Diversified Production and Market Power: Theory and Evidence from Renewables*

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Abstract

We show that market power can either exacerbate or mitigate fluctuations in energy prices due to renewable energy availability and provide empirical evidence from the Colombian energy sector, where hydropower generation is prevalent and energy suppliers have a diversified technology portfolio. Incentives to crowding-out rivals make a supplier produce more during a drought if it has access to other technologies with capacities unaffected by the drought. During abundance, instead, access to other technologies reduces a firm's supply compared to a scenario where these technologies are owned by its rivals, as rivals cannot crowd-out the firm experiencing abundance as easily. Jointly, these two effects create a U-shaped relationship between market concentration and prices when firms have diversified production technologies, which applies more broadly to other industries. Initially, transferring high-cost capacity to a large firm with the most efficient technology lowers prices, but eventually leads to unilateral price increases.

JEL classifications: L25, Q21, D47
Keywords: diversified production technologies, energy transition, renewable energy, hydropower, storage, supply function equilibrium, oligopoly

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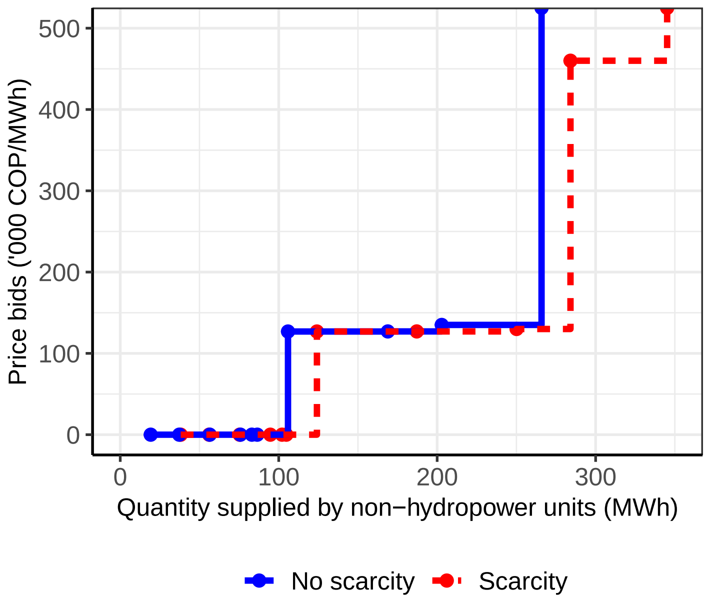
1 Introduction

The question of ownership of the means of production has long been contentious, particularly in transitioning economies (e.g., Murphy *et al.*, 1992), and the pursuit of the green transition is no exception. With our current energy mix serving as the primary contributor to global emissions (IEA, 2023), there is a pressing need for decarbonization investments in the energy sector, compelling energy firms to diversify their production technologies towards carbon-free renewable sources. Yet, there remains a gap in understanding how firms make production decisions when they have access to multiple technologies, as much of the economic literature consider capital as a homogeneous input (e.g., Olley and Pakes, 1996). This consideration is particularly significant in the energy market, where environmental challenges intersect with socioeconomic issues exacerbated by the regressivity of electricity prices (e.g., Reguant, 2019, Haar, 2020).

How do diversified firms wield their market power? This paper delves into this question by examining the Colombian wholesale energy market, where suppliers own both renewable resources, such as dams, and conventional thermal generators, like fossil fuels. During droughts, a firm's capital diminishes due to reduced water stock. This leads to a drop in hydropower supply and a subsequent price increase. Our key finding is that the same firm offsets the price spike by strategically increasing its supply of less efficient technologies, such as thermal energy, to still crowd out competitors while saving water. Figure 1 illustrates this response, showing that a firm's conventional supply during droughts (dotted red line) expands compared to normal times (solid blue line). Furthermore, we observe that the firm would have reduced its hydropower supply even more if it lacked access to alternative technologies, which alleviate its overall capacity constraints. Hence, the mere availability of alternative technologies prompts firms to produce more with the most efficient ones, highlighting a degree of "complementarity" across technologies even without direct synergies. This paper proposes a theory and presents empirical evidence to unveil the implications of having multiple technologies with different capacities and efficiency for a firm's excercise of market power and market outcomes.

We demonstrate that the complementarities within diversified firms reveal a novel U-shaped relationship between market prices and industry concentration. Highly efficient technologies can disrupt a firm's competitors by producing at their marginal cost, potentially crowding them out. Additionally, further diversification of these firms by reallocating less efficient capacity from non-diversified competitors can decrease market prices by enhancing these complementarities within the receiving firm. However, complete crowding out may not always be the optimal strategy, particularly if the firm's capacity falls short of meeting total demand. In such scenarios, similar diversification incites the receiving firm to exploit its size advantage, resulting in a reduction of production and an increase in prices. Thus, the consequences of concentration hinge on two

Figure 1: Impact of scarcity on non-affected generators



The figure plots the supply schedule of the non-hydropower generators owned by a Colombian diversified energy firm when it either faces scarcity (red dashed line) or not at its dams. Scarcity is defined as observing a water inflow in the first two deciles of its distribution. The red supply schedule was submitted by ENDG on December 12, 2010 at noon, whereas the blue schedule was submitted two weeks before. Total demand differ by less than 1% in the two markets.

countervailing factors: the efficiency of each technology a firm owns and its total capacity, which respectively create Bertrand and Cournot forces. As a result, market prices exhibit a downward trend for small capacity reallocations as firms employ more of their most efficient technology, but they increase for larger reallocations, as predicted by standard trade models (Atkeson and Burstein, 2008), forming a U-shaped relationship.

Building upon these insights, our structural model further supports these findings, demonstrating that doubling the thermal capacity of the market leader through capacity transfers from its competitors results in a 10% reduction in market prices during droughts. However, larger capacity transfers may backfire, leading to price hikes as the firm can increase its prices without fear of losing significant market share. Therefore, our results highlight a novel interplay between ownership, technologies, and market power, offering new perspectives on anticompetitive behaviors associated with firm size, which are of interest to maintain the ongoing transition towards renewable energy sources affordable.

More broadly, in oligopolistic industries where the efficient technology is scarce, a larger diversified market leader might result in smaller market prices than if its inefficient technology were alloacted to a different firm.

We theoretically examine the behavior of diversified firms through a static homogeneous-good oligopoly game where firms confront demand uncertainty and own both low- and high-cost technologies, representing hydropower and thermal generation, respectively. Each technology features its own cost curve, which becomes vertical at capacity. A firm's total cost is the horizontal sum of its technologies' cost curves, and, hence, it is increasing in the quantity produced. The equilibrium price is determined by firms submitting supply schedules detailing the quantity they are willing to produce at various market prices, following the supply function equilibrium concept proposed by Klemperer and Meyer (1989). This concept, unlike traditional models such as Cournot and Bertrand, is ex-post optimal and encompasses them as extreme cases by permitting any non-negative slope at different market prices.[1]

Initially, in this market, no firm is diversified and the largest firm also has the most efficient technology. We then diversify it by reallocating high-cost capacity to this market leading firm in different scenarios. We find that the transfer reduces its rivals' ability to compete, leading to higher price, if the leader's low-cost capacity was substantially larger than that of its rivals before the transfer, as under abundance of hydropower. Therefore, when the leader's market power comes from its total size, reallocating capacity to the leader effectively removes resources from the market, as, according to the merit order, the leader prioritizes its low-cost technology to the high-cost one.

Conversely, if the leader faces scarcity of the efficient technology even though being the largest firm in the market, it exploits the new high-cost capacity to capture market shares at high prices for high-demand scenarios, prompting rivals to increase production at slightly lower prices to safeguard their market shares by undercutting the leader. As strategic behavior unravels, each firm expands its supply schedule. Although the leader's efficient capacity stay unchanged after the transfer, it prices its efficient technology more aggressively, resulting in a smaller equilibrium price despite the higher industry concentration. Our results illustrate two sources of market power when firms are diversified: total capacity, driving prices up, and relative efficiency, driving them down.

Alternatively, if a significantly large portion of high-cost capacity is transferred to the market leader – imagine the extreme scenario where it becomes a monopolist – we demonstrate that market prices invariably increase. This is because the firm can now reduce its production to raise prices without fear of losing inframarginal units, explaining the U-shaped relationship between prices and concentration.

Our empirical investigation centers on the Colombian energy market for several reasons. Firstly, all major players in this market operate diversified production, utilizing a mix of hydropower and thermal energy. Secondly, regulatory requirements ensure the availability of data on firms' desired production for each technology they employ, a rarity in many other industries. Thirdly, natural fluctuations in weather patterns provide an exogenous factor affecting hydropower capacity, allowing us to study market power and

[1]This theoretical framework (see also Wilson, 1979, Grossman, 1981) has found several applications not only in energy markets (Green and Newbery, 1992), but also in financial markets (Hortaçsu *et al.*, 2018), government procurement contracts (Delgado and Moreno, 2004), management consulting, airline pricing reservations (Vives, 2011), firm taxation (Ruddell *et al.*, 2017), transportation networks (Holmberg and Philpott, 2015), and also relates to nonlinear pricing (e.g., Bornstein and Peter, 2022).

concentration without relying on potentially endogenous events like mergers.

To quantify the impact of diversification on market prices, we extend the theoretical model to account for the main features of the Colombian energy market. In particular, thermal capacity is consistently available, while dry and abundant spells directly influence a firm's hydropower capacity by altering the opportunity cost of its supply. We show that generators of any technology internalize a firm-level drought through this opportunity cost: if a generator holds market power, it raises its current production to reduce the market price so that a smaller portion of the firm's hydropower supply goes into production, thereby saving water while crowding out competitors. These responses underscore the abovementioned "complementarity" across technologies, which reduces the marginal cost of hydropower production if more thermal is available.

As a result, prices decrease as we increase concentration around the most efficient firm by reallocating thermal generators from its competitors. However, at the same time, the firm's residual demand becomes steeper, as the larger firms face a more inelastic demand. Hence, considering this novel tradeoff between capacity and efficiency might help policymakers achieve a second-best scenario, especially in settings where the first-best (perfect competition) is not feasible due to large barriers to entry.

To causally identify this U-shape in the data, we simulate market prices in different scenarios where we exogenously endow the market-leading firm with increasing fractions of its competitors' thermal capacity. The model primitives – the marginal cost of thermal and hydropower generators and the intertemporal opportunity cost of holding water – are identified from the first-order conditions.[2] We estimate the model on hourly markets between 2010 and 2015 and show that the model fits the data well.

Our findings reveal that during droughts, average market prices decline by up to 10% if we double the size of the market leader's thermal capacity. However, for larger reallocations, prices increase substantially, aligning with the conclusions from models featuring non-diversified firms. During wet spells, reallocations diminish rivals' competitiveness, resulting in higher market prices. Notably, the disparity in prices between droughts and wet spells can be significant, with prices during droughts reaching up to ten times higher. This underscores the welfare benefit of diversification, particularly evident in situations where the low-cost technology is scarce.

Earlier investigations have warned against joining renewable and thermal generators because when firms compete à la Cournot, they benefit by reducing their thermal supplies when they also have renewables, as renewables induce a more inelastic demand (Bushnell, 2003, Acemoglu *et al.*, 2017). In contrast, concurrent work by Fabra and Llobet (2023) show that diversified suppliers competing à la Bertrand can lead to lower prices if a firm has private information about the realized renewable capacity at its disposal, as it

[2] We build on the multi-unit (e.g., Wolak, 2007, Reguant, 2014) and dynamic auctions literature (e.g., Jofre-Bonet and Pesendorfer, 2003), and examine externalities across generators (e.g., Fioretti, 2022).

happens for solar and wind farms. In their setting, higher renewable capacity leads sibling thermal generators to bid more aggressively for extra market shares because having more renewables makes the firm's supply inframarginal. However, we observe the opposite in Colombia, as firms increase thermal generation when they face scarcity.[3]

We provide a unifying account featuring results from both streams of literature that allows us to discuss when diversifying production increases or decreases market prices. Instead of asymmetric information, as Colombian suppliers are aware of each others' water stocks, we explain the thermal generators' strategies through their market power, which pushes them to steal market shares when they internalize higher prices due to scarcity at a sibling dam. As the storability of solar and wind resources continues to improve (Schmalensee, 2019, Koohi-Fayegh and Rosen, 2020, Andrés-Cerezo and Fabra, 2023), we expect our results to apply also to other renewables, in which case firms could substitute across renewables technologies, without the need for polluting thermal generators, thereby speeding the transition by solving renewables' intermittency problems (Gowrisankaran *et al.*, 2016, Vehviläinen, 2021) and making it more affordable (Butters *et al.*, 2021).

How might our findings guide policy decisions? Antitrust regulation emerges as an innovative tool for driving down the costs of the green transition, complementing standard approaches like subsidies (Acemoglu *et al.*, 2012, Abrell *et al.*, 2019, Ambec and Crampes, 2019). While existing literature examines subsidy regulations for renewable capacities and grid integration to foster competition and maintain low energy prices (e.g., De Frutos and Fabra, 2011, Ryan, 2021, Elliott, 2024, Gowrisankaran *et al.*, 2022, Gonzales *et al.*, 2023), it often overlooks how ownership of new and old technologies affects pricing. Our findings open new questions regarding firms' efficient ownership structures. For example, Colombia limits firms to holding no more than 25% of the total installed capacity to prevent market power abuses. However, this threshold also hampers the advantages of diversified production. Although determining the ideal threshold exceeds the scope of this paper, we contend that it should vary according to a firm's technological capabilities.

Although an illustrious literature questioned the opportunity to consider capital as a homogeneous input (e.g., Robinson, 1953, Solow, 1955, Sraffa, 1960), the literature primarily investigates either competition across multiproduct firms (e.g., Nocke and Schutz, 2018b) or capacity constraints at firms with a single production technology (Kreps and Scheinkman, 1983, Bresnahan and Suslow, 1989, Staiger and Wolak, 1992, Froeb *et al.*, 2003).[4] In this paper, we show that diversification results in strategic complementarities both within a firm and across competitors. Two implications arise. First, production

[3]Also Garcia *et al.* (2001) and Crawford *et al.* (2007) studied competition across energy firms with multiple generators but do not examine the downward price pressure created by capacity reallocations.

[4]In such models, concentration typically leads to higher markups (De Loecker *et al.*, 2020, Benkard *et al.*, 2021, Grieco *et al.*, 2023), with adverse effects on productivity (Gutiérrez and Philippon, 2017, Berger *et al.*, 2022) and the labor share (Autor *et al.*, 2020). The endogeneous growth literature is a notable exception (e.g., Aghion *et al.*, 2024), as firms can exhibit multiple production technologies if they have both green and brown patents, but does not consider capacity constraint.

function estimation techniques might fail to recover productivity even allowing for factor-augmenting technologies (e.g., Demirer, 2022), in the absence of technology-specific data. Second, our results have direct implications for required divestitures that antitrust bodies often require to merging parties (Compte *et al.*, 2002, Friberg and Romahn, 2015). Divestitures may defeat their purpose if they result in higher market prices due to less technology diversification.[5]

The paper is structured as follows: Sections 2 and 3 introduce the Colombian wholesale market, describe the data, and present empirical patterns of supply decisions during 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 by discussing our contributions to antitrust policies and the green transition.

2 The Colombian Wholesale Energy Market

This section provides an overview of the Colombian energy market, focusing on the available technologies and market dynamics.

2.1 Generation

Colombia boasts a daily energy production of approximately 170 GWh.[6] Between 2011 and 2015, the market featured around 190 generators owned by 50 firms. However, it exhibits significant concentration, with six major firms possessing over 50% of all generators 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 sources such as fossil fuel-based generators (coal and gas). Additional sources comprise renewables like wind farms and run-of-river, which utilizes turbines on rivers without water storage capabilities. Figure 2a 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.

[5]Relatedly, Nocke and Whinston (2022) propose that antitrust authorities diagnose the anti-competitiveness of mergers through HHI thresholds varying based on merger-induced synergies. The "synergy" we uncover differs from standard cost synergies, where the merged entity's marginal cost equals the minimum marginal cost of the merging firms (e.g., Paul, 2001, Verde, 2008, Jeziorski, 2014, Miller *et al.*, 2021, Demirer and Karaduman, 2022). The literature also identifies buyer concentration as another source for lower consumer prices (Morlacco, 2019, Alviarez *et al.*, 2023).

[6]For regional context, neighboring countries' energy production in 2022 included 227 GWh in Venezuela, 1,863 GWh in Brazil, 165 GWh in Peru, 91 GWh in Ecuador, and 33 GWh in Panama. Globally, figures were 11,870 GWh in the US, 1,287 GWh in France, and 2,646 GWh in Japan.

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, production varies over time, as shown in Panel (b) of the same figure, which contrasts production across technologies with dry seasons represented by periods of high temperature or low rainfall at dams (gray bars). During dry spells, hydropower production decreases, and thermal generation compensates for water scarcity.[7] Firms strategically stockpile fossil fuels like coal and gas ahead of anticipated dry spells (Joskow, 2011), with their prices closely tied to global commodity markets. 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 3 highlights that wholesale energy prices more than double during scarcity periods.[8] 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 2 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 generators 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 day-ahead (spot) market. The spot 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 quantity and price-bids to produce energy the following day. Through this bidding process, each generator submits one quantity bid per hour and one price bid per day.[9] 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 (*sibling*) generators owned by the same firm.

Spot market-clearing. Before bidding, the market operator (XM) provides all generators 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*

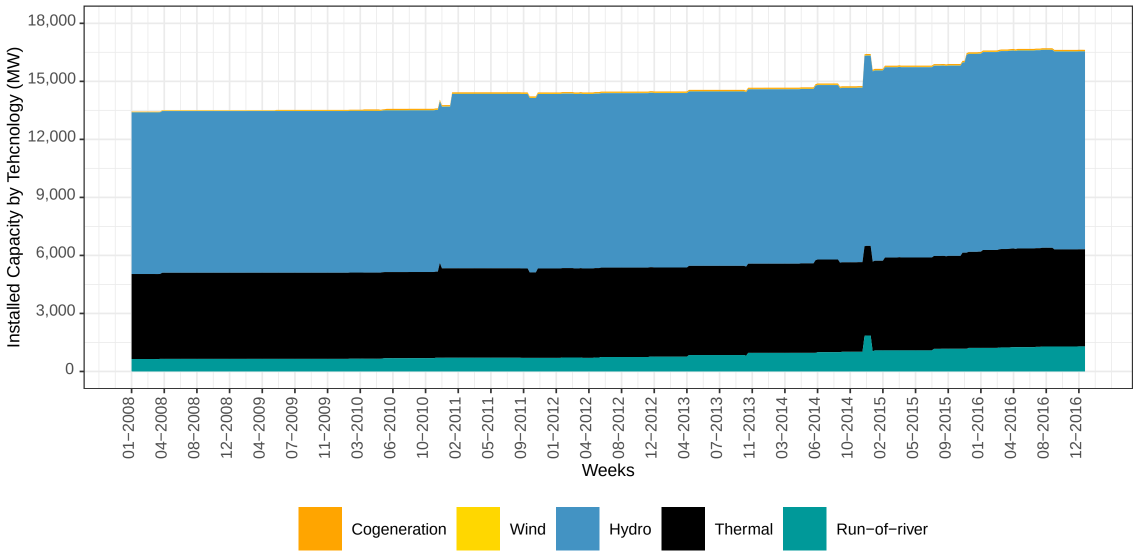
[7]Data reveals a correlation between thermal production and minimum rainfall at Colombian dams of -0.32 (p-value ≤ 0.01) and 0.27 (p-value ≤ 0.01) for hydropower generation.

[8]The correlation of the average hourly price and droughts 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.

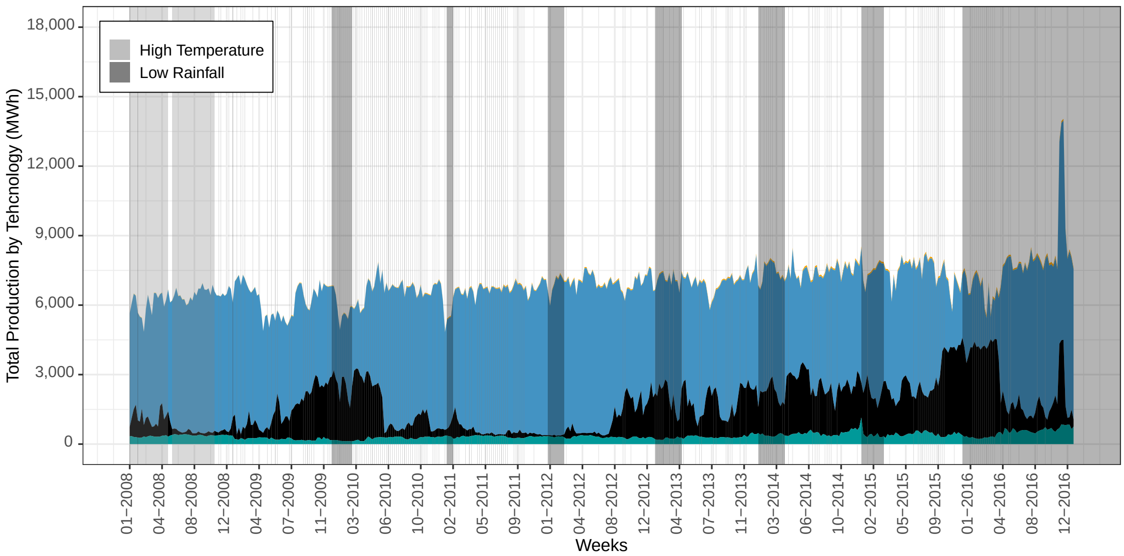
[9]Participation in the spot market is mandatory for large generators with capacity over 20MW.

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

(a) Total installed capacity by technology



(b) Total weekly production by technology



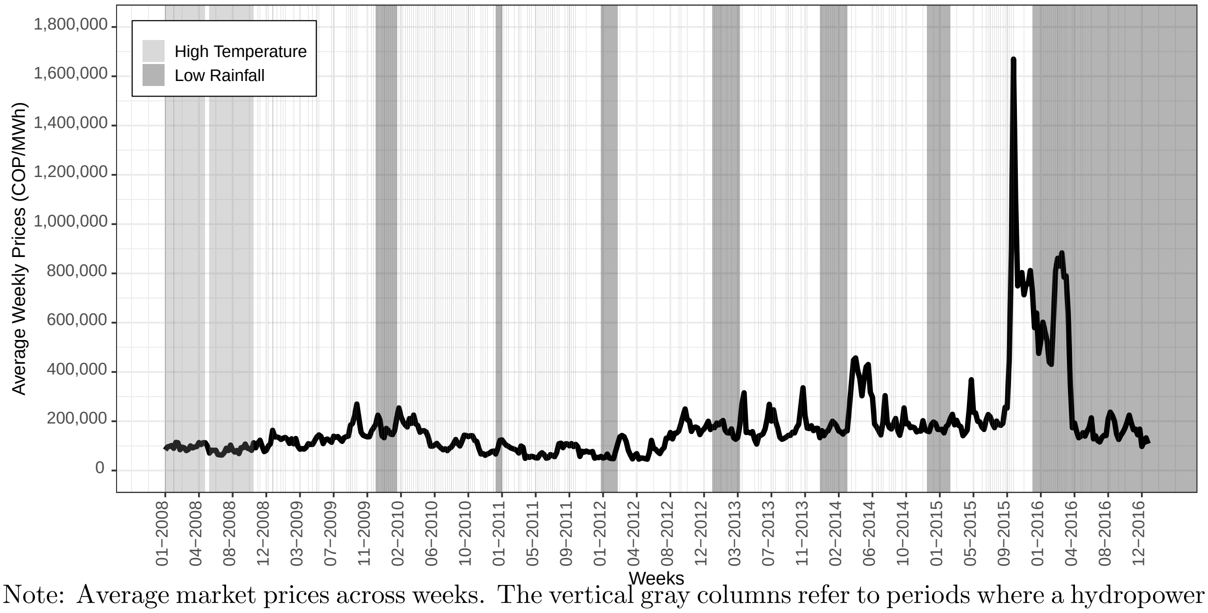
Note: The figure illustrates the total installed capacity (top panel) and production volumes (bottom) by technology. The vertical bars in Panel (b) refer to periods where a hydropower generator experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average.

to all generators. During the production day, actual generation may differ due to production constraints or transmission failures. The spot hourly price is set at the value of the price bid of the marginal generator, with all dispatched units paid the same price.[10]

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

[10] The price paid to thermal generators can vary due to startup costs, which are reimbursed (Balat *et al.*, 2022). Despite high barriers to entry, a central factor sustaining firms' coordination efforts (Levenstein and Suslow, 2006), there is no evidence of a cartel in the period we study (Bernasconi *et al.*, 2023).

