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

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Abstract

We show that when firms operate multiple technologies with different marginal costs and capacities, transferring high-cost capacity to the largest, most-efficient firm can lower prices as all firms expand supply to gain (leader) or defend (rivals) market shares. However, large transfers are anticompetitive, as substantial capacity differences make undercutting competitors unprofitable. Exploiting renewable intermittencies in Colombia's electricity market, where firms are technology-diversified, we consistently find that prices are U-shaped in concentration. Counterfactuals reveal how technologies' capacity and efficiency shape firms' market power: prices drop 10% when doubling the leader's high-cost capacity but rise for larger transfers.

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

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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, production 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, from fossil fuel to renewable plants. Understanding how technology-driven misallocation shapes market power in the energy sector is crucial for designing policies that enhance efficiency and improve consumer welfare.

How do firms with diversified technology portfolios compete? When firms rely on a single technology, competition is limited, as only the most efficient firm can undercut its rivals. In contrast, diversification fosters competition by ensuring firms face rivals with similar marginal costs (Fabra and Llobet, 2024). However, promoting diversification is not straightforward, as investments in new technologies often have long-term horizons and may depend on firms' prior knowledge and expertise (Elliott, 2024, Fioretti *et al.*, 2025). One potential strategy that avoids the need for new capacity investments is for regulators to permit mergers between firms with different technologies. Yet, this approach also increases concentration, which is widely believed to raise prices. Then, this reasoning opens the question: Does diversified production offset concentration?

Our contribution is to demonstrate 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, challenging conventional expectations. We test these predictions in the context of the Colombian wholesale electricity market, where firms rely on both hydropower and fossil fuel sources. The frequent variation in hydropower availability, influenced by natural climatic conditions, offers a unique quasi-experimental setting for this analysis. We then use our model to quantify the price effects of concentration and diversification by simulating capacity transfers between firms. An advantage of our approach is that it avoids relying on mergers to alter firms' capacities, thus mitigating endogeneity concerns common in merger studies.

Examining concentration in markets with technology-diversified firms reveals novel aspects of competition. Our empirical evidence suggests a more intricate 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—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 an abundance of renewables, consistent with standard models where size amplifies market power.

To interpret these patterns, consider a market where firms operate multiple technologies, each with its own marginal cost and capacity. To maximize profits, a firm prioritizes lower-cost technologies before turning to more expensive alternatives, as all technologies produce the same good. Rather than pricing at marginal cost, firms submit supply schedules, committing portions of their capacities at different prices. Since these commitments are made before actual market demand materializes—a common feature of electricity markets—firms face uncertainty about their residual demand.

We show that 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 gain shares, while in high-demand scenarios, it prefers to withhold capacity to push the price up. We show that a transfer of high-cost capacity to the market leader from its rivals alters this tradeoff, allowing it to deploy more of its low-cost technology to compete aggressively when demand is low. At the same time, the additional high-cost capacity helps it capture a larger market share at high prices if demand turns out to be high.[1] This supply expansion triggers aggressive responses from rivals, who also expand their own supplies to defend their market shares, ultimately driving the price down.

In essence, while a "small" transfer strengthens the leader's market power by incentivizing it to reduce supply and raise prices—exploiting its rivals' weakened positions—two counteracting forces more than offset this effect. First, *diversified production* encourages the leader to deploy more capacity to undercut competitors. Second, *strategic substitution* leads competitors to expand their own supply to defend market shares. However, this result does not hold for all transfer sizes. When a transfer is "large" enough to severely constrain rivals' supply, they cannot defend their market shares aggressively. As a result, the leader can exercise market power by reducing its supply at all prices, raising the equilibrium market price, ceteris paribus. Thus, depending on the size of the transferred capacity, market prices may increase or decrease with concentration. Finally, whether a transfer is "large" or "small" depends on the relative gap in marginal costs and the capacities of the available technologies.

Thus, the impact of concentration on prices depends on two key factors: technologies' *efficiencies* and firms' *capacities*, which together create a U-shaped relationship between prices and concentration when firms use diverse technologies. This U-shape disappears when firms specialize in a single technology, even if efficiency varies across firms, as in

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

models with asymmetric firms. For instance, if a market leader has *abundant* low-cost capacity, it can freely adjust supply across demand scenarios. Reallocating capacity from less efficient rivals reduces their supply without meaningfully diversifying the leader, which continues prioritizing its cheaper resource. As a result, competition across technologies does not intensify, and without economies of scale—such as in our setting, where simulated unit transfers lack synergies—prices can only rise with concentration.

We bring this model to the data to assess the extent to which diversified production can counterbalance the effects of market 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 where we reallocate fractions of thermal capacity from competitors to the market leader. Quantitatively, we find that doubling the leader's thermal capacity can lower prices by up to 10%, particularly during droughts. However, for larger transfers, prices rise substantially, consistent with both our theoretical predictions and reduced-form results.

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 results suggest that when firms are diversified, HHI measures lose their relevance. Specifically, the monotonic relationship between HHI and prices—a key indicator of consumer welfare in energy markets where demand is typically inelastic—breaks down.

For instance, standard Cournot games preserve the monotonicity between prices and concentration because reallocating technology from one firm to another lowers prices only if the recipient is smaller than the sender, as expanding total supply requires greater symmetry among firms. Alternatively, when symmetric firms with capacity constraints set prices rather than quantities, expanding both firms' capacities lowers prices. However, 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).[4]

[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). Since electricity can be stored via dams and firms operate multiple units, our structural model accounts for dynamic considerations and externalities across generating units (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).

[4]Notably, Kreps and Scheinkman (1983) show that the Cournot equilibrium arises in a two-stage Bertrand model, where firms first choose capacity before competing on prices.

Our approach integrates both the supply reductions typical of Cournot competition and 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 show that prices can rise or fall with concentration, explaining the empirical patterns observed in Colombia while ensuring a unique equilibrium.[5] 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, as firms competing à la Cournot may have incentives to withhold renewable capacity to raise market prices.[6] Consider Acemoglu *et al.* (2016), where diversified firms excercise their market power only through their high-cost thermal capacity, with their renewable supply always dispatched in full. Intuitively, transferring low-cost resources from large to small firms is pro-competitive, as it reduces size asymmetries across firms. More recently, Fabra and Llobet (2024) show that technology diversification can intensify competition relative to specialization by comparing equilibrium prices in two industry structures within a multi-unit auction contest: a specialized industry, with two firms each operating a different technology, and a diversified one, in which both firms are identically diversified owning the same capacities of each technology. They find that prices are weakly lower in the latter, as firms in this structure compete more aggressively at each price level by owning each technology.

Our results have implications for the green transition in electricity markets. In Colombia, the legacy of dam ownership from the 1990s privatizations has concentrated adjacent dams under single firms, clustering ownership across geographies. Given the current energy mix, which includes little solar or wind power, a more geographically diverse allocation of dams would have allowed firms to hedge against droughts using faraway dams rather than thermal units of the same firm, reducing emissions. Such diversification could even ease the energy transition by mitigating the intermittency of renewables without requiring additional policies or battery investments (e.g., Gowrisankaran *et al.*, 2016, Schmalensee, 2019, Vehviläinen, 2021, Butters *et al.*, 2021, Andrés-Cerezo

[5] 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 theoretical framework has been applied in industries such as energy markets (Green and Newbery, 1992), financial markets (Hortaçsu *et al.*, 2018), government procurement contracts (Delgado and Moreno, 2004), management consulting, airline pricing and reservations (Vives, 2011), firm taxation (Ruddell *et al.*, 2017), and transportation networks (Holmberg and Philpott, 2015). It also relates to nonlinear pricing, as unlike Cournot and Bertrand models, it allows for nonlinear supply schedules.

[6] 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.

and Fabra, 2023). As Colombia expands its renewable energy sources, a more suitable allocation across firms and space could further 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 impact of technology ownership—both new and old—on pricing. Our findings raise important 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 instance, in Colombia, firms are limited to holding no more than 25% of the total installed capacity to prevent market power abuses. Nevertheless, this cap may also constrain the benefits of diversified production. While determining the optimal threshold is beyond this paper's scope, ignoring these factors could lead to inefficient firm size and technology diversification, particularly in hydropower generation, where a dam may be far larger than other types of generation.

Outside the energy literature, several papers have empirically examined how capacity constraints affect oligopoly outcomes and market power when firms operate a single technology (e.g., Bresnahan and Suslow, 1989, Staiger and Wolak, 1992, Froeb *et al.*, 2003). We contribute to this literature by allowing firms to manage a portfolio of technologies with capacity constraints, whereas the related market power literature typically accounts for such constraints through diseconomies of scale or relies on cost-minimization due to data limitations that prevent microfounding cost curves with data on technologies.[7]

Building on this perspective, the paper shows that technology diversification creates strategic complementarities within and across firms. Our findings have two key implications. First, for research: standard production function estimation methods capture only a firm's average costs, not the marginal cost of each technology it employs if the latter is unobserved, making counterfactual analysis like ours impossible (e.g., Olley and Pakes, 1996). Second, for policy: our results inform antitrust regulation on merger-related divestitures, showing that such policies could unintentionally raise prices if they reduce technology diversification (Compte *et al.*, 2002, Friberg and Romahn, 2015).[8]

More broadly, we believe that our framework applies to other industries where firms face capacity constraints and uncertain demand, as already an old literature in the 1950s investigated the implication for firms supplies and market outcomes of allowing firms to have heterogeneous technologies (Robinson, 1953, Sraffa, 1960). First, we argue that

[7] In such models, concentration generally raises markups (De Loecker *et al.*, 2020, Benkard *et al.*, 2021), preventing the observation of the mechanism we identify in this paper.

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

similar trade-offs to those highlighted in this paper also arise for multi-product firms with diversified production technologies, as our equilibrium concept naturally extends to differentiated products (Klemperer and Meyer, 1989, page 1267-1270). Second, this equilibrium concept was recently applied in macroeconomics, where firms commit to supply decisions before multiple uncertainties (e.g., inflation) materialize (Flynn *et al.*, 2023), drawing parallels to other industries. For instance, in alumina manufacturing, firms operate across multiple technologies (Collard-Wexler and De Loecker, 2015), while in labor markets, they balance workforce diversification in skills, education, and employment size (e.g., Bonhomme *et al.*, 2019, Choné and Kramarz, 2024).

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 scarcity and abundance periods. 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 the our primary contributions.

2 The Colombian Wholesale Energy Market

2.1 Generation

Colombia boasts a daily energy production of approximately 170 GWh.[9] 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 generator 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 generation (approximately 20% of total production) and run-of-river (5%). However,

[9]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.

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). During dry spells, hydropower production decreases, and thermal generation compensates for water scarcity.[10] In contrast, run-of-river energy lacks storage capabilities, limiting its ability to offset hydropower shortages.

Thermal generation typically incurs higher marginal costs than hydropower. Figure 2 highlights that wholesale energy prices more than double during scarcity periods.[11] 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 generator. 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 generator and hour and one price bid per generator every day.[12] Quantity bids state the maximum amount (MWh) a generator is willing to produce in a given hour, while price bids indicate the lowest price (COP/MW) acceptable for production. Each generator 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 generator.

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* 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

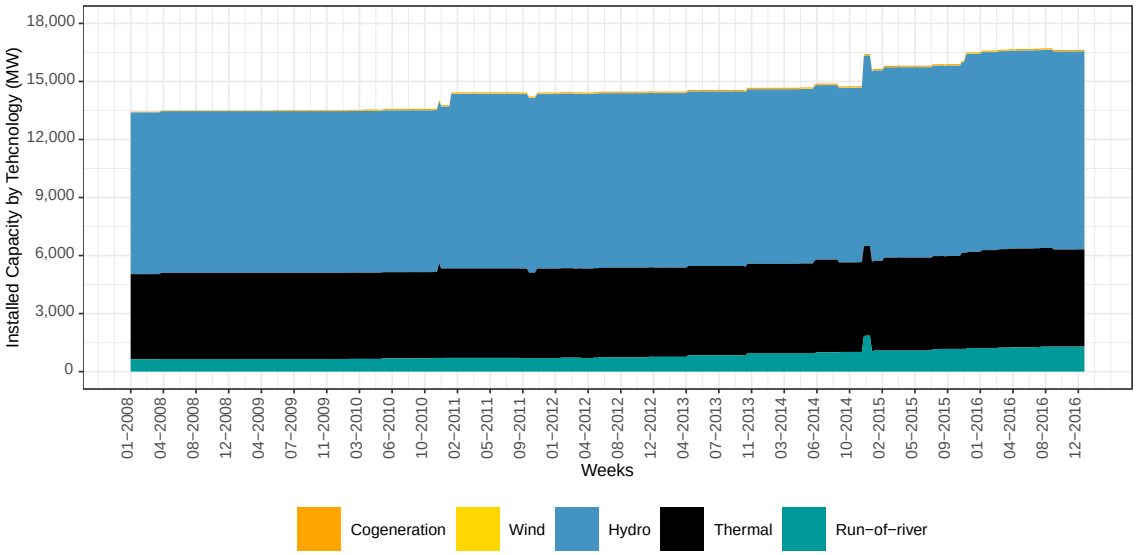
[10] Data reveals a correlation between thermal production and minimum rainfall at Colombian dams of -0.32 (p-value ≤ 0.01) and 0.27 (p-value ≤ 0.01) for hydropower generation.

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

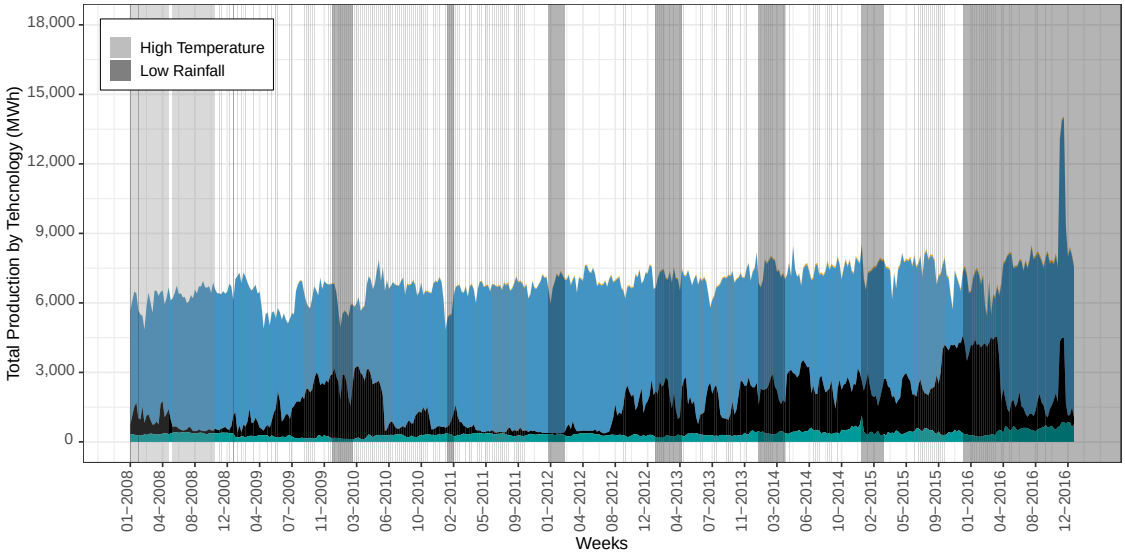
[12] Participation in the spot market is mandatory for large units with capacity over 20MW.

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

(a) Total installed capacity by technology



(b) Total weekly production by technology



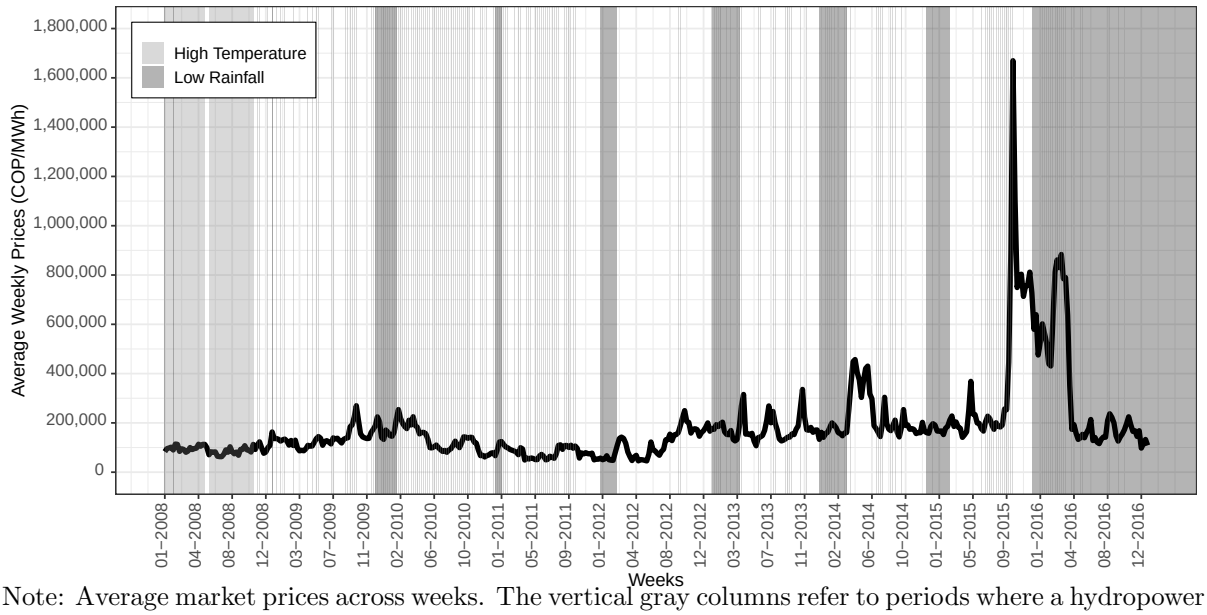
Note: The figure illustrates the total installed capacity (top panel) and production volumes (bottom) by technology. The vertical bars in Panel (b) refer to periods where a hydropower generator experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average.

bid of the marginal generator, with all dispatched units paid the same price.[13]

Forward market. The forward market comprises bilateral contracts between pairs of agents. These contracts allow agents to decide the financial position of each generator weeks in advance, serving to hedge against uncertainty in spot market prices. In our

[13]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 generator experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average. 2,900 COP $\simeq$ 1 US$.

dataset, we observe each generator'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 generator, 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.[14]

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.[15] ENSO forecasts, published on the 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.

