regressions

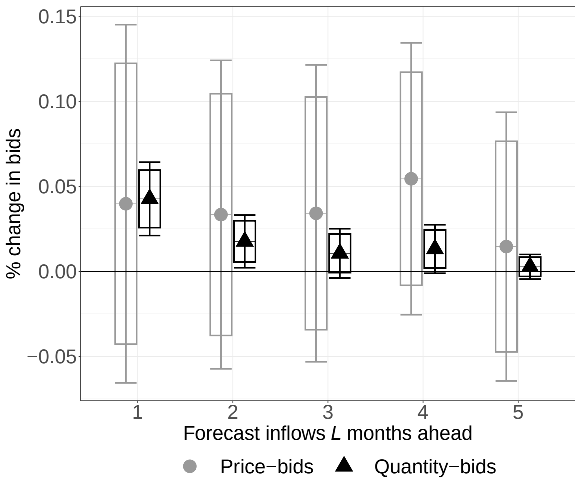


(a) Expected inflows (standardized forecasts)

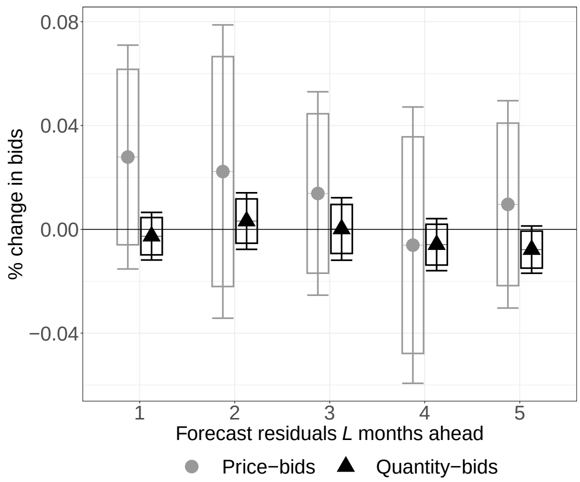


(b) Unexpected inflows (forecast residuals)

Bottom Panel. Separate regressions for each month-ahead forecast



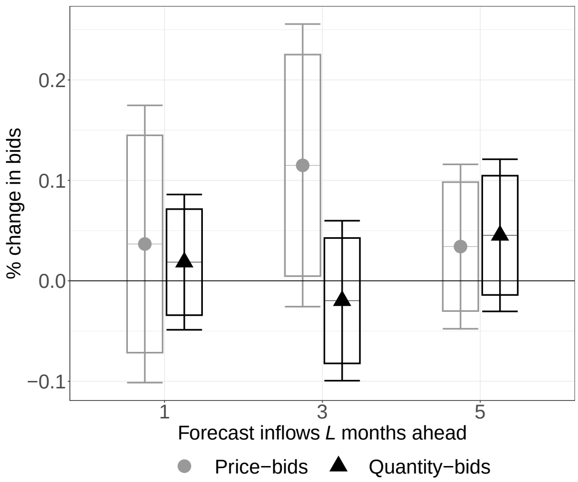
(c) Expected inflows (standardized forecasts)



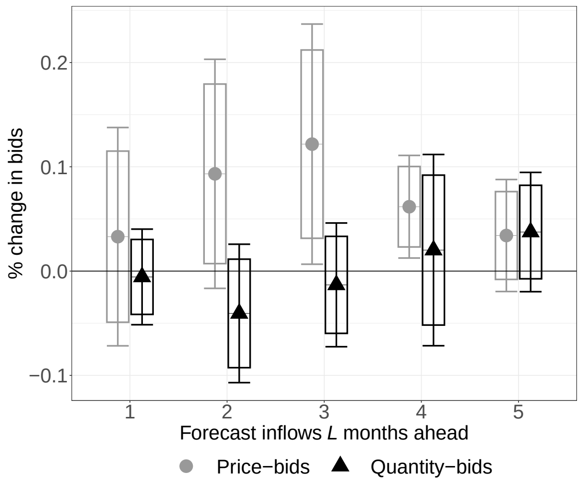
(d) Unexpected inflows (forecast residuals)

Notes: All plots report estimates of $\{\beta_l\}_l$ from (C1) for one, three, and five months ahead using either price- (gray) or quantity-bids as dependent variables. The bottom panels report coefficients for separate regressions (one for each month-ahead forecast). Left and right panels use the forecasted inflows or the forecast errors from the prediction exercise as independent variables, respectively. Error bars (boxes) report the 95% (90%) CI.

Figure C2: Symmetric response of sibling thermal units



(a) Single regression



(b) Separate regressions

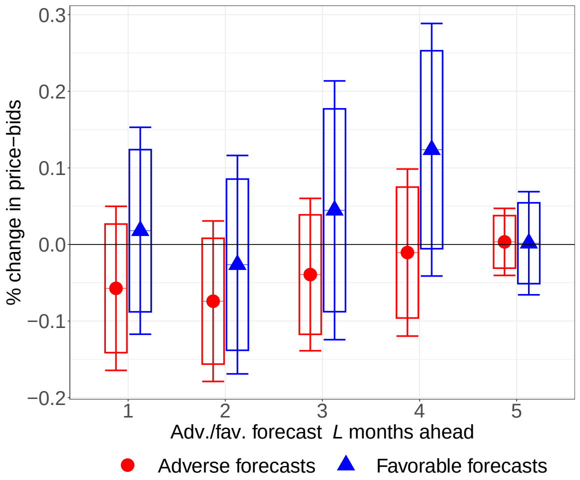
Notes: Estimates of β_{ll} from a modified (C1) focus on firm-level rather than unit-level water inflows one to five months ahead. As forecasts may be correlated over time, Panel (b) plots estimates from five separate regressions, each for a specific month. Error bars (boxes) show 95% (90%) CIs.

C.2 Robustness: Autocorrelation in Inflow Forecasts

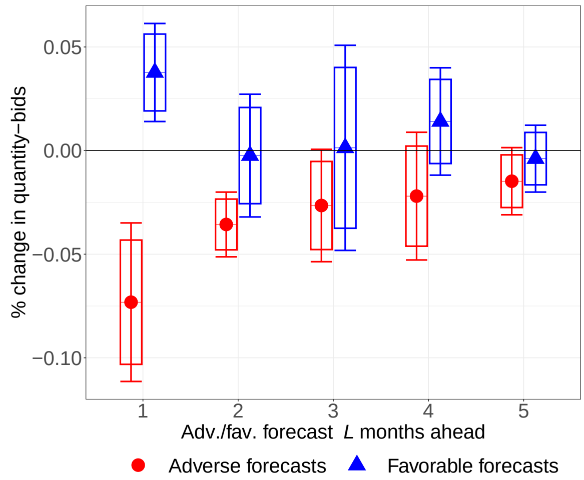
To break the correlation across monthly forecasts, we run five separate regressions, each corresponding to a forecast l months ahead ($l = 1, 2, 3, 4, 5$), rather than estimating three coefficients in a single regression (as in (1), Section 3). Figure C3 shows estimates for dams (top panels) and their sibling thermal units (bottom panel). The results align with Figure 3: dams adjust supply one month ahead of forecasted droughts (wet periods) by increasing (reducing) quantity bids, though the effect fades over time. Sibling thermal plants respond in the opposite direction, primarily through price bids, with the strongest reaction three months before an adverse or favorable event, remaining stable thereafter. The estimated effects are also comparable in magnitude to Figure 3.