Figure 3: 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$.

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 dataset, we observe each generator's overall contract position for each hourly market.

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.[11]

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.[12] ENSO forecasts, published on the 19th of each month, provide probability forecasts for the following nine months, aiding

[11]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 generators and stations. We account for the orography of the country when computing the distance between generators and weather measurement stations, using information from the *Agustin Codazzi Geographic Institute.*

[12]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, though occasionally lasting a few years, as indicated by the large gray bar toward the end of the sample in Panel (b) of Figure 2.

dams in predicting inflows. We have monthly information from 2004 to 2017.

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) generators.

3 Diversified Production: Empirical Evidence

This section leverages exogenous variations in water inflow forecasts, impacting the capacities of dams, to offer novel perspectives on the production decisions made by diversified firms. Sections 3.1 and 3.2 delineate the empirical methodology and present the primary findings. Finally, Section 3.3 scrutinizes the ramifications for market clearing prices.

3.1 Empirical Strategy

This section outlines the empirical strategy used to assess the responses of a firm's hydro and thermal supplies to variations in its hydropower capacity, utilizing data from periods of drought and abundance within firms.

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 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.

We investigate generators' reactions to forthcoming inflows by analyzing the equation:

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

This equation explores how generator j of firm i updates its current supply schedule $y_{ij,th}$ based on anticipations of favorable ($\text{favorable}_{ij,t+l}$) or adverse ($\text{adverse}_{ij,t+l}$) forecasts, l months ahead relative to its average forecast. To minimize autocorrelation, we aggregate bids over weeks (t) per hour (h). Instances where a generator's quantity bid falls below the 5^{th} percentile of the distribution of quantity bids placed by generators of the same technology are excluded to mitigate contamination from unobserved maintenance periods within a week. Importantly, this truncation does not qualitatively impact the results.

The definition of the variables $\{\text{adverse}_{ij,t+l}\}_l$ and $\{\text{favorable}_{ij,t+l}\}_l$ 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 generators – 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.

We control for changes in market conditions in $\mathbf{x}_{ij,t-1,h}$ utilizing 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 generators 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_t) and hour levels (τ_h). The standard errors are clustered by generator, month, and year.[13]

Exclusion restriction. Identification in (1) relies on the credible assumption that a firm's current bidding does not directly depend on past temperatures and rains at the dams but only indirectly through water inflows. This restriction is credible because a generator should only care for its water availability rather than the weather per se – due to their rural locations, the local weather at the dam is unlikely to influence other variables of interest to a generator, like energy demand in Colombia, which is controlled for in the estimation. Appendix C is dedicated to robustness checks and also proposes an alternative estimation strategy where generators respond symmetrically to favorable and adverse forecasts. The Appendix also discusses the information content of our inflow forecasts by showing that generators' responses to forecast errors – the observed inflow minus the forecasted inflow – are insignificant.

3.2 Results

3.2.1 Hydropower Generators

Figure 4 displays the coefficients, $\{\beta_l^{low}, \beta_l^{high}\}_l$, from (1). The dependent variable is the logarithm of hydropower generator j's price bid in Panel (a) and quantity bid in Panel (b). Coefficient magnitudes represent percentage changes when facing an adverse forecast (red circles) or a favorable forecast (blue triangles) one, three, or five months ahead.[14]

Dams strategically adjust their supply schedules in anticipation of extreme events. They adapt their supplies mainly by changing their quantity bids rather than their price bids because, having low marginal costs, they always produce and the market asks for

[13]Alternatively, spatial clustering of standard errors is a potential approach. However, hydrology literature (Lloyd, 1963) suggests that a riverbed acts as a "fixed point" for all neighboring water flows, making shocks at neighboring dams independent. Moreover, determining an appropriate distance for thermal generators remains unclear. Hence, we do not pursue spatial clustering in this analysis.

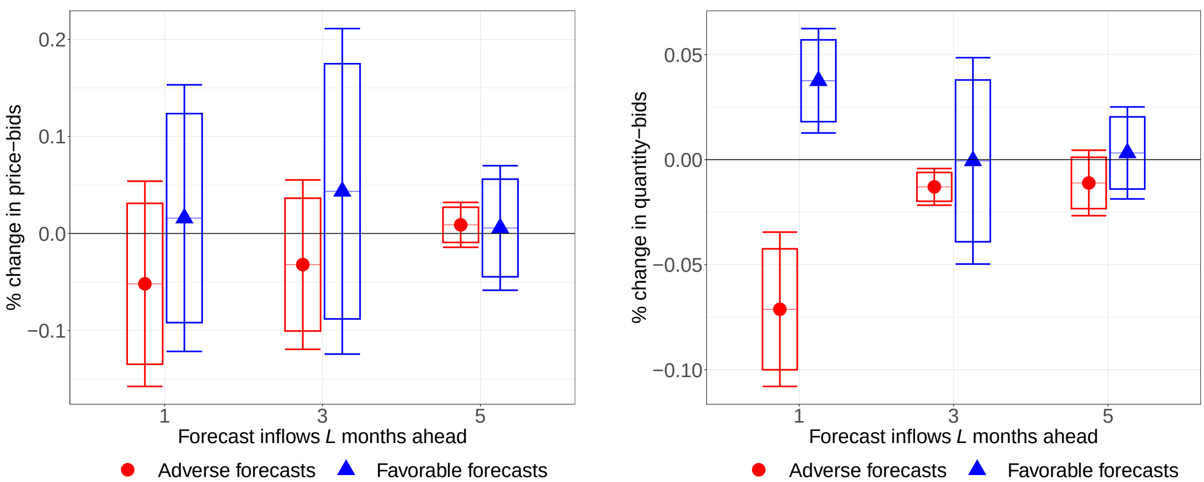
[14]The chosen timing accounts for the limited correlation across monthly inflow forecasts, with a correlation of 0.2 between forecasts two months apart and 0 for forecasts further apart.

hourly quantity bids but only daily price bids. We find that dams decrease their supply schedules ahead of adverse events, recognizing the negative impact of capacity constraints (e.g., Balat *et al.*, 2015), and increase them ahead of favorable forecasts. Notably, generators are more responsive to adverse events: generation decreases by 7.1% for one-month adverse forecasts and 1.3% for two-month adverse forecasts, whereas it only increases by approximately 3.7% one month ahead of a favorable forecast.[15]

3.2.2 "Sibling" Thermal Generators

Figure 5 presents the estimation results of (1) on thermal generators that are sibling to dams. Due to the absence of water stocks for thermal generators, we include a control for a firm's lagged total water stock in $\mathbf{x}_{ij,t-1}$. The results unveil distinct responses of sibling thermal generators to forecast inflows compared to hydropower generators. Sibling thermal generators increase their supply schedule before favorable events (blue triangles) and decrease it before adverse ones (red circles). They primarily adjust through their price bids because, given their high marginal costs, they are not operational at all times and lack the flexibly to vary production across hourly markets. Finally, although the analysis indicates that they respond to extreme events well before hydropower generators, it is worth noting that this analysis focuses on extreme firm-level forecasts rather than generator-level forecasts as in the previous section, which might be less severe.[16]

Figure 4: Hydropower generators' responses to inflow forecasts



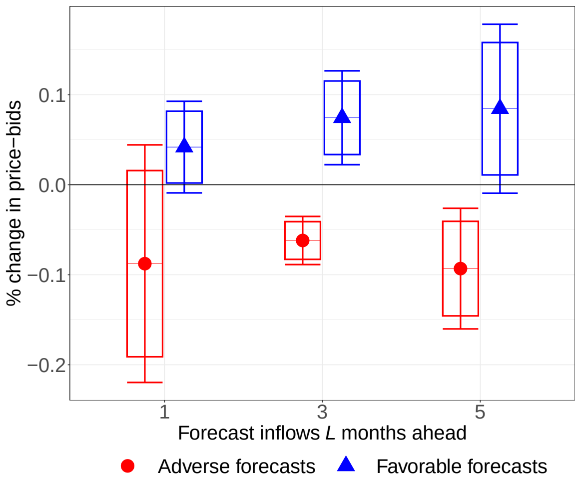
(a) Price bids (b) Quantity bids

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts according to (1). Each plot reports estimates 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.

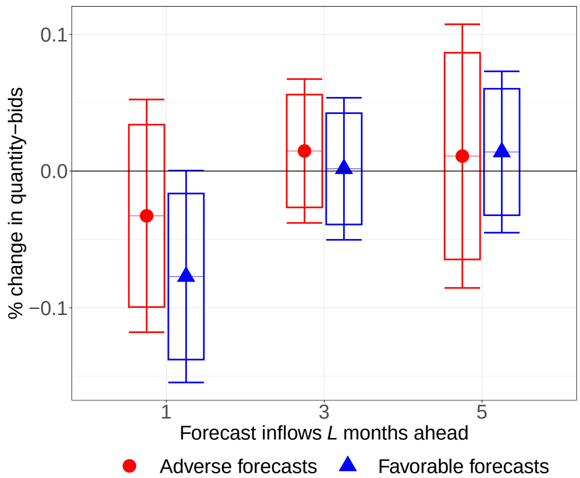
[15] The results are consistent to to different forecast horizons (Appendix Figure C4) and to running (1) separately for each monthly forecast so to break any possible correlation across months (Figure C5).

[16] Appendix Figure C6 shows that generators respond already two months ahead of adverse forecasts.

Figure 5: Thermal generators responses to sibling hydro generators' inflow forecasts



(a) Price bids



(b) Quantity bids

Notes: The figure studies how sibling thermal generators respond to favorable or adverse future water forecasts according to (1). Each plot reports estimates 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.

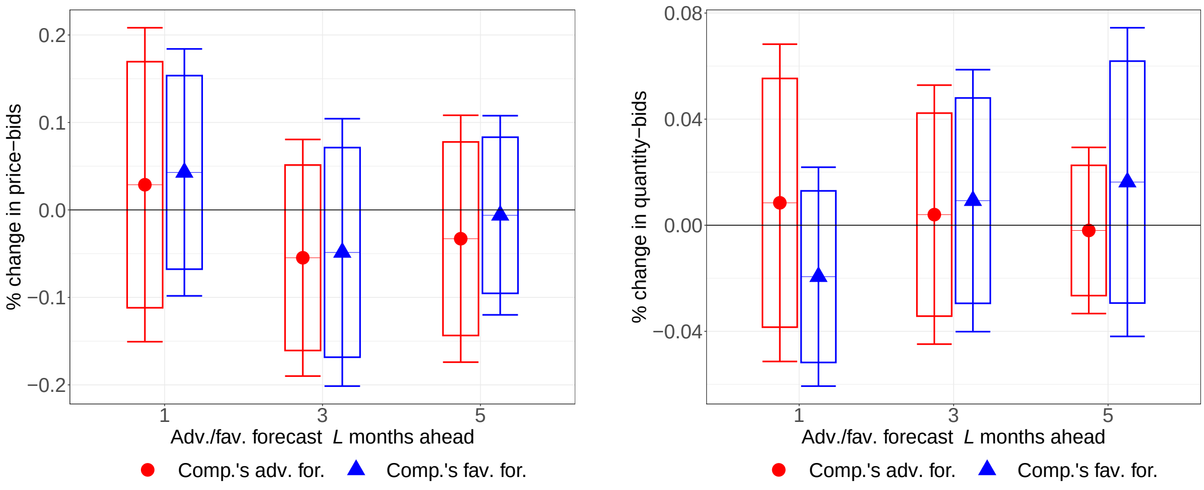
3.2.3 Competitors' Inflow Forecasts

To comprehensively understand firms' responses to future shocks, we explore whether hydropower generators 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 6 reveals minimal movement in a firm's bid concerning its competitors' forecasts, with magnitude changes generally within $\pm 1\%$ and lacking statistical significance. Joint significance tests for adverse and favorable forecasts do not reject the null hypothesis that they are zero at standard levels.[17]

Appendix C.1.3 further extends this analysis in two dimensions. First, it demonstrates that generators respond to their own inflow forecasts but not to the inflow forecasts of competitors. Second, despite the potential informativeness of competitors' water stocks, it offers suggestive evidence against this hypothesis. Consequently, generators do not appear to react substantially to the crucial potential state variables of their competitors. This observation, while potentially counterintuitive in a competitive context, finds parallels in industrial organization literature. For instance, Hortaçsu *et al.* (2021) show that airline carriers employ simple heuristics in pricing, disregarding the pricing of other airline companies. Similar to hydropower generators, airline firms grapple with forecasting seat demand (inflows) across various routes (dams). In both scenarios, focusing on their own state variable while overlooking those of competitors may simplify a complex problem.

[17] Appendix Figure C7 confirms similar results on a shorter forecast horizon (one to three months).

Figure 6: Responses to competitors' inflow forecasts



(a) Price bids

(b) Quantity bids

Notes: The figure studies how generators respond to favorable or adverse future water forecasts accruing to competitors according to (1). Each plot reports estimates 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.

3.3 Implications for Market Prices

Firms strategically deploy their thermal technology differently during periods of abundance (high inflows) and scarcity (low inflow). To assess whether a greater unshocked capacity (i.e., thermal) can alleviate the price hike resulting from dry spells, we capitalize on the exogenous occurrence of such periods across firms with different thermal capacity.

We base our analysis on the following regression model,

$$\begin{aligned} \ln(p_{th}) = &\sum_{l=1}^{L} \Big[\gamma_l^{low} \sum_i \Big(\text{adverse}_{i,t+l}\, K_{it}^T\Big) + \gamma_l^{high} \sum_i \Big(\text{favorable}_{i,t+l}\, K_{it}^T\Big)\Big] \\ &+ \sum_{l=1}^{L} \Big[\beta_l^{low} \sum_i \text{adverse}_{i,t+l} + \beta_l^{high} \sum_i \text{favorable}_{i,t+l}\Big] \\ &+ \gamma^{cap} \sum_i K_{it}^T + \mathbf{x}_{t-1,h}\alpha + \tau_{th} + \epsilon_t, \end{aligned} \tag{2}$$

where the logarithm of the hourly average weekly price is on the left-hand side. On the right-hand side, the first line of (2) features the interaction between whether a firm expects adverse or favorable inflow forecasts l-months ahead with its total sibling thermal capacity in GWh, K_{it}^T. We expect that the greater thermal capacity available to generators with adverse forecasts, the lower the price ($\gamma_l^{low} < 0$), and vice-versa for favorable inflows ($\gamma_l^{high} > 0$) if thermal generators do not operate in similar periods (cf. Figure 5). The remaining two lines of (2) control for the direct effect of adverse and favorable forecasts and total thermal capacity on spot prices. Finally, $\mathbf{x}_{t-1,h}$ includes lagged market outcomes, such as hourly average weekly demand and forward contracts, in logs. As error terms are likely correlated across seasons and hourly markets, we cluster the standard errors at the month and year level.

Table 1: The impact of technology substitution on spot prices

	(1)	(2)	(3)	(4)
	Hourly average weekly price ($\ln p_{ht}$)			
Adverse inflows (3 months)	0.166	0.210**	0.334**	
	(0.284)	(0.058)	(0.077)	
Adverse inflows (5 months)	0.413**	-0.127	-0.241	
	(0.126)	(0.094)	(0.117)	
Thermal cap. available to adv. inflows (3 months)	-1.303	-1.746**	-2.769**	
	(2.539)	(0.540)	(0.747)	
Thermal cap. available to adv. inflows (5 months)	-3.508***	0.875	1.979	
	(0.492)	(0.721)	(0.944)	
Favorable inflows (3 months)	0.032	0.021		-0.162**
	(0.203)	(0.037)		(0.044)
Favorable inflows (5 months)	0.374	0.001		-0.368*
	(0.195)	(0.083)		(0.154)
Thermal cap. available to fav. inflows (3 months)	-0.038	-0.045		1.380**
	(1.654)	(0.249)		(0.348)
Thermal cap. available to fav. inflows (5 months)	-2.939	0.064		3.133*
	(1.722)	(0.741)		(1.322)
Total sibling thermal capacity (GW)	-0.012**	-0.007***	-0.005***	-0.020***
	(0.003)	(0.001)	(0.001)	(0.003)
Lag demand (ln)	✓		✓	✓
Lag contract position (ln)	✓		✓	✓
Lag water stock (ln)	✓			
Lag spot price (ln)		✓		
FE: Hour	✓	✓	✓	✓
FE: Year-by-season	✓			
FE: Year-by-month		✓	✓	✓
Subset	All	All	Dry season	Wet season
N	7,464	7,464	2,424	5,040
R2 Adj.	0.639	0.934	0.920	0.915

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

Notes: This table shows the estimated coefficients from (2). The main regressors are the number of adverse (rows 1 and 2) and favorable inflows (rows 5 and 6) and their interactions with the thermal capacity available to the firms that expect an adverse (rows 3 and 4) and a favorable inflow (rows 7 and 8). All variables are standardized. Column 1 includes fixed effects by year-by-season, while the remaining columns have fixed effects by year-by-month. Column 3 examines adverse inflow in dry seasons (from December to March) and Column 4 examines favorable inflows in wet seasons (from April to November). Standard errors clustered by year and month.

Table 1 presents the results, where we focus on forecasts three and five months ahead to avoid the correlation between the current total water stocks and earlier forecasts (e.g., one month ahead). Column (1) controls for current market conditions using lag demand and forward contract position, as well as hydropower availability using total water stock. Fixed effects are at the hour and at the year-by-season (dry or rainy) level. Column (2) utilizes lag spot prices to control for market conditions and month-by-year fixed effects to account for hydropower availability. All regressors, including those that are a function of multiple variables, are standardized.

The estimates indicate that a one standard deviation increase in the number of adverse inflows expected three to five months ahead increases current prices. However, a concurrent one-standard-deviation increase in the sibling thermal capacity available partially compensates for these higher prices. Column (2) produces qualitatively similar findings, with the primary difference being that the largest effect appears three months ahead instead of five. This result can be attributed to the different controls, as including the lagged water stock in Column (1) captures some variation pertainig to three-month forecasts, as the current water stock correlates more strongly with the three-month forecasts than the five-month ones.

On the other hand, the results are less clear for favorable inflows, likely stemming from a correlation across forecasts. To gain deeper insights into the impact of favorable inflows on market prices, we refine our analysis by subsetting the sample in Columns (3) and (4). Specifically, we focus on adverse forecasts during dry seasons and favorable forecasts during wet seasons to further highlight the capacity constraint mechanism. Following the same mechanism described above, the benefits of diversified production are apparent during droughts. However, the opposite holds during wet seasons (Column 4). Here, prices are, on average, lower ahead of favorable inflows as dams expand their supplies. At the same time, thermal generators decrease their own supplies according to the mechanism outlined in Section 3.2.2. Therefore, more thermal capacity at firms expecting abundance increases market prices as these firms "take capacity out of the market" by decreasing their thermal supplies.

These findings hold significant implications for policy. The concentration of thermal capacity around firms expecting droughts may potentially decrease market prices, while conversely, it could raise prices during periods of expected abundance of renewables. To address these complexities, the following sections introduce an oligopoly model to examine how diversified firms wield their market power under diverse capacity configurations. Then, we extend and estimate the model using data from the Colombian wholesale energy market, conducting counterfactual exercises to quantify the price benefits resulting from moving thermal capacity to renewable suppliers.

4 A Competition Model With Diversified Firms

This section introduces an oligopoly model that reproduces the key empirical findings from the preceding section. Firms exhibit *diversified production*, enabling each to produce the same homogeneous good by means of technologies with differing marginal costs and capacities. We observe that a firm's market dominance hinges on either its superior *efficiency* or its larger *overall capacity*. When a firm dominates in capacities, it acts as a monopolist on the market unsatisfied by its competitors. Conversely, having the most efficient technology helps a firm "crowd out" its competitors by selling below the latters' marginal cost. We find that the opposing impacts of these two sources of market power on market outcomes produces the empirical patterns in Section 3.2.

The firm's problem. Consider an oligopolistic market where firms sell a homogeneous good, such as electricity and face an inelastic market demand, $D(\epsilon)$, subject to an exogenous shock ϵ shifting demand horizontally, with a strictly positive density in $[\underline{\epsilon}, \overline{\epsilon}]$. Before ϵ is realized, Firm i commits to a supply schedule, $S_i(p)$, which maximizes

$$\max_{S_i(\cdot)} E_\epsilon\big[\pi_i\big] = E_\epsilon\big[p \cdot S_i(p) - C_i(S_i(p))\big], \ \text{ s.t. } \ S_i(p) = D(\epsilon) - \sum_{j \neq i} S_j(p), \tag{3}$$

where $C(\cdot)$ is Firm i's cost of producing $S_i(p^*)$ at the market price, p^*. The market clearing constraint forces Firm i's supply to equate its residual demand, $D_i^R(p^*, \epsilon) \equiv D(\epsilon) - \sum_{j \neq i} S_j(p^*)$, which is the share of demand not satisfied by i's competitors at p^*.

We adopt the the supply function equilibrium (SFE) concept proposed in the seminal work of Klemperer and Meyer (1989), in which firm i selects $S_i(p)$ by best-responding to the supply of its competitors, $S_{-i}(p)$, to maximize (3). SFEs come with two key advantages. First, we need no assumption on firm's beliefs about the random demand shock ϵ: Klemperer and Meyer (1989) demonstrate that maximizing (3) with respect to a function, $S_i(p)$, is equivalent to choosing the optimal price p for every possible demand realizations $D(\hat{\epsilon})$, or $\max_p \pi_i(p, \hat{\epsilon}) = p \cdot D_i^R(p, \hat{\epsilon}) - C_i(D_i^R(p, \hat{\epsilon}))$. By varying $\hat{\epsilon}$, we obtain all possible realizations of $D_i^R(p, \hat{\epsilon})$ in which Firm i best responds to all its competitors: these quantity-price combinations, $(D_i^R(p(\hat{\epsilon}), \hat{\epsilon}), p(\hat{\epsilon}))$, depict the $S_i(p)$ that solves (3).

Second, this ex-post optimality property does not apply to other standard models of competition like Bertrand and Cournot under demand uncertainy and increasing marginal costs, making SFEs a natural equilibrium concept to examine the behavior of a firm with technologies displaying different marginal costs. Moreover, by allowing any non-negative supply slope, SFEs encompass these competition models as limiting cases, as submitting a horizontal schedule – a price for all possible quantities – is consistent with Bertrand, whereas a vertical schedule – a quantity for all prices – implies Cournot competition.