[14]For each generator, 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*.

[15]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.

This dataset is complemented with 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 Firm's Supply When Capacity Changes

We investigate units' reactions to forthcoming inflows through:

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

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).[16] 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 either a standard deviation higher or lower than its long-run average (for the period 2008-2016), and zero otherwise, respectively. 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 the dams owned by i. The forecasting approach is explained below.[17]

$\mathbf{x}_{ij,t-1}$ 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 generator-by-month and firm-by-year levels ($\mu_{j,m(t)}$). Macro unobservables, such as variations in demand, are captured through fixed effects at the week-by-year (τ_y) and hour levels (τ_h). The standard errors are clustered by generator, month, and year.[18]

[16] 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.

[17] 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 (1) for each l. We perform this analysis in Section C.2 and find similar results.

[18] 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 neighboring dams independent (Lloyd, 1963). Moreover, spatial distance has no meaning for thermal units. Hence, we do not pursue spatial clustering in this analysis.

Forecasting approach. We construct inflow forecasts for each hydropower generator employing a flexible autoregressive distributed-lag (ARDL) model (Pesaran and Shin, 1995). In essence, these forecasts are derived through OLS regressions of a generator'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. The forecasting technique is discussed in detail in Appendix B, which also presents goodness of fit statistics.

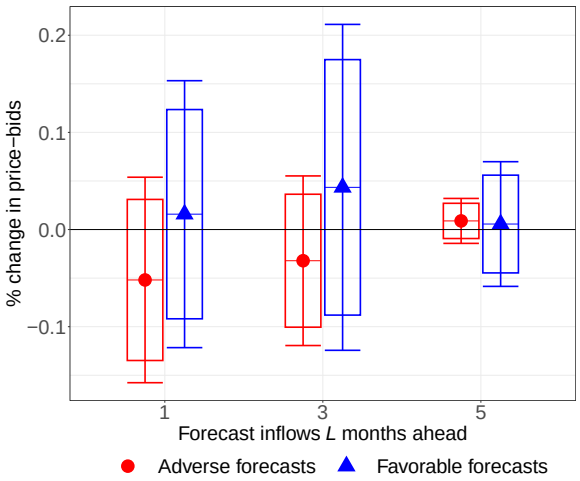
Exclusion restriction. Identification of $\{\beta_l^{low}, \beta_l^{high}\}_l$ relies on the assumption that a firm's current supply schedule does not *directly* depend on lagged variables used for forecasting "adverse$_{ij,t+l}$" and "favorable$_{ij,t+l}$." To the extent that the (lagged) water stock 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. Appendix C.1 discusses the information content of our inflow forecasts by showing that units' responses to forecast errors—the observed inflow minus the forecasted inflow—are insignificant.

Results: hydro. 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).

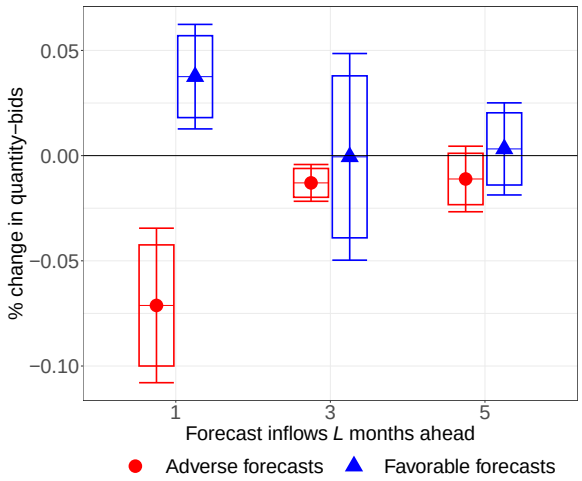
Results: "sibling" thermal units. shows sibling thermal units increasing supply schedules before favorable events (blue triangles) and decreasing them before adverse ones (red circles). Adjustment happen primarily through price bids because these units are not operational at all times due to high marginal costs and lack the flexibly to vary production across hourly markets. The analysis indicates that they respond to extreme events earlier than hydropower units, likely because this analysis focuses on extreme firm-level forecasts, which may be less severe than the generator-level forecasts used in the previous paragraph.

Figure 3: Responses to inflow forecasts

Top panel: Responses of dams to own inflow forecasts

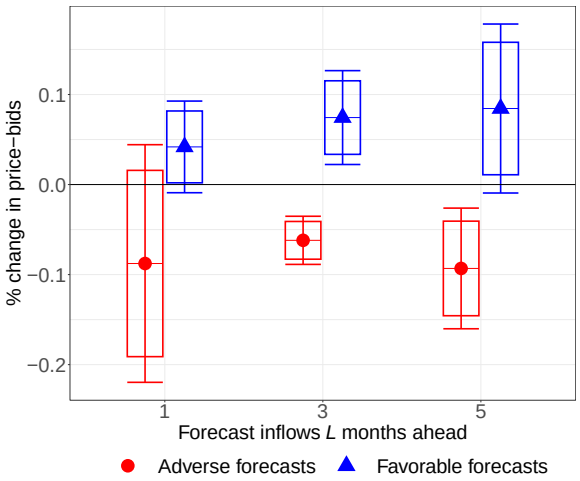


(a) Price bids

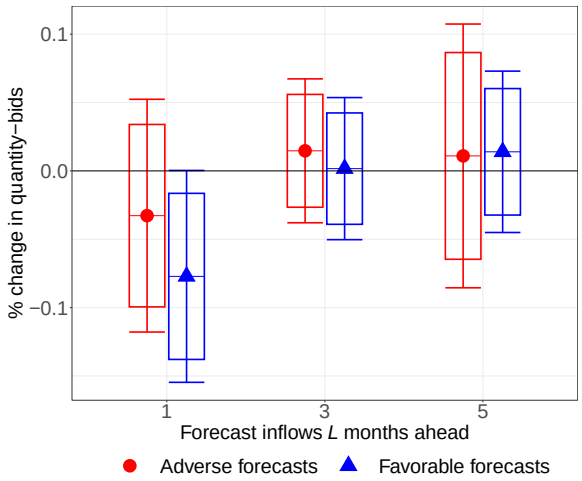


(b) Quantity bids

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 demonstrates that firms increase their thermal supply in anticipation of a drought. This finding raises the question of whether providing firms with greater thermal capacity could help mitigate price hikes during scarcity, even if it leads to increased industry concentration. To explore this, we leverage the exogenous occurrence of droughts across firms of varying sizes as follows. From the previous section, let

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

which takes a value of 1, 0, and -1 for adverse, moderate, and favorable l-month ahead forecasts, respectively— "adverse$_{i,t+l}$" and "favorable$_{i,t+l}$" are defined in Section 3.1. The change in industry concentration due to these forecasts can be measured as:

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

The variable Δ_{t+l} measures the expected change in a capacity-based HHI due to the l-month inflow forecasts, weighting the net adverse inflow forecast by each firm's squared capacity share. 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]

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

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 across t given h—HHI, total water stock, hourly forward contracts, demand, and price—and month-by-hour and year fixed effects (τ_{mhy}).[21]

Results ($\hat{\gamma}_1$). Figure 4 presents estimates of a version of (2), which allows for different slopes for γ_1 and intercepts for positive and negative Δ_{t+3} in the style of a piece-wise linear regression. The 95% confidence intervals for $\hat{\gamma}_1$ are $[-0.817, -0.682]$ and $[0.301, 0.465]$ for the left and right slopes, respectively. Appendix Figure C4 shows a similar result without controlling for $\mathbf{x}_{t-1}$ in (2), indicating that the (forecast) treatment is not solely driven by covariates. An analogous result is in Appendix C.3, which studies non-linearities by including a squared Δ_{t+3} term in (2). The estimated coefficient for Δ^2_{t+3} is positive and

[19] Unlike HHI based on market shares, capacity-based HHI does not introduce simultaneity bias since it is not a function of spot prices. For this reason, we lag capacity shares when computing Δ and HHI. Appendix C.3 shows consistent results whether capacity shares include only thermal capacity, which do not vary over time, or both thermal and (lagged) hydro, which instead vary.

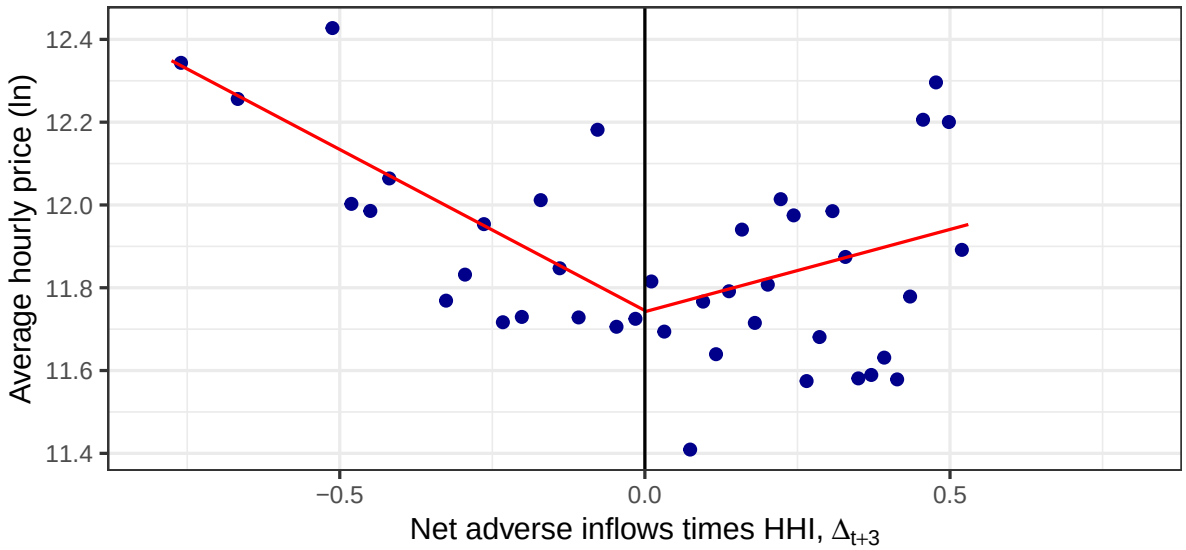
[20] We find qualitatively similar results for forecast horizons $l \neq 3$ (unreported for space considerations).

[21] Although our goal is to present an empirical fact, a causal interpretation is possible if ε_{th} is uncorrelated with forecasts and capacities. Note that the market-clearing price is determined by the difference between market demand—which does not depend on forecasts and lagged capacities (in particular, the thermal capacities are fixed)—and the horizontal sum of firms' supply functions from (1). Thus, a causal interpretation relies on the exogeneity of forecasts and capacities in (1), as discussed in Section 3.1.

significant, indicating higher prices at the lowest and highest concentration levels.

Results (operating costs). In addition, $\hat{\gamma}_0$, 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 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 documented for other intermittent renewables such as wind, where operating costs do not exhibit systematic co-movement with wind capacity (Petersen *et al.*, 2024).

Figure 4: How technology diversification and concentration affect market prices



Notes: Bin scatter plot of $ln(p_{ht})$ on Δ_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_{t+3}.

Discussion. Our analysis indicates that diversification can offset the adverse effects of concentration. Greater capacity to the most efficient firm in a Bertrand setting would drive prices down, as the most efficient firm undercuts its competitors (as for $\Delta_{t+3} < 0$). However, for large concentration levels such as for $\Delta_{t+3} > 0$ in Figure 4, market prices rise with concentration as in Cournot competition. The next section develops a competition model for technology-diversified firms, shedding light on the mechanisms behind these findings.

4 A Competition Model With Diversified Firms

In most industries, the largest *and* most efficient firm typically assumes the role of market leader. We demonstrate that when this leadership primarily stems from its superior efficiency relative to competitors, increased industry concentration of the leader can lower prices. In essence, the leader's efficiency enables it to produce more than others at any given price. When it does so, its capacity constraint can become binding, and reallocating inefficient capacities from competitors may allow the leader to expand production. Competitors will respond aggressively to avoid losing market shares. Conversely, if the leader does not face binding capacity constraints, greater concentration invariably amplifies its market power, resulting in higher prices.

The firm's problem. Consider an oligopolistic market where firms sell a homogeneous good (electricity). They face an inelastic demand, $D(\epsilon)$ that is random with ϵ as an exogenous 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), observe that suppose firm i could hold up its supply decision. Given a strategy profile of other firms and the realization ϵ, firm i's optimal ex post profit, if market clears at p, is

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

where $C_i(q)$ denotes firm i's cost of supplying quantity q. By maximizing (4), one can find a quantity-price pair $(q(\epsilon), p^*(\epsilon))$ with the most-preferred market-clearing price $p^*(\epsilon)$ that maximizes i's ex post profit π_i as soon as i produces the quantity $q(\epsilon) = D_i^R(p^*(\epsilon), \epsilon)$. As ϵ varies, the set of quantity-price pairs maximizing (4) define an ex post optimal supply schedule. The supply function equilibrium is the fixed point when each firm i commits to this ex post optimal supply schedule, taking other firms' supply schedules as given. Formally, the Supply Function Equilibrium of this game is defined below.

Definition 4.1 ***Supply Function Equilibrium (SFE).*** *An SFE is an N-tuple of*

[22] Demand is a random variable because firms only receive demand forecasts in the day-ahead market, lack information about bilateral forward contracts of other firms, and submit a single daily bid per plant despite hourly uncertainty. These factors result in substantial variation in hourly market supply, whose standard deviation is as high as 72% of the hourly demand.

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.[23]

Proposition 1 ***Markup.*** *When differentiability holds at* p*, firm* i*'s markup satisfies*

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

where $s_i(p)$ *is* i*'s market share, and* η *is its price elasticity of demand. When* S_{-i}'' *is fixed, 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 $\eta \equiv \frac{p}{D} / \frac{dp}{dD} = \frac{p}{\sum_l S_l(p)} \frac{d}{dp} \sum_l S_l(p)$. 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—a numerical example in Section 4.1 provides a detailed illustration. Consider firm i as the market leader due to its larger capacity and superior technology. Assume further that there exists a price p^0 at which firm i's supply is constrained, such that it prefers to produce a larger quantity S_i^0 rather than the $S_i(p^0)$ from (5). This situation may arise for several reasons. First, the firm might face a direct capacity constraint at $S_i(p^0)$. Second, the capacity constraint could bind at a higher price $p^1 > p^0$, at which price, i may prefer to supply more than its capacity if $D^R(p^1)$ is sufficiently high, effectively limiting its output also for all prices p such that $p < p^1$. Consider a "small" capacity transfer to firm i from its competitors, increasing industry concentration. The first-order effect is to relax i's constraint, expanding $S_i(p^0)$ to S_i^0 around p^0. As a result, the residual demand faced by i's competitors shrinks.

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, $(1 - S_i'/D_i')$ must decrease since η does not depend on firm i,

[23] The piece-wise smoothness conditions are satisfied in the equilibrium analysis in Section 4.1. See Lemma A.4.

meaning that $S'_{-i}(= -D'_i)$ must increase. In other words, i's competitors will raise their supplies at p^0—i.e., $S'_j(p^0)\,\forall j \neq i$—to undercut firm i and prevent losing market share after the transfer.

Thus, heuristically, *strategic complementarity* implies that both i and its competitors will increase their production rates near p^0. As all firms expand supply, the equilibrium price falls, explaining the price drop in the negative orthant of Figure 4, despite the higher 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 full proof is in Appendix A.

4.1 Analytical Solution

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 $0 \leq c^l < c^h < c^f < \infty$. Firm i's *technology portfolio* $K_i = (K_i^l, K_i^h, K_i^f)$ details i's capacity of each technology. Hence, $C_i = \sum_{\tau\in\{l,h,f\}} c^\tau \cdot S_i^\tau(p)$ depends on its non-decreasing, right-continuous technology-specific supply S_i^τ at price p with $0 \leq S_i^\tau(p) \leq K_i^\tau$. The firm's total supply is $S_i(p) = \sum_\tau S_i^\tau(p)$.

We consider a market with two strategic firms, Firm 1 and Firm 2, and they do not possess fringe capacity, i.e. $K_1^f = K_2^f = 0$. The remaining $N-2$ firms belong to the *non-strategic fringe* who only possess fringe capacity. Their portfolio 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 fringes, or the highest possible demand is bounded so that the market always clears.[24] As a tie-breaking rule, at any price p, the demand is served first by the supply from strategic firms, then by the non-strategic fringes if the former supply is insufficient.[25]

Baseline scenario. For the following numerical illustration, none of the $N > 1$ firms is diversified at baseline. We consider the capacities, or the technology portfolios are

[24]Fringe firms ensure that the residual demands for each strategic firms decerases in p. A price cap can serve the same role and is commonly used in the literature, or we can assume that the market demand decreases in p, as in Klemperer and Meyer (1989).

[25]This rule is WLOG, since a strategic firm can, in principle, undercut the fringe by an infinitesimal price reduction.

$K_1 = (K_1^l, 0, 0)$ 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*.[26] We numerically illustrate the equilibrium outcomes in this market in the left panels (a and c) of Figure 5, which refer to the case of abundance and scarcity of the low-cost technology K_1^l, respectively. The cost curves are in red and blue dotted lines for Firm 1 and Firm 2, respectively. Under abundance (Panel a), $K_1^l = 9$ but only $K_1^l = 5$ under scarcity (Panel c), while the other primitives are constant across scenarios at $c^l = 0$, $c^h = 1$, $c^f = 2$, and $K_2^h = 4$. In each panel, the solid red line is Firm 1's supply, $S_1(p)$, while its residual demand, $D_1^R(p) = D - \sum_{j>1}^N S_j(p)$, is in black. Without loss of generality, we fix market demand at 6 (gray line).

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 non-zero 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 $\forall\, p^0 \in [c^h, c^f]$, 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.