Figure C3: Responses to inflow forecasts. Each estimate from a different regression

Top panel: Responses of dams to own inflow forecasts

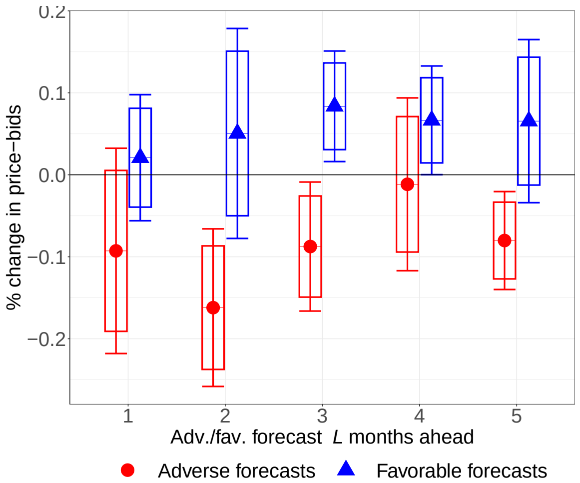


(a) Price bids

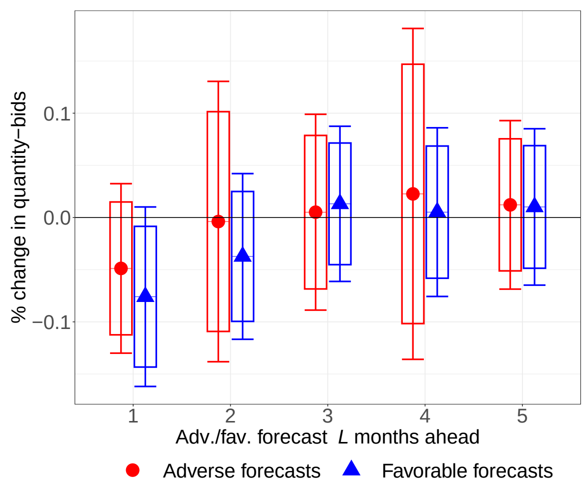


(b) Quantity bids

Bottom panel: Responses of thermal units to sibling dams' forecasts



(c) Price bids



(d) Quantity bids

Notes: Estimates of $\{\beta^{low}, \beta^{high}\}$ from (1) from five regressions per panel, with each regression focusing on l being either 1, 2, 3, 4, or 5 months. Error bars (boxes) report the 95% (90%) CI.

C.3 Non-monotonic Effect of Concentration on Price

In this section, we propose an alternative way to study non-linear effects of HHI on concentration by modifying (2) as follows:

$$\begin{aligned} \ln(p_{th}) = \gamma_0 \Big[\sum_i \text{Net Adverse}_{t+3} \Big] + \gamma_1 \, \Delta_{t+3} + \gamma_2 \, \Delta^2_{i,t+3} \\ + \alpha_1 \, \text{HHI}_{t-1} + \mathbf{x}_{t-1,h} \, \alpha + \tau_{mh(t)} + \tau_{y(t)} + \epsilon_{th}, \end{aligned} \tag{C2}$$

where we explore the non-linearity of price on concentration through $\Delta^2_{i,t+3}$. Its inclusion allows us to test the effects of concentration: if positive (negative), high (low) prices are expected when concentration is either smallest or highest, displaying a U-shape of prices on concentration. If zero, instead, we expect prices to increase linearly in concentration. The remaining terms are as in (2). We cluster the standard errors at the level of month and year, but similar results are obtained when clustering by week (not reported).

Table C1 presents the estimated coefficients in (2). First, note that the expectation of future net future inflows has no effect on current market prices (once we control for total water stocks). Hence, larger inflows may expand a firm's capacity without influencing its marginal cost but only its average cost, which does not affect market prices in equilibrium.

The second key result is that prices exhibit a convex relationship with Δ, as indicated by the positive and statistically significant coefficient γ_2, while γ_1 remains statistically insignificant across all columns. In particular, Column (1) reveals that prices are highest either when Δ is at its smallest—negative due to future favorable inflows expanding large firms' capacities—or when Δ is at its largest—positive due to adverse forecasts limiting the capacity of the largest firms.

This pattern holds consistently across all specifications. Columns (1) and (2) compute concentration using only firms' thermal capacities, which are not prone to inflow shocks, while Columns (3), (4), and (5) extend the analysis to include total capacities, relying on lagged water stock data instead of current values. Additionally, the results remain robust when excluding periods in which no firms face moderate forecasts (i.e., all firms have either an adverse or a favorable forecast) (Columns 2 through 5).

Importantly, the observed convexity in prices is driven by firms' strategic responses to inflow forecasts, rather than by seasonal fluctuations, as the effect is evident in both dry and wet seasons (Columns 4 and 5).

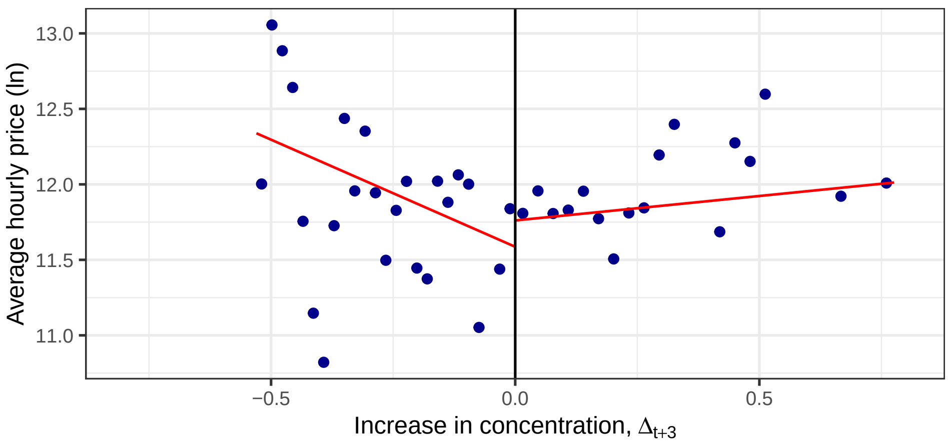
Table C1: Market price and weather-induced changes in concentration (squared Δ_{t+3})