Diversified firms. Three technologies are available to $N\,(> 1)$ firms: a low-, a high-, and a fringe-cost technology, with constant unit costs c^l, c^h, and c^f, respectively, with $c^l < c^h < c^f$, non-negative, and finite. Firm i's technology portfolio K_i is a vector detailing its capacity of low-, high- and fringe-cost technologies, namely, $K_i = (K_i^l, K_i^h, K_i^f)$. Hence, $C_i = \sum_\tau c^\tau \cdot S_i^\tau(p)$ depends on its technology-specific supply, $S_i^\tau(p)$, at the price p.

First, we characterize the equilibrium where no firm is diversified. The technology portfolios of the strategic firms are $K_1 = (K_1^l, 0, 0)$ for Firm 1 and $K_2 = (0, K_2^h, 0)$ for Firm 2. Firm 1 can be viewed as a supplier of cheap renewable energy, such as a dam, and Firm 2 as a fossil-based generator. Given the size of dams in the empirical application, we assume that $K_1^l > K_2^h > 0$, making Firm 1 the market leader. The technology portfolio of fringe firm $i \in (3, ..., N)$ is $K_i = (0, 0, K_i^f)$ and includes only the fringe technology: since K_i^f is small, these firms are price takers.[18]

The equilibrium supply for strategic Firm i depends on the market price. Its supply is 0 for $p < c^h$, as producing would imply a loss for Firm 2, while Firm 1 can unilaterally inflate p to c^h by not producing for any $p \in [c^l, c^h)$. For $p \in [c^h, c^f]$, Firm i's FOC is:

$$S_i(p) = S'_{-i}(p) \cdot (p - c^\tau), \qquad i \in (1, 2). \tag{4}$$

Hence, $S_i(p)$ depends on the slope of its competitors's supply, $S'_{-i}(p)$, and the unit cost of the marginal technology that Firm i uses in production $\tau \in (l, h)$, resulting in different slopes given a different market price and marginal technology. At $p = c^f$, Firm i exhausts all its capacity to prevent being crowded out by the fringe firms. $S_i(p)$ are continuous for any p as a discontinuous supply provides opponents with a profitable deviation by increasing production at a slightly lower price (the details are in Appendix A.1).

Second, we counterfactually diversify Firm 1 by considering a reallocation of $\delta > 0$ unit of high-cost technology from Firm 2 to Firm 1, changing their technology portfolios to $\tilde{K}_1 = (K_1^l, \delta, 0)$ and $\tilde{K}_2 = (0, K_2^h - \delta, 0)$, respectively. This counterfactual theoretically replicates the analysis in Table 1 where we studied market price changes when the firm experiencing a drought (low K_1^l) or abundance (high K_1^l) had more or less thermal capacity ($K_1^h = 0$ or $K_1^h = \delta > 0$). The following proposition summarises our results:

Proposition 1 *A marginal capacity transfer from Firm 2 to Firm 1 increases the equilibrium price if* $K_1^l > \frac{c^f - c^l}{c^f - c^h} K_2^h$ *(abundance scenario) and decreases it if* $K_1^l < \frac{c^f - c^l}{c^f - c^h} K_2^h$ *(scarcity scenario).*

Proof. See Appendices A.1.1 – A.1.4. □

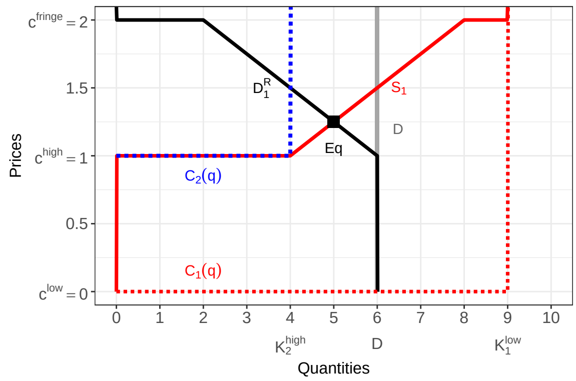
The proposition demonstrates that the lower (higher) prices observed when the firm experiencing scarcity (abundance) has more high-cost thermal capacity, as depicted in Table 1, are attributable to strategic competition. The intuition for this result is in Figure 7, which simulates the market outcomes from the two scenarios. The red (blue) dotted line reports the assumed cost structure of Firm 1 (Firm 2). Under abundance (top panel), Firm 1's low-cost capacity is $K_1^l = 9$ but only $K_1^l = 5$ under scarcity (bottom panel). The other primitives are constant across scenarios at $c^l = 0$, $c^h = 1$, $c^f = 2$, and $K_2^h = 4$. The right plots show the new cost structures after the capacity reallocation of $\delta = 0.5$ units of high-cost capacity from Firm 2 to Firm 1 in either scenario. Each plot illustrates the equilibrium strategies from the point of view of Firm 1. The solid red line is Firm 1's supply, $S_1(p)$, and its residual demand, $D_1^R(p)$, is in black. The right plots display the

[18] Fringe firms ensure that the two strategic firms face decreasing residual demands. A price ceiling can replace this assumption as in Fabra and Llobet (2023), or we could assume that the market demand $D(p, \epsilon)$ decreases in p as in the original work of Klemperer and Meyer (1989).

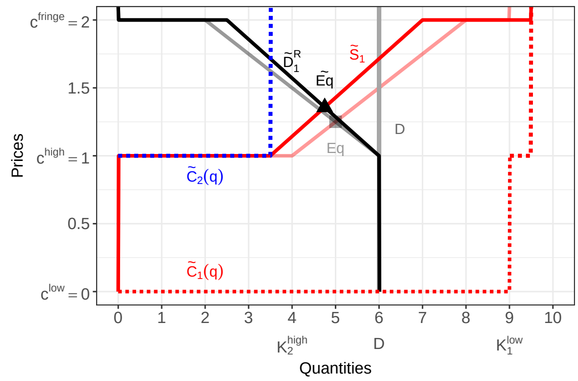
original S_1 and D_1^R before the transfer using shaded red and black lines. Without loss of generality, we fix the realized market demand at 6 (vertical gray line).[19]

Figure 7: Costs (dotted) and market outcomes (solid) from diversifying Firm 1

Top panel: Abundance of low-cost technology

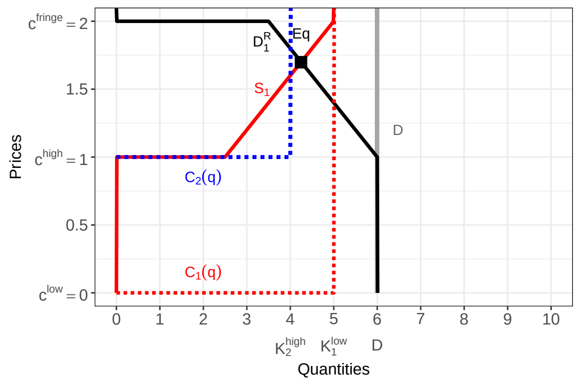


(a) Before the transfer
$K_1 = (9, 0, 0)$ & $K_2 = (0, 4, 0)$

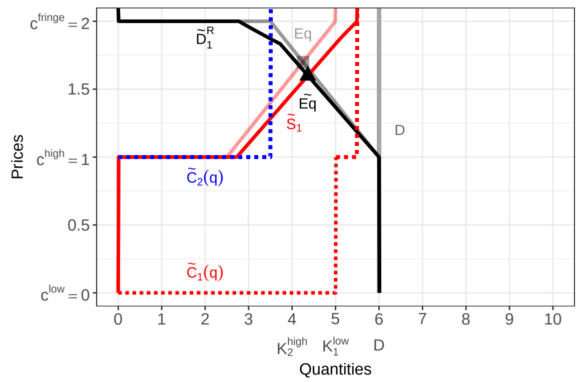


(b) After the transfer
$\tilde{K}_1 = (9, 0.5, 0)$ & $\tilde{K}_2 = (0, 3.5, 0)$

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). Left plots show outcomes before a capacity transfer, and right plots show 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 plots represents 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 $c^f = 2$.

The shape of S_1 is quite similar across scenarios. As mentioned above, $S_1(p) = 0$ for $p < c^h$. At the price level $p = c^h$, Firm 1 undercuts its opponent thanks to the *greater efficiency* of its low-cost technology, similar to the equilibrium that we would observe under Bertrand competition with asymmetric firms. Unlike Bertrand, Firm 1 does not employ all its capacity at this price because firms have incentives to reduce their

[19]The equilibrium supply of Firm 2 is in Appendix Figure A1, but it can also be determined as the horizontal difference between D and D_1^R.

production similar to a Cournot game. For every $p \in [c^h, c^f]$, the FOC in (4) entails comparing the profits from pricing the marginal unit at p against the alternative case of selling at $p' > p$, thereby losing the marginal unit to competitors while raising higher revenues from the inframarginal ones. Hence, the slope of S_1 becomes positive for $p > c^h$ at large enough quantities, and similarly for Firm 2. This tradeoff disappear at $p = c^f$, the price at which fringe firms flood the market. Therefore, either firm supplies all its capacity at $p = c^f$.

There is one central difference across scenarios: the identity of the firm enjoying extra capacity at the highest possible price. In equilibrium, at least one of the two firms must exhaust all its capacity. If that were not the case, they would find optimal to undercut their rival by producing more at lower prices. In Panel (a), Firm 2 exhausts all its capacity as $p \to c^f$, while Firm 1 is willing to sell its last one full unit of capacity only at $p = c^f$. This outcome is reversed under scarcity in Panel (c). Here, Firm 2 has a greater ability to unilaterally raise prices for greater demand realizations since Firm 1's capacity is smaller. As both firms raise their supplies, Firm 1 exactly exhausts its capacity as $p \to c^f$, while Firm 2 has idle capacity at this price. Scarcity does not prevent Firm 1 from crowding out Firm 2 for low-demand realizations; however, the horizontal segment of S_1 is now shorter compared to that in Panel (a) as Firm 1 rumps up production earlier to exhaust capacity at $p \to c^f$. Equilibrium prices are higher in Panel (c) than in Panel (a), echoing the results in Table 1, which shows that adverse inflows and lower capacities are associated with higher prices.

The right plots of Figure 7 find that diversifying Firm 1 has opposite effects on market prices in the two scenarios. First, notice that the new marginal cost curves, $\tilde{C}_1$ and $\tilde{C}_2$, denote a greater capacity concentration around Firm 1 in Panels (b) and (d) compared to Panels (a) and (c), respectively. Panel (b) presents the standard effects of concentration in oligopolistic markets: as Firm 1 prioritizes its low-cost capacity to its new high-cost one – the so-called, *merit order* – it employs this capacity only at $p = c^f$. Before the transfer, this capacity was sold by Firm 2 for $p < c^f$. As a result, the transfer effectively removes capacity from the market: both firms react by increasing their supply schedules, leading to higher prices, consistent with the role of greater thermal concentration during wet periods, as shown in Table 1.

In contrast, a similar technology transfer decreases prices under scarcity. In Panel (d), Firm 1 has more capacity than in Panel (c) but it still exhausts its overall capacity $(K_1^l + \delta)$ at $p = c^f$ in equilibrium because δ is small. However, the extra δ capacity alters Firm 1's trade-off between marginal and inframarginal units at all $p \in [c^h, c^f]$, allowing the firm to use its low-cost technology to crowd out its rivals more than in Panel (c) even though K_1^l stays unchanged, while using its new high-cost units for $p \to c^f$. Although hardly visible in the plot, Firm 1's supply function becomes flatter for quantities greater than K_1^l as the following marginal units cost the firm c^h instead of c^l. At this level, also

Firm 2's slope changes to best respond to its competitor, as visible in $\tilde{D}_1^R$. Therefore, Firm 2's supply also expands at all $p \in [c^h, c^f]$ to limit its revenue loss due to Firm 1's more aggressive pricing. As Firm 2 priced the transferred δ units exactly at c^f before the transfer, but Firm 1 sells them for $p \leq c^f$ after it, equilibrium prices decrease compared to Panel (c). This result is analogous to the finding in Table 1 that greater thermal capacity associated to firms expecting a drought mitigates price hikes.

The role of diversification. Diversification incentivizes a *more efficient* usage of the low-cost technology. If firms had the same technologies, moving capacity from a small to a large firm would always result in higher prices: without Bertrand forces, capacity is the sole source of market power, leading to higher prices. Similarly, if both Firms 1 and 2 were both diversified with the same capacity profile $(K^l, K^h, 0)$ with $K^l > 0$ and $K^h > 0$, moving high-cost capacity from Firm 2 to 1 raises market prices as Firm 2 becomes less competitive at high prices due to Firm 1's larger high-cost capacity (Appendix A.1.5).

Concentration & market power. Our analysis underscores a novel U-shaped relationship between concentration and market prices when efficiency dominates. To see it, focus on the scarcity scenario and imagine that all the capacity of Firm 2 is transferred to Firm 1 instead of just $\delta = 0.5$ units, making $S_2(p) = 0\,\forall p$. Due to such a dominant capacity position, Firm 1 will best respond by selling *all* its capacity at c^f, meaning a higher equilibrium price than in Panel (d).

Therefore, if firms are diversified, a small δ-reallocation to the most efficient firm pushes price down as the receiving firm expands its supply to crowd out its competitors – i.e., Bertrand forces. Further increases in δ lead to smaller marginal drops in prices, as the greater capacity provides the firm with the standard monopolistic incentives to exclude consumers by raising prices – i.e., Cournot forces. Prices will first drop, reach a plateau, and then increase as shares of capacities are transferred. When capacity dominates instead, any capacity transfers of less efficient technologies to the dominant firm can only raise prices due to the merit order.

General framework. Extending the game presented in the previous section to N strategic players and a downward-sloping market demand, Appendix A.1 finds that when the market clears and uncertainty resolves,

$$\underbrace{\frac{p - c_i(S_i(p))}{p}}_{\text{Markup}} = \underbrace{\frac{s_i}{\eta}}_{\substack{i\text{'s share of}\\ \text{price elasticity}}} \times \underbrace{\left(1 - \frac{S_i'(p)}{D_i^{R\prime}(p)}\right)}_{\substack{\textit{Crowd out ratio}\\ (\geq 1)}}. \tag{5}$$

As in Cournot, the left-hand side portrays firm i's markup. Unlike Cournot, the right-hand side features not only the price elasticity of demand faced by firm i but also the ratio of the slopes of firm i's supply and residual demand at price p, which we term "*crowd out.*" The ratio in parenthesis is non-negative: if greater than one, i gains market shares from its rivals and loses to them when smaller than one, as p changes marginally. The equilibrium supply balances a firm's efficiency, as measured by the merit order of i's production technologies, $c_i(S_i(p))$, with a firm's capacity dominance, which relates the firm's technology portfolio to that of its competitors through $S_i'(p)$ and $D_i^{R\prime}(p)$.

To gain intuition, imagine either plot in Figure 7 as a grid where prices and quantities are discretized: if at a given price increase $p+h$ competitors increase their supply more than i, then i loses quotes of the market as $S_i(p+h) - S_i(p) < D_i^R(p) - D_i^R(p+h)$. In standard oligopoly games, firms only internalize that increasing production decreases prices through the price elasticity, (s_i/η),[20] but do not internalize the strategic response of their competitors through the slope of their supplies $(D_i^{R\prime}(p) = D'(p) - S'_{-i}(p))$. As a result, firms' equilibrium schedules in (5) are *strategic complements.*

In the remainder of the paper, we use the insights developed in this section to quantify the benefits of diversification in the Colombian wholesale energy market.

5 Quantitative Model

This section extends the previous framework 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. The latter will provide exogenous variation in low-cost capacity, which we use to quantify the trade-off between efficiency and capacity from Section 4.

Institutions. Each firm i is equipped with $J_i \geq 1$ generators indexed by j. For simplicity, as illustrated in Figure 2, we focus on two technologies: hydro, characterized by a marginal cost c^H, and thermal, with a marginal cost c^T. Let $\mathcal{H}_i$ $(\mathcal{T}_i)$ represent the set of hydropower (thermal) generators owned by firm i. If both sets $\mathcal{H}_i$ and $\mathcal{T}_i$ are not empty, then firm i is diversified with technology portfolio $K_i = (K_i^h, K_i^t)$. This analytical framework can be extended seamlessly to incorporate additional technologies.

In the day-ahead market at time t, each generator j from firm i submits a price bid, b_{ijt}, along with hourly quantity bids, $\{q_{ijht}\}_{j=0}^{23}$. As in the previous section, the hourly demand, denoted as $D_{ht}(\epsilon_{ht})$, is vertical and is only known to firms up to a noise parameter, ϵ_{ht} with zero-mean and full support. The system operator crosses the supply schedules submitted by each firm, $S_{iht}(p_{ht}) = \sum_{j=1}^{J_i} \mathbb{1}_{[b_{ijt} \leq p_{ht}]} q_{ijht}$, against the realized

[20]Since demand is vertical, the demand elasticity to prices, η, is not defined in our model. Hence, in an abuse of notation, s_i/η in (5) is firm i's share of the demand elasticity of market prices, $(-\partial \ln p/\partial \ln D) \cdot S_i/D$ with market demand D, which is analogous to the demand elasticity of prices s_i/η faced by a firm in the Cournot and in the homogeneous-good Bertrand models.

demand $D_{ht}(\hat{\epsilon})$ to ascertain the lowest price, $p_{ht}(\hat{\epsilon})$, such that demand equals supply:

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

Thus, firm i's profits in hour h of day t hinge on ϵ_{ht} and p_{ht} and can be expressed as:

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

Here, the first term is i's spot market profits similar to that in (3). 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 reliability charge mechanism, known as *cargo por confiabilidad*, mandates generators to produce $\bar{q}_{ijt}$ whenever the spot price exceeds a scarcity price, $\bar{p}_t$, also contributes to firm i's overall profits.[21]

Law of motion of water. Hydropower capacity depends on water inflows and firms take it into account in their pricing decisions, as shown in Section 3.2. Drawing from the hydrology literature (e.g., Lloyd, 1963, Garcia *et al.*, 2001), a generator'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, the law of motion of a firm's overall water stock can be summarised through the following "water balance equation" as,

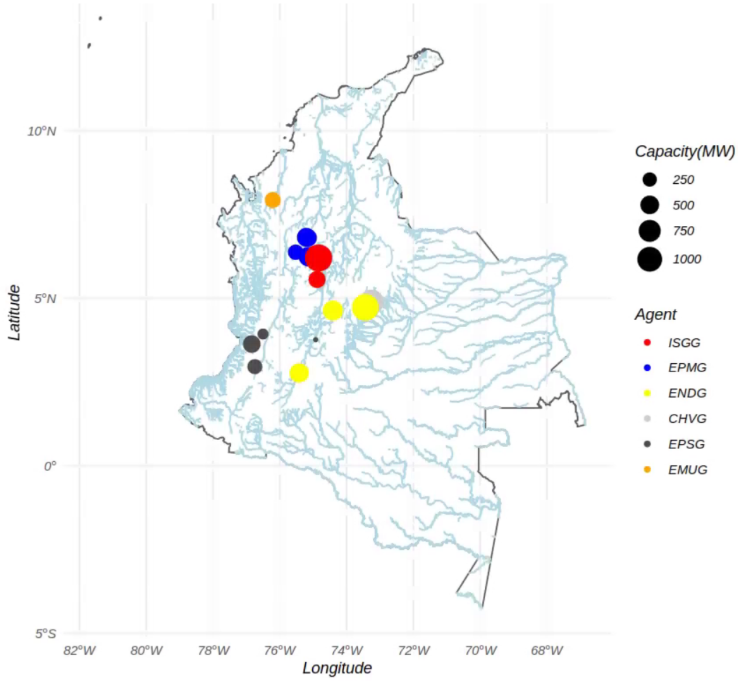
$$w_{it+1} = w_{it} - \underbrace{\sum_{h=0}^{23} S^H_{iht}(p_{ht})}_{\text{Water used in production}} + \underbrace{\sum_{j \in \mathcal{H}_i} \delta_{ijt}}_{\text{Water inflows}}, \tag{8}$$

where $w_{it}\,(\in [\underline{w}_i, \overline{w}_i] \equiv \mathcal{W}_i)$ denotes the observed water stock of firm i in period t in MWh, $S^H_{iht}(p_{ht}) = \sum_{j \in \mathcal{H}_i} \mathbb{1}_{[b_{ijt} \leq p_{ht}]}\, q_{ijht}$ is hydropower supplied by firm i's generators at the market price in each market hour, and δ_{ijt} is the water inflow of generator j in day t.

The law of motion in (8) is at the firm level for various reasons. First, our findings indicate that the generators 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 8), 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. Such a low correlation depends on riverbeds acting as "fixed points" for the perturbation in an area: given the spatial distribution of dam ownership in Colombia, local rainfalls accrue to just one firm, reducing the correlation across firms.

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

Figure 8: Dam locations



Notes: The plot displays dams location in Colombia by firm (color) and capacity (dam's size). Colombia's West border is with the pacific oceans while river streaming East continue through Brazil and Venezuela. To give a sense of the extension of Colombia, the country is approximately the size of Texas and New Mexico combined.

Strategic firms. We consider all firms with at least a dam as strategic. For these firms, the actual value of holding water results in a trade-off between current and future production. To the extent that firms take into account future inflows, a firm will choose a supply schedule to maximize the sum of its current and future profits according to

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

where the expectation is taken over the market demand uncertainty, ϵ_{ht}, and $\beta \in (0,1)$ is the discount factor. Using a recursive formulation, a firm's objective function becomes

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

where 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), whose inputs in $\mathbf{\Omega}_t$ are the water stocks, the realized hydropower productions, and water inflows on day t.

Competitive fringe. The supply schedule for fringe firms is zero for prices below their marginal cost. They supply all their capacity for higher prices.

5.1 Market Power and Market Prices with Diversified Firms

In this section, we derive the optimal quantity bid submitted by generator j of firm i. Our focus on quantity bids is grounded on the fact that generators submit hourly quantity bids but only daily price bids, providing greater flexibility in selecting quantities than price bids. We then study how market power affects pricing with differentiated firms.

Generators' supply schedules are characterized by step functions, which makes them not differentiable (Kastl, 2011). To study the first-order conditions (FOCs) from (9), we smooth supply schedules for each firm following Wolak (2007) and Reguant (2014). We analyze the change in discounted profits for firm i resulting from a marginal change in generator j's quantity bid, q_{ijht}, where j is either a hydro ($\tau_{ij} = H$) or thermal ($\tau_{ij} = T$) generator.[22] Omitting the expectation with respect to ϵ and refraining from indexing technology τ by ij for clarity, the FOCs are:

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

The derivative of firm i's current revenues from (7) with respect to q_{ijht} is in the first line of (10). The first term in parenthesis is the marginal revenue in the spot market. Market power lowers marginal revenues below market prices, p_{ht}, 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, akin to the capacity effect witnessed in Panel (b) of Figure 7, in which market power resulted from an exogenous capacity transfer. 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 marginal costs, $\{c^H, c^T\}$, in line two, and its intertemporal opportunity cost, in the remaining lines of (10), which endogeneizes

[22] Appendix E outlines the smoothing procedure.

the firm's capacity constraint through a tradeoff between current and future production. By allocating more capacity to the current hydro supply, this tradeoff intensifies as it decreases the firm's future water stock and profits. Hence, the integral in line three 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 $\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}} = 0$.