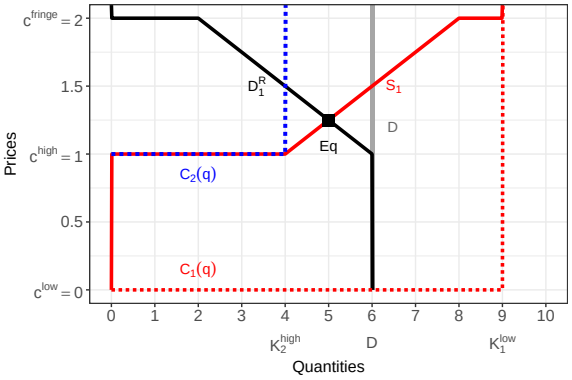
Because of strategic complementarities, Firm 2's supply is less aggressive in (c) than in (a), as shown in Appendix Figure A1, which plots Firm 2's supply across all scenarios. Therefore, since both firms supply more in (a) than in (c), but market demand is constant, the market clearing price is strictly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

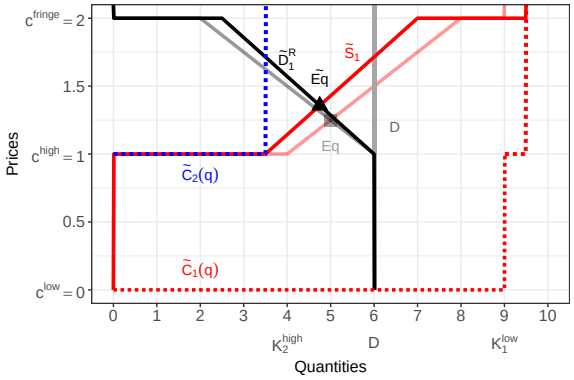
[26] At baseline Firms 1 and 2 can be viewed as owning a dam and a fossil-fuel plant, respectively.

Figure 5: Equilibrium before and after diversifying Firm 1

Top panel: Abundance of low-cost technology

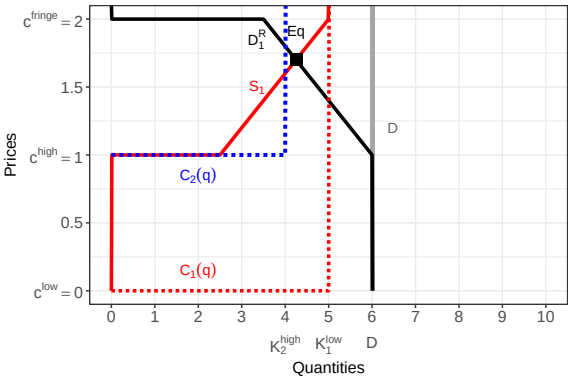


(a) Before the transfer
$K_1 = (9, 0, 0)$ & $K_2 = (0, 4, 0)$

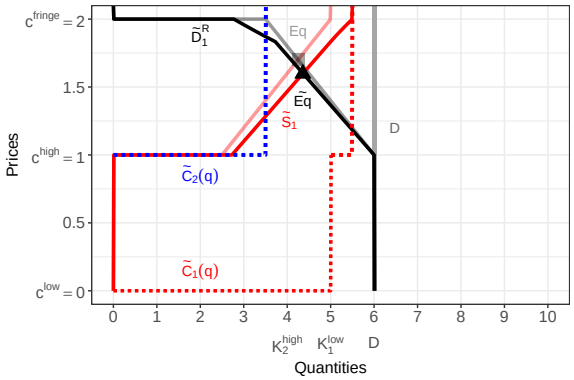


(b) After the transfer
$\tilde{K}_1 = (9, 0.5, 0)$ & $\tilde{K}_2 = (0, 3.5, 0)$

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 symbols with a $\sim$ denote post-transfer equilibrium variables. Each subcaption details the technology profile of each firm as $K_i = (K_i^l, K_i^h, K_i^f)$. Market demand is constant at 6 (gray solid line), and the cost parameters are $c^l = 0$, $c^h = 1$, and $c^f = 2$.

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.

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 $\gamma_0 = 0$ 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* $j \geq 3$. *Then, assuming* $K_2^h \geq \delta$,

1. *there exists a unique SFE for every* $\delta \geq 0$
2. *moreover, 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* $K_1^l > \frac{c^f - c^l}{c^f - c^h} K_2^h$ *(e.g., 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 (e.g., scarcity scenario).*

Proof. See Appendix A.2.□

The assumption $K_2^h \geq \delta$ avoids 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 marginal cost of the two technologies ($\frac{c^f - c^l}{c^f - c^h}$), a δ-transfer from Firm 2 to Firm 1 always leads to higher (lower) prices, corresponding to the abundance (scarcity) scenario in the top (bottom) panels of Figure 5. Under scarcity, point 2.b requires that after 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, ample high-cost capacity relaxes Firm 1's constraint in scarcity, so transfers from Firm 2 will only incentivize Firm 1 to cut supply to raise prices if it already has plenty, further highlighting the *capacity-efficiency* tradeoff in diversified firms.

Concentration & market power. Thus, Firm 1's market power stems from its larger *capacity* relative to competitors in point 2.a of Proposition 2. At point 2.b, it is driven by its *efficiency*, demonstrating how these two components of market power differently impact market-clearing prices after capacity transfers.

[27] This restriction holds in Colombia, as firms with dams have very little thermal capacity. For instance, only $\approx 20\%$ of the market leader's capacity is thermal, as shown in Appendix Figure F1.

Now consider a larger increase in δ. For example, what would the price be if Firm 1 were to acquire all of Firm 2's capacity? The newly consolidated firm would price all its units at c^f, undercutting fringe firms. Thus, while prices decrease for small reallocations, they increase for larger ones, resulting in the *U-shaped* relationship between concentration and prices depicted 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 maximized when firms are symmetric in their ownership of technologies:

Proposition 3 ***Symmetric SFE.*** *When* $K_1 = (K^h, K^l + \delta, 0)$ $K_2 = (K^h, K^l - \delta, 0)$, *there exists a unique SFE for every* δ *such that* $K_i \in \mathbb{R}^3_{\geq 0}$ *for all* i. *The equilibrium market supply at the transfer* δ *satisfies* $S^{\delta_1} > S^{\delta_2}$ *for* $0 \leq \delta_1 < \delta_2$.

Proof. See Section A.3. □

The proposition states that before the transfer, both firms submit identical supplies. After the transfer, 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 apply this model to the data to test if the *capacity* and *efficiency* channels replicate the price-concentration patterns observed in Section 3.2.

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.

Institutions. As in the previous section, the system operator crosses the supply schedules, $S_{iht}(p_{ht}) = \sum_{j=1}^{J_i} \mathbb{1}_{[b_{ijt} \leq p_{ht}]} q_{ijht}$—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 $p_{ht}(\epsilon)$,

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

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,

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

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, $S^H_{iht}(p^*_{ht}) = \sum_{j \in \mathcal{H}_i} \mathbb{1}_{[b_{ijt} \leq p^*_{ht}]}\, q_{ijht}$ 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 correlation across firms' water stocks – after accounting for seasons and lagged inflows – is less than 0.2.

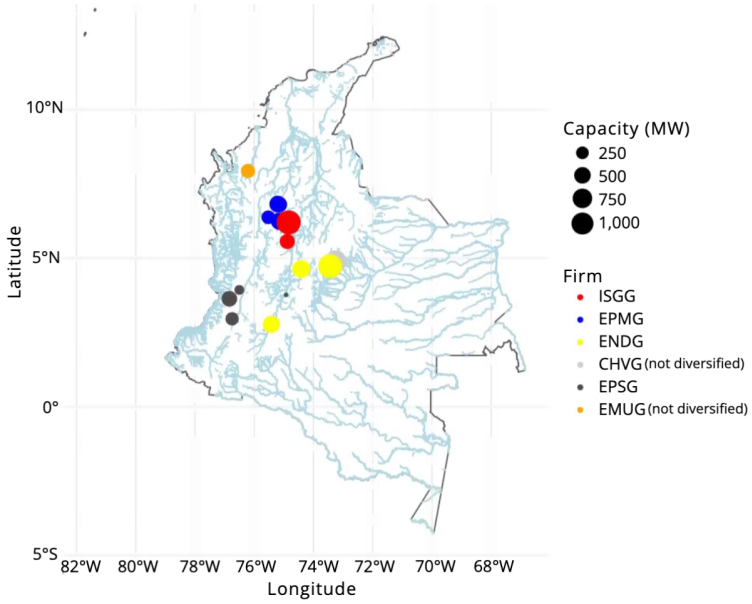
Objective function. Since diversified firms take into account future inflows, its supply schedule will maximize the sum of its current and future profits,

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

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

[28] Scarcity prices are updated monthly and computed as a heat rate times a gas/fuel index plus other variable costs, with scarcity quantities, $\overline{q}_{ijt}$, determined through yearly auctions (Cramton and Stoft, 2007, Cramton *et al.*, 2013).

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.

becomes,

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

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 $f(\cdot|\mathbf{\Omega}_t)$ following (8). The inputs in $\mathbf{\Omega}_t$ are the water stocks, the realized hydropower productions, and the water inflows on day 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 out version of the first-order conditions because the actual supply schedules are characterized by step functions, which makes the analysis intractable (Wolak, 2007, Kastl, 2011, Reguant, 2014). The smoothing procedure is in Appendix E.

For clarity, we omit the expectation with respect to ϵ and the firm and unit indices (ij) of the technology τ_{ij}, where $\tau_{ij} = H$ if j is a dam and $\tau_{ij} = T$ if it is a thermal unit. The first-order conditions (FOCs) are then given by:

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

Although this FOC cannot be rearranged as in (5), with the markup as a function of elasticities, it recreates a similar trade-off between *capacity* and *efficiency* as that depicted in Section 4. Let us describe each term first.

The first term in parenthesis in the first row of (10) is the marginal revenue in the spot market. Market power lowers marginal revenues below market prices if $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$. Conversely, if the firm is a price taker ($\frac{\partial p_{ht}}{\partial q_{ijht}} = 0$), it is paid precisely p_{ht} on its marginal unit. This *capacity channel* prompts firm i to reduce q_{ijht} for all its technologies when market power increases. The second term in the same line addresses how the forward contract position and the reliability payment system influence bidding in the spot market.

Market power affects equilibrium outcomes also through an *efficiency channel*. The actual marginal cost is the sum of its operating costs, $\{c^H, c^T\}$, in line two, and its intertemporal opportunity cost, in the remaining two lines of (10), which endogeneizes the firm's capacity constraint through a tradeoff between current and future production. By increasing the current hydro supply, this tradeoff intensifies as it decreases the firm's future water stock. Hence, the integral in the third row of (10) is non-positive. Since c^τ is constant over time, this intertemporal opportunity cost contracts or expands i's cost curve for different realizations of $\mathbf{\Omega}_t$ setting the firm under scarcity when $\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}} < 0$, or abundance when $\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}} = 0$.

Unit j adjusts its response to scarcity based on its market power. In the absence of market power, when $\frac{\partial p_{ht}}{\partial q_{ijht}} = 0$, the firm experiences a decrease in its future profits that is equal to the change in its water stock, $\frac{\partial S^H_{iht}}{\partial q_{ijht}} > 0$, times the expected change in future profits—the integral in row three. The introduction of market power, denoted as $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$, counteracts this loss, as the firm recognizes that increasing q_{ijht} marginally decreases p_{ht}, resulting in a smaller portion of its hydro supply schedule being dispatched

in equilibrium as $\frac{\partial S^H_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} < 0$. Therefore, the two terms in parentheses in the third row of (11) exert opposing influences on marginal costs ahead of a scarcity.

Note also that thermal units cannot directly impact the firm's hydropower supply (i.e., $\frac{\partial S^H_{iht}}{\partial q_{ijht}} = 0$ for j being thermal). The net effect is negative for them, prompting a firm to raise its thermal supply ahead of a drought to preserve its hydro capacity. This result is consistent with results in the bottom panel of Figure 3, where the market leading firm expands its supply after receiving thermal capacity from its smaller rival.

The latter observation suggests that having more thermal units decreases the marginal benefit of holding water because thermal capacity reduces future water requirements, diminishing the value of holding water in the current period.We formalize this observation in Proposition A.1 in Appendix A.4, which demonstrates, through the lens of our model, that the marginal benefit of holding water decreases with a firm's thermal capacity. [29] This effect is stronger under scarcity, when dams are constrained, which is in line with the theoretical result in Section 4.

Finally, the last line of (10) considers how a change in a competitor's hydropower generator impacts $\mathbf{w}_t$ and, thus, i's expected profits through the market clearing ($\frac{\partial S^H_{kht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \leq 0$). Because this channel does not affect firm i's thermal and hydro units differently, it does not shed light on the implications of diversified technologies, on which this paper focuses.

5.1.1 Capacity and Efficiency Channels in the Data

Combining the *capacity* and *efficiency channels* described above, Figure 7 illustrates the relationship between market prices (y-axis) and the slope of a firm's residual demand (x-axis). This slope, given by $\frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, lies between 0 and 1 by construction.[30] Specifically, a slope of 0 indicates the firm is a price taker in the corresponding market-hour combination, while a slope of 1 represents a vertical curve. The figure is a bin scatter plot, summarizing the large variation across hourly markets and units owned by a firm into 100 bins per firm. Each dot represents the average price faced in markets where firm i's residual demand slope falls within that bin.[31]

By examining variation in market power driven by differences in firms' technology portfolios under scarcity as in Figure 4, the figure reveals a U-shaped relationship between

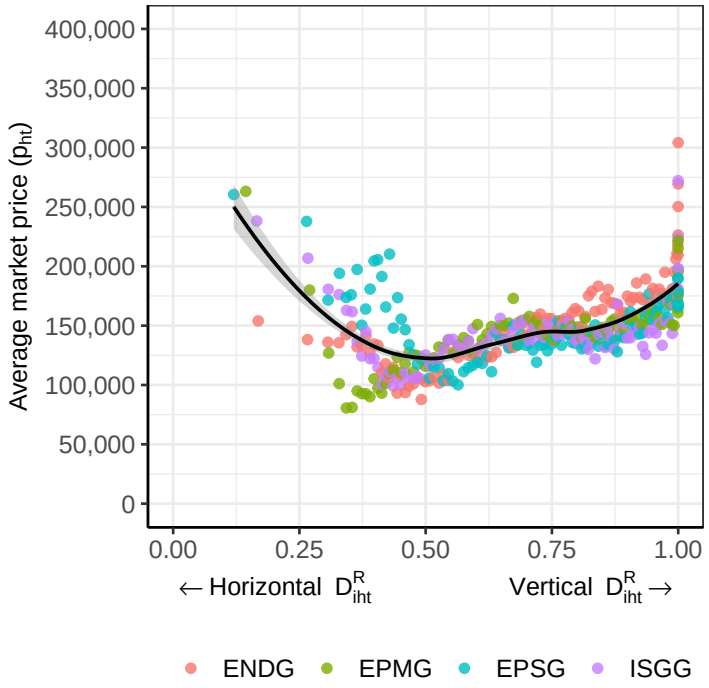
[29] See the appendix section for a formal proof.

[30] Note that this slope differs from the demand slope in a Cournot game, where only the second term matters. In supply function competition, a firm's quantity bid affects prices and, through market clearing, also influences competitors' supply schedules, altering firm i's residual demand. It is straightforward to verify that the slope is bounded between 0 and 1. This slope has an economic interpretation consistent with (5): applying the envelope theorem to (6) gives $\frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \propto (1 - \frac{S'_{iht}}{D^R_{iht}})^{-1}$, which drives the strategic complementarities in Proposition 1.

[31] We exclude markets where prices exceed $\bar{p}$ to avoid confounding our mechanism with firms' incentives to unilaterally raise prices when they expect prices is close to $\bar{p}$ (McRae and Wolak, 2024). Removing this restriction does not change the results qualitatively.

prices and market power, consistent with the discussion in Section 4. When market power is low, efficiency effects dominate, leading to an initial decline in market prices as demand becomes more inelastic. However, as market power increases, firms reduce production across all technologies, driving prices higher as larger firms benefit more by raising the price of the marginal unit. Interestingly, the U-shape relationship also seem to hold within firms.

Figure 7: A U-shaped relationship between prices and market power



Notes: The figure presents binned scatter plots of the market prices (y-axis) for different slopes of a firm's residual demand (x-axis), computed as $\frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, with 100 bins per firm. Only diversified firms with dams whose bids are dispatched at prices below $\bar{p}$ are considered. The black line fits the data through a spline (the 95% CI is in gray).

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, 2019), 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.

Our proposed solution approximates the value function with a low-dimensional function of the state space, denoted as $V(w) \simeq \sum_{r=1}^{R} \gamma_r \cdot B_r(w_r)$, where $B_r(w_r)$ are appropriately chosen basis functions.[32] This approach echoes the work of Sweeting (2013), who

[32]These can be basic polynomials or, as suggested by Bodéré (2023), neural networks.

introduced a nested iterative procedure. In his procedure, given an initial policy function σ detailing the optimal course of action for each generator in a market, the algorithm (i) simulates forward the static profits π_{iht} in (9) for $M > 1$ days for each potential initial value of firm i's water stock w given a discount factor β, (ii) regresses the discounted sum of the M daily profits on w to estimate the γ_r parameters of $V(w)$, and (iii) finally estimates the cost parameters in (9) given the approximated $V(w; \hat{\gamma}, B)$. The iterative process halts when the implied policy from maximizing $V(w; \hat{\gamma}, B)$, σ', is sufficiently close to the previous one. Alas, we cannot simulate forward the contribution of forward markets to current profits π_{ijht} in step (i), as we do not observe the price of forward contracts in (7), PC_{iht}. Therefore, the regression in step (ii) of the sum of forward static profits in (7) without observing forward contract prices on water stocks will not identify the γ_r coefficients, as the left-hand side is a poor proxy of discounted cumulative profits, $V(w)$—i.e., $\sum_{t=1}^{M} \beta^t \sum_h \pi_{ijht}(w) - PC_{iht}(w) \cdot QC_{iht}(w)$, where $\{PC_{iht+l}, QC_{iht+l}\}_{l=1}^{M}$ could depend on the water stock, w, as the firm may re-optimize its forward contract position with changes in w.

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

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

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^{τ} and $\beta V(\cdot)$, while all the other terms can be estimated separately. Given the linearity of the FOCs, variation in X^{τ} and $\tilde{X}^{H}$ identifies c^{τ} and the coefficient vectors $\{\gamma_r\}_{r=1}^{R}$ approximating $V(\cdot)$. We postpone the analysis of the policy function to the next section, which runs counterfactuals.

5.2.1 Estimation

Estimation requires fixing the number of coefficients, R, and the bases B_r, for approximating $V(\cdot)$. Typically, a standard spline approximation of a univariate function necessitates five bases, or knots (e.g., Stone and Koo, 1985, Durrleman and Simon, 1989). Hence, five parameters must be estimated to approximate a function in one dimension. With four firms, allowing for interactions between all the bases would require estimating 5^4 parameters, which is not feasible, given that we need to instrument them.