	(1)	(2)	(3)	(4)	(5)
	HHI based on thermal capacity		HHI based on total capacity (Thermal and water stock)		
Dependent var: average weekly price in hour h ($\ln p_{ht}$)					
Net adverse inflows (3 months), γ_0	-0.017	-0.017	-0.008	-0.025	0.005
	(0.011)	(0.015)	(0.015)	(0.022)	(0.015)
Δ_{t+3} (Net adverse inflows times HHI), γ_1	-0.087	-0.074	0.029	-0.071	0.067
	(0.101)	(0.119)	(0.135)	(0.089)	(0.079)
Δ^2_{t+3} (Squared net adverse inflows times HHI), γ_2	-0.797*	-0.909*	-0.325**	-0.205*	-0.444*
	(0.367)	(0.390)	(0.089)	(0.094)	(0.195)
HHI	✓	✓	✓	✓	✓
Lagged controls	✓	✓	✓	✓	✓
FE: Year	✓	✓	✓	✓	✓
FE: Month-by-hour	✓	✓	✓	✓	✓
Subset	All	All shocked	All shocked	All shocked	All shocked
Season	All	All	All	Dry	Wet
N	7,464	7,200	7,200	3,528	3,672
R2 Adj.	0.896	0.893	0.893	0.880	0.903

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

Notes: This table shows the estimated coefficients from (C2). The controls include (in logs) lagged market demand, lagged total water stock, lagged total contract position, and lagged hourly price. The first column includes all weeks from 2010 to 2015 while the columns (2)-(5) exclude weeks where no firm expects either a favorable or an adverse forecast three months ahead. Column (4) examines dry seasons (from December to March, July and August) and Column (5) examines wet seasons (from April to November). The computations of Δ and HHI variables use lagged capacity shares. Standard errors clustered by year and month.

Figure C4: Market price and weather-induced changes in concentration—no covariates

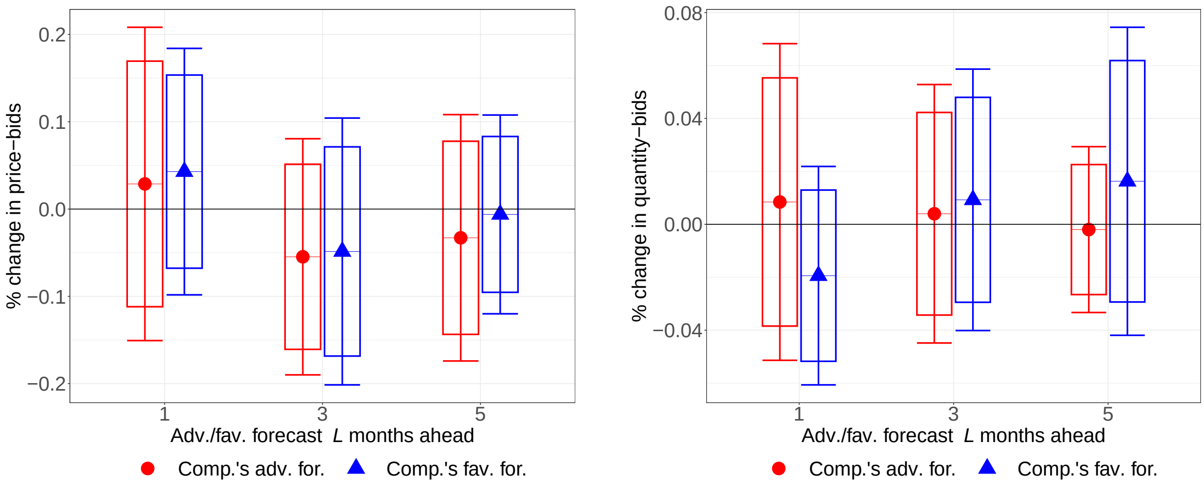


Notes: Binned scatter plot of $\ln(p_{ht})$ on Δ_{t+3}. The regression slopes are the coefficient estimates of Δ_{t+3} for a version of (2), which allows for different slopes for positive and negative Δ. No covariates are used in the regression.

C.4 The Response to Competitors' Inflow Forecasts

To comprehensively understand firms' responses to future shocks, we explore whether hydropower units incorporate reactions to competitors' forecasts. We model adverse and favorable inflows in (1) based on the sum of inflows at a firm's competitors. We allow for distinct slopes for each unit's water stock to control adequately for current water availability at various dams in $\mathbf{x}_{ij,t-1}$. Figure C5 reveals minimal movement in a firm's bid concerning its competitors' forecasts, with magnitude changes generally within $\pm 1\%$ and lacking statistical significance. Separate joint significance tests for adverse and favorable forecasts do not reject the null hypothesis that they are zero at standard levels.

Figure C5: Responses to competitors' inflow forecasts



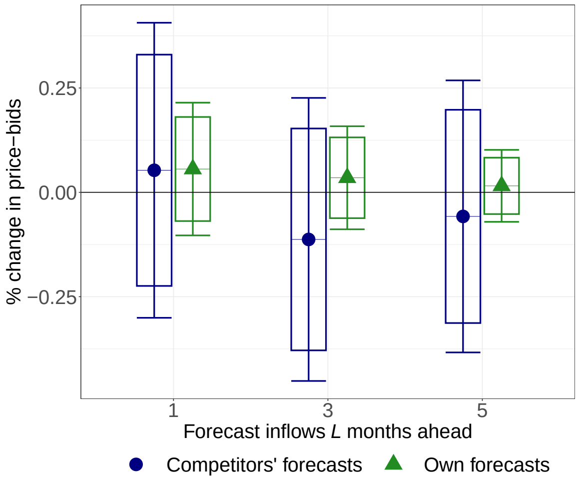
(a) Price bids (b) Quantity bids

Notes: The figure shows how units respond to favorable or adverse future water forecasts for competitors, as in (1). Plots display estimates of $\{\beta_l^{low}\}$ (red) and $\{\beta_l^{high}\}$ (blue) for one, three, and five months ahead, with error bars (boxes) representing 95% (90%) CIs.

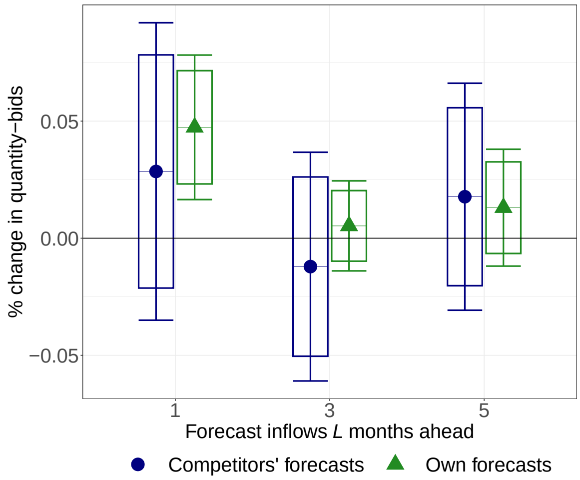
Symmetric responses to forecats. We include $\widehat{\text{infolow}}_{-i,t+l}$, the sum of the forecasted inflows of firm i's competitors l months ahead, in (C1) and estimate coefficients for both own-forecasts and competitors' forecasts. Figure C6 shows the estimated coefficients for competitors' and own's forecasts in blue and green, respectively. Two results emerge. First, units do not respond to competitors. We test and do not reject the joint hypothesis that the coefficients pertaining to the competitors are jointly equal to zero. Second, a dam's responses to its own forecasts are quantitatively similar to those in Panel (a) of Figure C1, indicating little correlation between its own forecasts and competitors' forecasts.