Generator 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 its equal to the change in the water stock, $\frac{\partial S^H_{iht}}{\partial q_{ijht}} > 0$, times the expected value of future profits as in the integral in line three. The introduction of market power, denoted as $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$, counteracts this loss. With market power, the firm recognizes that increasing q_{ijht} marginally decreases p_{ht}, resulting in a smaller portion of its hydropower supply being satisfied in equilibrium as $\frac{\partial S^H_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} < 0$. Consequently, the two terms in parentheses in the third line of (11) exert opposing influences on marginal costs during scarcity events, leading to a net positive effect for hydropower generators, which is consistent with a drop in supply ahead of droughts in Figure 4. In contrast, thermal generators cannot directly impact the firm's hydropower supply ($\frac{\partial S^H_{iht}}{\partial q_{ijht}} = 0$). In this case, the net effect is negative, prompting a firm to raise its thermal supply ahead of a drought to preserve its hydropower capacity. This observation is in line with results in Figure 5 and with the theoretical analysis in the bottom panels of Figure 7, where the availability of high-cost supply slacks Firm 1's resource constraint, leading it to increase its hydro production.

We join these observations regarding the supplies of hydro and thermal generators in the following proposition,

Proposition 2 *If a firm's revenue function is strictly concave and twice differentiable, the marginal benefit of holding water decreases in its thermal capacity K_i, i.e.,* $\frac{\partial^2 V_i(\cdot)}{\partial w_i \partial K_i} < 0$.

Proof. See Appendix A.2. □

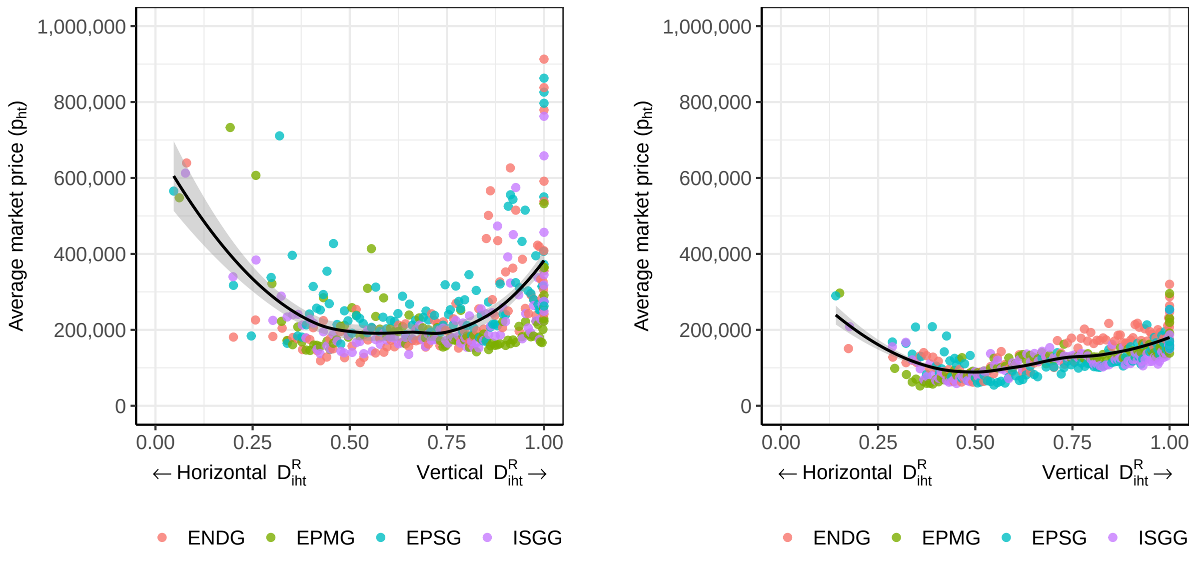
This proposition reveals that a firm's hydropower production increases in its thermal capacity. Intuitively, thermal capacity slacks future water requirements, thereby diminishing the intrinsic value of holding water in the current period. Thus, when examining the *efficiency channel* in isolation, it becomes evident that the output of a diversified firm surpasses those of two specialized firms, each with either thermal or hydro generators.

5.1.1 Capacity vs. Efficiency in the Data

Combining the *capacity* and *efficiency channels*, Figure 9 illustrates the relationship between market prices (y-axis) and the slope of a firm's residual demand (x-axis), which is flat at 0 (indicating the firm is a price taker) and vertical at 1. In Panel (a), the focus is on scarcity periods where firm i has water stocks below its 30^{th} percentile, whereas Panel (b) considers water-abundant periods with firm i's water stock above its 70^{th} percentile. Each scatter plot represents the average of hour-by-day markets with similar (x, y) coordinates over 100 points per firm.

Viewing variation in market power as induced by variation in the technology portfolio of the firms facing scarcity, Panel (a) reveals a U-shaped relationship between prices and market power similar to that discussed in Section 4. Efficiency dominates when market power is low, causing an initial drop in market prices. As market power increases, firms opt to reduce production across all technologies, leading to higher prices due to the marginal revenue effect. In contrast, the U-shape is less pronounced in Panel (b) of Figure 9, where $\frac{\partial f(\cdot|\mathbf{\Omega}t)}{\partial Siht^H} \to 0$, reducing the dependence of future profits on current production. Interestingly, this U-shape relationship is entirely driven by the *crowd out ratio*, which we introduced in (5), as seen in Appendix Figure D1:[23] if $D_{iht}^{R\,\prime}(p) \to \infty$, the firm gains by decreasing its supply at every price to raise the equilibrium price. In contrast, the firm can gain by expanding its supply for flatter $D_{iht}^{R\,\prime}(p)$, decreasing the equilibrium price.

Figure 9: A U-shaped relationship between prices and the slope of the residual demand



(a) Scarcity periods (b) Abundant periods

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 $\frac{\partial D_{iht}^R}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, with 100 bins per firm. Only diversified firms with dams whose bids are dispatched are considered. The black line fits the data through a spline (the 95% CI is in gray). Panel (a) focuses on markets where firm i has less than the 30^{th} percentile of its long-run water stock. Panel (b) focuses on periods where i's water stock is greater than its 70^{th} percentile.

Finally, notice that the state space includes all firms' current water stocks, $\mathbf{w}_t$: 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 ($\frac{\partial S_{kht}^H}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \leq 0$). Because

[23]An application of the envelope theorem to (6) finds that $\frac{\partial D_{iht}^R}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \propto (1 - S'_{iht}/D_{iht}^{R\,\prime})^{-1}$.

this channel does not affect firm i's thermal and hydro generators differently, it does not shed light on the implications of diversified technologies, on which this paper focuses.

5.2 Identification and Estimation

The extensive state space outlined in (10) presents a dimensionality challenge in estimating the relevant primitives. Existing literature offers two primary strategies to address this issue. The first method involves leveraging terminal actions (Arcidiacono and Miller, 2011, 2019), which eliminates the need to compute the value function during estimation. This approach is not applicable to our study since we do not observe exits.

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.[24] This approach echoes the work of Sweeting (2013), who 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 $V(w;\gamma,B)$. The iterative process halts when the implied policy from maximizing $V(w;\gamma,B)$, σ', is sufficiently close to the previous one. However, we cannot simulate forward the contribution of the forward market to current profits π_{ijht} in step (i), as we do not observe the price of forward contracts in (7), PC_{iht}. Therefore, disregarding PC_{iht} in the regression of discounted profits in step (ii), $\sum_{t=1}^{M} \beta^t \sum_h \pi_{ijht}(w)$, on water stocks, w, will not identify the γ_r coefficients, as the left-hand side is a poor proxy of discounted cumulative profits, $V(w)$.

To overcome these problems, we follow Wolak (2007) and Reguant (2014) and 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:

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

where we grouped known terms into the following variables. The left-hand side, mr, is the marginal revenue or the first line of (10). On the right-hand side, we denote the sum of the direct and indirect effects, $\frac{\partial S^{\tau}_{iht}}{\partial q_{ijht}} + \frac{\partial S^{\tau}_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, by X^{τ}; the superscript τ indicates the firm's hydro (H) and the thermal (T) supply schedules. A tilde $\tilde{X}^H$ denotes the sum of the indirect effects at i's competitors in the last line of (10). Appendix E details how to compute these derivatives following Wolak (2007). The only unknown terms are c^{τ} and

[24] Basic polynomial functions or, as suggested by Bodéré (2023), neural networks can serve as suitable basis functions.

$\beta V(\cdot)$. 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 $V(\cdot)$.

After estimation, we conduct a counterfactual experiment similar to that in Section 4 where we transfer thermal capacity to the market leader from its competitors. We examine energy price changes under different industry structures to highlight the trade-off between capacity and efficiency, assuming no change in the other players' strategies, so that the residual demand is fixed. This counterfactual analysis is identified in the spirit of Kalouptsidi *et al.* (2021).[25] Due to strategic complementarities, the assumption of fixing residual demand gives us a conservative bound to the price drop in the counterfactual.

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, echoed by the empirical results in Section 3.2.3, is that a firm only considers its future water stock when bidding. 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 $\mathbf{\Omega}_{it}$ and 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 (Pesaran and Shin, 1995). 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

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

factor is needed. Both the marginal costs and the value functions have a non-deterministic 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 employ variables shifting a generator's cost to control for endogeneity.[26] We also include various fixed effects in FE to account for constant differences across firms and generators – in the real world, generators' operating costs may differ based on their capacity and technology, an issue that we abstract from – and time-varying factors that affect equally all generators of a certain technology like changes in gas prices.

5.2.2 Estimation Results

We analyze (12) with daily data from January 1, 2010, to December 31, 2015. We use two-stage least squares and show the results in Table 2. 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 3) confirming that these units operate only during draughts, as Panel (b) of Figure 2 indicates. Consistently, the cost of operating hydropower is considerably lower, making this technology the inframarginal one. Finally, because of the spline approximation, the γ_r estimates have no economic interpretation.

Although direct comparison with other papers are challenging as engineer estimates often report the levelized cost of hydropower, which is the discounted sum of investments and operations over the lifetime of a dam, we can still compare our thermal marginal cost estimates. In USD, these costs range between \$45.57 and \$70.44 per MWh in US dollars, considering fluctuations in the peso-to-dollar exchange rate over the sample period. Our findings align with other studies and engineering assessments, which typically estimate operating costs for coal-fired plants between \$20 and \$40 per MWh and for gas-fired

[26]The set of instruments includes temperature at the dams (in logs) for hydropower generators and lagged gas prices (in logs) for thermal generators, which we interact with monthly dummies to capture unforeseen shocks (i.e., higher-than-expected evaporation or input costs), switch costs, which we proxy by the ratio between lagged thermal capacity employed by firm i's competitors and lagged demand, and its interaction with lagged gas prices (in logs) for thermal generators. Importantly, gas is a global commodity, and we expect that Colombian wholesale energy firms cannot manipulate its market price.

Table 2: Estimated model primitives

	(1)	(2)	(3)	(4)
Marginal Costs (COP/MWh)				
Thermal ($\psi^{thermal}$)	20,3677.62***	141,668.46***	22,1304.18***	144,744.21***
	(1,711.10)	(1,875.29)	(1,665.82)	(1,561.62)
Hydropower (ψ^{hydro})	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	✓	✓	✓	✓
Generator	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
Date			✓	✓
SW F ($\psi^{thermal}$)	194.34	162.86	1,919.25	168.62
SW F ($\psi^{thermal}$)	3,300.46	1,170.68	2,889.26	1,000.69
SW F (ψ^{hydro})	458.72	267.20	877.47	360.16
SW F (ψ^{γ_1})	272.15	201.92	274.58	214.83
SW F (ψ^{γ_2})	220.24	266.10	266.58	292.22
SW F (ψ^{γ_3})	466.55	494.96	291.98	491.58
SW F (ψ^{γ_4})	570.57	577.42	292.40	566.81
SW F (ψ^{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-fixed effects. The bottom panel provides diagnostic tests in the first stage. Robust standard errors. 2,900 COP ≃ 1 US$.

plants between $40 and $80 per MWh (e.g., Blumsack, 2023).[27]

We present several robustness checks in the appendix. First, we show that changing

[27] As an illustration, Reguant (2014) estimates that thermal production in Spain ranged between €30 and €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.

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).

In the next section, we use the estimated primitives to assess the price consequences of moving thermal capacity to the market leader.

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.

6.1 The Simulation Model

We base our simulation exercises on a firm's objective function (9) because the first-order conditions in (10) alone are not sufficient for optimality. 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.[28] In essence, we evaluate the model's performance by simulating the bids of EPMG, the leading firm in the market, while treating the bids of its competitor as given.[29]

To ensure a global optimum, the solver requires that we discretize the technology-specific supplies over K steps each. On each day t, the firm selects the K-dimensional vector of hourly quantities $\{\mathbf{q}^{\tau}_{ht,k}\}_{h=0}^{23}$ for each technology τ (hydro or thermal) to solve:

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

$$s.t.$$

$$\text{[Market-clearing:]}\ \ \bar{D}^R_{ht}(p_{ht}) = \sum_{\tau\in\{H,T\}}\sum_{k=1}^{K}q^{\tau}_{ht,k},\ \ \forall\, h, \quad (13)$$

[28] Note that not observing PC_{ht} is not a problem here because a firm's optimal action does not depend on it. We implement the analysis through the `Rcplex` package in `R` and the `IBM ILOG CPLEX` software to solve this mixed-linear integer problem, which are freely available for academic research at https://cran.r-project.org/web/packages/Rcplex/index.html, and https://www.ibm.com/it-it/products/ilog-cplex-optimization-studio.

[29] EPMG has the largest semi-elasticity of demand in the time period under analysis (Appendix Figure F2). Hydropower generation is over than 80% of its total capacity (Figure F1).

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

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

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

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 the market price, 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 2. 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.[30]

Our main focus is on the intertemporal allocation of production capacity across technologies during prolonged extreme events. Therefore, rather than simulating each daily market from 2010 to 2015, we aggregate the daily data across weeks and hours. We then determine EPMG's optimal response using (13) for each hour-week combination. This strategy significantly reduces computation time while maintaining precision, as we demonstrate next.

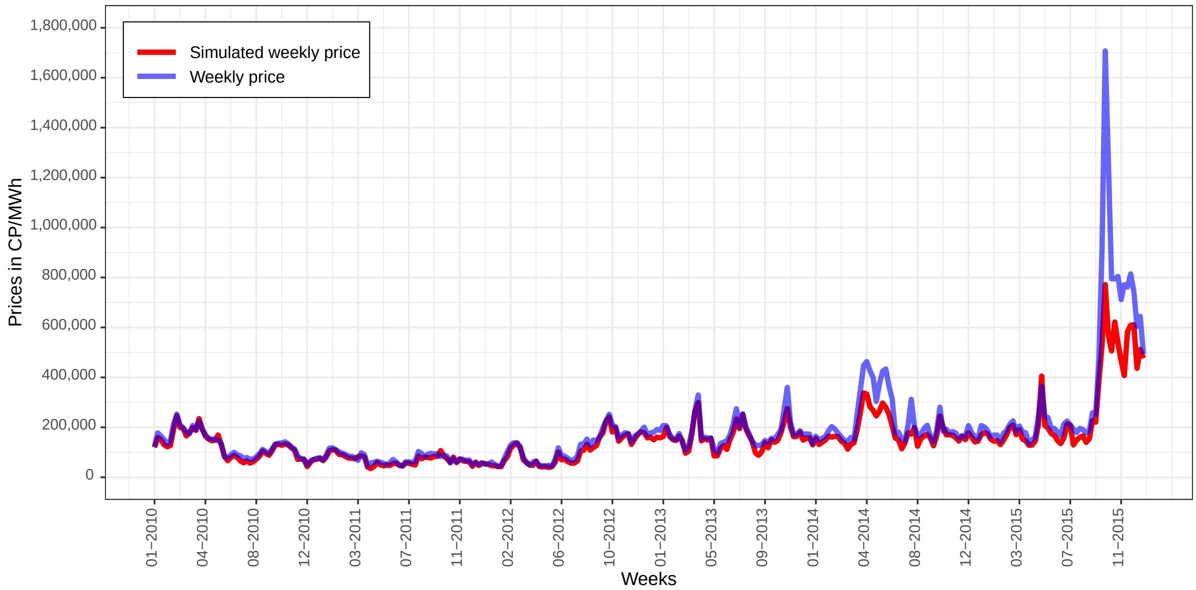
6.2 Model Fit

In Figure 10, we compare the observed average weekly prices (red line) with the simulated ones (blue line). The model demonstrates remarkable accuracy in reproducing price volatility, particularly over the initial four years. However, the occurrence of El Niño in 2016, an unprecedented dry spell in our sample, likely influenced the transition matrix in late 2015, resulting in a gap between simulated and observed prices. While the model doesn't capture the extreme spike observed in late 2015, where prices surged by over tenfold, it does predict a five to sevenfold increase. Appendix Table F1 examines price variation across hours, further demonstrating a strong fit.[31] Overall, despite being very parsimonious – using only seven parameters – the computational model effectively reproduces price volatility in Colombia over a substantial period.

[30] The optimization is subject to constraints. The first constraint requires that EPMG's hourly supply equals the residual demand at the equilibrium price, p_{ht}. The remaining constraints ensure that, at the prevailing market price, EPMG's residual demand, supply, and value function do not exceed their allotted capacity, and that supply functions are overall increasing (not reported).

[31] 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).

Figure 10: 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$.

6.3 Counterfactual Exercises

To quantify the two sources of market power introduced in 4, this section simulates market prices by varying EPMG's thermal capacity through capacity transfers from its competitors. Using the computational model (13), the counterfactuals slack EPMG's thermal capacity constraint and affect its residual demand. Note that the estimated value function parameters ($\{\gamma_r\}_r^R$) 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 we could solve for the new equilibrium parameters ($\{\gamma_r'\}_r^R$), Proposition 2 suggests that the marginal benefit of holding water decreases with a firm's thermal capacity: we would expect EPMG to offload even more water than our counterfactual predicts for every possible demand realization, meaning lower prices on average.[32]

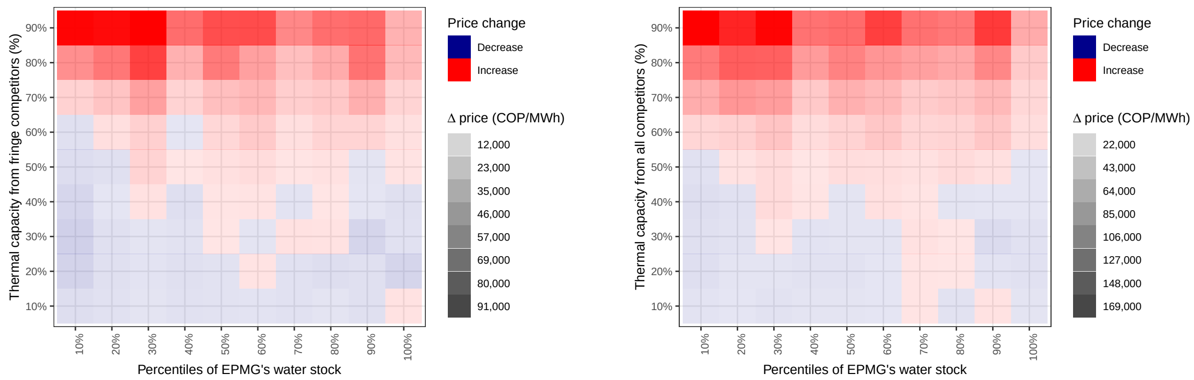
Figure 11 summarises the results from the counterfactual exercises. In Panel (a), we move capacity from fringe firms (i.e., all the firms with no dams). The generators of these firms submit positive quantity bids for prices equal to their marginal cost: when we transfer $x\%$ of generator k's capacity, we do not update generator k's supply if its unused capacity is large enough. Otherwise, we reduce k's quantity bid accordingly. We transfer capacity from all firms in Panel (b), including EPMG's strategic competitors. Theoretically, we should update the bids of the strategic firms in every scenario according to (13), but it is computationally infeasible. However, because of strategic complemen-

[32]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 2.

tarities in bidding (Section 4), price changes can be interpreted as lower bounds for the magnitude of the actual price drop (increase) when EPMG expands (reduces) its supply after a change in its thermal capacity.

Each panel displays a heatmap depicting market rankings based on the severity of drought experienced by EPMG on the x-axis (categorized into deciles of water stock) and the magnitude of capacity transfer on the y-axis. Each cell within the heatmap illustrates the average disparity 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 serves as a basic measure of drought, devoid of considerations for future inflows. Appendix G provides additional robustness checks using inflows on the x-axis. Given that these metrics only partially capture drought occurrences, the transition from red to blue across columns in the heatmap may appear somewhat irregular.

Figure 11: The price effect of a capacity transfer to the market leader (EPMG)



(a) Transferring x% from all fringe firms

(b) Transferring x% from all firms

Notes: The figure presents the results from comparing 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) with baseline prices. Top (bottom) panels proxy scarcity by grouping markets based on the deciles of the firm'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. The left (right) panels move capacity from fringe (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., across columns. In the first row of in Panel (a), EPMG is endowed with 10% of the fringe 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 shows 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.[33]

[33]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, prices first decrease for low transfers and reach a bottom level before increasing for higher transfers – a similar pattern to that observed in Panel (b) of Figure 7 where the capacity channel dominates the efficiency channel.

Varying drought severity. We now turn to comparing outcomes across drought severity – i.e., across rows. Panel (a) suggest 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, and especially so in the first row (10% transfer). Thus, the gains from the transfers are generally larger in dry spells compared to wet periods.

Percentage price changes. A 10,000 COP price increase during drought is very different compared to a similar change during an abundant period, where prices are lower. To better compare prices across columns, we rebase the difference between counterfactual and simulated prices by the simulated market price and present its average value in each cell (i.e., $\frac{1}{H \cdot T}\sum_{h,t}^{H,T}\frac{p_{ht}^{x\%}-p_{ht}^{base}}{p_{ht}^{base}}$, where superscripts $x\%$ and *base* denotes counterfactual and baseline prices, respectively). Appendix Figure G2 presents the same analysis produced above using these percentage deviations. Also after controlling for baseline market prices, there are no gains from transferring thermal capacity when the firm has a large amount of hydropower capacity, but there are gains in the order of 10% of market prices from limited reallocations of capacity during scarcity.

Reallocating from fringe or strategic firms? Finally, Panel (b) of Figure 11 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. Large transfers from strategic firms reduce the capacity available to them, decreasing the extent of market competition more than if capacity transfers were from fringe firms only.

7 Discussion and Conclusion

Conventional wisdom holds that market power hinges on demand factors such as elasticities, while supply factors act more like benchmarks (e.g., Nocke and Whinston, 2022). Mergers, for instance, are scrutinized for potential anti-competitive effects if they are expected to exceed the claimed cost synergies. Our paper diverges from this standard narrative by placing technology at the forefront of market power analysis. We argue that firms should be viewed as portfolios of various technologies, each with its own marginal cost and production capacity, rendering them "diversified."

Drawing from the Colombian energy sector, whose regulatory framework mandates energy suppliers to report production by technology, we demonstrate both empirically and theoretically that oligopolistic competition among diversified firms results in a trade-off between capacity and efficiency forces. The former is driven by a firm's total capacity: larger firms can cover a greater portion of the market demand, incentivizing them to decrease production to raise prices. In contrast, the latter forces are specific to each technology, as monopolistic rents may results from a technology's relative efficiency. Moreover, we show that the mere availability of multiple technologies creates complementarities within a firm, as access to more expensive technologies relaxes the capacity constraints of lower-cost ones, prompting firms to increase production across the board. These findings have implications for the way we measure capital, antitrust policies and the transition toward greener energy markets, which we discuss further in the following sections.