Our working assumption for estimation is that a firm only considers its future water stock when bidding.[33] With this assumption, the transition matrix $f(\mathbf{w}|\mathbf{\Omega}_t)$ simplifies to $f(w|\mathbf{\Omega}_t)$, and a firm's future profits, $\beta V(w)$, depend on its future water stock and its law of motion (8) through $\mathbf{\Omega}_{it}$ but on $\mathbf{w}_{-it}$ only through D^R_{iht}.

We allow the transition matrix to vary across firms, $f_i(\cdot|\mathbf{\Omega}_{it})$. We model firm-level water inflows using an ARDL model mirroring the estimation of inflow forecasts in Section 3. The unexplained portion, or model residual, informs the probability that firm i will have a certain water stock tomorrow, given the current water stock and net inflows. For each firm, we fit this data with a Type IV Pearson distribution, a commonly used distribution in hydrology. This distribution's asymmetric tails assist in exploring firms' behaviors during water-scarce and abundant periods. Appendix B outlines the estimation of the transition matrix and discusses its goodness of fit.

Under these assumptions, the moment condition is expressed as:

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

where we modeled $\beta \cdot V(w) \simeq \sum_{r=1}^{5} \gamma_r \cdot B_r(w_r)$ so that no assumption about the discount factor is needed. We assume that the marginal costs has a non-deterministic i.i.d. component, which gives rise to the error term ε_{ijht} in (12).

The estimation of $\{c^\tau\}_{\tau\in\{H,T\}}$ and $\{\gamma_r\}_{r=1}^5$ requires instruments as unobserved variation in supply and demand (e.g., an especially hot day) might be correlated with X^τ.

We construct instruments using temperatures at dam locations and global gas price fluctuations, which shift dams' capacities and the marginal costs of thermal units, respectively. These variables are interacted with month dummies to capture seasonal differences. Despite government-regulated fuel prices for the energy sector, which include reserves sold at lower rates to units, global energy prices partially pass through to domestic costs as the formulas the government use to set prices depends on global fuel prices (Abdallah *et al.*, 2019). In our data, the elasticity of electricity prices to global gas prices is 0.8, indicating substantial pass-through.[34] We also include thermal units' start-up costs, which we proxy by the ratio of lagged thermal capacity used by a firm's competitors to lagged demand, as regulations prioritize the supply of thermal units that are already on so to amortize their starting costs, and its interaction with lagged gas prices.

We also include fixed effects (FE) to account for constant differences across firms and units—in the real world, units' operating costs may differ within the hydro and thermal categories—and time-varying factors that affect equally all units of a certain technology

[33] This assumption is needed for estimation but not for identification. Appendix C.4 supports it through various exercises showing that competitors' forecasts have only second-order effects on a firm's supply schedule, which is primarily driven by the firm's own forecasts, once accounting for time fixed effects.

[34] The t-stat is 34.9 and the R^2 of the regression is 53% with month and year fixed effects.

like changes in national gas prices to electricity firms.

5.2.2 Results

We estimate (12) on daily data from January 1, 2010, to December 31, 2015. We use two-stage least squares and show the results in Table 1. We change the fixed effects used in each column. Columns (1) and (2) have fixed effects by week, while Columns (3) and (4) use daily fixed effects. Columns (2) and (4) also include month-by-technology fixed effects, in addition to fixed effects by firm, generator, and time. These adjustments help us control for seasonal factors differently affecting technologies over time.

The table has four panels. The first two panels show estimates for thermal (c^T) and hydro (c^H) marginal costs and for the five value function parameters (γ_r). The third panel indicates the fixed effects, whereas the last panel displays test statistics for the IVs.

Focusing on Columns (2) and (4), which control for seasonal variation by technology, we find that thermal marginal costs are about 140K Colombian pesos (COP) per MWh, or about the average price observed in the market between 2008 and 2016 (Figure 2) confirming that these units operate only during droughts, as Panel (b) of Figure 1 indicates. Consistently, the cost of operating hydropower is considerably lower, making this technology the inframarginal one. Because of the spline approximation, the γ_r estimates have, instead, no economic interpretation.

While direct comparison with engineering hydropower studies is not possible, as they typically report the levelized cost of hydropower—the discounted sum of investment and operational costs over a dam's lifetime—we can compare our thermal marginal cost estimates with findings from other studies. Our estimates, ranging from \$45.57 to \$70.44 per MWh (USD), account for peso-to-dollar exchange rate fluctuations during the sample period. These findings align with prior studies and engineering assessments, which place operating costs for coal-fired plants at \$20–\$40 per MWh and for gas-fired plants at \$40–\$80 per MWh (e.g., Blumsack, 2023).[35]

We present several robustness checks in the appendix. First, we show that changing the number of knots to approximate $\beta V(\cdot)$ is inconsequential. Appendix Table D1 estimates the model using four knots instead of five and finds similar results. We also find consistent results when we use a normal distribution for the transition matrix instead of a Pearson Type IV distribution either (Appendix Tables D2 and D3).

[35] As an illustration, Reguant (2014) estimates that thermal production in Spain ranged between €30-€36 per MWh in 2007, when oil and gas prices were significantly lower compared to the period under our consideration. In 2007, the average yearly oil price stood at \$72 per barrel, while from 2010 to 2015, it averaged \$84.70 per barrel, with peaks exceeding \$100 per barrel.

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. Robust standard errors. 2,900 COP $\simeq$ 1 US$.

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 a firm's objective function (9) because the first-order conditions in (10) alone are only necessary. However, solving for the supply function equilibrium of the whole game for each firm and hourly market of the six years in our sample is computationally unfeasible. Therefore, following the approach of Reguant (2014), we construct a computational model based on (9). This model numerically determines a firm's optimal response given the strategies of other firms in each hourly market, employing a mixed-linear integer programming solver.[36] In essence, we simulate the bids of the leading firm in the market (*EPMG*), while treating those of its competitor as given.[37]

The objective function below is similar to that in Proposition 1: the firm selects a supply for each hour and technology (τ)—discretized in K steps for computation reasons, $\{\mathbf{q}^{\tau}_{ht,k}\}_{h=0}^{23}$—which, given a realized residual demand (D^R_{ht}) spits out a market price. In particular, the firm solves:

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

$$s.t. \tag{13}$$

$$\text{[Market-clearing:]}\ \ \bar{D}^R_{ht}(p_{ht}) = \sum_{\tau\in\{H,T\}}\sum_{k=1}^{K}q^{\tau}_{ht,k},\ \ \forall\, h,$$

$$\text{[Constraints on residual demand steps:]}\ \ 0 \le D^R_{ht,z}(p_{ht}) \le \sum_{\tau\in\{H,T\}} cap^{\tau}_{ht}/Z,\ \ \forall\, h,z,$$

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

$$\text{[Constraints on value function steps:]}\ \ 0 \le \mathbb{E}\hat{V}_{t+1,m} \le w_{ht}/M,\ \ \forall\, h,\tau,m.$$

Here, 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 $\bar{D}^R_{ht}(p_{ht}) = \sum_{z=1}^{Z}\mathbb{1}_{[p_{ht,z}\le p_{ht}]}D^R_{ht,z}$, a step function composed of Z steps describing how EPMG's residual demand varies with p_{ht}. The cost function is equal to the cost of producing $\sum_k q^{\tau}_{ht,k}$ MWh of energy using the technology-specific marginal costs estimated in Column (4) of Table 1. The remaining 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 Section 5.2.2. We discretize the value function over M steps.[38]

[36] Not observing PC_{ht} is not a problem here because a firm's FOCs do not depend on it.

[37] We choose EPMG because it has the largest demand semi-elasticity in the period under analysis (Appendix Figure F2). 80% of its total capacity is in hydropower (Figure F1).

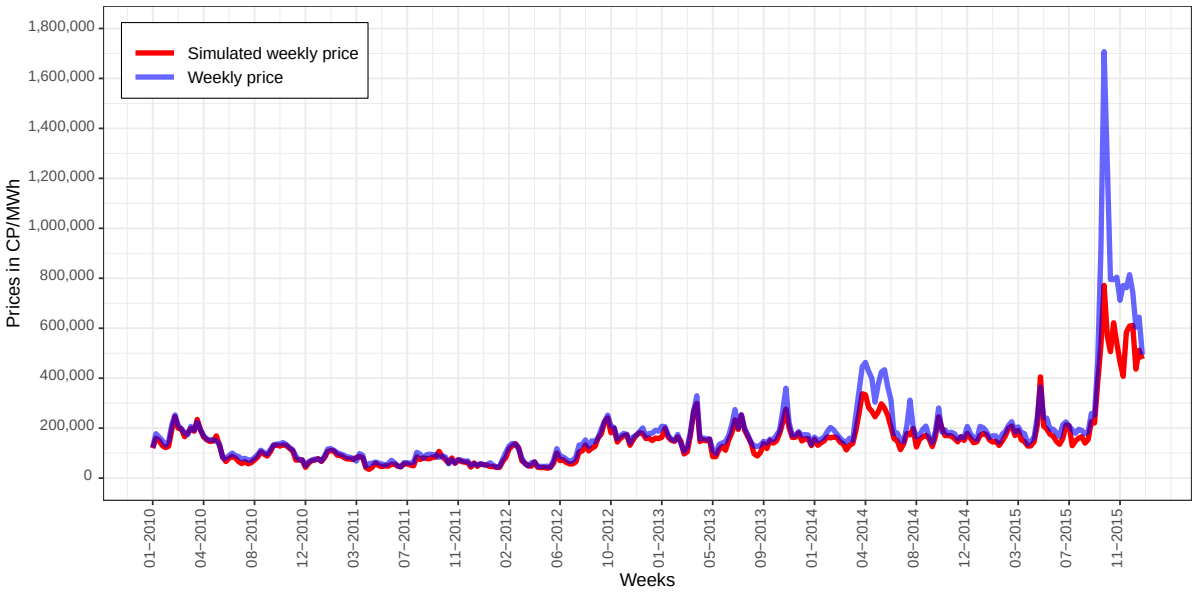
[38] The optimization is subject to constraints. The first ensures EPMG's hourly supply matches the residual demand at the equilibrium price. Subsequent constraints keep EPMG's residual demand, supply, and value function within capacity limits, with supply functions remaining increasing (not reported).

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.

6.2 Model Fit

In Figure 8, we compare the observed average weekly prices (red line) with the simulated ones (blue line). The model accurately captures price volatility, particularly over the first four years. However, the El Niño event in 2016, an unprecedented dry spell, likely influenced the transition matrix in late 2015, leading to a gap between simulated and observed prices. While the model fails to capture the extreme spike in late 2015, where prices surged more than tenfold, it predicts a five to sevenfold increase. Appendix Table F1 examines price variation across hours, which is generally within 10% from the actual price, confirming the model's strong fit.[39] Overall, despite being highly parsimonious with only seven parameters, the model effectively reproduces price volatility in Colombia over an extended period.

Figure 8: Model fit: simulated (red) vs. observed prices (blue)



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

Since $cap^H_{ht} = w_{ht}$, the firm's water stock, the third constraint prevents a water deficit. Notably, such extreme droughts are rare in our data, as we observe only four occurrences where a dam exhaust its water stock in four days in six years, and the 1st percentile of the water stock distribution exceeds the median hydro quantity bid by more than ten times.

[39]This simulation uses ten steps for demand, supply, and value function ($M = K = Z = 10$). Increasing the number of steps does not affect the goodness of fit (Appendix Figure F3).

6.3 Counterfactual Exercises

The counterfactuals slack EPMG's thermal capacity constraint by reallocating thermal capacity from its competitors in line with Section 4. Note that the estimated value function parameters ($\{\gamma_r\}_{r=1}^R$) might vary under different industry configurations if we viewed them as equilibrium objects. To solve for the new parameters, we would need to observe the counterfactual quantity submitted, which is unfeasible.

However, if one could solve for the new equilibrium parameters ($\{\gamma_r'\}_{r=1}^R$), the first-order change would be a decrease in the marginal benefit of holding water as thermal capacities of EPMG has increase (see e.g., Proposition A.1). Therefore, we would expect EPMG to offload even more water than our counterfactual predicts for every possible demand realization, meaning lower prices on average.[40] Therefore, this counterfactual analysis is identified in the spirit of Kalouptsidi *et al.* (2021).[41]

Figure 9 summarizes the results from the counterfactual exercises. In Panel (a), we reallocate capacity from firms without dams, while in Panel (b), we transfer thermal capacity from all of EPMG's competitors.[42] Although bids for EPMG's competitors should be updated according to (13) after each reallocation, this exercise is computationally infeasible because each firm's hourly D^R depends on the bids of others in every hourly market over the six-year period.

To address this issue, we leverage the strategic complementarities identified in Proposition 1 to simplify the corrections of the supplies of EPMG's competitors. Specifically, when transferring $\kappa\%$ of unit k's capacity, we leave its supply unchanged if its unused capacity is sufficient; otherwise, we reduce k's quantity bid accordingly. Notably, EPMG's competitors, such as Firm 2 described in Section 4, have market power, which typically leads them to submit bids below their capacity.[43] Consequently, price changes in this exercise should be interpreted as lower bounds on the actual price reduction (or increase) when EPMG expands (or contracts) its supply after a thermal capacity transfer, owing to the reinforcing effects of strategic complementarities.

Each panel displays a heatmap. The x-axis ranks markets according to the severity of drought experienced by EPMG, categorizing them into deciles based on EPMG's water

[40] Alternatively, since we estimate the model on the whole industry, we could interpret the $\{\gamma_r'\}_r^R$ coefficients as reflecting the industry preference for holding water, which we assume constant in Table 1.

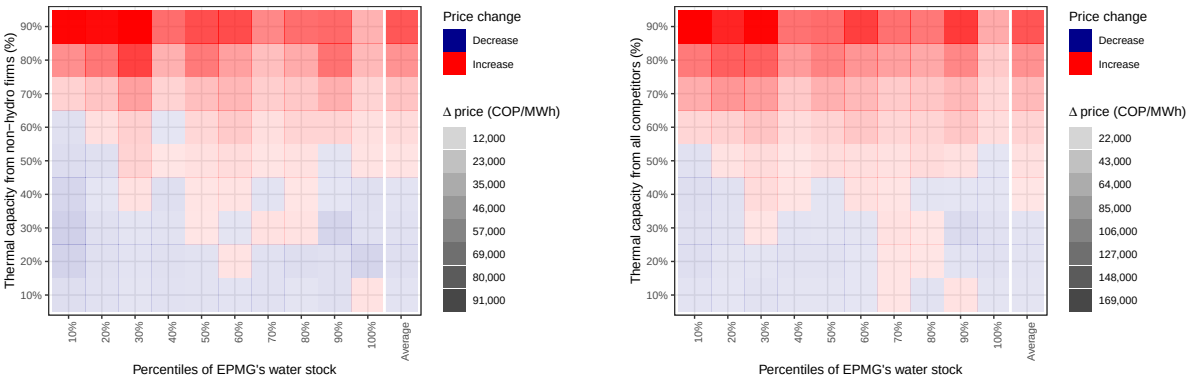
[41] Transferring thermal generation to the market leader firm provides it with only one reasonable extra action because of the merit order ("use the newly added capacity when all other capacities are exhausted"). As the added strategy does not affect the transition matrix, Proposition 4 of Kalouptsidi *et al.* (2021) holds: given a residual demand, the marginal profit of taking the new action depends only on the total capacity, ensuring that the counterfactual is identified.

[42] We do not consider transfers solely from firms with dams because Proposition 3 finds that, any high-cost capacity transfer leads to higher prices with symmetrically diversified firms.

[43] We define a unit's capacity as its maximum observed bid. Results remain qualitatively unchanged if technical capacity is used instead. We also exclude units that do not bid in specific markets, as "non-bidding" may result from technical constraints. Including these units would artificially inflate the market's total capacity in such cases.

stocks. The y-axis shows the magnitude of the capacity transfer, expressed as a fraction of EPMG's competitors' thermal capacity in each simulation. Each cell within the heatmap represents the average difference between the counterfactual and status quo market prices: darker shades of blue (red) indicate lower (higher) counterfactual prices. It's important to note that the water stock is used here as a basic measure of drought, without accounting for future inflows. Appendix G presents additional robustness checks where inflows are included on the x-axis. Since these metrics only partially capture drought events, the color transitions across columns need not be smooth.

Figure 9: 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 status quo with different shades of red and blue colors based on the sign and magnitude of the change. The left (right) panels move capacity from non-hydro (all) firms. The average market price is approximately 150,000 COP/MWh. 2,900 COP $\simeq$ 1 US$.

Varying capacity transfers. We first compare outcomes across transfer levels – i.e., within columns. In the first row of in Panel (a), EPMG is endowed with 10% of the non-hydro firms' thermal capacity. We find lower energy market prices on average across almost all periods but the highest decile. Zooming in on transfers lower than 50% to better appreciate the magnitude changes, Panels (a) and (c) of Appendix Figure G1 show that most of the price gains are in dry periods (southwest portion of the plot). Here, price gains can be substantial, reaching values between 8,000 and 13,000 COP/MWh (slightly less than 10% of the average energy price) when moving 20% to 30% of the capacity available to the fringe firms. To give an idea of the transfer size, it would double EPMG's thermal capacity.

In contrast, counterfactual prices mostly increase for large transfers, especially in the driest periods. During these periods, EPMG behaves as the standard textbook model would predict for a non-diversified firm that faces an increasingly vertical residual demand: it lowers output, leading to higher prices. Hence, on average (right-most column),

prices first decrease for low transfers and reach a bottom level before increasing for higher transfers—a similar U-shaped pattern to that in Figure 4 and discussed in Section 4.

Varying drought severity. We now turn to comparing outcomes across drought severity – i.e., within rows. Panel (a) suggests a diagonal division between red and blue areas running South East (abundance and low transfers) from the North West side of the plot (scarcity and high transfers). Zooming in again on transfers smaller than 50% in Appendix Figure G1, we find that, given a transfer decile (row), cells become gradually less blue. Thus, the gains from the transfers are generally larger in dry spells compared to wet periods.