Responses to water stocks. Intrigued by the fact that units do not respond to dry spells accruing to competitors, we extend our analysis to investigate firms' responses to other firms. We propose a simple framework where we regress a firm's hourly quantity- and price-bids (in logs) on a firm's current water stock, the water stock of its competitors, and the interaction of these two variables. As before, we average variables across weeks. We account for unobserved heterogeneity at the level of a unit or the macro level (e.g., demand) using fixed effects by units, week-by-year, and market hours. Table C2 finds that firms only respond to their own water stocks: not only the response to competitors is not statistically significant, but also its magnitude is shadowed by that observed for

Figure C6: Units' response to competitors (blue) and own forecasts (green)



(a) Price bids



(b) Quantity bids

Notes: The figure reports estimates from a modified version of (C1) with both a unit's inflow forecasts (green) and those of its competitors (blue). Joint test p-values for competitors' forecasts are 0.6763 for price bids and 0.594 for quantity bids. Error bars (boxes) are 95% (90%) CIs.

own water stocks. In addition, the interaction term is small and insignificant, indicating that firms do not strategize based on their potential competitive advantage.[3]

[3]We also perform a "two-by-two exercise" where we study, for instance, a unit's bids when its current water stock is high but its competitors' water stock is low. Panel a of Table C3 shows that units react only to their own water stock, disregarding others. Panel b interacts these two variables but finds that the interactions are mostly insignificant and small. Thus, competitors' water stocks hardly explain bids.

Table C2: Firm response to competitors' water stock

	(1)	(2)	(3)	(4)	(5)	(6)
	Quantity-bids (ln)			Price-bids (ln)		
Ln competitors' water stock (std)	–0.106*	0.169	0.225	0.250	0.368	0.522
	(0.042)	(0.087)	(0.126)	(0.194)	(0.275)	(0.312)
Ln firm i's water stock (std)		0.537**	0.584**		0.231	0.359*
		(0.179)	(0.191)		(0.185)	(0.148)
Ln competitors' water stock (std) × Ln firm i's water stock (std)			–0.029			–0.079
			(0.030)			(0.061)
Constant	5.778***	5.778***	5.762***	11.716***	11.716***	11.670***
	(0.001)	(0.009)	(0.016)	(0.000)	(0.008)	(0.038)
FE: unit, week-by-year, and hour	✓	✓	✓	✓	✓	✓
Clustered s.e. by unit, month, and year	✓	✓	✓	✓	✓	✓
N	135,048	135,048	135,048	135,048	135,048	135,048
Adjusted R-squared	0.7776	0.7856	0.7858	0.6246	0.6259	0.6277

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

Notes: This table presents the coefficient estimates from the following regression

$$\ln bid_{ijht} = \alpha_0 + \beta_i \ln w_{it} + \beta_{-i} \ln w_{-it} + \beta_{int} \ln w_{it} \cdot \ln w_{-it} + FE_{jht} + \varepsilon_{ijht},$$

where t indices weeks, so that price- and quantity-bids are averaged across weeks for each hour. w_{it} and w_{-it} are the average weekly water stocks of firm i and firm i's competitors in week t. Continuous variables are standardized.

Table C3: Firm response to competitors' water stock (high vs. low w_{it})

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Quantity-bids (ln)				Price-bids (ln)			
Panel a. *Controlling for a Competitors' Water Stocks*								
Low water stock for i	–0.166		–0.160		0.004		0.004	
	(0.101)		(0.092)		(0.085)		(0.086)	
Low water stock for i's comp.	–0.044	0.043			0.003	0.004		
	(0.085)	(0.068)			(0.055)	(0.079)		
High water stock for i		0.062**		0.048		–0.089		–0.077
		(0.021)		(0.028)		(0.061)		(0.068)
High water stock for i's comp.			–0.096	–0.061			0.105	0.050
			(0.055)	(0.071)			(0.092)	(0.115)
N	135,048	135,048	135,048	135,048	135,048	135,048	135,048	135,048
Adjusted R-squared	0.7874	0.7850	0.7877	0.7850	0.6316	0.6323	0.6319	0.6324
Panel b. *Responding to Competitors' Water Stocks*								
Low water stock for i	–0.196	–0.167			–0.047	0.006		
	(0.133)	(0.095)			(0.107)	(0.096)		
Low water stock for i's comp.	–0.069		0.042		–0.041		0.015	
	(0.103)		(0.066)		(0.025)		(0.077)	
Low water stock for i × Low water stock for i's comp.	0.090				0.155			
	(0.114)				(0.122)			
High water stock for i's comp.		–0.102		–0.061		0.107		0.072
		(0.054)		(0.089)		(0.094)		(0.109)
Low water stock for i × High water stock for i's comp.		0.130				–0.048		
		(0.092)				(0.195)		
High water stock for i			0.060*	0.047			–0.073	–0.054
			(0.025)	(0.048)			(0.055)	(0.064)
High water stock for i × Low water stock for i's comp.			0.028				–0.249	
			(0.051)				(0.235)	
High water stock for i × High water stock for i's comp.				0.003				–0.066
				(0.077)				(0.044)
N	135,048	135,048	135,048	135,048	135,048	135,048	135,048	135,048
Adjusted R-squared	0.7876	0.7877	0.7850	0.7850	0.6321	0.6319	0.6327	0.6324
FE: unit, week-by-year, and hour	✓	✓	✓	✓	✓	✓	✓	✓
Clustered s.e., unit, month, and year	✓	✓	✓	✓	✓	✓	✓	✓

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

Notes: The top panel presents the coefficient estimates from the following regression

$$\ln bid_{ijht} = \alpha_0 + \beta_i \mathbb{1}_{it} + \beta_{-i}\mathbb{1}_{-it} + \beta_2 \delta_{ijt} + FE_{jht} + \varepsilon_{ijht},$$

where t indices weeks, so that price- and quantity-bids are averaged across weeks for each hour. The definition of $\mathbb{1}_{it}$ varies across "Low water stocks," when it takes the value of one if the sum of the water stocks of firm i in week t is below its 20^{th} percentile, or "High water stocks," when the sum is above its 80^{th} percentile. $\mathbb{1}_{-it}$ is defined analogously for firm i's competitors. Panel b also includes $\mathbb{1}_{it} \cdot \mathbb{1}_{-it}$ as a regressor, namely the interaction between a firm's current status (whether i's water stock is above or below a certain threshold and that of its average competitor). All regression control for a unit's current inflow (δ_{ijt}, unreported), and unit, week-by-year, and hour-fixed effects.