7.1 Capital and Antitrust Policies

Capital, in economic models, is typically treated as a homogeneous input, representing the aggregate of all investments a firm has made since its inception (e.g., Olley and Pakes, 1996). While economists recognize this as oversimplified, there has been limited exploration into the implications of this assumption due to several factors. Firstly, if introducing heterogeneity merely minimizes measurement errors, the benefits might be outweighed by the loss of tractability. Secondly, data on production categorized by technology is scarce, making it uncertain whether firms truly engage in diversified production.

Our paper addresses this gap by revealing that heterogeneous capital holds strategic significance within standard oligopoly models. Specifically, when a less expensive technology with limited capacity is introduced alongside a more costly one, its value increases. This dynamic prompts the firm to ramp up production, aiming to dominate the market. In response, competitors adopt aggressive pricing strategies to safeguard their market share, even if it means sacrificing revenues on marginal units.

The key takeaway from our analysis is that concentration need not be necessarily feared. In industries with high barriers to entry where firms have significant pricing power, achieving the optimal technology mix can drive prices down more than policies focused solely on limiting firm size. For instance, Colombian regulations cap firm capacity at 25% of the industry, hindering diversification due to the scale of dam projects. As data from energy markets indicate that firms often possess multiple production technologies, our conclusions may extend to other industries as well. For example, Collard-Wexler and De Loecker (2015) demonstrate various methods for alumina production, while labor inputs may also exhibit diverse efficiency and capacity (Bonhomme *et al.*, 2019).

Our findings are not driven by standard synergies typically associated with merging parties benefiting from economies of scale or scope. For example, it's common to model the marginal cost of a merger between two firms, each with costs c^a and c^b, as $\min c^a, c^b$, often attributed to improved managerial practices (e.g., Braguinsky *et al.*, 2015, Demirer and Karaduman, 2022) or technological advancements (e.g., Ashenfelter *et al.*, 2015, Miller and Weinberg, 2017). However, in our framework, synergies arise from equilibrium responses as firms expand their marginal cost curves at the expense of others. These synergies resemble those observed in mergers involving multiproduct firms in aggregative games (Nocke and Schutz, 2018a), where a firm's markup balances demand elasticity with self-cannibalization effects across its products (Nocke and Schutz, 2018b).

These insights shed light on the landscape of horizontal merger policies, which traditionally rely on concentration as a primary gauge of market distortions. Recent research has linked concentration to various economic trends, including declines in labor shares (Barkai, 2020, Autor *et al.*, 2020), sluggish productivity growth (Gutiérrez and Philippon, 2017), and higher markups (De Loecker *et al.*, 2020). We contribute to this literature by demonstrating the interplay of concentration and production technologies. Our results carry implications for the standard tools used by antitrust agencies to curb concentration post-merger in diversified-product industries, such as divestitures (Compte *et al.*, 2002, Friberg and Romahn, 2015). Forced divestiture, beyond simply reducing capacities, can also diminish firms' diversification, thereby limiting their ability to respond to scarcity events like periods of high input costs. This could trigger adverse market dynamics for competitors and potentially lead to higher market prices.

7.2 Ownership in the Green Transition

Energy prices, like those of other utilities, decrease consumers' disposable income, disproportionately hitting low income consumers (Reguant, 2019, Haar, 2020). These markets are also associated with high barriers to entry in generation and consumer inertia in distribution, underscoring the necessity for governmental agencies to actively manage and mitigate market power. With the energy sector being responsible for a large share of global CO_2 emissions (IEA, 2023), the sector must transition to less-carbon intensive technologies such as renewables (Elliott, 2024). Although inexpensive on average, these energy sources are intermittent, exposing consumers to high prices in periods of scarcity.

To encourage generators to produce more during scarcity events, governments have implemented policies like the reliability charge outlined in Section 5. These policies require generators to produce a set amount of energy when prices rise above a certain threshold, with subsidies as incentives. However, such approaches are costly due to subsidies and can backfire by giving companies reasons to hold back output, thus creating scarcity despite efforts to prevent it (McRae and Wolak, 2020).[34]

Our research introduces a fresh approach to tackle intermittencies in the energy sector. We find that generators unaffected by scarcity can absorb the scarcity experienced by renewable generators owned by the same firm, especially when the firm holds market power. While perfect competition would ideally lead to the first-best outcome, wherein firms price at marginal cost, we reveal that optimal diversification strategies for a firm may result in a second-best scenario. In this case, unaffected generators lower their markups to ease supply constraints faced by their struggling renewable siblings. Our analysis suggests that transferring non-renewable capacity to a firm anticipating a drought could reduce price spikes by around 5 to 10% (see Appendix Figure G2), a meaningful reduction particularly during drought periods with little cost during abundance periods.

In Colombia, hedging against energy scarcity predominantly relies on fossil fuels, contributing to increased CO_2 emissions and impeding the transition to green energy. This reliance stems from the geographical concentration of dam ownership, a legacy of privatizations in the 1990s. Had dam ownership been more diversified across regions (as depicted in Figure 8), reliance on dams with varying inflow cycles could have provided an alternative form of hedging, potentially reducing emissions and enhancing welfare compared to the current situation.

As of 2023, Colombia's renewable energy capacity from solar and wind sources remained limited, constituting only 1.5% of the total installed capacity. However, there were notable developments, with twelve wind projects totaling 2,072 MW and six solar projects totaling 908 MW under construction by the end of 2022. Additionally, the Colombian governmental agency responsible for natural resource management, Unidad de Planeación Minero Energética, approved several other solar and wind farm projects set to commence operations by 2027 (Arias-Gaviria *et al.*, 2019, Rueda-Bayona *et al.*, 2019, Moreno Rocha *et al.*, 2022). Once operational, these projects are projected to contribute approximately 38% of Colombia's installed capacity (SEI, 2023). With ongoing advancements in storage technology and declining battery costs (Koohi-Fayegh and Rosen, 2020), renewables are poised to emerge as a more cost-effective alternative to fossil fuels for hedging against energy scarcity, particularly for hydropower.

Diversified firms, equipped with generators experiencing surplus, are well-positioned to internalize scarcity effectively. Further investments in renewable energy infrastructure promise to facilitate a swift and economical transition toward a greener economy.

[34]Since firms can anticipate scarcity events (Figure 4), forward contract markets serve as an additional hedging avenue (e.g., Anderson and Hu, 2008, Ausubel and Cramton, 2010). However, their effectiveness is limited. Our model demonstrates that firms only internalize dry spells through ownership connections, and this is further diminished by evidence indicating that forward prices track spot market prices (de Bragança and Daglish, 2016, Huisman *et al.*, 2021).

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Online Appendix

A Theoretical Appendix

The first three sections of this Appendix proves Proposition 1 from Section 4. Appendix A.1 defines supply function equilibria and derives the FOCs using ex post optimization. Appendix A.1.1 proposes two examples for which we can assess the impact of technology reallocation analytically. These counterfactual exercises are in Appendices A.1.2, A.1.3, and A.1.4. Appendix A.1.5 solves for a different counterfactual where firms are symmetric and have access to both technologies. Appendix A.1.6 hosts a set of lemmas used in the analytical proofs.

Appendix A.2 proves Proposition 2, which we introduced in the structural model in Section 5. It demonstrates that the marginal benefits of holding water decrease in a firm's thermal capacity.

A.1 Theoretical Model of Section 4

An industry has N firms producing an homogeneous good. The industry demand is inelastic D and is subject to an exogenous shock ϵ, where ϵ is a scalar random variable with strictly positive density everywhere in $[\underline{\epsilon}, \overline{\epsilon}]$. $Q = D(\epsilon)$, where, for all ϵ, $-\infty < D < \infty$, with $D_\epsilon > 0$. That is ϵ translates $D(\epsilon)$ horizontally as in Klemperer and Meyer (1989).

For now, assume that Firm $i \in (1, ..., N)$ has marginal cost c_i and capacity $0 < K_i < \infty$, so that a firm can produce all its capacity at the same marginal cost. Section A.1.1 makes specific assumptions about technologies to derive analytical solutions.

A strategy for firm i is a continuously differentiable function mapping prices into a level of output for i: $S_i : [0, \infty) \rightarrow (0, \infty)$.

Firms choose their supply functions simultaneously without knowledge of the realization of ϵ. The market price, p^*, is the smallest p such that $D(\epsilon) = \sum_j S_j(p)$. That is industry demand matches industry supply according to the market clearing condition:

$$p^*(\epsilon) = \arg\min_{p \in [0,\infty)} D(\epsilon) - \sum_j S_j(p) = 0 \tag{A1}$$

We denote $p^*(\epsilon)$ simply by p^* to reduce notation from now on.

After the realization of ϵ, supply functions are implemented by each firm producing at a point $(p^*, S_i(p^*))$. Firm i sells $S_i(p^*)$ and gets p^* on each unit it sells. Its profit is

$$\pi_i(p^*) = p^* \cdot S_i(p^*) - c_i \cdot S_i(p^*). \tag{A2}$$

Due to the market clearing condition, i's supply must equate its residual demand in equilibrium. We denote i's residual demand as $D_i^R(p, \epsilon) = D(\epsilon) - \sum_{j \neq i} S_j(p)$. Hence, firm i's equilibrium profit becomes

$$\pi_i(p^*) = (p^* - c_i) \cdot D_i^R(p^*, \epsilon). \tag{A3}$$

Ex post optimization. As in Klemperer and Meyer (1989), the assumptions about demand and costs (see next section) ensure that the set of *ex post* profit-maximizing points for each firm varies for different realization of its residual demand curve. When the other firms are also using their equilibrium strategy, this mapping can be described by a supply function which intersects each residual demand curve once and only once. Since ϵ is a scalar, the set of profit-maximizing points along $D_i^R(p,\epsilon)$ as ϵ varies is a one-dimensional curve in price-quantity space. If this curve can be described by a supply function $q_i = S_i(p)$ that intersects each realization of i's residual demand curve once and only once, then by committing to $S_i(\cdot)$, i can achieve ex post optimal adjustment to the shock. In this case, $S_i(\cdot)$ is clearly i's unique optimal supply function in response to $(S_l(\cdot))_{l\neq i}$.[1]

Equilibrium concept. The focus is on pure strategy Nash equilibria in supply functions. Such an equilibrium consists of a N-vector of strategies $(S_l(p))_{l=1}^N$, such that $S^i(p)$ maximizes i's expected profit in (A4), where the expectation is taken over ϵ, given that each firm $j \neq i$ chooses $S_j(p)$.

FOCs using ex post optimality. Since the set of ex post profit-maximizing points for i can be described by a supply function, in solving for i's optimal supply function, we can replace the maximization of expected profits by the maximization with respect to p of profits for each realization of ϵ. Firm i solves:

$$\max_p \pi_i(p) = (p - c_i) \cdot \left(D(\epsilon) - \sum_{j\neq i} S_j(p) \right) = (p - c_i) \cdot D_i^R(p,\epsilon), \tag{A4}$$

which admits the following FOCs.

$$p\frac{\partial D_i^R(p,\epsilon)}{\partial p} + D_i^R(p,\epsilon) - c_i \cdot \frac{\partial D_i^R(p,\epsilon)}{\partial p} = 0 \iff (p - c_i)\, S'_{-i}(p) = S_i(p), \tag{A5}$$

where the second equality follows from (A1) and we use $S_{-i}(p) = \sum_{j\neq i} S_j(p)$. If (A4) is globally strictly concave in p, then (A5) implicitly determines i's unique profit maximizing price $p_i^0(\epsilon)$ for each value of (ϵ). The corresponding profit maximizing quantity is $D(\epsilon) - \sum_{j\neq i} S_j(p_i^0(\epsilon)) \equiv q_i^0(\epsilon)$.

Since $D_\epsilon > 0$, no two realizations of i's residual demand curve can intersect. This condition, together with uniqueness of $p_i^0(\epsilon)$ for each ϵ, implies that $S_i(p)$ intersects i's residual demand curve once and only once for each ϵ, at $p_i^0(\epsilon)$. Hence $S_i(p)$ is i's optimal supply function in response to $(S_l(p))_{l\neq i}$.

FOCs through calculus of variation. We can obtain the same FOCs as in (A5) by assuming that ϵ come from a location family distribution.

Proof. Assume that $\epsilon \sim F(\cdot)$. Then, $D^R(p,\epsilon)$ is a random variable for each p, s.t. $F(p,q) = \Pr(\epsilon | D^R(p,\epsilon) \leq q)$. Because $D^R(p,\cdot)$ is downward sloping in p, we have that $F(p_1,\cdot)$ first order dominates $F(p_2,\cdot)$ for $p_1 \leq p_2$.

Suppose i submits a supply schedule $S_i(p)$ that is monotonic and differentiable. The probability that the market clearing $p^* \leq p$ is:

$$\Pr(\epsilon | D^R(p,\epsilon) \leq S_i(p)) = F(p, S_i(p)),$$

[1] Note that neither Bertrand or Cournot conduct models are ex post optimal with uncertain demand and increasing marginal costs. That is, committing to a constant vertical or horizontal supply slope is not optimal: once ϵ realizes the firm would like to change its strategy. Hence, ex ante optimality does not necessarily imply ex post optimality. Klemperer and Meyer (1989) shows that equilibrium supply functions are both ex ante and ex post optimal.

which is a monotonic function w.r.t. p. Hence, the likelihood that the market clearing price is exactly p is

$$\frac{d}{dp}F(p, S_i(p)) = F_1(p, S_i(p)) + S_i'(p)F_2(p, S_i(p)).$$

Therefore, i's expected profit is

$$\pi(S_i(p), C) \equiv \int_{\underline{\epsilon}}^{\overline{\epsilon}} (p \cdot S_i(p) - C(S_i(p))) \cdot \frac{d}{dp}F(p, S_i(p))dp,$$

where $C(q)$ is the cost of providing q units of output, which we can rewrite as $c_i \cdot S_i(p)$ for $S_i(p) \leq K_i$ as above.

The Euler-Lagrange equation gives

$$(p - C'(S_i(p)) \cdot F_1(p, S_i(p)) = S_i(p) \cdot F_2(p, S_i(p)).$$

If we are willing to assume that $F(\cdot)$ belong to a location family distribution, so that $F(p, q) = F(q - \mu(p))$, the Euler-Lagrange equation becomes:

$$(p - C'(S_i(p)) \cdot (-\mu'(p)) = S_i(p).$$

Given our cost-side assumptions, this equation becomes

$$S_i(p) = -\mu'(p) \cdot (p - c_i),$$

where $\mu'(p)$ is negative, so $S_i(p) \geq 0$. We obtain the same FOC as in (A5) because in equilibrium $\mu(\cdot) = D^R(\cdot)$, whose slope is the same as that of $S_{-i}(p)$ in absolute value at every p. □

Strategic complementarities. The slopes of the firms' supply functions are strategic complements. From (A5), $S_i(p)$ increases if its competitors behave more aggressively ($S'_{-i}(p)$ increases). In addition, differentiating the FOC (A5) w.r.t. p, we obtain

$$(p - c_i)\, S''_{-i}(p) + S'_{-i} = S'_i(p).$$

Clearly, firms react by bidding more aggressively (increase S'_i) when opponents bid more aggressively. Hence, both the intercept and the slope of $S_i(p)$ increase with the supply of the competitors, indicating strategic complementarity.

Business stealing. i's markup at the market clearing price, p^*, depends on i's share of elasticity and its business stealing.

Denote $S(p) := \sum_{j=1}^{N} +S_j(p)$ and $s_i := \frac{S_i(p)}{S(p)}$, we can rewrite (A5) as

$$\begin{aligned}
(p - c) \cdot S'_{-i}(p) &= S_i(p) \\
(p - c) \cdot S'_{-i}(p) \cdot \frac{S'(p)}{S'(p)} &= S_i(p) \\
\frac{p - c}{p} \cdot \underbrace{\left(\frac{S'(p)}{S(p)} \cdot p\right)}_{\eta} \cdot \frac{S'_{-i}(p)}{S'(p)} &= \frac{S_i(p)}{S(p)}
\end{aligned}$$

$$\frac{p-c}{p} \cdot \eta = \frac{S'(p)}{S'_{-i}(p)} \cdot \underbrace{\frac{S_i(p)}{S(p)}}_{s_i}$$

$$\frac{p-c}{p} = \frac{s_i}{\eta} \cdot \frac{S'(p)}{S'_{-i}(p)}$$

$$\frac{p-c}{p} = \frac{s_i}{\eta} \cdot \left(\frac{S'_i(p)}{-D_i^{R\prime}(p)} + 1 \right),$$

where we use the fact that $S(p) = D(\epsilon)$ to obtain the price elasticity of demand η.[2] In particular, we have $S'(p) \cdot \frac{dp}{dD} = 1$, and hence $S'(p) = \frac{dD}{dp}$. Define η as $S'(p) \cdot \frac{S(p)}{p}$, then $\eta = \frac{dD}{dp} \cdot \frac{S(p)}{p} = \frac{dD}{dp} \cdot \frac{D}{p}$ in equilibrium. Hence $\frac{1}{\eta} = \frac{dp}{dD} \cdot \frac{p}{D}$ is the price elasticity of demand. *Corrigendum:* earlier drafts of this paper missed the "+1" in the business stealing term because of a typo. All the results carry through.

A.1.1 Examples with Analytical Solutions

We now turn to the two cases studied in the main text where we can get an anlytical solutions for $S_i(p)$ $\forall i \in (1, ..., N)$.

Costs. Firms have access to three types of technologies, high-, low-, and fringe-cost, such that $c^l < c^h < c^f$. The technology set is $\mathcal{T} = \{c, l, f\}$. The cost of firm i is $C_i(p) \equiv \sum_{\tau \in \mathcal{T}} c^\tau S_i^\tau(p)$, where we denote i's supply of technology τ by $S_i^\tau(p)$. Firm i has a given capacity of each technology K_i^τ, so that $S_i^\tau \in [0, K_i^\tau]$.

Capacities. A firm is described by a technology portfolio, that is a vector $K_i = (K_i^l, K_i^h, K_i^f)$, describing the capacity available to each firm for each technology.

Baseline capacities. We first introduce the general model where K_1^l is non-negative, and then focus on the setting in Figure 7 where $K_1^l = 0$.[3] Firm 1's technology portfolio is $K_1 = (K_1^l, K_1^h, 0)$, Firm 2's technology portfolio is $K_2 = (0, K_2^h, 0)$, and non-strategic (fringe) firm i's technology portfolio for $i \in (3, ..., N)$ is $K_i = (0, 0, K_i^f)$, with $K_1^h \geq 0$, and $K_1^l, K_2^h, K_i^f > 0$. We also assume that K_i^f is of negligible size for all fringe firms.

Counterfactual scenario. We move δ units of K_2^h from Firm 2 to Firm 1. The new technology portfolios are $\tilde{K}_1 = (K_1^l, K_1^h + \delta, 0)$, $\tilde{K}_2 = (0, K_2^h - \delta, 0)$, and $\tilde{K}_i = (0, 0, K_i^f)$ for $i \in (3, ..., N)$.

Demand. Demand is inelastic and subject to a shock ϵ as in the previous section.

Market clearing. There is a large enough number of non-strategic firms. These firms enter the market only when the price at least covers their marginal cost, c^f. At this price, they supply all their capacity. Hence, their supply function is $S_i = 1_{\{p > c^f\}} K_i^f$ for $i \in (3, ..., N)$ and $\sum_{j=3}^N K_j^f$ is large enough, so that the market always clears for $p \geq c^f$.[4]

[2] Since the demand is vertical, the elasticity of the demand to prices is not defined in our model (η), but the elasticity of prices to demand is $(1/\eta)$.

[3] Notice that the supply functions of Firms 1 and 2 change slope when Firm 1 exhausts K_1^l. The exposition is cleaner if we derive the full model with Firm 1 being diversified and work out the comparative statics changing K_1^h and K_2^h. The analysis still applies for $K_1^h = 0$ at baseline as in the simulations.

[4] Different assumptions are possible. For instance, we could obtain a downward sloping residual demand assuming a price cap, which is often employed in energy markets, a stochastic $c^f \sim F(\cdot)$, or

Without loss of generality, we assume that the strategic firms have priority in production over the fringe firms at price $p = c^f$.[5] Hence, for any realization D of $D(\epsilon)$, given the schedules $S_i(p)$, the following market clearing equation

$$p = \min\Big\{c^f, \inf\big\{x\big|\sum_i^N S_i(x) \geq D\big\}\Big\}, \tag{A6}$$

replaces (A1).

Residual demand. Firm i's residual demand function is

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

where $S_{-i}(p) \equiv \sum_{j \neq i} S_j(p)$.

Profits. We update (A4) according to the new cost functions. Given the opponent's strategy, the profit of firm i with cost function $C_i(p)$ at the market clearing price p is $\pi_i(p) = D_i^R(p,\epsilon) \cdot p - C_i(p)$.

Definition of SFE. *Strategic firm $i = \{1, 2\}$ takes all the opponents' strategies $S_j(p)$ for $j \neq i$ as given, and chooses a supply schedule $S_i^\tau(p)$ for each technology $\tau = \{l, h\}$ to maximize the ex-post profit*

$$S_i(p) \cdot p - \sum_\tau c^\tau S_i^\tau(p)$$

at every realized level of $D(\epsilon)$ and for which the price p clears the market. At each price, Firm i's supply is s.t. $S_i(p) = \sum_\tau S_i^\tau(p)$ and $S_i^\tau(p) \leq K_i^\tau$ for $\tau \in (l, h)$. Each non-strategic firm commits to sell its entire capacity if $p \geq c^f$ and do not produce otherwise.

Properties of supply functions. These lemmas are useful to compute the SFE, on which we turn next.[6]

1. Lemma A.1: no firm exhausts its total capacity for $p < c^f$. *Intuition*: when such p is realized, the constrained firm can reduce production by ϵ, causing the price to have a discrete jump to c^f, a profitable deviation.

2. Lemma A.2: one of the two firms will exhaust its capacity as $p \to c^f$ from below. *Intuition*: If both firms do not exhaust their capacity at c^f, one of them can deviate and choose to exhaust the capacity at price $c^f - \epsilon$ to engage in a Bertrand style competition to increase its profit.

3. Lemma A.3: production decisions based on the *merit order* are optimal (i.e., a diversified firm first exhausts its low-cost capacity before moving to the high-cost one).

a downward sloping demand curve. Obtaining an analytical solution will then depend on the specific distribution $F(\cdot)$ or on the elasticity of the market demand.

[5]This is w.l.g. because, due to a standard Bertrand argument, Firm 1 and Firm 2 could sell at a price $p = c^f - \epsilon$ for a small $\epsilon > 0$ and get the whole market.

[6]Lemmas A.2, A.3, and A.4 can be generalized to more than two strategic firms, in which case, $S_{-i}(p)$ should be interpreted as the horizontal sum of the supplies of i's rivals.

4. Lemma A.4: supply functions are differentiable almost everywhere for $p \in (c^h, c^f)$. *Intuition*: $(S_i(p))_{i=\{1,2\}}$ are the solutions of a system of differential equations that, according to Lemma A.1, are increasing and continuous. The only point where $S_i(p)$ is not differentiable is at $\hat{p}$ s.t. $S_1(\hat{p}) = S_1^l(\hat{p}) = K_1^l$, that is the price at which Firm 1 exhausts its low-cost capacity and starts producing with its high-cost capacity.