Percentage price changes. A 10,000 COP price change during is very different during droughts and abundant periods. To better compare prices across columns, Appendix Figure G2 rebases the difference between counterfactual and baseline prices by the latter and present its average value 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 superscripts $\kappa\%$ and *base* denotes counterfactual and baseline prices, respectively). The results indicate that transferring thermal capacity does not yield gains when the firm holds a large amount of hydro capacity. This finding aligns with the results in Figure 5, which shows that such concentration-increasing transfers raise prices under abundance (Panel b). In contrast, during scarcity, limited reallocations of capacity result in price gains of about 10%.

Reallocation from all firms Finally, Panel (b) of Figure 9 investigate when the thermal capacity transfers come from all firms, including the other diversified firms. In this case, the magnitude of the price increase (gains) is larger (smaller) compared to Panel (a) as EPMG's residual demand is now steeper. This is consistent with Proposition 3, which finds that moving high-cost capacity from one firm to another across symmetrically diversified firms results in higher market prices as concentration forces are stronger than undercutting motives from efficiency gains. In conclusion, transfers from firms of comparable size to EPMG reduce the capacity available to them, decreasing the extent of market competition more than if capacity transfers were from fringe firms only.

6.4 Discussion

Our results have significant implications for antitrust policy. Traditional competition analysis often focuses on market concentration and cost synergies when evaluating mergers and acquisitions. However, our paper challenges this view by emphasizing that synergies in diversified firms arise from their ability to manage supply responses across different technologies, rather than simply from economies of scale or scope, which are absent in our analysis. This insight suggests that antitrust regulators should consider the strategic value of a firm's technological diversity (i.e., the combination of marginal cost and capacity for each technology), rather than just firm size, when evaluating the potential

competitive effects of mergers. For example, in Colombia, a 25% capacity cap limits the ability of firms to diversify their technology mix, potentially leading to less efficient market outcomes.

Of course, despite these "synergies," prices generally remain above the perfect competition benchmark, as firms' supply schedules deviate from their marginal cost curves (compare the solid and dotted red lines in Figure 5). However, we theoretically demonstrate, through a parametrization of our oligopoly model, that an industry configuration in which firms' production portfolios are symmetrically diversified leads to the highest level of competition and the lowest prices (Proposition 3). Our counterfactual exercises confirm this result, providing a new benchmark for policy in industries with multiple production technologies.

One advantage of studying electricity markets is that firms' pricing strategies and capacities are directly observable—information typically unavailable in other industries. However, we believe our model and results extend beyond this setting. First, drawing on Klemperer and Meyer (1989), we argue that our insights apply to multi-product firms, where businesses with diverse product lines face similar trade-offs between capacity and efficiency. Second, our framework relies on demand uncertainty, with firms committing to a supply curve before actual demand is realized. This feature has recently been used to study firm dynamics in macroeconomics, where firms operate with partial knowledge of market demand and competitors' supply decisions (Flynn *et al.*, 2023). These parallels make our model relevant to other sector or even labor markets, where firms manage diversification in workforce skills, education levels, and employment size (Bonhomme *et al.*, 2019).

The transition to greener energy systems, particularly in developing economies like Colombia, introduces new challenges. While renewable energy sources such as wind and solar are increasingly cost-competitive, their intermittent nature can lead to price spikes during periods of low generation. This can exacerbate inequalities, as lower-income consumers are disproportionately affected by rising energy costs. Our research suggests that in such contexts, a diversified ownership structure—where firms can leverage both renewable and non-renewable generation—can reduce price spikes and internalize scarcity effects more efficiently.

In addition, the current reliance of Colombia on fossil fuels for hedging against energy scarcity contributes to CO_2 emissions and hinders the green transition. The legacy of dam ownership from privatizations in the 1990s has led to a geographically concentrated energy market, limiting the ability to hedge against regional droughts. A more geographically diversified ownership structure of dams could have mitigated this issue, allowing firms to better face inflow scarcity periods at one dam and reduce the reliance on fossil fuels.

Looking ahead, Colombia's renewable energy sector is poised for significant growth, with numerous solar and wind projects under development. These projects, expected

to contribute up to 38% of the country's installed capacity by 2027, represent a critical step in reducing the energy sector's carbon footprint (Arias-Gaviria *et al.*, 2019, Rueda-Bayona *et al.*, 2019, Moreno Rocha *et al.*, 2022). However, to maximize the benefits of this transition, Colombia must focus not just on expanding renewable energy capacity, but also on fostering diversified firms to reduce the need for expensive fossil fuel-based backup. As storage technologies improve and battery costs decline, renewables will become an increasingly viable alternative for hedging against shortages of other renewables, enhancing both environmental and economic outcomes.

In conclusion, our study underscores the importance of viewing firms as diversified portfolios of technologies in both market power analysis and green transition policy. By embracing this perspective, we can design more effective regulatory frameworks that promote both competition and sustainability, helping to accelerate the transition to a greener, more resilient economy.

7 Conclusion

US energy supplier Duke Energy generates electricity using nuclear, gas-fired, and hydroelectric plants. The Anglo-Dutch oil major Shell supplies global markets with oil from various basins, including light crude from Kurdistan and heavy crude from Brazil. Similarly, aluminum producers utilize different technologies, such as mini mills and vertically integrated plants (Collard-Wexler and De Loecker, 2015). Hospitals combine medical doctors and artificial intelligence for radiology (Agarwal *et al.*, 2023). Toyota used around 100 different car platforms until 2020 (Reynolds, 2015). The list of examples where firms use multiple technologies in production, each with its own marginal cost and capacity, is endless, spanning both homogeneous goods, like commodities, and differentiated goods, such as cars. A common factor across these examples is that, when choosing how much to produce with each technology, the producer may not know the actual market demand for its products. This paper proposes a theory and empirical analysis to study competition among similarly diversified firms.

Drawing from the Colombian energy sector, we empirically and theoretically demonstrate that oligopolistic competition among firms with diversified technology portfolios creates a trade-off between capacity and efficiency. On the one hand, larger firms can meet a greater share of market demand, incentivizing them to reduce output and raise prices. On the other hand, monopolistic rents driven by technology efficiency may lead firms to undercut competitors, lowering prices. Our model shows that diversification fosters complementarities within a firm, as the availability of higher-cost technologies allows a firm to allocate more of its lower-cost capacity to undercut competitors. In such cases, reallocating a small share of capacity to the market leader increases output and reduces prices. However, for larger reallocations, prices inevitably rise as the leader has

an incentive to withhold production and raise the market price. We present empirical evidence of this U-shaped relationship between prices and concentration, leveraging exogenous capacity changes among Colombian electricity firms, which are diversified across hydropower and fossil fuel generation.

Through structural estimation and counterfactual simulations, we assess the impact of reallocating fossil fuel capacity to the market leader. The benefits of diversification are most pronounced when the market leader faces scarcity. In these periods, we estimate that doubling its fossil fuel capacity through reallocation from competitors can reduce market prices by up to 10%. However, larger capacity transfers eventually lead to higher prices, as the pro-competitive effects of diversification are outweighed. In conclusion, our findings are novel in demonstrating that diversification can effectively offset the negative effects of concentration, and we outline the conditions under which this occurs. These insights have important implications for antitrust policy and the transition to greener energy markets.

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

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Online Appendix

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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

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

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*

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

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

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

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:

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

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

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

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 $p \le c^f$. 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 Decreasing Marginal Benefit of Holding Water

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.

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

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

where we suppress the notation of V's possible dependency on the previous realized history of δ_t, 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). The proposition below shows this concavity is sufficient to imply that the marginal benefit of holding water decreases as thermal capacity increases.

Proposition A.1 *If GR_ϵ is strictly concave and twice differentiable for all ϵ, then $\frac{\partial^2 V(\cdot)}{\partial w \partial K} < 0$.*

Proof. First, observe that standard arguments show that when δ_t and ϵ_t are Marko-

vian, 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

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

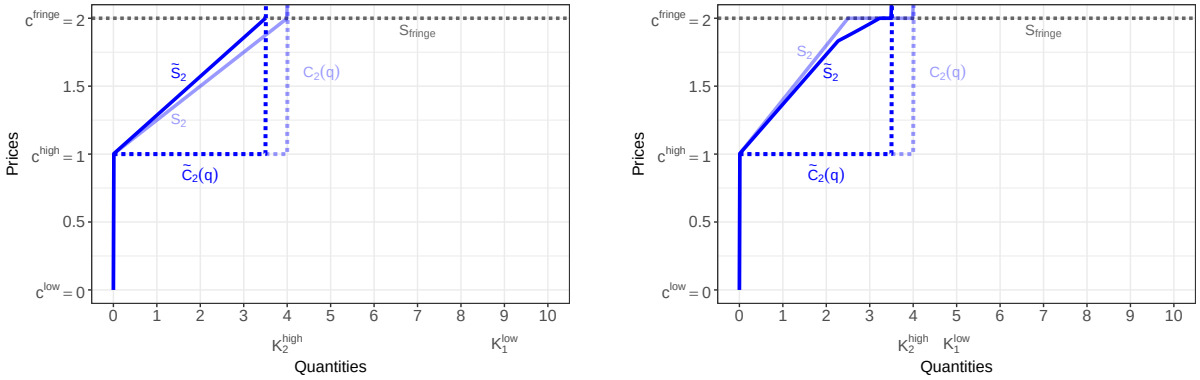
Recall that we have shown $\frac{\partial w_{t+1}}{\partial w_t}\in(0,1)$ for all $t\geq 0$, therefore for all t,

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

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

A.5 Omitted Figures from the Theory Model

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

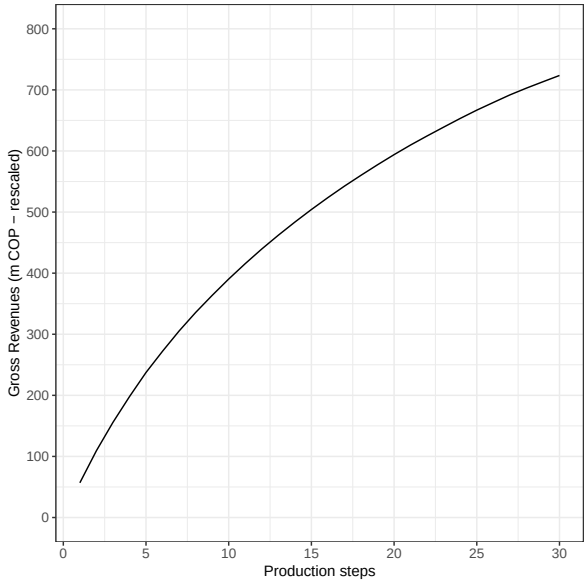


(a) Abundance scenario
$K_1 = (9, 0, 0)$ & $K_2 = (0, 4, 0)$

(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 generator j as dependent variable,

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

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:

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

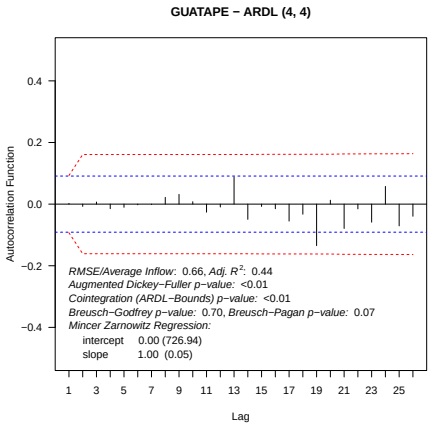
where K denotes the number of control variables in $\mathbf{x}_{j,t-q}$.

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.

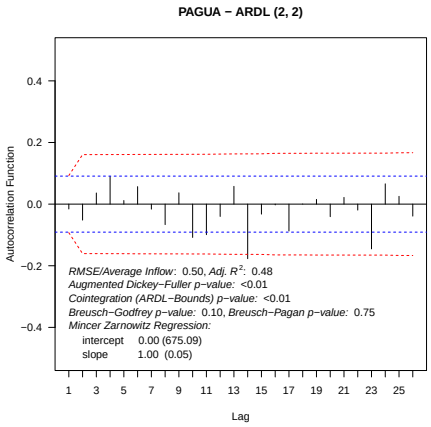
Quality of the fit. Figures B1 and B2 report the autocorrelation function and the Ljung-box test for the error term ϵ_t in (B2) for the largest dams in Colombia in the period we consider. The p-values of Ljung-box test never reject the null of autocorrelation.

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 early dummies to better account 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.

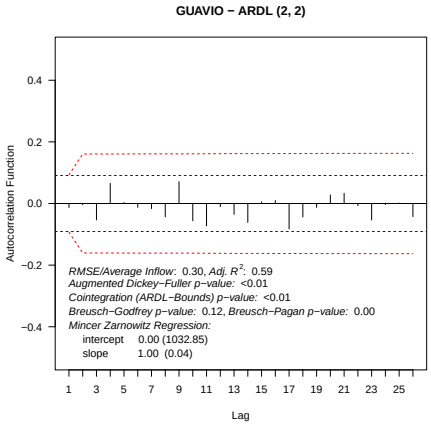
Figure B1: ARDL model diagnostics for some of the largest dams in Colombia in our sample period



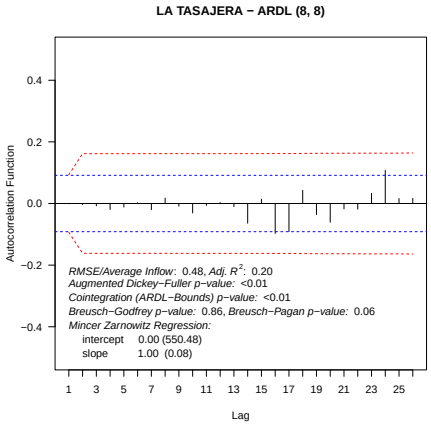
(a) Guatape



(b) Pagua



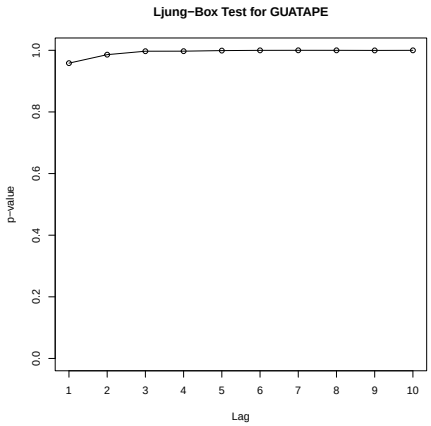
(c) Guavio



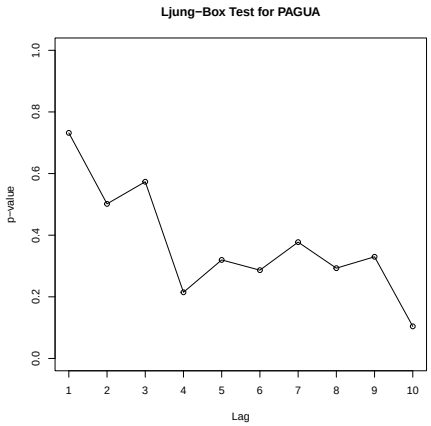
(d) La Tasajera

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.

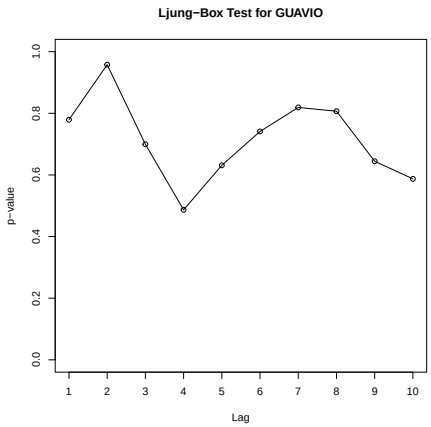
Figure B2: Ljung boxes for some of the largest dams in Colombia



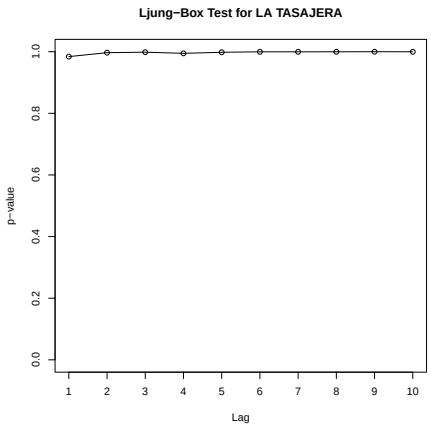
(a) Guatape



(b) Pagua



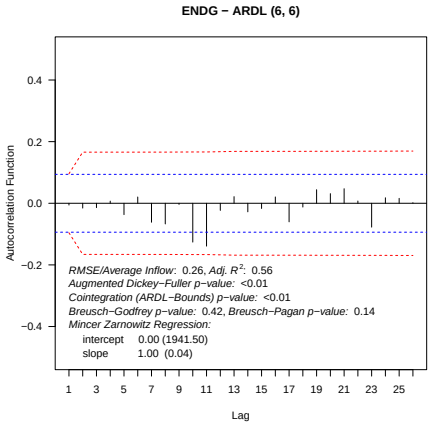
(c) Guavio



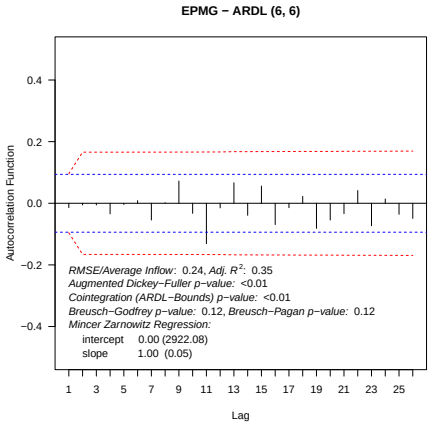
(d) La Tasajera

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.