D Exhibits from the Structural Model

Table D1: Estimated model primitives—employing 4 polynomials for $V(\cdot)$

	(1)	(2)	(3)	(4)
Marginal costs (COP/MWh)				
Thermal (c^T)	204460.10***	151965.08***	213177.19***	149699.10***
	(1,880.65)	(1,840.22)	(1,626.95)	(1,624.97)
Hydropower (c^H)	76,022.12***	28,820.29***	44,941.37***	51,297.15***
	(6,601.03)	(6,290.74)	(3,368.43)	(4,638.29)
Intertemporal value of water (COP/MWh)				
Spline 1 (γ_1)	–2,216.01***	6,992.47***	2,297.60***	10,797.46***
	(710.63)	(524.16)	(372.92)	(474.35)
Spline 2 (γ_2)	–2.773e-03***	–2.668e-03***	–3.672e-03***	–3.576e-03***
	(2.612e-04)	(1.550e-04)	(1.398e-04)	(1.402e-04)
Spline 3 (γ_3)	5.359e-09***	1.386e-08***	5.512e-09***	1.382e-08***
	(6.862e-10)	(6.043e-10)	(4.654e-10)	(5.307e-10)
Spline 4 (γ_4)	2.364e-08***	–1.893e-08***	1.220e-08***	–1.996e-08***
	(2.347e-09)	(1.773e-09)	(1.382e-09)	(1.536e-09)
Fixed Effects				
Firm	✓	✓	✓	✓
Unit				✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
Date			✓	✓
SW F ($c^{thermal}$)	2,314.39	760.89	3,458.28	700.41
SW F (c^{hydro})	425.23	245.77	866.70	333.94
SW F (γ_1)	318.26	242.54	392.31	269.99
SW F (γ_2)	244.94	275.53	366.43	323.50
SW F (γ_3)	623.17	484.66	519.66	491.27
SW F (γ_4)	394.17	448.36	445.26	446.16
Anderson Rubin F	1,213.31	1,395.05	1,527.77	1,539.08
N	1,451,592	1,451,592	1,451,592	1,451,592

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

Notes: This table presents the coefficients obtained estimating (12) by two-stage least squares on daily data between January 1, 2010, and December 31, 2015. Unlike the results presented in the main text (Table 1), these estimates are based on an approximation of the value function over four knots instead of five, meaning that we estimate only four $\{\gamma\}_{r=1}^{4}$. The top panels separate the marginal cost estimates and the value function parameters from the fixed effects used in estimation, which vary across columns. Our favorite specification is in Column (4), which includes day-fixed effects. The bottom panel provides diagnostic tests in the first stage. 2,900 COP $\simeq$ 1 US$

Table D2: Estimated model primitives—employing a normal density for the transition matrix and 5 polynomials for $V(\cdot)$

	(1)	(2)	(3)	(4)
	Marginal costs (COP/MWh)			
Thermal (c^T)	204727.14***	143319.87***	220441.60***	146635.86***
	(1,803.36)	(1,843.71)	(1,644.41)	(1,529.32)
Hydropower (c^H)	46,491.28***	28,163.59***	28,458.10***	60,353.00***
	(7,097.17)	(5,026.09)	(3,774.68)	(3,616.79)
	Intertemporal value of water (COP/MWh)			
Spline 1 (γ_1)	–797.45	–6,751.10***	–9,712.11***	–3,744.90***
	(1,018.26)	(504.77)	(526.92)	(364.28)
Spline 2 (γ_2)	–3.346e-03***	–3.154e-04**	–2.173e-04	–1.064e-03***
	(3.548e-04)	(1.421e-04)	(1.806e-04)	(1.016e-04)
Spline 3 (γ_3)	–4.894e-09***	2.009e-08***	–1.621e-08***	1.837e-08***
	(1.497e-09)	(1.055e-09)	(1.093e-09)	(8.171e-10)
Spline 4 (γ_4)	4.070e-08***	–3.179e-08***	4.205e-08***	–2.848e-08***
	(2.795e-09)	(1.931e-09)	(1.926e-09)	(1.508e-09)
Spline 5 (γ_5)	–2.216e-08***	8.949e-08***	4.422e-08***	8.251e-08***
	(3.405e-09)	(2.893e-09)	(2.274e-09)	(2.500e-09)
	Fixed Effects			
Firm	✓	✓	✓	✓
Unit	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
FE: Date			✓	✓
SW F (c^T)	3,129.14	1,257.31	2,991.60	1,097.29
SW F (c^H)	443.62	272.74	883.91	367.55
SW F (c^{γ_1})	251.73	213.67	285.62	225.96
SW F (c^{γ_2})	219.64	273.32	270.25	300.83
SW F (c^{γ_3})	441.27	476.05	297.84	482.88
SW F (c^{γ_4})	522.38	550.59	296.71	553.52
SW F (c^{γ_5})	403.80	1,255.92	485.36	1,018.15
Anderson Rubin F	1,213.31	1,395.05	1,527.77	1,539.08
N	1,451,592	1,451,592	1,451,592	1,451,592

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

Notes: This table presents the coefficients obtained estimating (12) by two-stage least squares on daily data between January 1, 2010, and December 31, 2015. Unlike the results presented in the main text (Table 1), these estimates assume that the transition matrix is normally distributed. The top panels separate the marginal cost estimates and the value function parameters from the fixed effects used in estimation, which vary across columns. Our favorite specification is in Column (4), which includes day-fixed effects. The bottom panel provides diagnostic tests in the first stage. 2,900 COP ≃ 1 US$

Table D3: Estimated model primitives—employing a normal density for the transition matrix and 4 polynomials for $V(\cdot)$

	(1)	(2)	(3)	(4)
Marginal costs (COP/MWh)				
Thermal (c^T)	195271.35***	152621.02***	194831.41***	151112.79***
	(1,605.71)	(1,807.59)	(1,229.58)	(1,573.39)
Hydropower (c^H)	120408.48***	32,919.28***	128840.47***	59,085.78***
	(1,313.47)	(5,997.03)	(871.55)	(4,459.66)
Intertemporal value of water (COP/MWh)				
Spline 1 (γ_1)	–2,720.98***	6,297.20***	1,569.04***	10,291.14***
	(635.73)	(515.56)	(329.00)	(461.14)
Spline 2 (γ_2)	–2.752e-03***	–2.829e-03***	–3.485e-03***	–3.836e-03***
	(2.242e-04)	(1.588e-04)	(1.235e-04)	(1.425e-04)
Spline 3 (γ_3)	7.278e-09***	1.527e-08***	1.025e-08***	1.538e-08***
	(7.491e-10)	(6.213e-10)	(4.369e-10)	(5.414e-10)
Spline 4 (γ_4)	1.844e-08***	–2.010e-08***	–4.491e-09***	–2.165e-08***
	(2.351e-09)	(1.804e-09)	(1.222e-09)	(1.550e-09)
Fixed Effects				
FE: Firm	✓	✓	✓	✓
FE: Unit		✓		✓
FE: Month-by-technology		✓		✓
FE: Hour	✓	✓	✓	✓
FE: Week-by-year	✓	✓		
FE: Date			✓	✓
SW F (c^Y)	36.41	113.62	34.13	94.59
SW F (c^H)	124.43	300.57	139.18	2,474.37
SW F (γ_1)	616.23	652.90	483.22	617.59
SW F (γ_2)	1,401.71	364.00	194.38	284.03
SW F (γ_3)	76.56	93.11	644.24	248.55
SW F (γ_4)	45.66	86.99	1,139.58	82.71
Anderson Rubin F	19.74	111.61	196.42	106.90
KP Wald	7.16	10.80	6.61	19.28
N	1,451,592	1,451,592	1,451,592	1,451,592