5. Lemma A.5: technical step proving that the conditions under which the equilibrium supply functions computed in the next section are unique.

The proof to the lemmas is in the Appendix

Computing the SFE. From the FOCs in (A5), Firm i's best response to $-i$ is

$$S_i(p) = (p - c^\tau)S'_{-i}(p)$$

for each firm $i = (1, 2)$. We partition $S_i(p)$ in 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 $S_1^l(p) = K_1^l$,[7]
4. $p \geq c^f$.

Because of Lemma A.4, $S_i(p)$ must be continuous across these intervals, and thus we proceed to characterize $S_i(p)$ in each interval separately.

1. *Interval:* $p < c^h$.
To avoid negative profits, firm i does not produce using the τ technology for prices p s.t. $p < c^\tau$, meaning that $S_i^\tau(p) = 0$ at these prices (Lemma A.3). In addition, since $S_2(p) = 0$ for $p < c^h$, also $S_1(p) = 0$ in this range because Firm 1 has no incentive to produce as it is the monopolist in this interval and can raise the price all the way to c^h by not producing as in Bertrand competition. Hence, both $S_1(p)$ and $S_2(p)$ exhibit a discrete jump at $p = c^h$. The equilibrium supply functions in this interval are:
$$\begin{cases} S_1(p) = 0, & \text{if } p < c^h, \\ S_2(p) = 0, & \text{if } p < c^h. \end{cases} \tag{A7}$$

2. *Interval:* $p \geq c^h$ and $S_1^l(p) < K_1^l$.
From the FOCs (A5), Firm 1 solves:
$$S_1(p) = S_1^l(p) = S_2'(p) \cdot (p - c^l),$$
as Firm 1 will exhaust all its low-cost capacity before moving to the high-cost one (Lemma A.3). Firm 2's supply solves:
$$S_2(p) = S_1^{l\prime}(p) \cdot (p - c^h).$$

[7]The difference between intervals 2. and 3. is whether Firm 1 has exhausted its low-cost supply because, due to the merit order (Lemma A.3), the supplies of Firm 1 and Firm 2 vary in the two intervals.

Solving these two partial differential equations with WalframAlpha,

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

where c_1 and c_2 are the two undetermined coefficients. Taking the limit for $p \to c^h$, we get that $S_1(p) \to \infty$ and $S_2(p) < 0$, suggesting that $c_1 = 0$. Therefore, the supply schedules in this interval are,

$$\begin{cases} S_1^l(p) = c_1(p-c^l), & \text{if } p \geq c^h \;\&\; S_1^l(p) < K_1^l, \\ S_2(p) = c_1(p-c^h), & \text{if } p \geq c^h \;\&\; S_1^l(p) < K_1^l, \end{cases} \tag{A8}$$

where both $S_1^l(p)$ and $S_2(p)$ are non-negative and non-decreasing for an undetermined coefficient c_1 (we solve for c_1 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. Its total supply curve is

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

   At the same time, Firm 2's supply solves

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

   Using WalframAlpha again, this leads to the following system of differential equations for undetermined coefficients c_3 and c_4 (we solve for c_3 and c_4 later):

   $$\begin{cases} S_1(p) = c_3\left(p-c^h\right) + c_4\frac{1}{p-c^h}, & \text{if } p \geq c^h \;\&\; S_1^l(p) = K_1^l, \\ S_2(p) = c_3\left(p-c^h\right) - c_4\frac{1}{p-c^h} & \text{if } p \geq c^h \;\&\; S_1^l(p) = K_1^l. \end{cases} \tag{A9}$$

4. *Interval*: $p \geq c^f$
   Following Lemmas A.1 and A.2 it is optimal to exhaust a firm's capacity exactly at $p = c^f$ to prevent the entry of fringe firms.

   $$\begin{cases} S_1(p) = \sum_\tau K_i^\tau, & \text{if } p \geq c^f, \\ S_2(p) = \sum_\tau K_i^\tau, & \text{if } p \geq c^f. \end{cases} \tag{A10}$$

We now solve for $\{c_1, c_3, c_4\}$. Since there cannot be any discontinuity for $p \in (c^h, c^f)$, (A8), (A9), and the boundary condition $S_1(\hat{p}) = K_1^l$ yield a system of three equations in three unknowns $\{c_1, c_3, c_4\}$ 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 follows. Subtract the second line from the first line and rearrange to obtain $\hat{p} - c^h = \frac{2c_4}{c_1(c^h - c^l)}$. Then, substitute this equation in the first and third line to obtain

$$\begin{cases} K_1^l & = c_1(c^h - c^l) + \frac{2c_4}{c^h - c^l}, \\ \frac{c_4}{c^h - c^h} & = \frac{c_1^2(c^h - c^l)}{4(c_3 - c_1)}. \end{cases}$$

Use c_1 to solve for c_3 and c_4 to get

$$\begin{cases} c_4 & = \frac{(c^h - c^l)^2}{2}\left(\alpha - c_1\right), \\ c_3 & = \frac{c_1}{2}\left(1 + \frac{\alpha}{\alpha - c_1}\right), \\ \hat{p} - c^h & = \frac{(c^h - c^l)}{c_1}\left(\alpha - c_1\right), \end{cases} \tag{A11}$$

where we defined $\alpha \equiv \frac{K_1^l}{c^h - c^l}$ and the $\hat{p}$ in the last line is s.t. $S_i(p) = K_1^l$.

Inspecting (A11), we learn that $c_1 \in (0, \alpha)$. Notice that if $c_1 = \alpha$, then $c_3 \to +\infty$ since $\alpha > 0$. In addition, for $c_1 > \alpha$, c_4 is negative making $S_1(p)$ is downward sloping for $p \to c^h$ in (A9), a contradiction. Furthermore, $c_1 \leq 0$ would lead to negative supply slopes. Since negative, infinite, and zero supplies are not optimal for $p \geq c^h$, then the solutions to $\{c_1, c_3, c_4\}$ in (A11) should maintain that $c_1 \in (0, \alpha)$. Taking advantage of Lemmas A.2 and Lemma A.5, the solution to (A11) can be pinned down by monotonically increasing $c_1 \in (0, \alpha)$ until the first c_1 that satisfies the boundary condition $S_i(c^f) = \sum_\tau K_i^\tau$ is found for some $i \in \{1, 2\}$. We leverage this observation in the next section.

A.1.2 Reallocation of Capacities

We consider a small capacity reallocation $\delta > 0$ from Firm 2 to Firm 1, so that the new technology portfolios become $\tilde{K}_1 = (K_1^l, K_1^h + \delta, 0)$, $\tilde{K}_2 = (0, K_1^h - \delta, 0)$, and $\tilde{K}_l = (0, 0, K_l^f)$ for fringe firm $l = (3, ..., N)$.

Proposition 1 *A marginal capacity transfer from Firm 2 to Firm 1 increases the equilibrium price if $K_1^l > \frac{c^f - c^l}{c^f - c^h} K_2^h$ (abundance scenario) and decreases it if $K_1^l < \frac{c^f - c^l}{c^f - c^h} K_h^2$ (scarcity scenario).*

Proof. We prove the part relating the abundance scenario in Appendix A.1.3 and the part relating to the scarcity scenario in Appendix A.1.4. □

A.1.3 Reallocation Under Abundance

Proposition 3 *The market price, p, increases in δ under abundance.*

Proof. Since Firm 2 exhausts its capacity in equilibium, from the second equation in (A8), we have that $S_2^l(p) = c_1 \cdot (p - c^h)$. For $p \to c^f$, $S_2^l(p) \to K_2^h$, pinpointing $c_1 = \frac{K_2^h}{c^f - c^h}$. Since Firm 1 still has low-cost capacity in this interval, from the first equation in (A8), we have that $S_1(p) = S_1^l(p) = \frac{K_2^h}{c^f - c^h} \cdot (p - c^l)$, which means that, in this scenario, as $p \to c^f$, $K_1^l > \frac{p - c^l}{c^f - c^h}\Big|_{p = c^f} \cdot K_2^h = S_1^l(c^f)$.[8] Given this value for c_1 we can compute c_3 and c_4 from (A11), thereby constructing $S_i(p)$ for $i = \{1, 2\}$.

[8]In the simulations, we pick values for $\{K_1^l, K_2^h, c^l, c^h, c^f\}$ so that $K_1^l > \frac{c^f - c^l}{c^f - c^h} K_2^h$.

Joining the systems (A7), (A8), and (A10) 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 locally reduce K_2^h to $K_2^h - \delta$ and increase K_1^h to $K_1^h + \delta$ for a small enough $\delta > 0$, 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. □

Intuition: Firm 1 is already very large. Reallocating capacity to Firm 1 exacerbates its position of market power vis-à-vis Firm 2. Since Firm 2 exhausts its capacity at baseline, all its supply is sold for prices smaller than $p = c^f$. Since $c_1 = \frac{K_2^h - \delta}{c^f - c^h}$, $\lim_{p \to c^{f-}} S_1(p) = (K_2^h - \delta) \cdot \frac{c^f - c^l}{c^h - c^l} < K_1^l < K_1^l + K_1^h + \delta$, meaning that Firm 1 uses the δ capacity only for $p = c^f$. Effectively, the transfers remove capacity from the market for $p \in (c^h, c^f)$, leading to higher prices for non-extreme realizations of $D(\epsilon)$. That is, Firm 1 gains from the inframarginal units sold at a higher market price.

We obtain the same result for any reallocation when the two firms are not diversified.

A.1.4 Reallocation Under scarcity

Proposition 4 *The market price, p, decreases in δ under scarcity.*

Proof. In this scenario, if Firm 1 has high cost capacity, there will be a price $\underline{p}$ such that, for $p \in [\underline{p}, c^f]$, $S_1^h(p) > 0$ and $S_1^l(p) = K_1^l$ as Firm 1 exhausts its low-cost capacity at $p = \underline{p}$. If Firm 1 is not diversified, $\underline{p} = c^f$.[9]

In addition, Firm 1 exhausts also its high-cost capacity in the limit as $p \to c^f$ if its high-cost capacity K_1^h is small enough. Suppose on the contrary that in equilibrium Firm 2 exhausts its capacity. From (A9), 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 thermal for $p \to c^f$, it must be that $S_1^l(p) = K_1^l$ for some $p \le c^f$. At this price $K_1^l = S_1^l(p) = \tilde{c}_1(p - c^l)$, which means that $\tilde{c}_1 = \frac{K_1^l}{p - c^l} \ge \frac{K_1^l}{c^f - c^l}$ since $c^f \ge p$ in this interval. Denote by

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

[9] Note that to the contrary, if Firm 2 were to exhaust its capacity before Firm 1, $c_1(c^f - c^h) = K_2^h$ by Lemma A.2, leading us to the abundance scenario.

where $\tilde{c}_3$ and $\tilde{c}_4$ are the corresponding coefficients evaluated at $\tilde{c}_1$. Since Firm 1 is also producing with the high-cost technology,

$$\tilde{S}_1(c^f) - K_1^l > 0.$$

Suppose that K_1^h is small enough so that $\tilde{S}_1(c^f) - K_1^l > K_1^h$, 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. Hence, $S_1(c^f) > K_1^l + K_1^h$ as $p \to c^f$, which is infeasible, a contradiction.

Therefore, 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 $p \to c^f$. Because of this lemma, the equilibrium parameter c_1' is uniquely solved for $\lim_{p \to c^{f-}} S_1(p) = K_1^h + K_1^l$

$$c_3(c^f - c^h) + \frac{c_4}{c^f - c^h} = K_1^h + K_1^l,$$
$$\Longleftrightarrow$$
$$\frac{c_1'}{2}\left(2 + \frac{c_1'}{\alpha - c_1'}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{c^f - c^h} = K_1^h + K_1^l,$$

where the second line follows from plugging in the coefficients from c_3 and c_4 from (A11). There exists a unique c_1', which can be found numerically.[10]

Joining the systems of equations (A7), (A8), (A9), and (A10) 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 $S_1^l(p) = K_1^l$. At this price, due to Lemma A.4 $\lim_{p \to \hat{p}^-} S_2(p) = \lim_{p \to \hat{p}^+} S_2(p)$, and hence $\hat{p}$ is found by expressing the c_3 a and c_4 in the second line of (A9) as a function of c_1' and equating it to the second line of (A8) as follows:

$$c_1'(\hat{p} - c^h) = \frac{c_1'}{2}\frac{2\alpha - c_1'}{\alpha - c_1'}(\hat{p} - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{\hat{p} - c^h},$$
$$c_1'\left(1 - \frac{2\alpha - c_1}{\alpha - c_1}\frac{1}{2}\right) = -\frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{(\hat{p} - c^h)^2},$$

[10] In the simulation, we pick values for $\{K_1^l, K_2^h, c^l, c^h, c^f\}$ so that $K_2^h > \frac{c^f - c^h}{c^f - c^l}K_1^l$ and $K_1^l > K_2^h$, which is feasible as $0 < \frac{c^f - c^h}{c^f - c^l} < 1$. To derive this condition, we assume that K_2^h is large enough so that $K_2^h > \tilde{c}_1(p - c^h)|_{p \to c^f} > S_2(p)|_{p \to c^f} = c_1'(p - c^h)|_{p \to c^f}$, where the second inequality follows from $c_1' < \tilde{c}_1$. Using $\tilde{c}_1 \geq \frac{K_1^l}{c^f - c^l}$, it must be that $K_2^h > \frac{c^f - c^h}{c^f - c^l}K_1^l$ as $p \to c^f$. Since we cannot solve analytically for c_1', other parameterizations are possible.

$$(\hat{p} - c^h)^2 = \left(\frac{\alpha - c_1'}{c_1'}\right)^2 \cdot \left(c^h - c^l\right)^2,$$
$$\hat{p} = c^h + \frac{\alpha - c_1'}{c_1'} \cdot \left(c^h - c^l\right).$$

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. □

Intuition. Helping the firm to still servicing high demand realizations, the δ-capacity increase incentivizes the firm to employ its low-cost technology to prevent Firm 2 for more realizations of $D(\epsilon)$. Hence, Firm 1's equilibrium supply schedule expands after the transfer (as long as Firm 1 exhausts all its capacity before Firm 2 for $p \to c^f$) because the greater capacity slacks the cost constraint faced by Firm 1. Firm 2's supply expands as well because of strategic complementarity (Section A.1). We call these two forces "business stealing." Loosely speaking, they arise because SFEs include Bertrand competition as an extreme case.[11]

A.1.5 Reallocation Under Symmetry

This section studies a similar capacity reallocation of high-cost technologies from Firm 2 to Firm 1 under the case where both Firm 1 and Firm 2 have the same technology portfolio $K_1 = K_2 = (K^h, K^l, 0)$. The technology portfolio of the fringe firms stay unchanged.

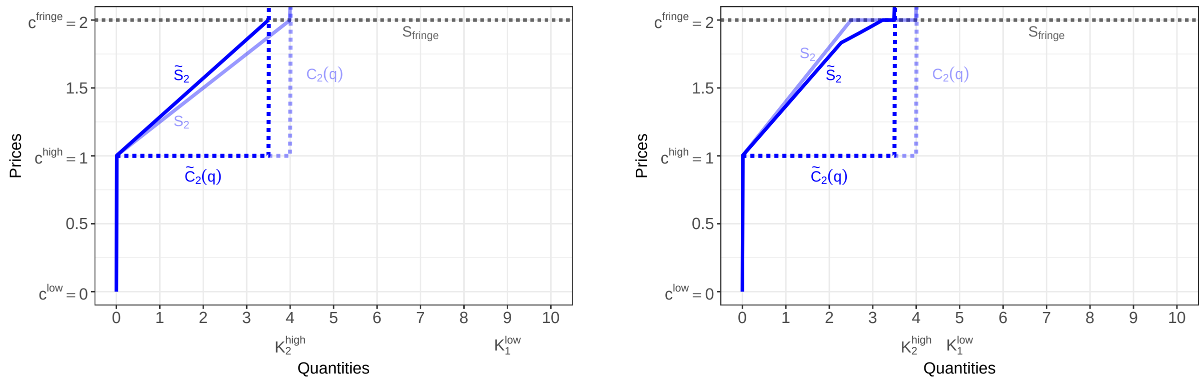
We start by describing i's supply. Between the extreme intervals where $S_i(p) = 0$ for $p < c^l$ and $S_i(p) = K^h + K^f$ for $p \geq c^f$, we have two more intervals. In each of them, each firm best responds to its competitors according to the FOCs in (A5):

$$S_i(p) = S_{-i}'(p) \cdot (p - c^\tau) \tag{A12}$$

Because of the merit order (Lemma A.3), in the interval for $p \in (c^h, \hat{p})$ firms compete using only $\tau = l$, so that $c^\tau = c^l$. $\hat{p}$ is the price at which $S_i(p) = K^l$. After this price, firms compete using $\tau = h$, so that $c^\tau = c^h$.

[11] Note that firms' optimal strategies are strategic complement in Bertrand as they are in SFEs. Lemma A.4 states that supply schedules do not display vertical jumps in equilibrium because they are smooth almost everywhere. Vertical supply schedules are typical under Cournot competition where a firm produces the same quantity at all prices. In fact, equilibrium strategies in Cournot games feature strategic substitution, unlike in the SFEs we study.

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 7. 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.

Let's first solve the system of equations (A12), for $p \in [\hat{p}, c^f)$. The solution is

$$\begin{cases} S_1(p) &= \frac{c_5}{p - c^h} + c_6 \cdot (p - c^h), \text{if } p \in [\hat{p}, c^f), \\ S_2(p) &= -\frac{c_5}{p - c^h} + c_6 \cdot (p - c^h), \text{if } p \in [\hat{p}, c^f). \end{cases} \tag{A13}$$

Because of symmetry (and the boundary condition), $c_5 = 0$. To pin down c_6, note that the firms exhausts $K^l + K^h$ exactly at $p = c^f$. 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:

$$K^l = \lim_{p \to \hat{p}^+} S_i(p),$$

$$\iff$$

$$K^l = \frac{K^l + K^h}{c^f - c^h} \cdot (\hat{p} - c^h),$$

$$K^l \cdot (c^f - c^h) = (K^l + K^h) \cdot (\hat{p} - c^h),$$

$$\hat{p} = \frac{c^h K^h + c^f K^l}{K^l + K^h}$$

Therefore, the optimal response in this interval is:

$$S_i(p) = \frac{K^l + K^h}{c^f - c^h} \cdot (p - c^h), \quad \text{if } p \in \left[\frac{c^h K^h + c^f K^l}{K^l + K^h}, c^f \right). \tag{A14}$$

Turning to the interval $p \in [c^l, \frac{c^h K^h + c^f K^l}{K^l + K^h})$, a similar system of differential equations to (A13) holds with c^l instead of c^h, c_7 instead of c_6, and $c_5 = 0$. To pin down c_7, notice that $S_i(p) = K^l$ for $p \to \frac{c^h K^h + c^f K^l}{K^l + K^h}$. Therefore,

$$K^l = \lim_{p \to \hat{p}^-} S_i(p),$$

$$\iff$$

$$K^l = c_7 \cdot \left(\frac{c^h K^h + c^f K^l}{K^l + K^h} - c^l \right)$$

$$c_7 = \frac{K^l (K^l + K^h)}{(c^h - c^l) K^h + (c^f - c^l) K^l}$$

Therefore, the optimal response in this interval is:

$$S_i(p) = \frac{K^l (K^l + K^h)}{(c^h - c^l) K^h + (c^f - c^l) K^l} \cdot (p - c^l), \text{if } p \in p \in \left[c^l, \frac{c^h K^h + c^f K^l}{K^l + K^h} \right). \tag{A15}$$

Joining all the intervals, we find that i supplies:

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

Substitute in any numbers $0 \le c^l < c^h < c^f$ and any $K^l, K^h > 0$. The residual demand is simply

$$D_i^R = \begin{cases} D(\epsilon) - S_{-i}, & p \in (0, c^f), \\ 0, & p \ge c^f. \end{cases}$$

Reallocation. We move δ units of high-cost capacity from Firm 2 to Firm 1. The new supply functions are:

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

and

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

That is, from $p \in (0, c^f)$ the two supply schedules are the same as each other, replacing K^h by $K^h - \delta$ in all the formula. When $p \ge c^f$ the supply of firm 1 jump to $K^l + K^h + \delta$ but firm 2 remains at $K^l + K^h - \delta$.

It is clear that the supplies decrease at every price level when δ increase.

For completeness, the residual demand curves after the transfer become

$$D_1^R = \begin{cases} D(\epsilon) - S_{-2}, & p \in (0, c^f), \\ \min\{D(\epsilon) - K^l + K^h - \delta, 2\delta\}, & p = c^f, \\ 0, & p > c^f, \end{cases}$$

$$D_2^R = \begin{cases} D(\epsilon) - S_{-1}, & p \in (0, c^f), \\ 0, & p \geq c^f. \end{cases}$$

Intuition. One can view the symmetric case as the optimal benchmark. No reallocation can increase competition in the market. Actually, reallocating high-cost capacities, decreases the competitivity of one firm similar to the abundance scenario.

Note that reallocating low-cost capacity can theoretically result also in lower costs because it increases a firm's efficiency at the cost of the other. However, this case it is hard to solve because you need to account for an additional step (the case where Firm 2 exhausts its low-cost technology but Firm 1 still has low-cost capacity).

A.1.6 Lemmas

Lemma A.1 *In equilibrium,* $S_i(p) < \sum_\tau K_i^\tau$ *for every* $p < c^f$*. Moreover,* $S_i(p)$ *is strictly increasing on the interval* (c^h, c^f)*.*

Proof. Suppose on the contrary that firm i exhausts all its capacity at some price s.t. $S_i(\hat{p}) = \sum_\tau K_i^\tau$ for $\hat{p} < c^f$. Since $S_i(p)$ is right continuous, let $\underline{p}$ be the smallest such price for i. Then the best response of i's competitor, denoted by j, satisfies $S_j(p) = S_j(\underline{p})$ on $p \in (\underline{p}, c^f)$. This is because if there exists $\dot{p} \in (\underline{p}, c^f)$ such that $S_j(\dot{p}) - S_j(\underline{p}) > 0$, then $S_j(p) = S_j(\underline{p})$ is not a best response and has a profitable deviation since j has capacity available and $\dot{p} > c^h$. In the event that this $\dot{p}$ clears the market, j can benefit from deviating to produce slightly less at $\dot{p}$ and causing the market clearing price to increase. Since $\dot{p}$ is arbitrary, $S_j(p) = S_j(\underline{p})$ is the best-response of $S_i(p) = S_i(\underline{p})$.

Now, if $S_i(p) = S_i(\underline{p})$ on $p \in (\underline{p}, c^f)$ for both $i \in \{1, 2\}$, then in the event where $\underline{p}$ clears the market, either firm can profitably deviate by slightly reducing production and causing the price to jump up to c^f. Hence, it is not optimal to exhaust capacity for $p < c^f$.