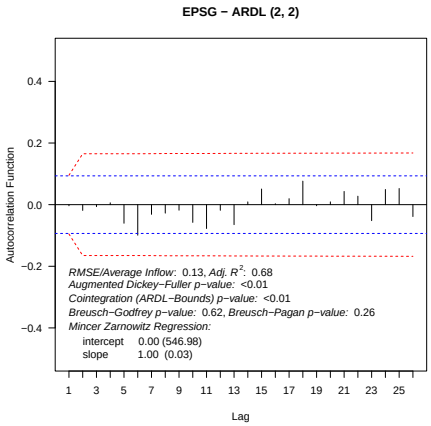
Figure B3: ARDL model diagnostics at firm level



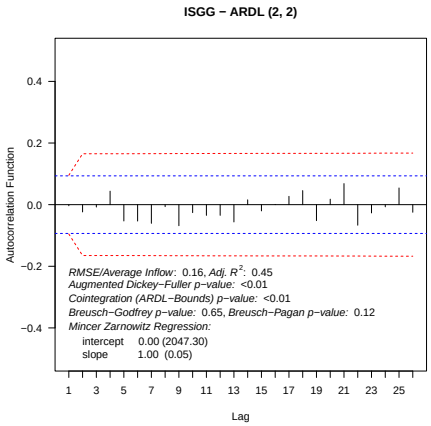
(a) ENDG



(b) EPMG



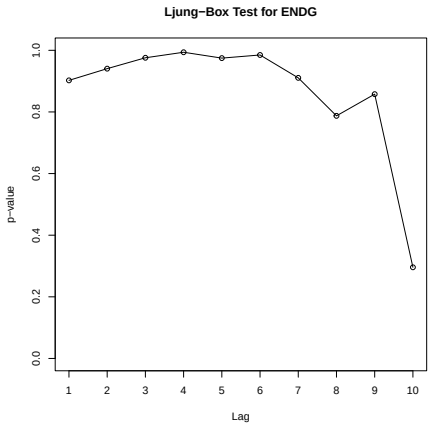
(c) EPSG



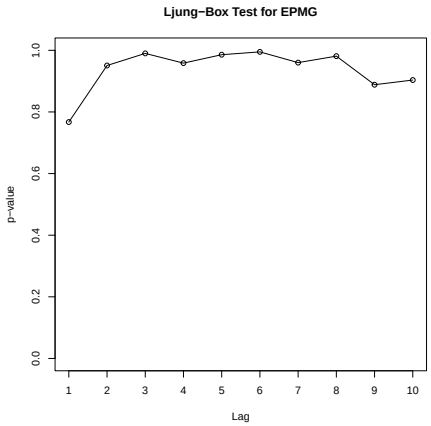
(d) ISGG

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.

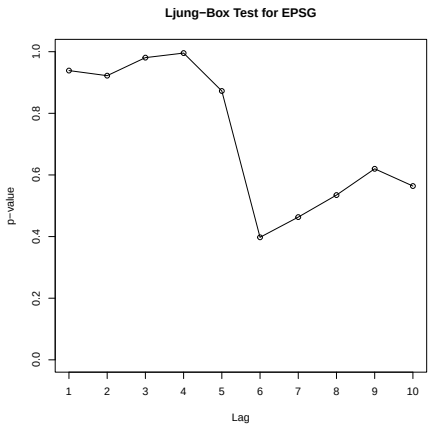
Figure B4: Ljung boxes at the firm level



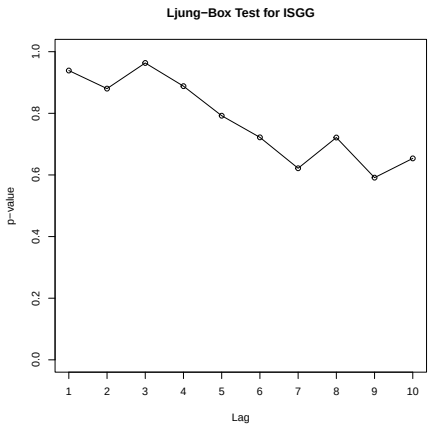
(a) ENDG



(b) Pagua



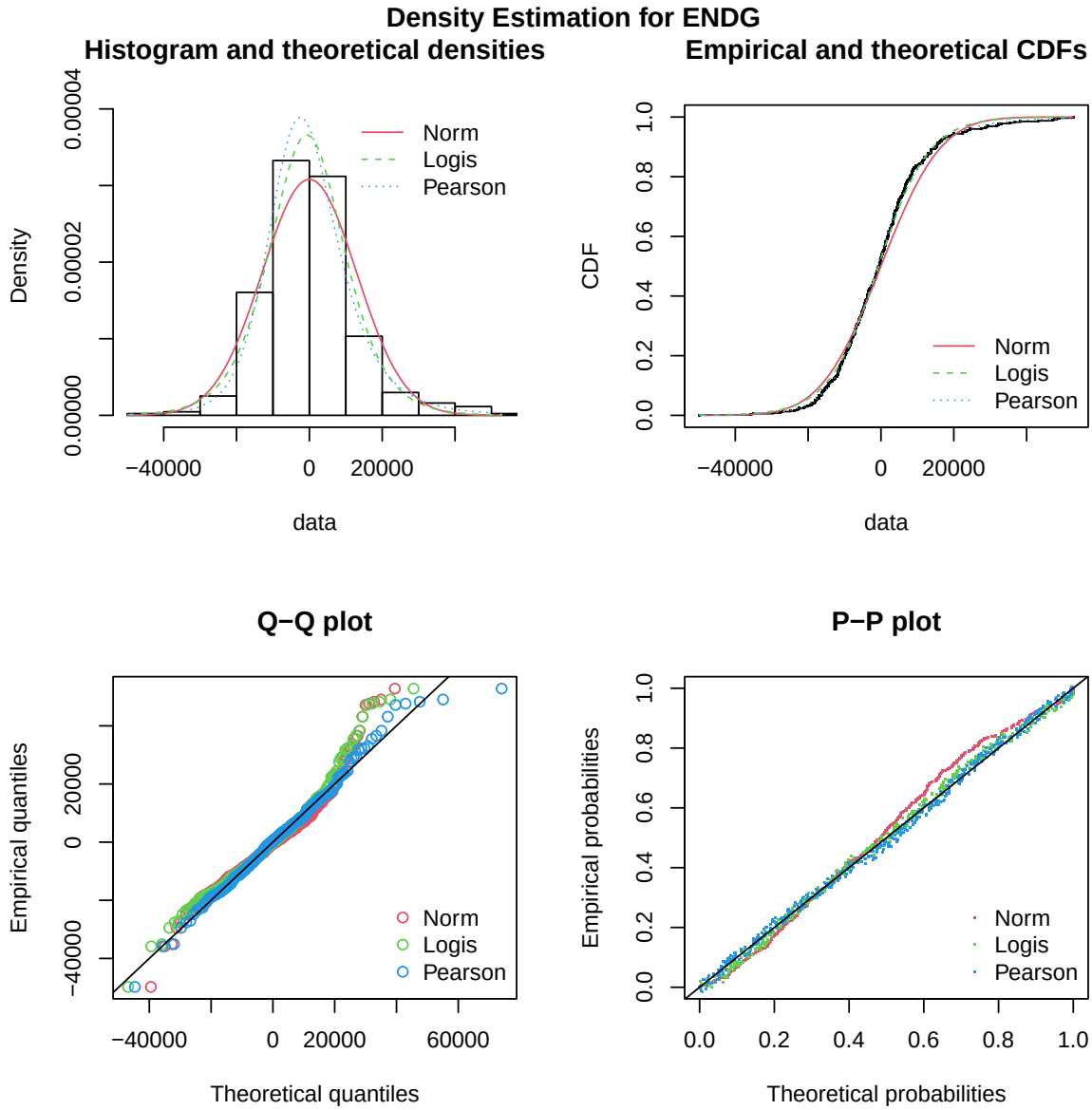
(c) EPSG



(d) ISGG

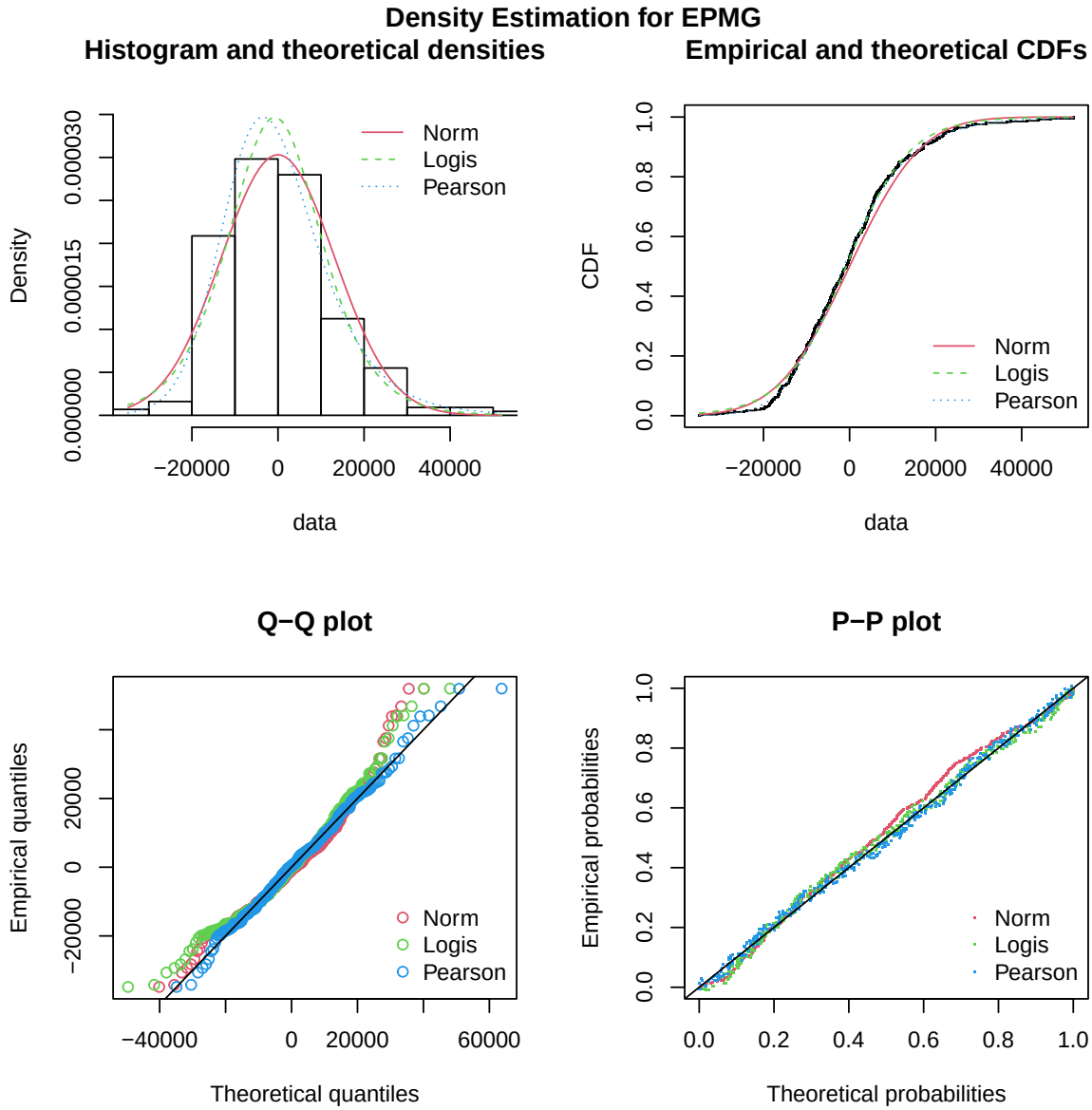
Notes: The plot shows the p-values of Ljung-box tests of whether any of a group of autocorrelations of a time series are different from zero.

Figure B5: Transition matrix for ENDG



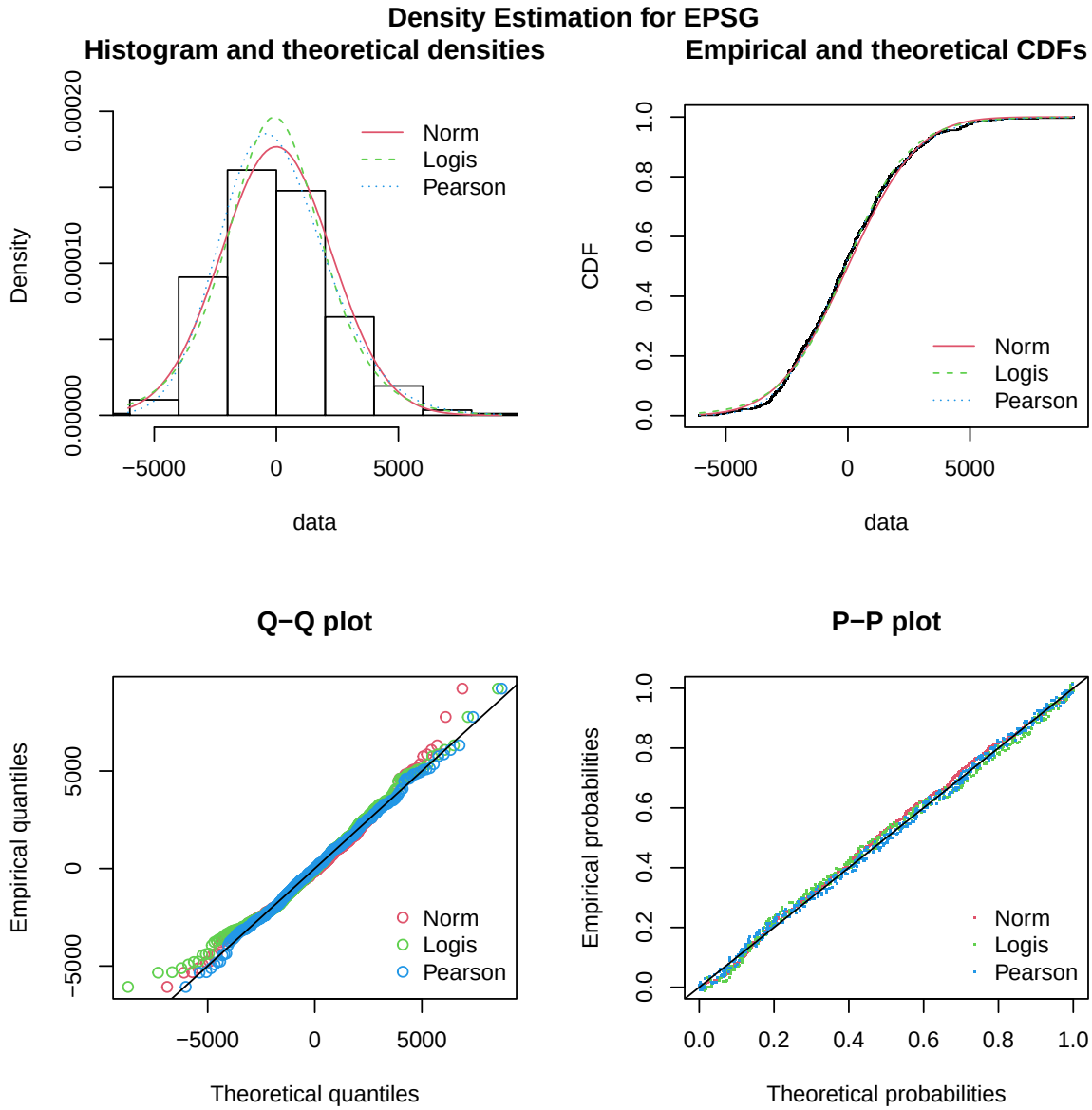
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B6: Transition matrix for EPMG



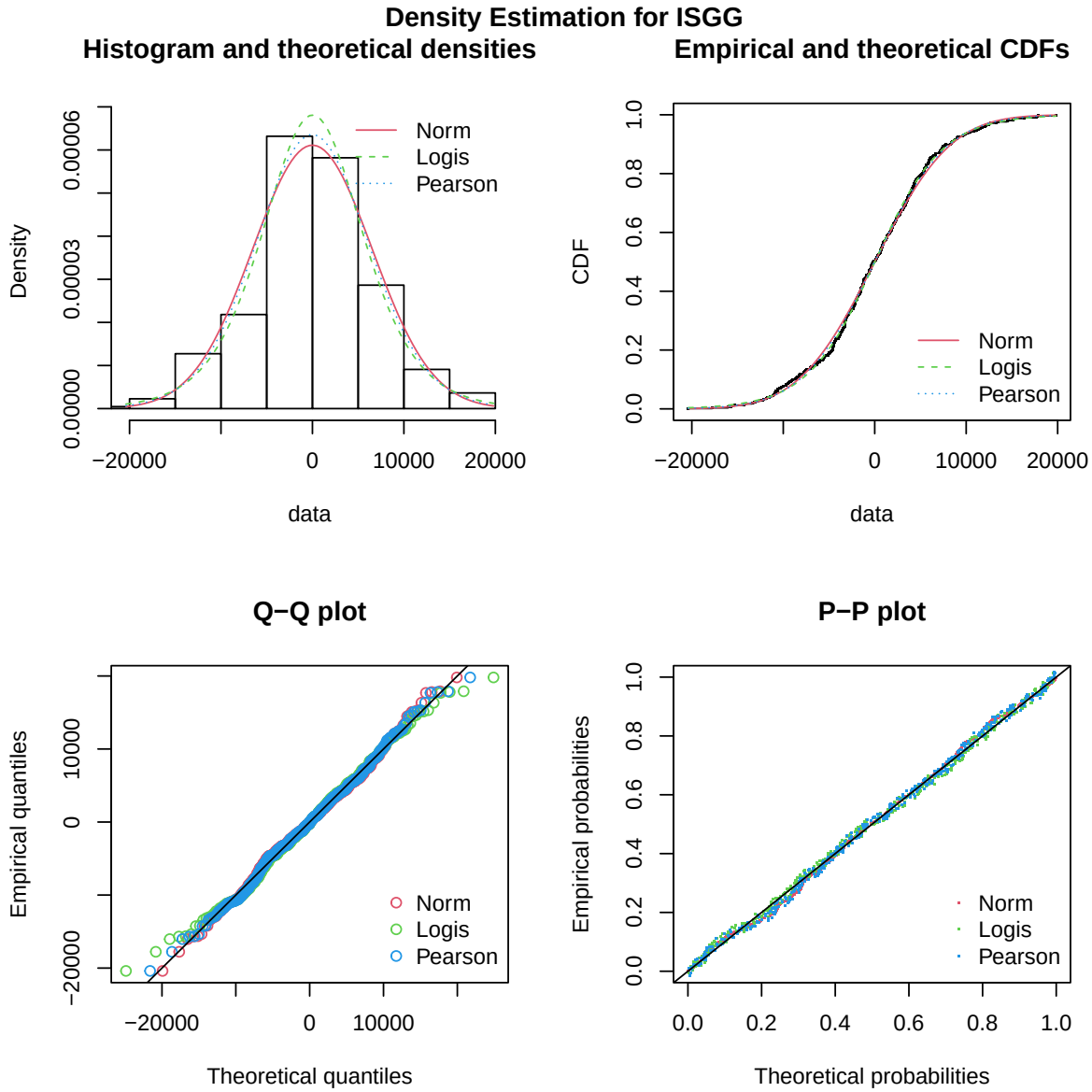
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

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). To show that our predictions 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.[2]

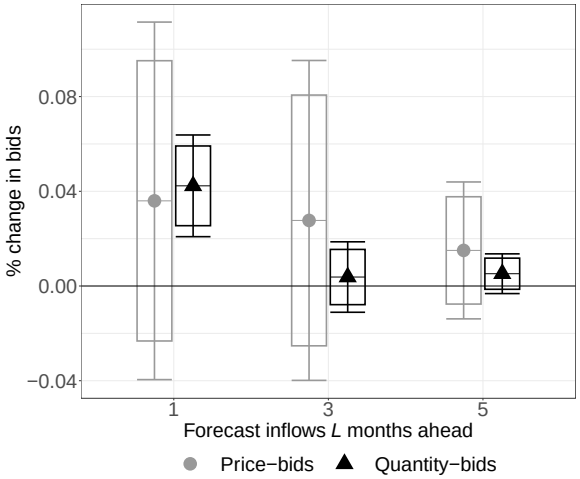
Correlation across monthly forecasts. To break the extent of correlation across monthly forecasts, the bottom panels plot the estimate from five separate regressions as in (C1) with each regression allowing for l being either 1, 2, 3, 4, or 5. This approach break the autocorrelation across monthly inflows 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.