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

Notes: This table presents the coefficients obtained estimating (12) by two-stage least squares on daily data between January 1, 2010, and December 31, 2015. Unlike the results presented in the main text (Table 1), these estimates assume that the transition matrix is normally distributed and are based on an approximation of the value function over four knots instead of five, meaning that we estimate only four $\{\gamma\}_{r=1}^{4}$. The top panels separate the marginal cost estimates and the value function parameters from the fixed effects used in estimation, which vary across columns. Our favorite specification is in Column (4), which includes day-fixed effects. The bottom panel provides diagnostic tests in the first stage. 2,900 COP $\simeq$ 1 US$

E Smoothing Variables

This section details the smoothing approach that allows interchanging differentiation and expectation in the FOC of the value function (9).

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.[4] 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 $D^R_{iht}(p,\epsilon)$ with respect to the market price in hour h and day t is

$$\frac{\partial \tilde{D}^R_{iht}(p,\epsilon)}{\partial p_{ht}} = -\sum_{m\neq i}^{N}\sum_{j=1}^{J_m} q_{mjht}\frac{\partial \mathcal{K}\left(\frac{p-b_{mjt}}{bw}\right)}{\partial p_{ht}}.$$

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,

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

The derivatives of the smoothed supply functions by technology τ are found analogously:

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

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

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

Market price. The derivatives of the market price with respect to price- and quantity-bids in (9) are computed using the envelop theorem. Their smoothed versions are

$$\frac{\partial p_{ht}}{\partial b_{ijt}} = \frac{\frac{\partial \tilde{S}_{iht}}{\partial b_{ijt}}}{\frac{\partial \tilde{D}^R_{iht}}{\partial p_{ht}} - \frac{\partial \tilde{S}_{iht}}{\partial p_{ht}}}, \qquad \frac{\partial p_{ht}}{\partial q_{ijht}} = \frac{\frac{\partial \tilde{S}_{iht}}{\partial q_{ijht}}}{\frac{\partial \tilde{D}^R_{iht}}{\partial p_{ht}} - \frac{\partial \tilde{S}_{iht}}{\partial p_{ht}}}.$$

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

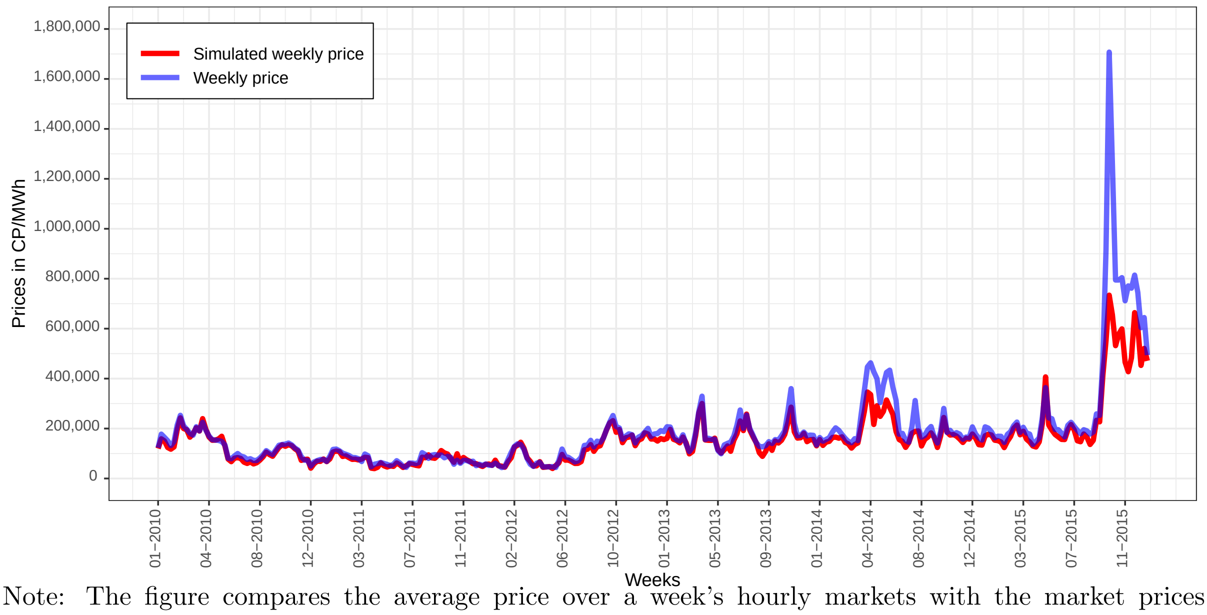
F Model Fit

Table F1: Hourly prices across simulations

Hour	(1) Avg.Prices Cop MWh	(2) Avg.Sim Prices Cop MWh	(3) Avg.Price Dif Cop MWh	(4) Avg.Price Dif Cop MWh%	Hour	(5) Avg. Prices Cop MWh	(6) Avg.Sim Prices Cop MWh	(7) Avg.Price Dif Cop MWh	(8) Avg.Price Dif Cop MWh%
10 steps for all variables									
0	161,252.60	135,273.40	-25,979.24	-6.26	12	195,531.40	163,482.30	-32,049.12	-11.77
1	156,664.90	130,628.70	-26,036.24	-6.95	13	194,709.30	163,511.20	-31,198.11	-11.86
2	152,892.30	128,465.70	-24,426.53	-6.08	14	196,454.30	164,380.80	-32,073.58	-12.15
3	151,443.70	128,594.40	-22,849.36	-6.03	15	194,546.70	162,841.40	-31,705.25	-12.01
4	154,896.60	129,640.90	-25,255.72	-7.31	16	191,133.60	160,444.40	-30,689.27	-11.30
5	163,513.80	135,057.40	-28,456.36	-8.86	17	189,147.60	159,043.90	-30,103.68	-10.45
6	165,598.20	136,721.60	-28,876.58	-9.43	18	211,991.70	177,970.30	-34,021.39	-13.46
7	174,317.70	142,618.10	-31,699.63	-10.85	19	225,075.80	185,115.50	-39,960.33	-15.82
8	183,744.00	151,396.80	-32,347.23	-11.71	20	207,064.00	173,728.10	-33,335.85	-12.43
9	188,755.90	155,528.70	-33,227.22	-12.04	21	194,239.10	162,719.60	-31,519.55	-11.23
10	194,980.90	162,327.90	-32,652.96	-12.38	22	181,601.30	151,125.00	-30,476.31	-9.83
11	200,586.40	166,731.60	-33,854.77	-13.54	23	170,168.10	139,515.30	-30,652.76	-10.08
30 steps for residual demand and value function, 10 steps for supply schedules									
0	161,252.60	138,807.00	-22,445.62	-5.30	12	195,531.40	164,607.50	-30,923.88	-9.30
1	156,664.90	133,723.50	-22,941.38	-5.33	13	194,709.30	164,046.20	-30,663.15	-9.26
2	152,892.30	132,266.60	-20,625.70	-3.92	14	196,454.30	165,683.90	-30,770.43	-9.46
3	151,443.70	132,024.60	-19,419.11	-4.10	15	194,546.70	163,824.30	-30,722.39	-9.47
4	154,896.60	133,081.20	-21,815.40	-5.82	16	191,133.60	161,973.50	-29,160.14	-9.27
5	163,513.80	138,363.60	-25,150.15	-7.21	17	189,147.60	160,533.10	-28,614.54	-8.59
6	165,598.20	141,354.20	-24,243.99	-7.42	18	211,991.70	180,689.50	-31,302.22	-11.04
7	174,317.70	147,567.70	-26,750.04	-8.10	19	225,075.80	187,535.60	-37,540.19	-14.00
8	183,744.00	153,035.40	-30,708.67	-10.45	20	207,064.00	175,701.60	-31,362.38	-10.01
9	188,755.90	157,682.30	-31,073.58	-9.70	21	194,239.10	162,380.70	-31,858.44	-10.22
10	194,980.90	163,022.50	-31,958.37	-10.36	22	181,601.30	152,607.30	-28,993.96	-7.55
11	200,586.40	167,918.50	-32,667.87	-11.56	23	170,168.10	144,076.90	-26,091.15	-7.36