To see the second assertion, if there exist two prices $\underline{p} < \overline{p}$ in the interval (c^h, c^f) such that $S_i(\underline{p}) = S_i(\overline{p}) < K_i$, we can apply a similar argument as above and conclude that the best response for j is $S_j(\underline{p}) = S_j(\overline{p})$. W.l.o.g., let $\overline{p}$ be the sup of all the prices for which this equality holds. In the case when $\overline{p} + \epsilon$ is the market clearing price for all small enough $\epsilon > 0$, increasing the production at the price $\overline{p}$ is a profitable deviation for at least one of the players. □

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

Proof. At least one of the firms exhausts its capacity in the left limit of c^f. This is because fringe firms enter and there will be no market for $p > c^f$. So any remaining capacity will be produced at c^f, that is $S_i(c^f) = \sum_\tau K_i^\tau$ for both i. If both firms do not exhaust their capacity in the left limit of c^f, then both supply schedules have a discrete jump at c^f. In the event that the market demand is met at c^f but $D(\epsilon) < \sum_{i,\tau} K_i^\tau$, one of them can deviate by exhausting its capacity at the price just epsilon below c^f to capture more demand, a profitable deviation. □

Lemma A.3 *The production cost for firm 1 at different market-clearing prices satisfies*

$$C_1 = \begin{cases} c^l S_1^h(p) & \textit{iff } S_1^h(p) < K_1^h; \\ c^l K_1^l + c^h S_1^h(p) & \textit{iff } S_1^l(p) = K_1^l. \end{cases}$$

Proof. Since C_i is the minimal cost function for producing a given quantity of electricity, because the marginal cost of hydro production is lower, firm 1 will necessarily first produce with hydro and only start thermal production when hydro capacity is exhausted. $\square$

Lemma A.4 *For $i \in \{1, 2\}$ the function $S_i(p) = S_i^l(p) + S_i^h(p)$ is continuous on the interval (c^h, c^f). It is continuously differentiable except possibly for $S_2(p)$ at p for which $S_1(p) = K_1^l$.*

Proof. The supply functions are non-decreasing by definition. Hence, a discontinuity of i's supply at some price $p \in (c^h, c^f)$ is, therefore, a discrete jump in i's production. In the event that such p clears the market, firm j has a profitable deviation to increase its production at $p - \epsilon$ for any ϵ small enough. Therefore, in equilibrium, the total supply function of each firm is continuous at every $p \in (c^h, c^f)$.

By Lemma A.3, it holds except for the case where $i = 1$ and $S_1(p) = S_1^l(p) = K_1^l$, that for any small enough interval $U \subset (c^h, c^f)$, there exists $\tau \in \{l, h\}$, such that all p, p' on that small interval,

$$C_i(S_i(p)) - C_i[S_i(p) + S_j(p) - S_j(p')] = -c^\tau (S_j(p) - S_j(p')) . \tag{A16}$$

Now consider the case that $p \in (c^h, c^f)$ clears the market, firm i is maximizing by producing $S_i(p)$ and $S_1(p) + S_2(p) = D(\epsilon)$. Therefore, any p' on the same interval satisfies

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

that is if i deviates its production so that the market clearing price changes to p', it would not be a profitable deviation. Therefore with (A16) we have

$$\begin{aligned} S_i(p) \cdot p - C_i(S_i(p)) &\geq [S_i(p) + S_{-i}(p) - S_{-i}(p')] \cdot p' - C_i[S_i(p) + S_{-i}(p) - S_{-i}(p')] \\ &\Leftrightarrow \\ S_i(p) \cdot (p - p') &\geq [S_{-i}(p) - S_{-i}(p')] \cdot [p' - c^\tau] \\ &\Leftrightarrow \\ \frac{S_i(p)}{p' - c^\tau}(p - p') &\geq S_{-i}(p) - S_{-i}(p'). \end{aligned}$$

Similarly, consider market clearing at p' gives

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

Therefore, for any $p, p' \in U$ with $p - p' = \delta > 0$ we have

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

Since this holds for all δ near 0, by continuity of S_i (Lemma A.3) we have

$$\limsup_{\delta \to 0-} \frac{S_{-i}(p + \delta) - S_{-i}(p)}{\delta} \leq \frac{S_i(p)}{p - c^\tau} \leq \liminf_{\delta \to 0+} \frac{S_{-i}(p + \delta) - S_{-i}(p)}{\delta}.$$

which implies S_{-i} is continuously differentiable on (c^h, c^f). The only exception is when $i = 1$ and $S_1(p) = K_1^h$, then $S_j(p) = S_2(p)$ is allowed to be non-smooth at p where $S_1(p) = K_1^h$. □

Lemma A.5 *Using c_3, c_4 solved in c_1 as in (A11), 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

$$\begin{aligned}
&c_3(c^f - c^h) - c_4/(c^f - c^h) - c_1(c^f - c^h) \\
=&\frac{c_1}{2}\left(1 + \frac{\alpha}{\alpha - c_1}\right)(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^f - c^h) \\
=&\frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h},
\end{aligned}$$

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

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

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

$$\begin{aligned}
&c_3(c^f - c^h) + c_4/(c^f - c^h) - c_1(c^f - c^l) \\
=&\frac{c_1}{2}\left(2 + \frac{c_1}{\alpha - c_1}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^f - c^l) \\
=&\frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^h - c^l).
\end{aligned}$$

Its derivative is increasing in c_1 and hence

$$\begin{aligned}
&\frac{2c_1(c^f - c^h)}{2(\alpha - c_1)} + \frac{c_1^2(c^f - c^h)}{2(\alpha - c_1)^2} - \frac{(c^h - c^l)^2}{2(c^f - c^h)} - (c^h - c^l) \\
\geq&\frac{c_1(c^f - c^h)}{(\alpha - c_1)} - (c^h - c^l) \\
=&\frac{\frac{K_1^l}{c^f - c^l}(c^f - c^h)}{\left(\frac{(c^f - c^h)K_1^l}{(c^h - c^l)(c^f - c^l)}\right)} - (c^h - c^l) = 0.
\end{aligned}$$

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

$$\begin{aligned}
&\frac{c_1}{2}\frac{c_1}{\alpha - c_1}(c^f - c^h) + \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1}{c^f - c^h} - c_1(c^h - c^l) \\
=&\frac{c_1}{2}(c^h - c^l) + \frac{1}{2}(c^h - c^l)\frac{K_1^l}{c^f - c^l} - -c_1(c^h - c^l) = 0.
\end{aligned}$$

□

A.2 Bounding Marginal Benefit of Water

This Section shows that that the marginal benefit of holding water decreases as thermal capacity increases. We begin by considering the Gross Revenue function at each time t as $GR(w_t + \delta_t - w_{t+1} + q_t)$, in which the quantity $w_t + \delta_t - w_{t+1} + q_t$ is the total output during period t and $w_t + \delta_t - w_{t+1}$ is the hydro output and q_t is the thermal output. 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

$$\Pi(w_t + \delta_t - w_{t+1}, q_t) := GR(w_t + \delta_t - w_{t+1} + q_t) - c^t q_t - c^h(w_t + \delta_t - w_{t+1})$$

Therefore, the value function for the dynamic optimization problem is given as below

$$V(w_0, K) := \mathbb{E}_\delta\left[\max_{\substack{w_{t+1}(w_t+\delta_t,K)\\ q_t(w_t+\delta_t,K)}} \sum_{t=0}^{\infty} \beta^t \Pi(w_t + \delta_t - w_{t+1}, q_t)\right] \tag{A17}$$

where 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. In particular, standard arguments shows that when δ_t is a Markovian process, the value function satisfies the functional equation

$$V(w_0, K) = \mathbb{E}_{\delta_0}\left[\max_{\substack{w_1 \le w_0+\delta_0 \\ q_0 \le K}} \{\Pi(w_0 + \delta_0 - w_1, q_0) + \beta V(w_1, K)\}\right] \tag{A18}$$

Proposition 2 *If a firm's revenue function is strictly concave and twice differentiable, the marginal benefit of holding water decreases in its thermal capacity* K_i, *i.e.,* $\frac{\partial^2 V_i(\cdot)}{\partial w_i \partial K_i} < 0$.

Proof. Since the gross revenue GR is strictly concave (Appendix Figure A2), it follows from standard arguments that $V(\cdot)$ is also strictly concave.

Consider formulation (A18) at time t, given δ_t, w_t, the future water stock w_{t+1} is determined by FOC:

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

which can be equivalently expressed as

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

Differentiating this FOC with respect to w_t gives

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

Rearranging the equation gives

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

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

Now consider formulation (A17). 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

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

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 $GR'(w_t + \delta_t - w_{t+1} + K) - c^t > 0$ when the optimal $q_t = K$.

Therefore, we have

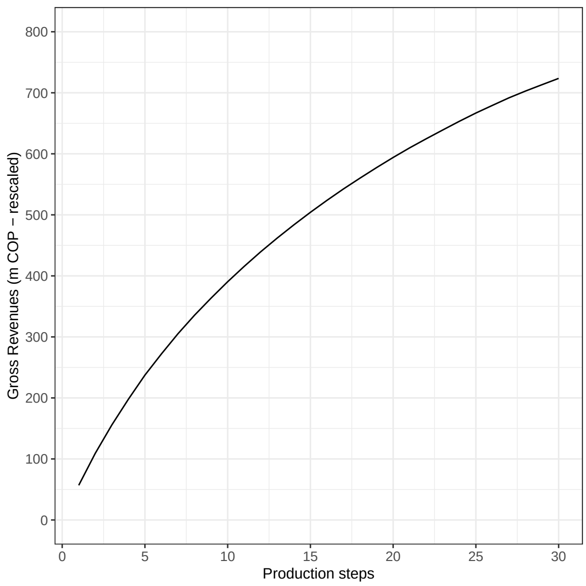
$$
\begin{aligned}
V_{21}(w_0, K) =& \frac{\partial}{\partial w_0}\frac{\partial}{\partial K}V(w_0, K) \\
=& \mathbb{E}_\delta\left[\sum_{t=0}^{\infty}\beta^t \frac{\partial}{\partial w_0}\left[GR'(w_t+\delta_t-w_{t+1}+K)-c^t\right]\mathbf{1}\{q_t=K\}\right] \\
=& \mathbb{E}_\delta\left[\sum_{t=0}^{\infty}\beta^t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

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

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:

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

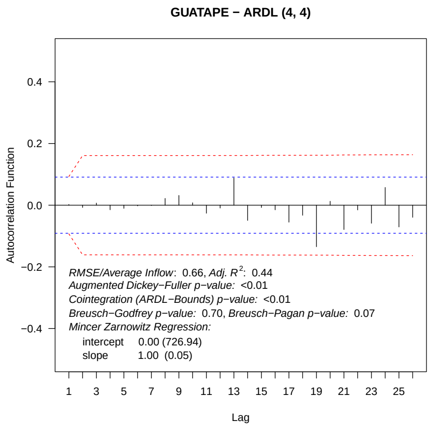
where K denotes the number of control variables in $\mathbf{x}_{j,t-q}$.

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.

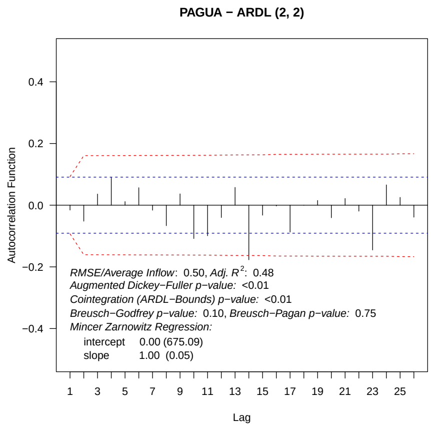
Quality of the fit. Figures B1 and B2 report the autocorrelation function and the Ljung-box test for the error term ϵ_t in (B2) for the largest dams in Colombia in the period we consider. The p-values of Ljung-box test never reject the null of autocorrelation.

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.

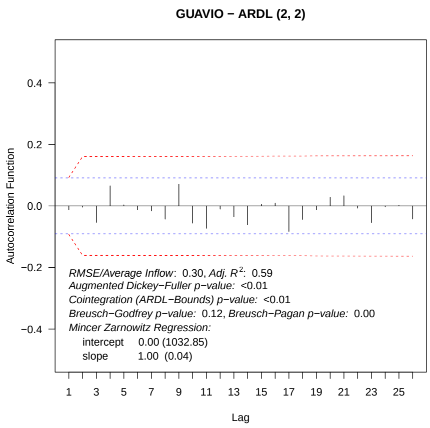
Figure B1: ARDL model diagnostics for some of the largest dams in Colombia in our sample period



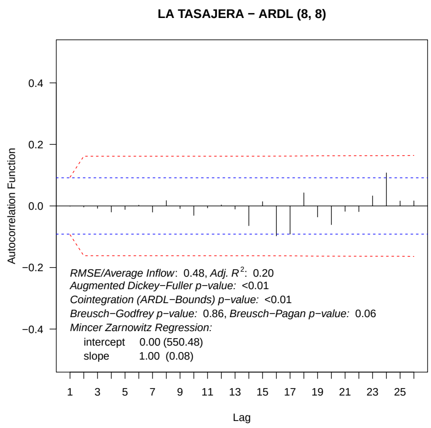
(a) Guatape



(b) Pagua



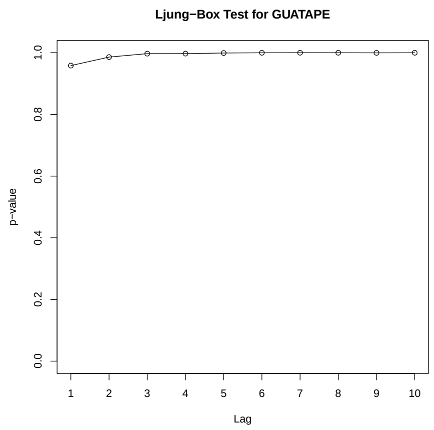
(c) Guavio



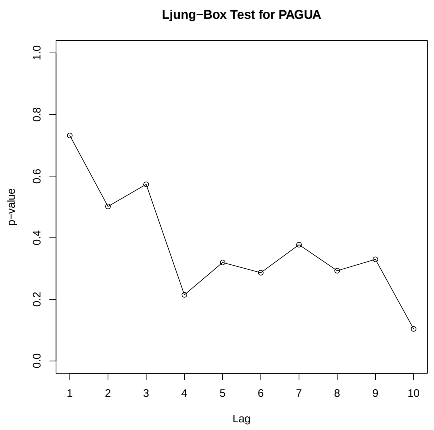
(d) La Tasajera

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.

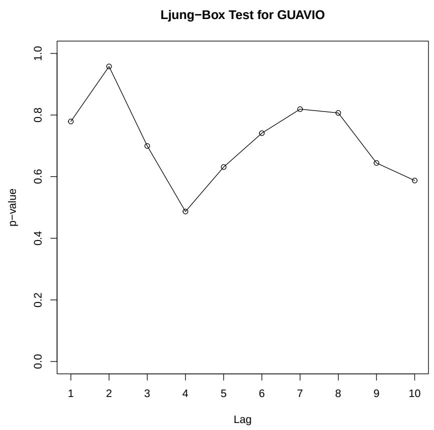
Figure B2: Ljung boxes for some of the largest dams in Colombia



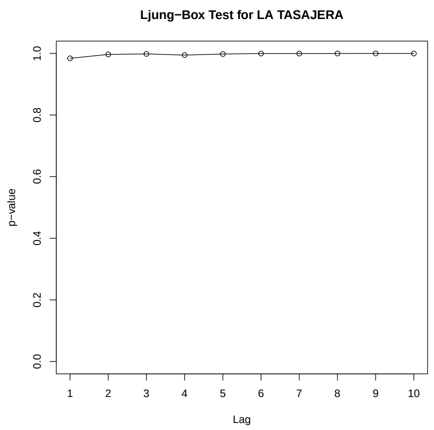
(a) Guatape



(b) Pagua



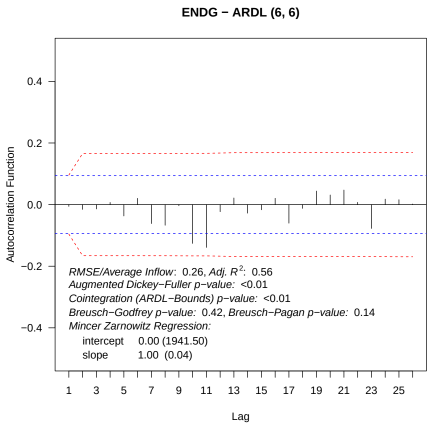
(c) Guavio



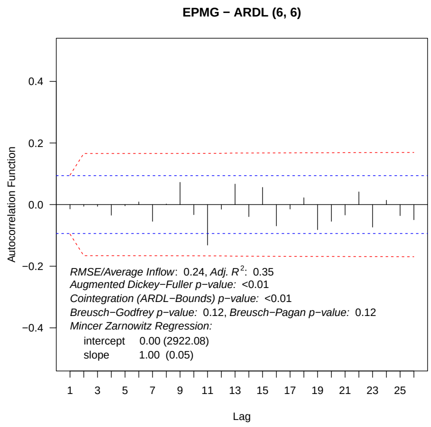
(d) La Tasajera

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.

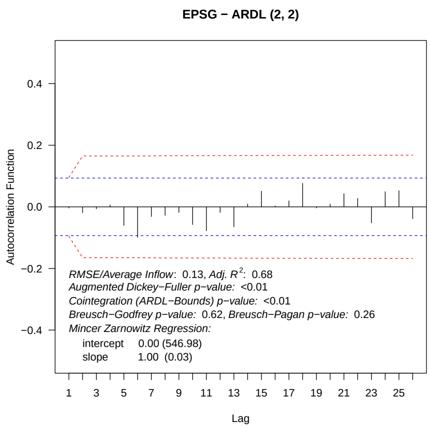
Figure B3: ARDL model diagnostics at firm level



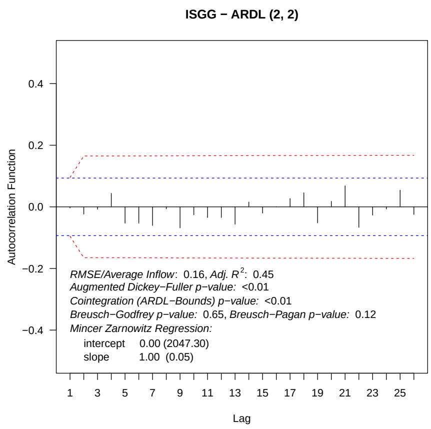
(a) ENDG



(b) EPMG



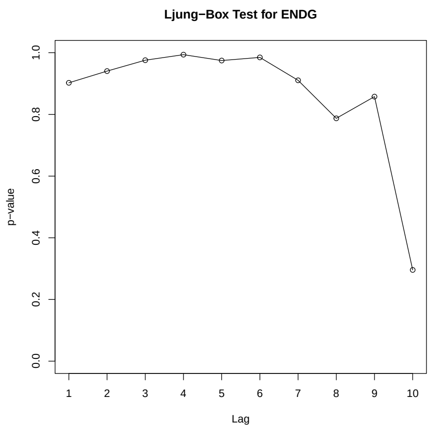
(c) EPSG



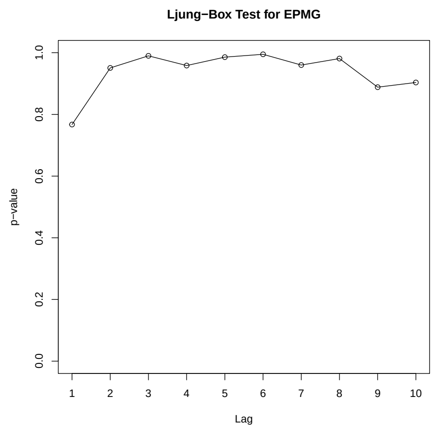
(d) ISGG

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.

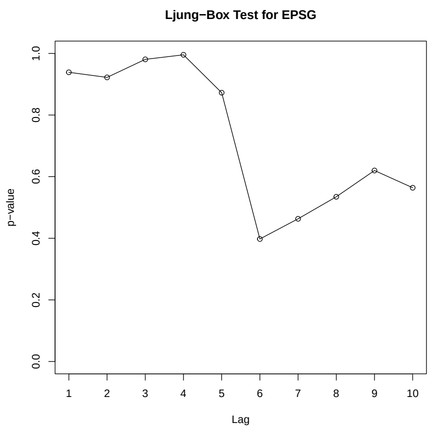
Figure B4: Ljung boxes at the firm level