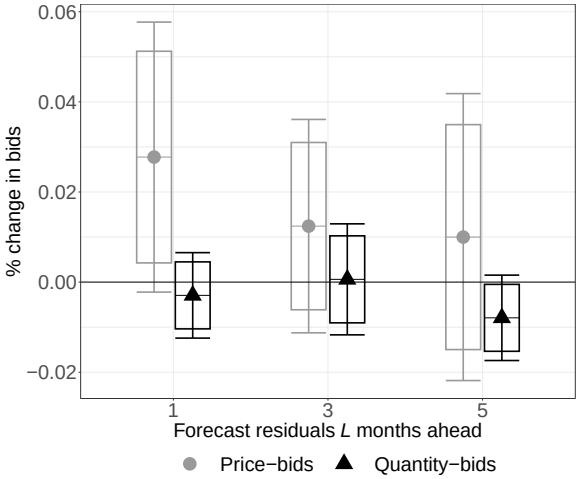
[2]Some price-bid coefficients are positive in Panel (a). However, this result is rather noisy, as suggested by the slightly higher response of price bids to the unexpected one-month forecast in Panel (b). The rationale is that units submit only one price bid per day but multiple quantity bids; thus, there is less variation in price bids. Reassuringly, if we were to control for lagged quantities (in logs) in the price-bids regressions (C1) and (1) reported in Panel (a) 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*

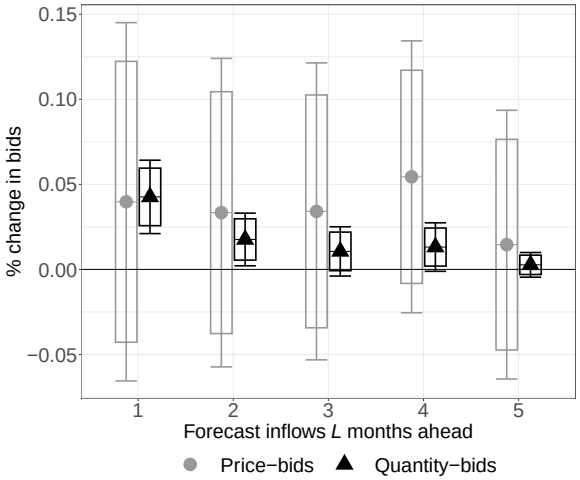


(a) Expected inflows (standardized forecasts)

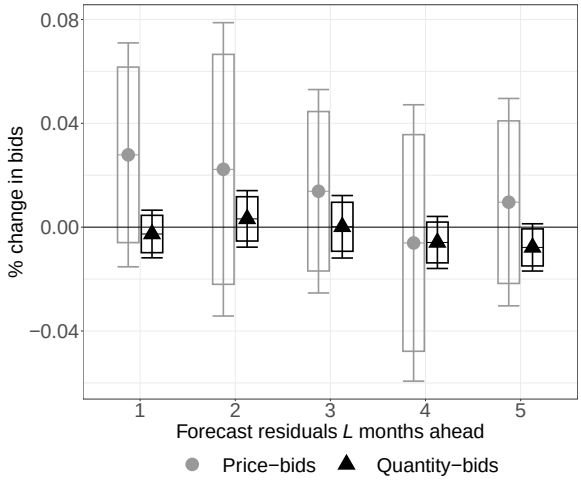


(b) Unexpected inflows (forecast residuals)

Bottom Panel. *Separate regressions for each month-ahead forecast*



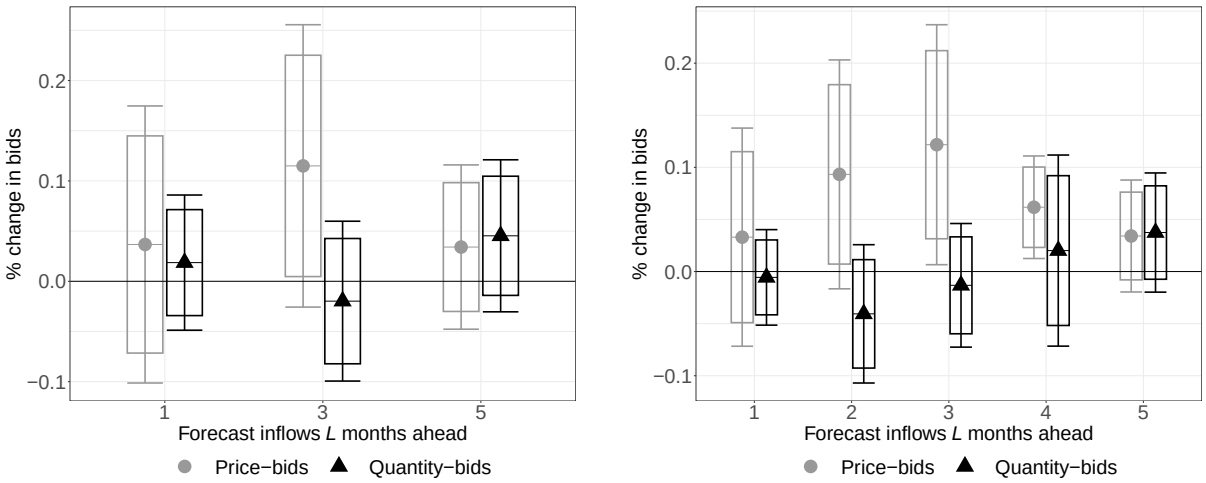
(c) Expected inflows (standardized forecasts)



(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

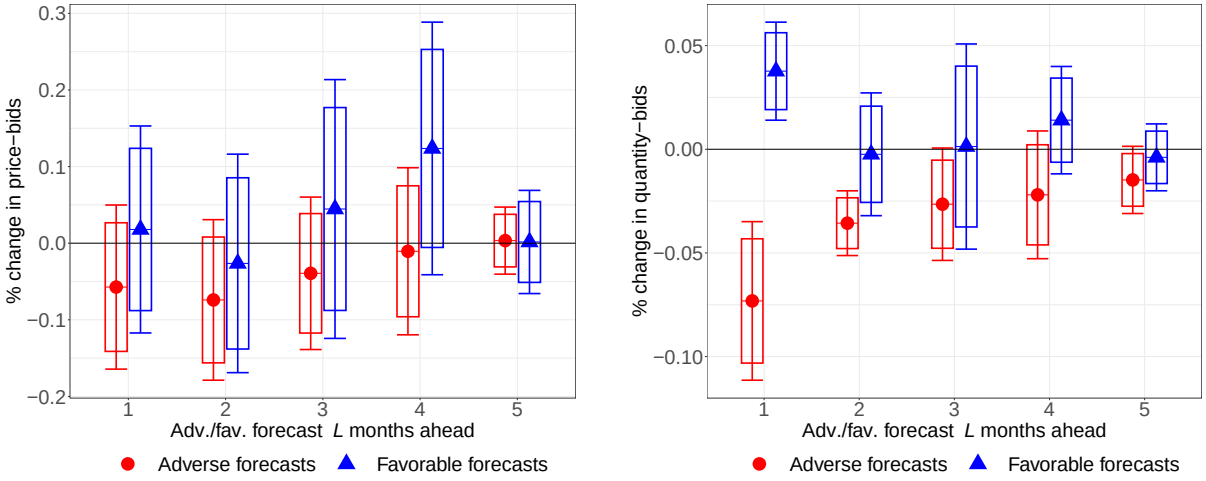
Notes: Estimates of β_{ll} from a modified (C1) focus on firm-level rather than generator-level water inflows one to five months ahead. As forecasts may be correlated over time, Panel (b) plots estimates from five separate regressions, each for a specific month. Error bars (boxes) show 95% (90%) CIs.

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

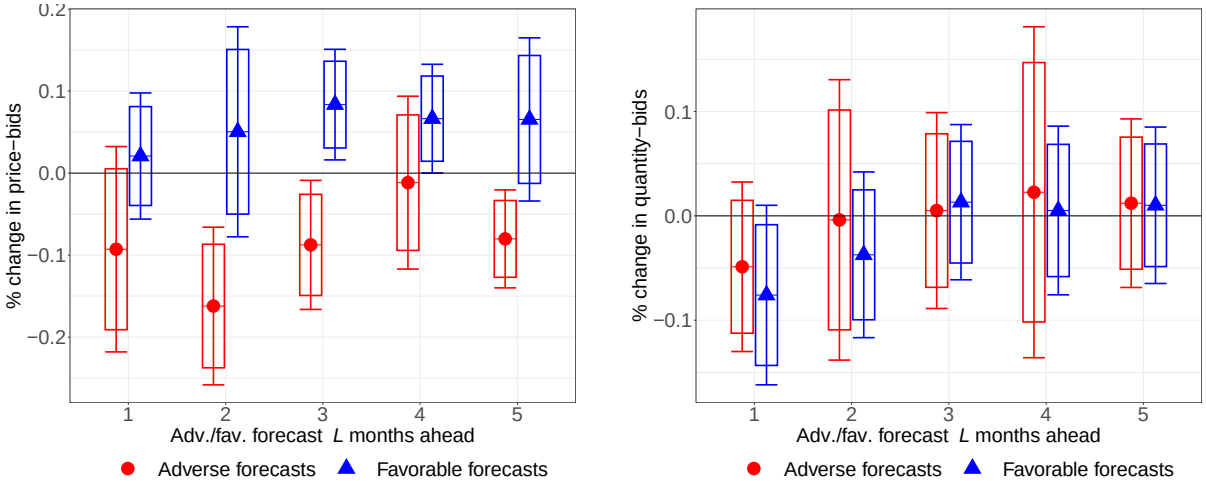
Top panel: Responses of dams to own inflow forecasts



(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:

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

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).

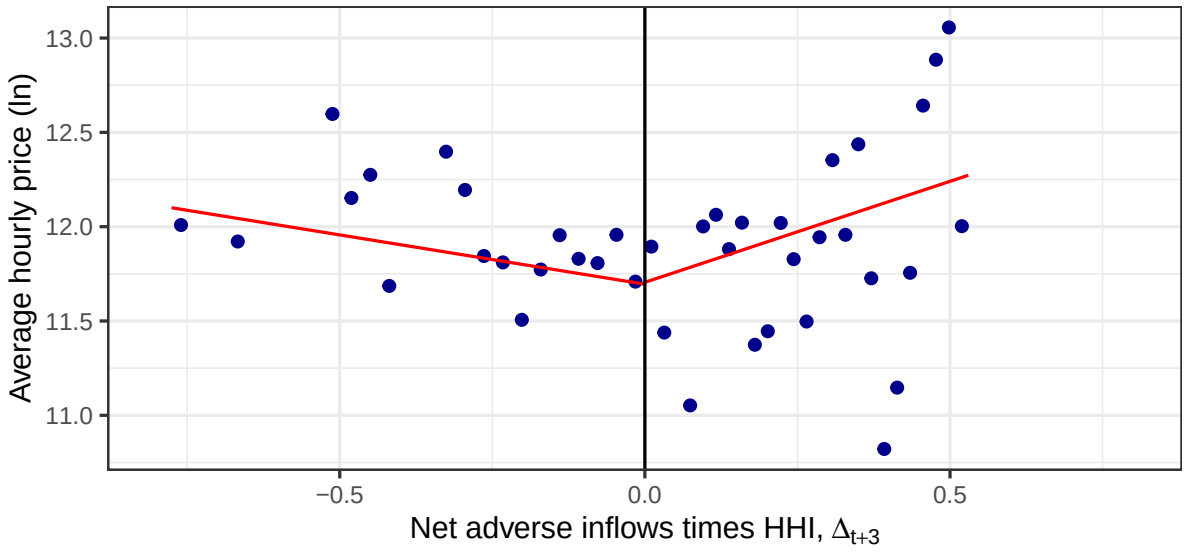
Table C1: How technology diversification and concentration affect spot prices

Dependent var: average weekly price in hour h ($\ln p_{ht}$)	(1)	(2)	(3)	(4)	(5)
	HHI based on thermal capacity		HHI based on total capacity (Thermal and water stock)		
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)
Net adverse inflows times HHI (3 months), γ_1	0.087	0.074	-0.029	0.071	-0.067
	(0.101)	(0.119)	(0.135)	(0.089)	(0.079)
Net adverse inflows times HHI squared (3 months), 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
Num.Obs.	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: How technology diversification and concentration affect spot prices

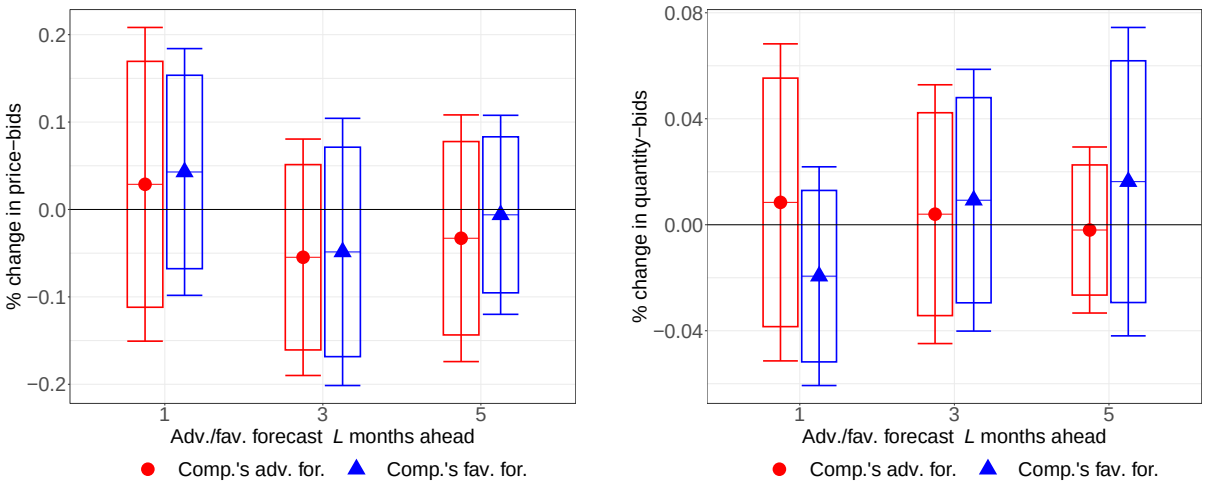


Notes: Bin scatter plot of $ln(p_{ht})$ on Δ_3. The regression slopes are the coefficient estimates of Δ_3 for a version of (2), which allows for different slopes for positive and negative Δ. No covariates are used in the regression.