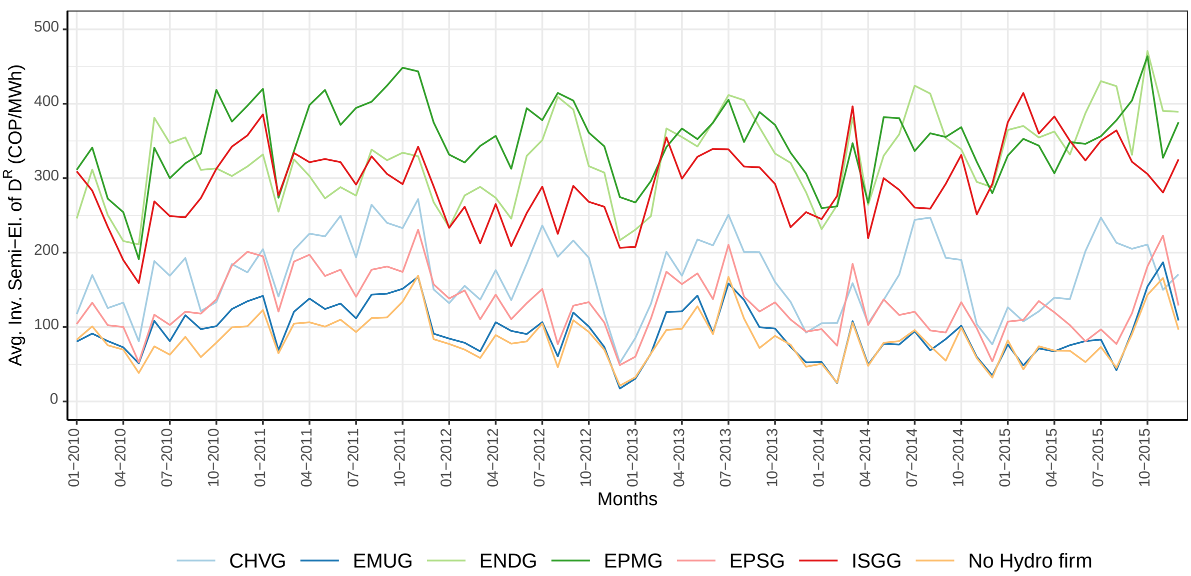
Notes: The table compares average hourly prices across the simulated and actual data. The simulation model is described in Section 6.2. The simulations in this table employ a different number of steps in the first and second panels. 2,900 COP $\simeq$ 1 US$.

Figure F1: Model fit (30 steps for residual demand and value function)



Note: The figure compares the average price over a week's hourly markets with the market prices obtained from solving EMPG's profit maximization problem (13) for each hourly market. The solver employs thirty steps to discretize the demand and the value function and 10 steps for each technology-specific supply ($M = Z = 30$, $G = 10$). 2,900 COP $\simeq$ 1 US$.

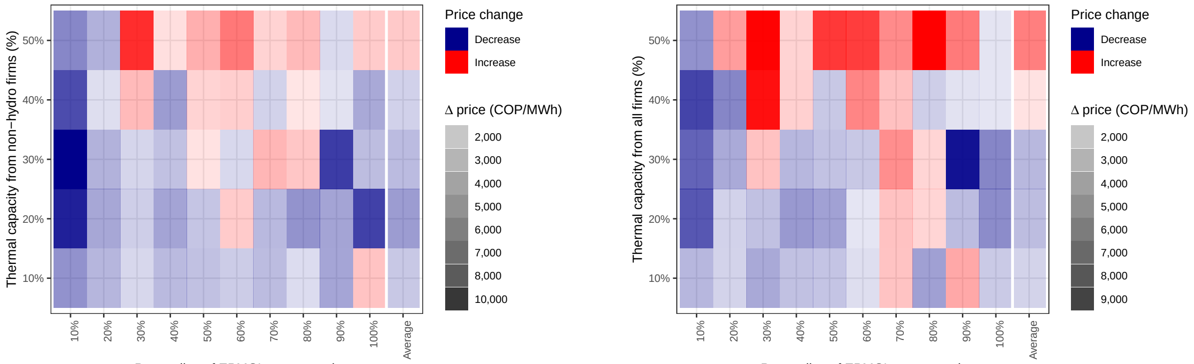
Figure F2: Monthly average inverse semi-elasticities by firm



Notes: The mean inverse elasticity for the six firms with hydro units and the average across all firms with no hydro units (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. 2,900 COP $\simeq$ 1US$.

G Counterfactual Analyses

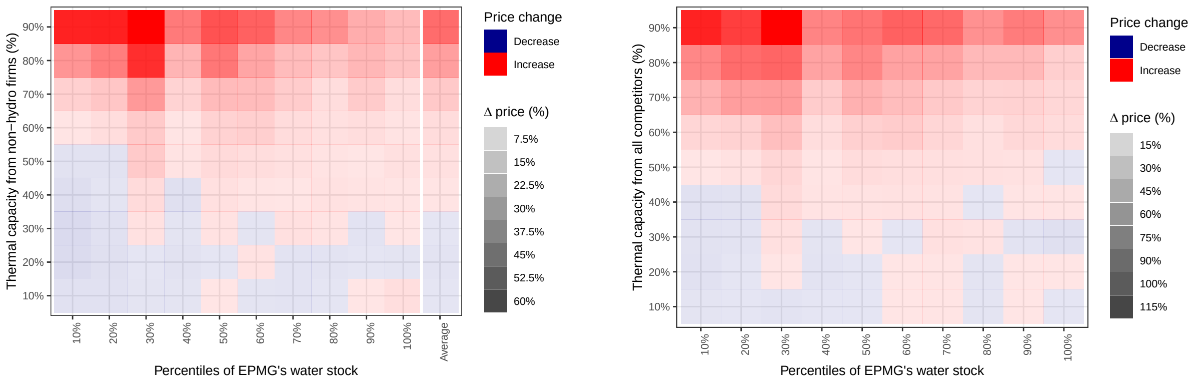
Figure G1: Price changes of capacity transfer to the leading firm - small transfers



(a) Transferring κ% from all non-hydro firms (b) Transferring κ% from all firms

Notes: The figure shows counterfactual price differences when the market leader is endowed with a fraction of competitors' thermal capacity (y-axis) across different scarcity levels (x-axis), proxied by deciles of its water stock. Each cell shows the average difference between simulated and baseline prices, with color indicating sign and magnitude. Left (right) panels transfer capacity from fringe (all) firms. Unlike Figure 8, transfers are capped at 50%. The average market price is 150,000 COP/MWh; 2,900 COP $\simeq$ 1 US$.

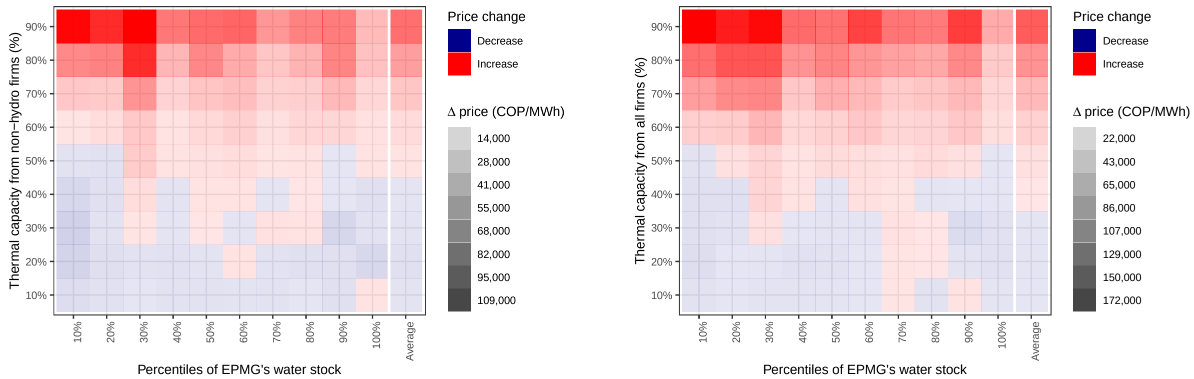
Figure G2: Percentage price changes due to a capacity transfer to the leading firm



(a) Transferring κ% from all non-hydro firms (b) Transferring κ% from all firms

Notes: The figure shows counterfactual percentage price differences as the market leader is endowed with a fraction of competitors' thermal capacity (y-axis) across scarcity levels (x-axis), proxied by deciles of its water stock. Each cell reports the average relative difference between counterfactual and baseline prices, $\frac{1}{H \cdot T}\sum_{h,t}\frac{p_{ht}^{\kappa\%}-p_{ht}^{\text{base}}}{p_{ht}^{\text{base}}}$, with color indicating sign and magnitude. Superscripts κ% and base denote counterfactual and baseline simulated prices, respectively. Left (right) panels transfer capacity from fringe (all) firms. Unlike Figure 8, which reports absolute price differences, this figure shows percentage changes.

Figure G3: The price effect of a capacity transfer to the market leader

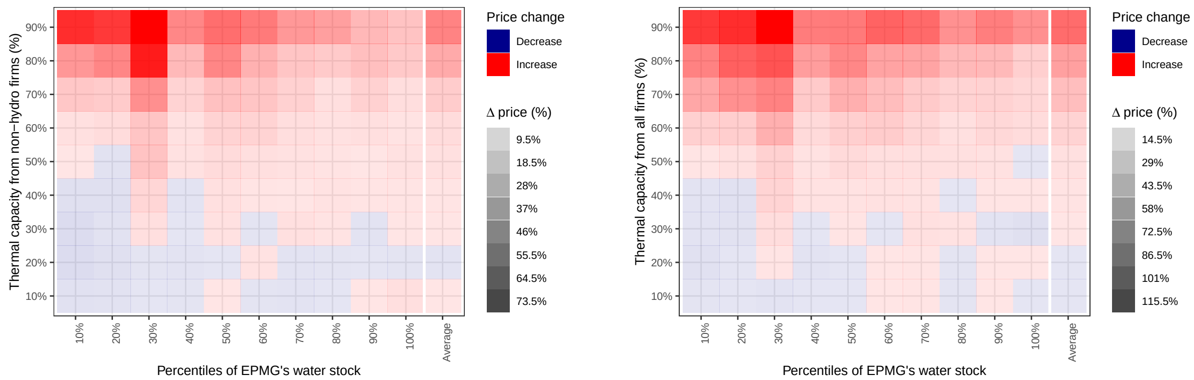


(a) Transferring κ% from non-hydro firms

(b) Transferring κ% from all firms

Notes: The figure compare baseline prices with counterfactual market prices as we endow the market leading firm with greater fractions of its competitors' thermal capacities (y-axis) for varying scarcity levels (x-axis). We proxy scarcity by grouping markets based on the deciles of the leader's water inflow (stock): each cell reports the average price difference between the simulated market and the simulated baseline price with different shades of red and blue colors based on the sign and magnitude of the change. The left (right) panels transfers capacity to EPMG from non-hydro (all) competitors. The average market price is approximately 150,000 COP/MWh. 2,900 COP $\simeq$ 1 US\$.

Figure G4: Percentage price changes due to a capacity transfer to the leading firm—only markets when EPMG has the largest water stock



(a) Transferring κ% from all non-hydro firms

(b) Transferring κ% from all firms

Notes: The figure shows counterfactual percentage price differences as the market leader is endowed with a fraction of competitors' thermal capacity (y-axis) across scarcity levels (x-axis), proxied by deciles of its water stock. Each cell reports the average relative difference between counterfactual and baseline prices, $\frac{1}{H\cdot T}\sum_{h,t}\frac{p_{ht}^{\kappa\%}-p_{ht}^{\text{base}}}{p_{ht}^{\text{base}}}$, with color indicating sign and magnitude. Superscripts κ% and base denote counterfactual and baseline simulated prices, respectively. Left (right) panels transfer capacity from fringe (all) firms. Unlike Figure 8, which reports absolute price differences, this figure shows percentage changes. The dataset includes only markets in which EPMG has the largest water stock (80%).

References in the Online Appendix

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