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 generator'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



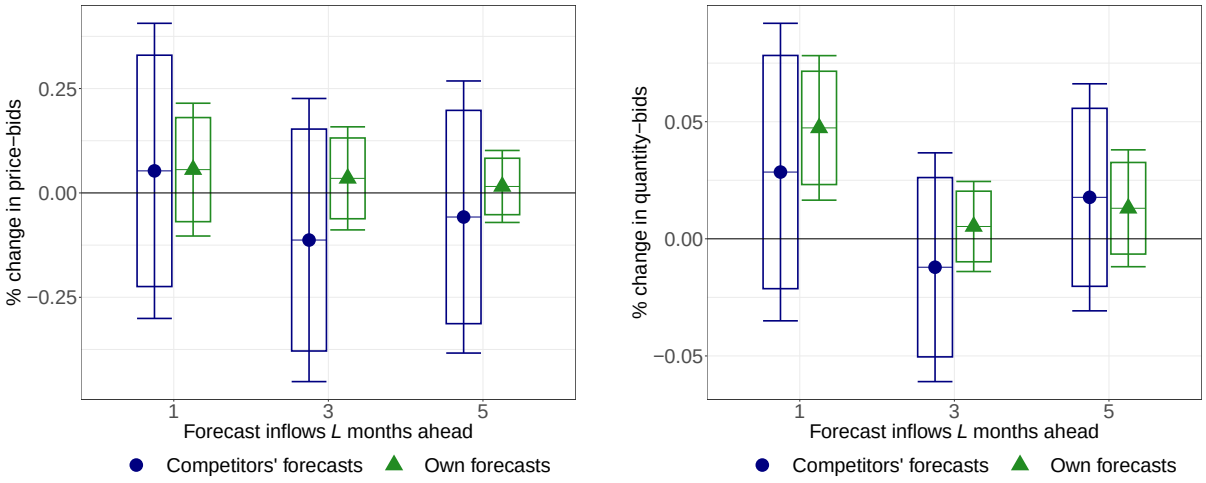
(a) Price bids (b) Quantity bids

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 generator 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

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.

observed for 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 generator'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 (two-by-two exercise)

	(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 primitives – four spline parameters

	(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 primitives – employing a normal density for the transition matrix

	(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 $\simeq$ 1 US$

Table D3: Estimated primitives – employing a normal density for the transition matrix

	(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, $\tilde{S}_{-iht}(p) = \sum_{m\neq i}^{N}\sum_{j=1}^{J_m} q_{mjht}\mathcal{K}\Big(\frac{p-b_{mjt}}{bw}\Big)$, 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

$$\frac{\partial \tilde{D}^R_{iht}(p,\epsilon)}{\partial p_{ht}} = -\sum_{m\neq i}^{N}\sum_{k=1}^{K_m} q_{mkht}\frac{\partial \mathcal{K}\big(\frac{p-b_{mkt}}{bw}\big)}{\partial p_{ht}}.$$

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

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

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

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

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

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

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

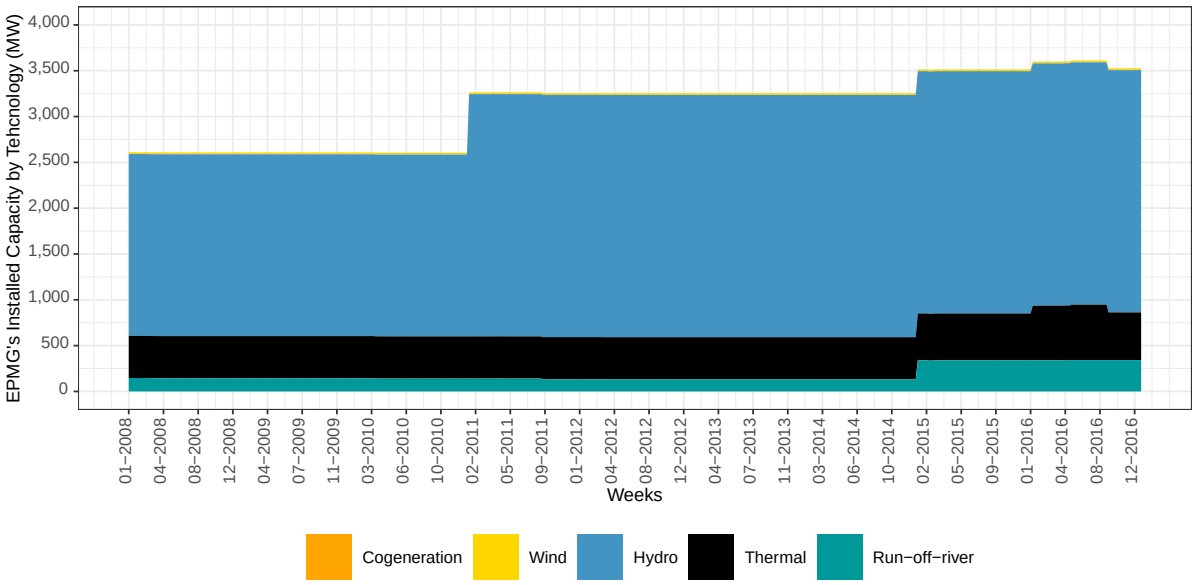
Table F1: Hourly prices across simulations

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

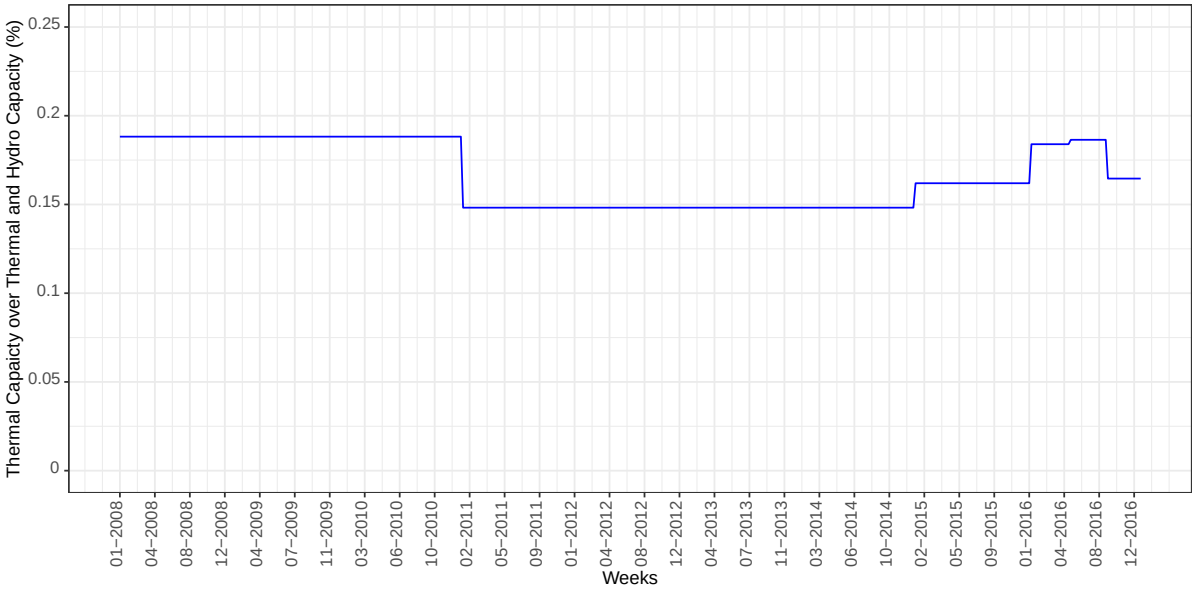
Notes: The table compares average hourly prices across the simulated and actual data. The simulation model is described in Section 6.2. The simulations in this table employ a different number of steps in the first and second panels. 2,900 COP $\simeq$ 1 US$.

Figure F1: EPMG's total installed capacity by technology

(a) EPMG's installed capacity over time

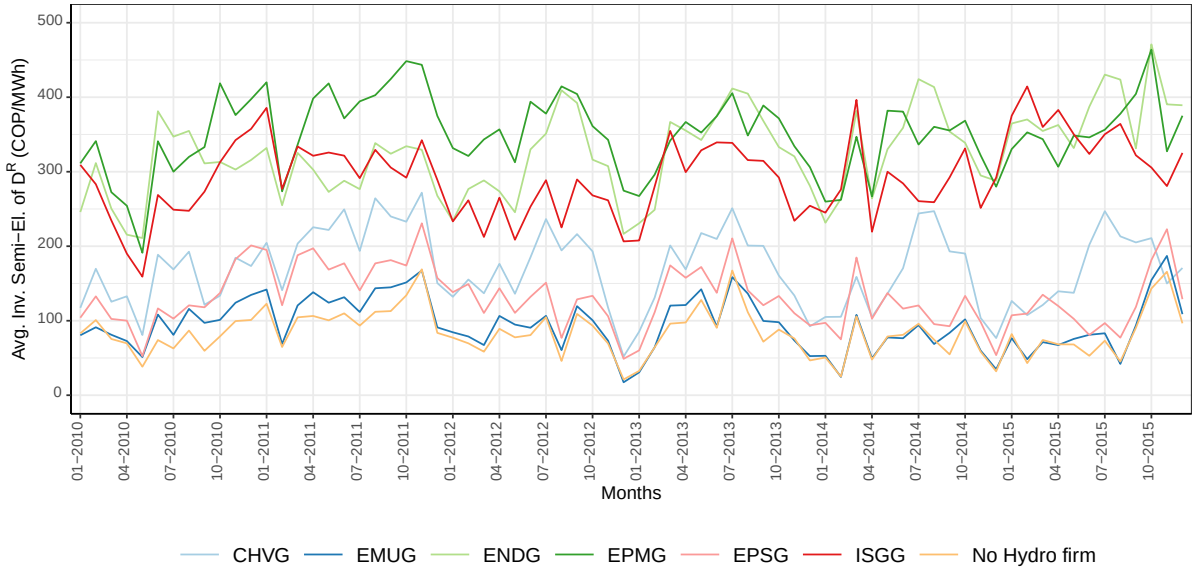


(b) Thermal capacity as a percentage of EPMG's thermal and hydro capacity



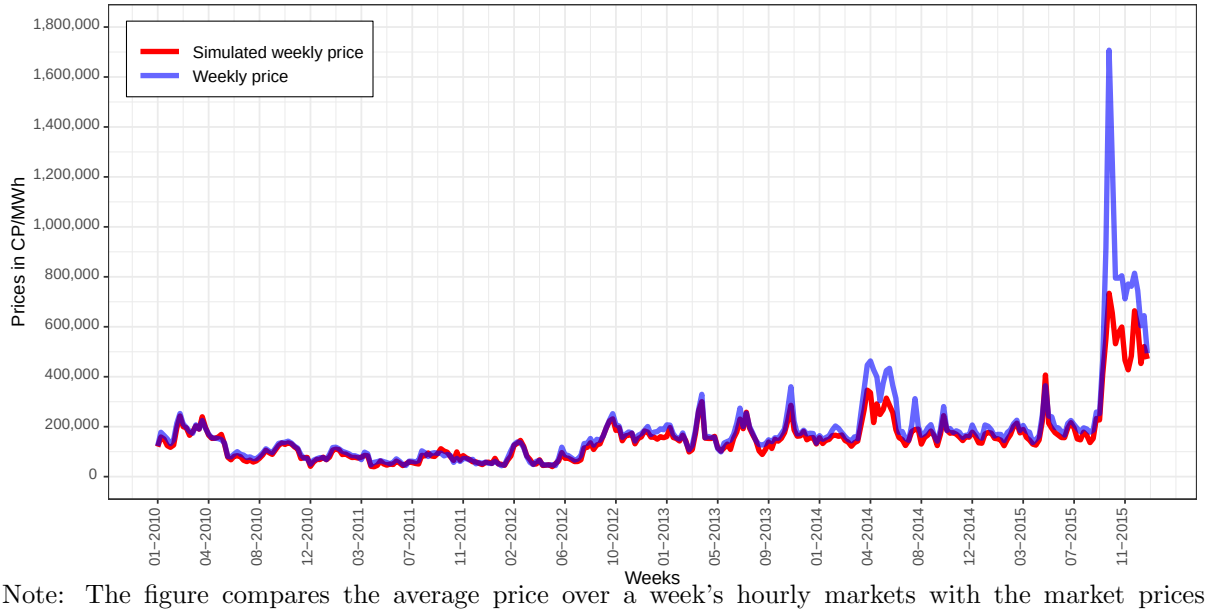
Note: The relative contribution of different technologies to EPMG's installed capacity over time.

Figure 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$.

Figure F3: Model fit (30 steps for residual demand and value function

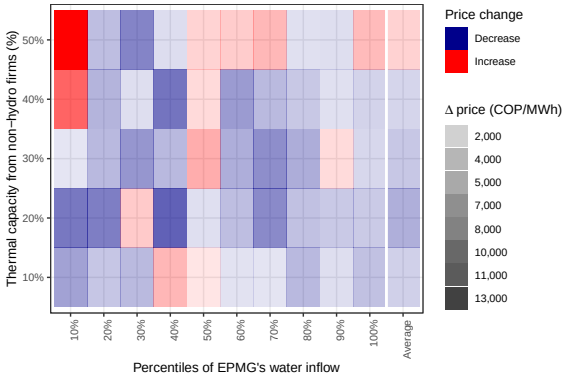


Note: The figure compares the average price over a week's hourly markets with the market prices obtained from solving EMPG's profit maximization problem (13) for each hourly market. The solver employs thirty steps to discretize the demand and the value function and 10 steps for each technology-specific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

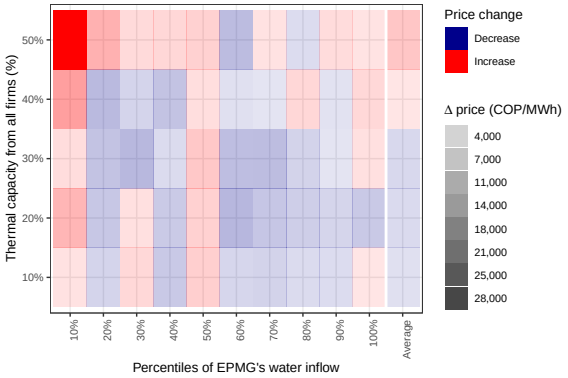
G Counterfactual Analyses: Tables and Figures

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

Top panel: the distribution of the leader's water inflows is on the x-axis

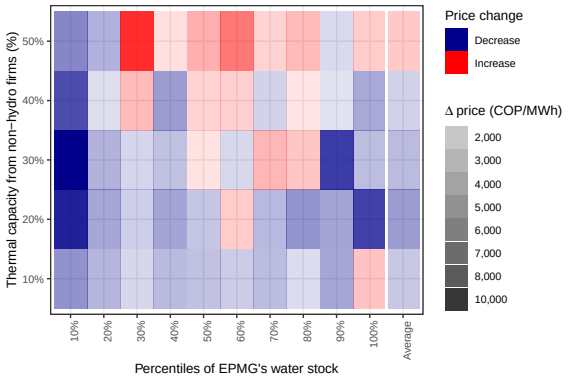


(a) Transferring κ% from all fringe firms

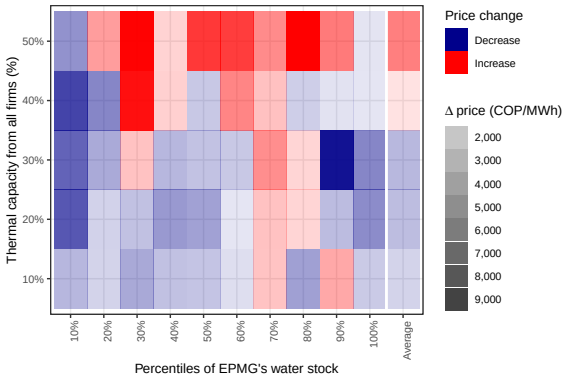


(b) Transferring κ% from all firms

Bottom panel: the distribution of the leader's water stock is on the x-axis



(c) Transferring κ% from all fringe firms

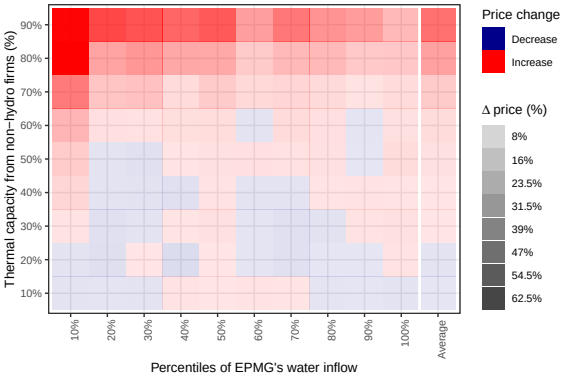


(d) Transferring κ% from all firms

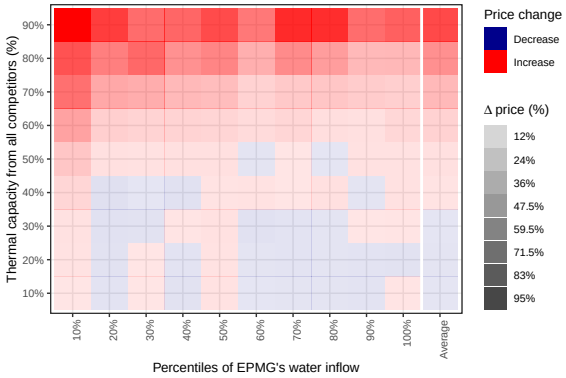
Notes: The figure presents the results from the counterfactual exercises discussed comparing observed prices with counterfactual market prices as we endow the market leading firm with a fraction of its competitors' thermal capacities (y-axis) for varying levels of scarcity (x-axis). Top (bottom) panels proxy scarcity by grouping markets based on the deciles of the firm's water inflow (water stock): each cell reports the average price difference between the simulated market and the status quo with different shades of red and blue colors based on the sign and magnitude. The left (right) panels move capacity from fringe (all) firms. Unlike the plots in Figure 9, these plots cap transfer fractions to 50%. The average market price is approximately 150,000 COP/MWh. 2,900 COP $\simeq$ 1 US$.

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

Top panel: the distribution of the leader's water inflows is on the x-axis

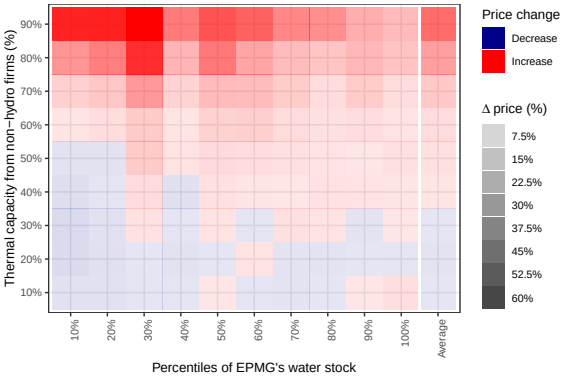


(a) Transferring κ% from all fringe firms

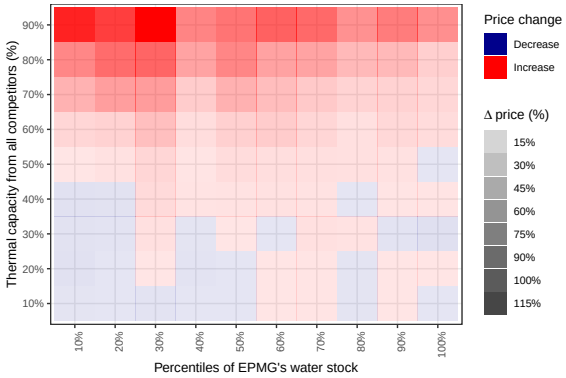


(b) Transferring κ% from all firms

Bottom panel: the distribution of the leader's water stock is on the x-axis



(c) Transferring κ% from all fringe firms



(d) Transferring κ% from all firms

Notes: The figure presents the results from the counterfactual exercises discussed comparing observed prices with counterfactual market prices as we endow the market leading firm with a fraction of its competitors' thermal capacities (y-axis) for varying levels of scarcity (x-axis). Top (bottom) panels proxy scarcity by grouping markets based on the deciles of the firm's water inflow (water stock): each cell reports the average difference between the simulated market and the status quo with different shades of red and blue colors based on the sign and magnitude. The left (right) panels move capacity from fringe (all) firms. Unlike the plots in Figure 9, which compares absolute price differences, this analysis compares percentage price differences by dividing each price difference by the baseline simulated market price ($\kappa\% = 0$).

References in the Online Appendix

Ryan, N. (2021). The competitive effects of transmission infrastructure in the indian electricity market. *American Economic Journal: Microeconomics*, **13** (2), 202–242.

Wolak, F. A. (2007). Quantifying the supply-side benefits from forward contracting in wholesale electricity markets. *Journal of Applied Econometrics*, **22** (7), 1179–1209.