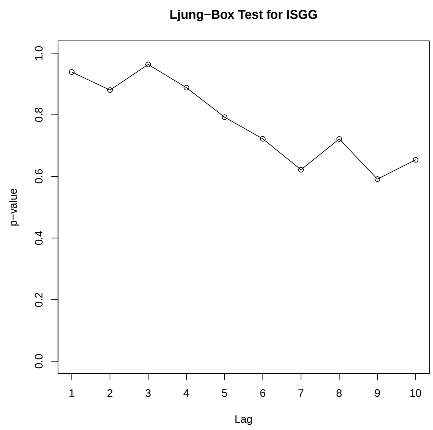
(a) ENDG



(b) Pagua



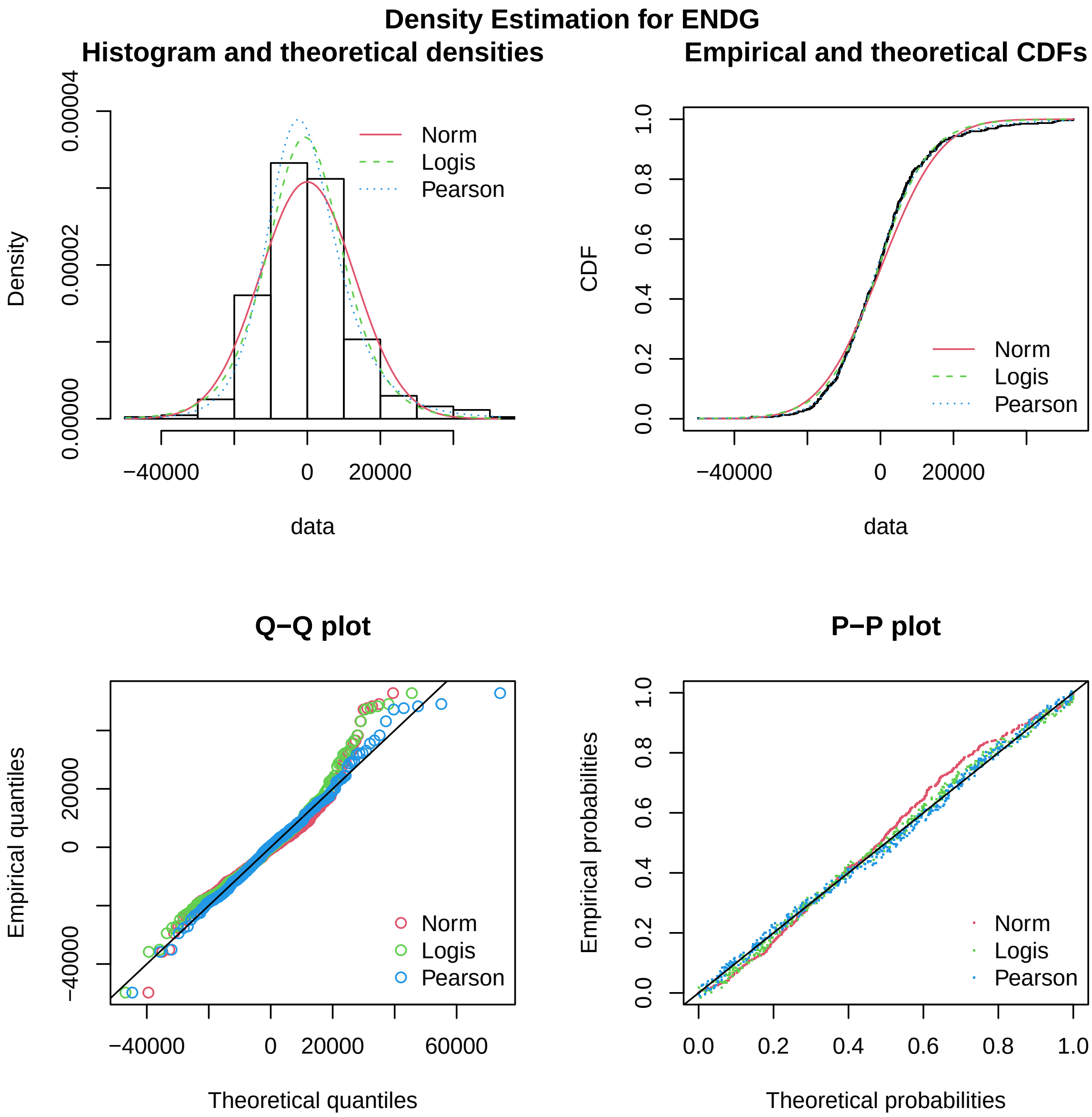
(c) EPSG



(d) ISGG

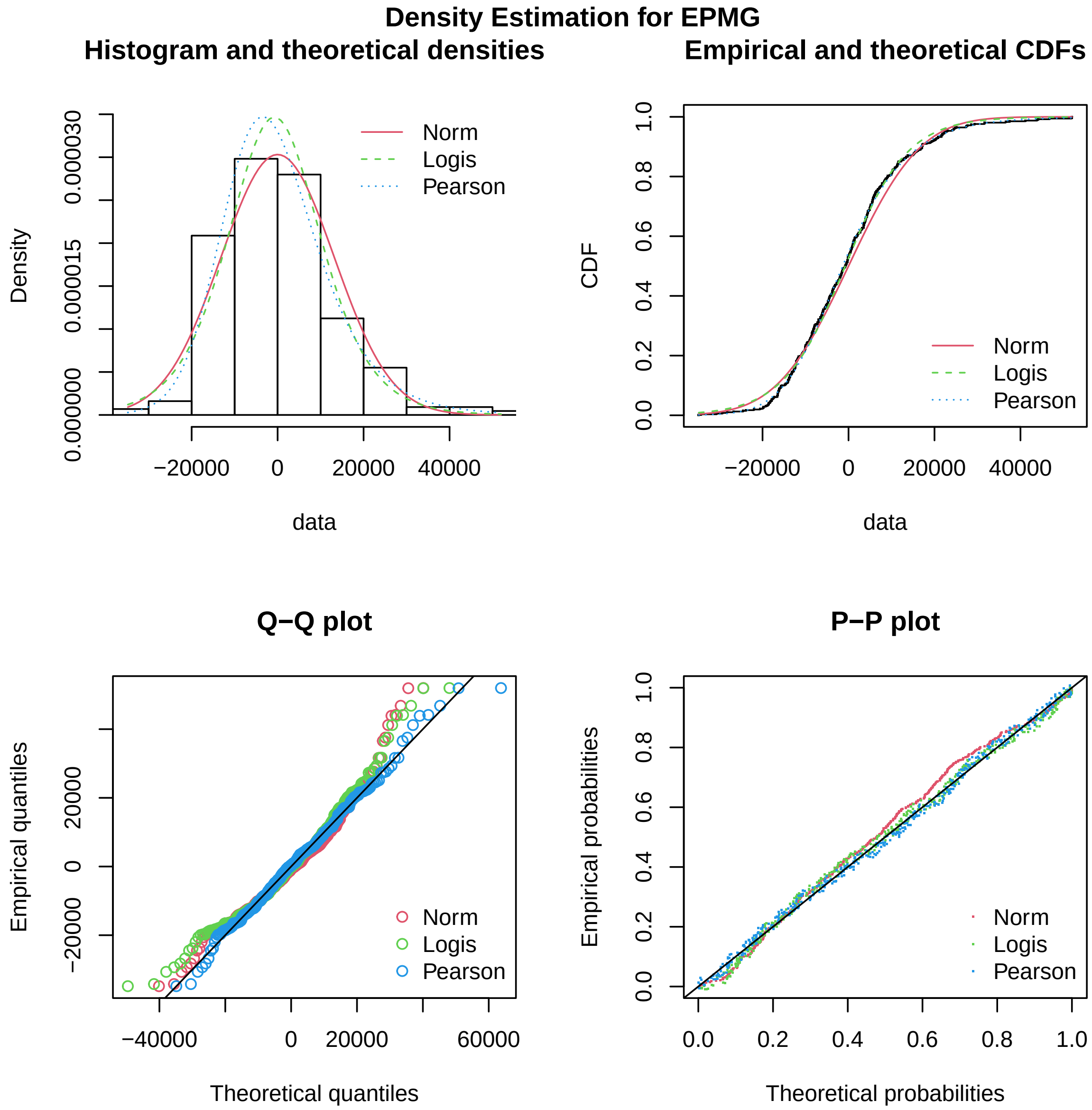
Notes: The plot shows the p-values of Ljung-box tests of whether any of a group of autocorrelations of a time series are different from zero.

Figure B5: Transition matrix for ENDG



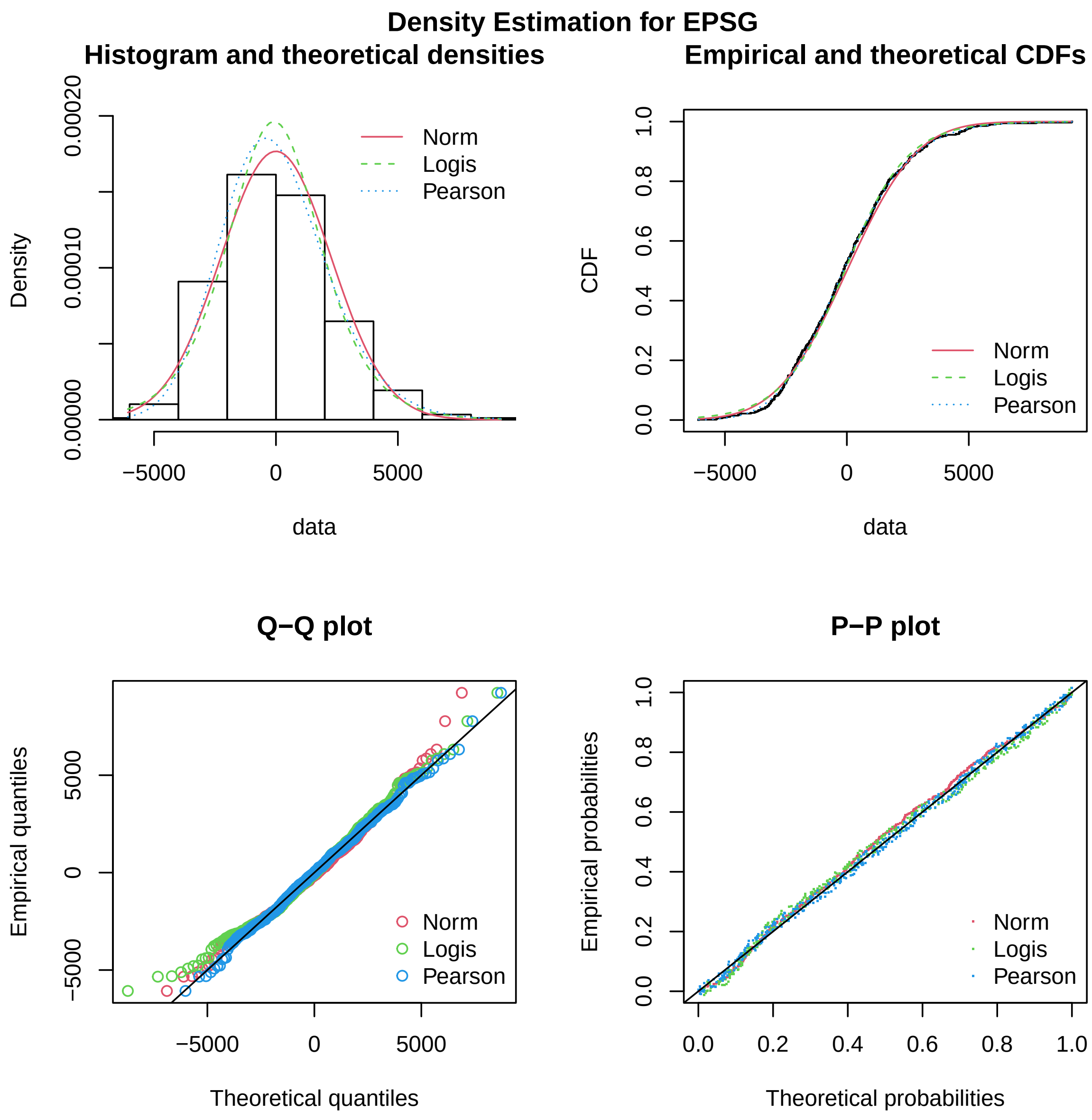
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B6: Transition matrix for EPMG



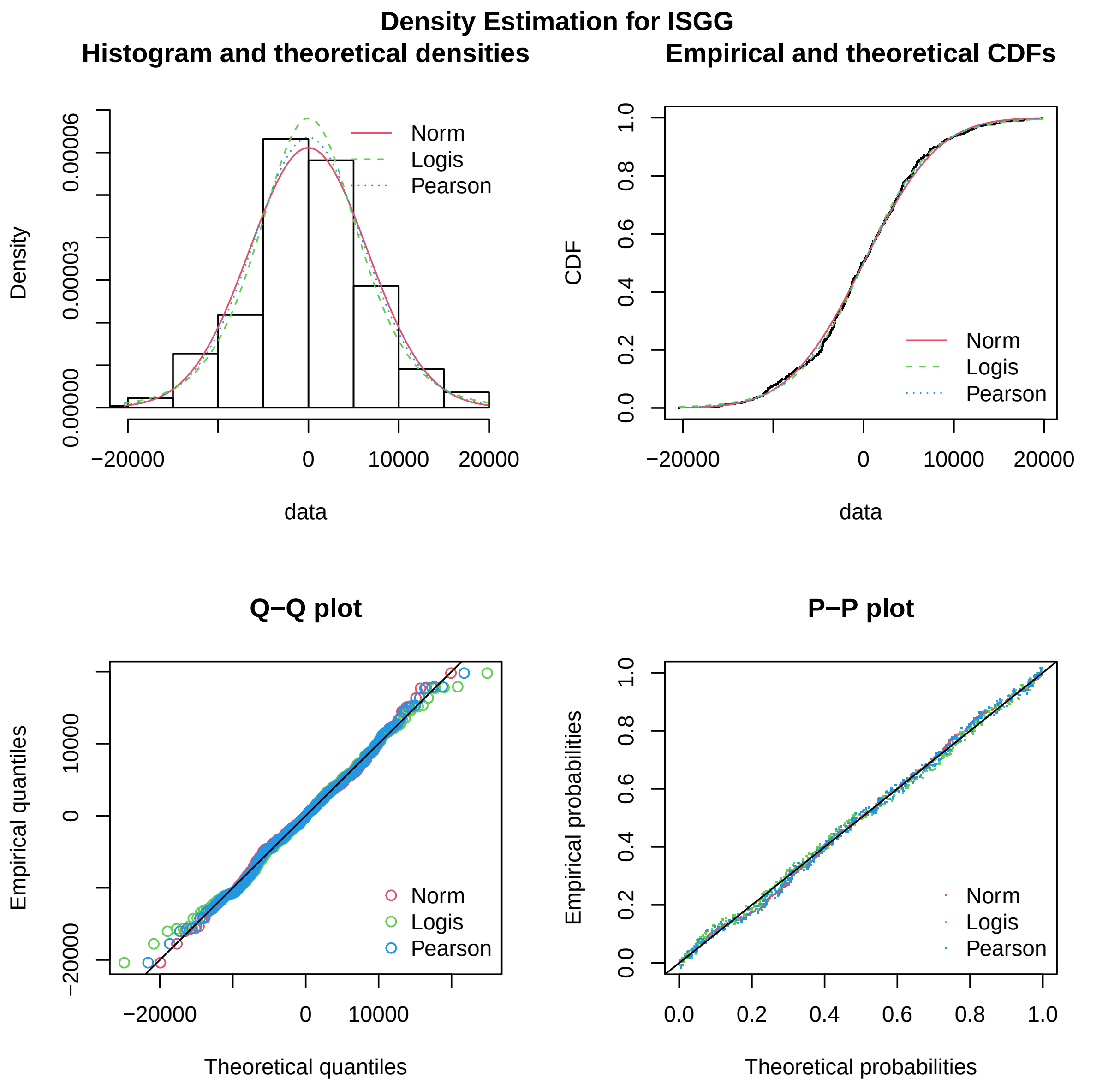
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

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 Generators' Responses to Inflow Forecasts

C.1 Symmetric Responses to Favorable and Adverse Forecasts

The main text focuses on generators' 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:

$$y_{ij,th} = \sum_{l=1}^{L} \beta_l \, \widehat{inflow}_{ij,t+l} + \mathbf{x}_{ij,t-1,h}\, \alpha + \mu_{j,m(t)} + \tau_t + \tau_h + \varepsilon_{ij,th}, \tag{B3}$$

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 generators to control for reservoir size across seasons to avoid the mechanical association between high forecast inflows and large reservoirs.

Zooming in on sibling thermal generators, 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 3.2.2. In this case, we let the slope of this variable vary across firms.

C.1.1 The Response of Hydropower Generators

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. Generators 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 (B3) 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.[12]

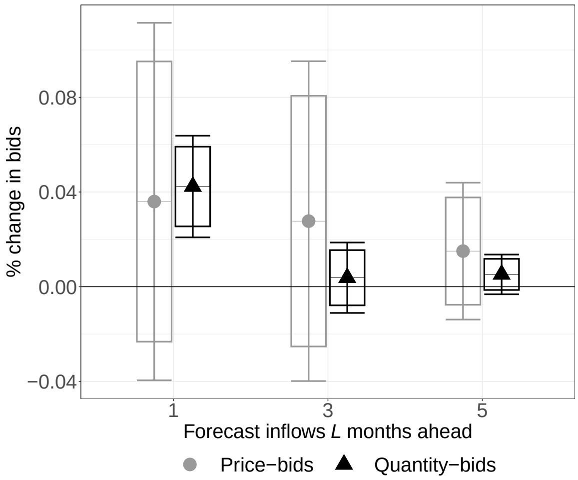
C.1.2 The Response of "Sibling" Thermal Generators

The coefficient estimates are in Figure C2. As in Section 3.2.2, sibling thermal generators respond mostly with their price-bids. The effect is particularly evident in Panel (b), which runs separate regressions for each monthly forecast in (B3) and shows that current thermal generators reflect inflow forecasts that are two to four months ahead.

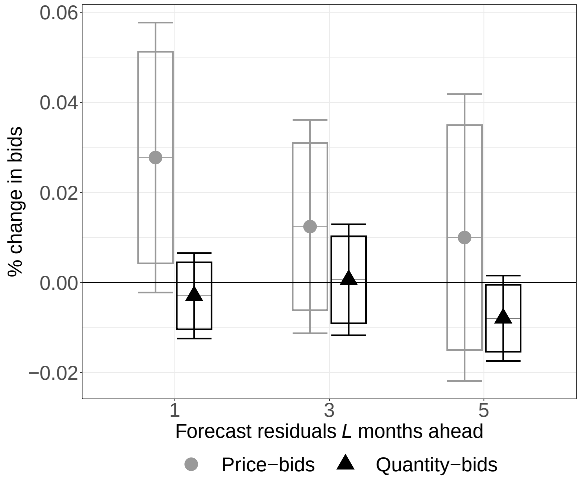
[12]Some price-bid coefficients are positive in Panel (a). However, this result is rather noisy, as suggested by the slightly higher response of price bids to the one-month forecast in Panel (b). The rationale is that generators submit only one price bid per day but multiple quantity bids; thus, there is less variation in price bids. Controlling for lagged quantities (in logs) in the price-bids regressions (B3) 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. The bottom panels plot the estimate from separate regressions analogous to (B3) to break the extent of autocorrelation across monthly inflows. Panel (c) shows a smooth decay in quantity bids, while price bids are highly volatile.

Figure C1: Symmetric hydropower generators' responses to inflow forecasts

Top Panel. *All l-forecasts in the same regressions*

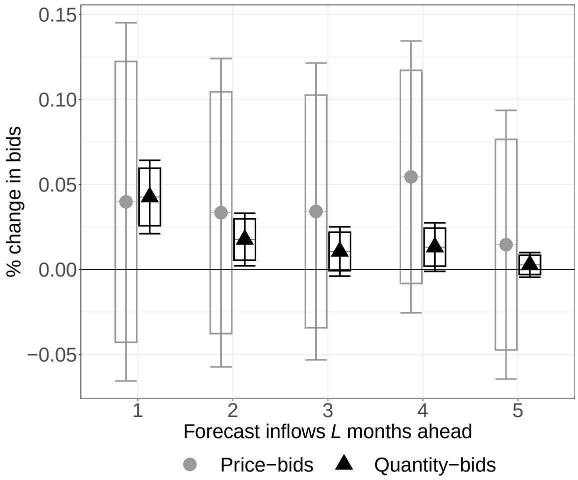


(a) Expected inflows (standardized forecasts)

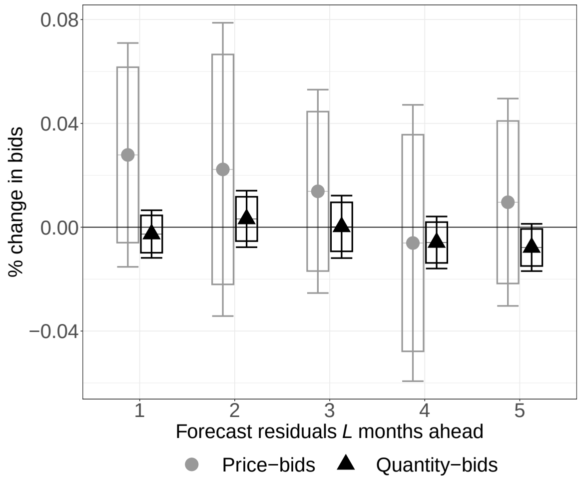


(b) Unexpected inflows (forecast residuals)

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



(c) Expected inflows (standardized forecasts)



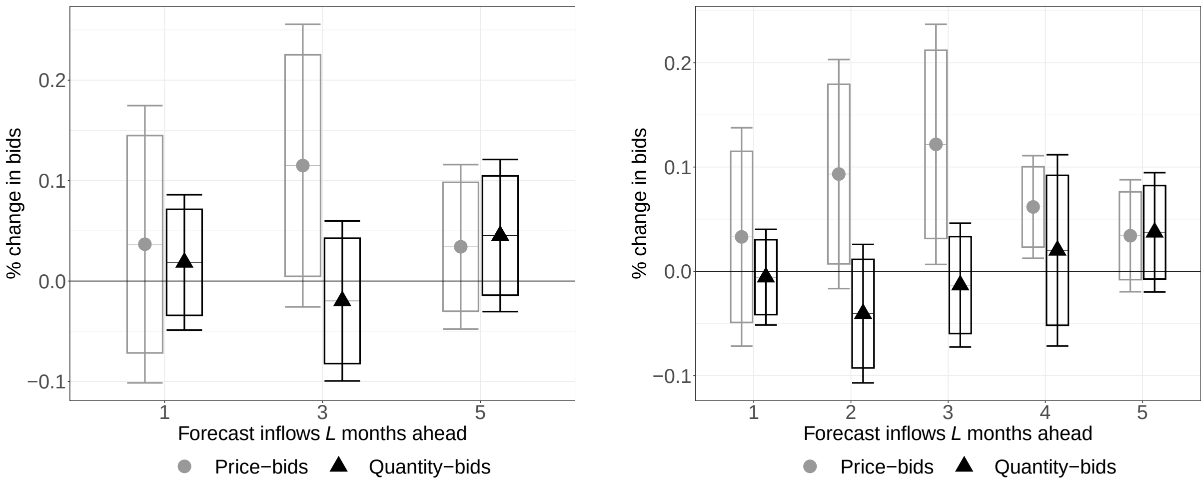
(d) Unexpected inflows (forecast residuals)

Notes: All plots report estimates of $\{\beta_l\}_l$ from (B3) 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.

C.1.3 The Response to Competitors' Inflow Forecasts

We include $\widehat{\text{infolow}}_{-i,t+l}$, the sum of the forecasted inflows of firm i's competitors l months ahead, in (B3) and estimate coefficients for both own-forecasts and competitors' forecasts. Figure C3 shows the estimated coefficients for competitors' and own's forecasts in blue and green, respectively. Two results emerge. First, generators 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.

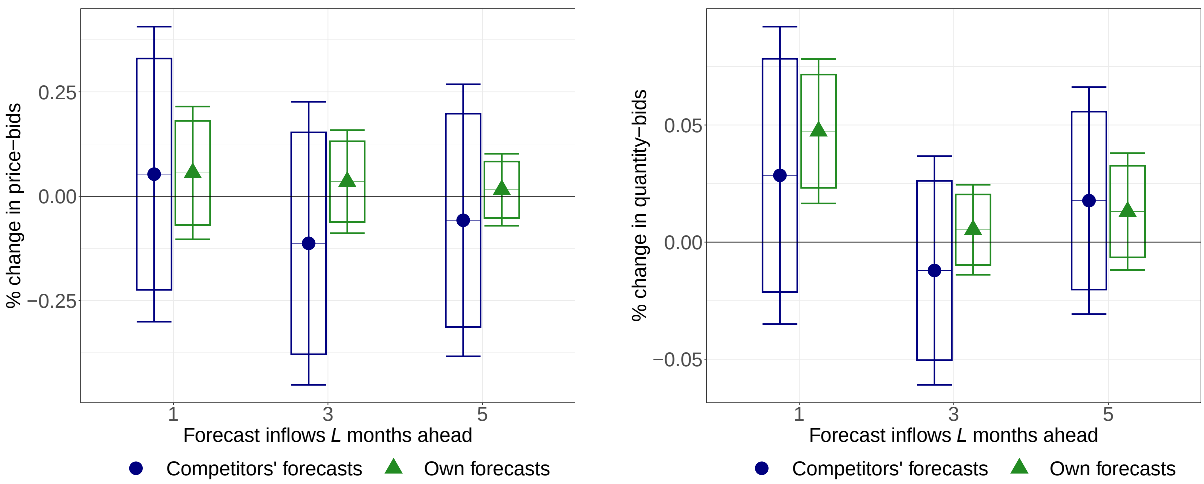
Figure C2: Symmetric response of sibling thermal generators



(a) Single regression (b) Separate regressions

Notes: The figure reports estimates of $\{\beta_l\}_l$ from a modified version of (B3) where the focus is on water inflows accruing to a firm rather than to a generator between one and five months ahead. Since water inflow forecasts can be correlated over time, Panel (b) plots the estimates from five separate regressions with each regression focusing on a specific month. Error bars (boxes) report the 95% (90%) CI.

Figure C3: Generators' response to competitors and own forecasts



(a) Price bids (b) Quantity bids

Notes: The figure reports the estimates from a modified version of (B3) where we include both a generator's water forecasted inflow (green) and that 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) report the 95% (90%) CI. Error bars (boxes) report the 95% (90%) CI.

Current water stocks. Intrigued by the fact that generators 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 generators, week-by-year, and market hours. Table C2 finds that firms only respond to their own water stocks: not only the response to competitors is not statistically significant, but also its magnitude is shadowed by that observed for own water stocks. In addition, the interaction term is small and insignificant, indicating that firms do not strategize based on their potential competitive advantage.[13]

Table C1: Firm response to competitors' water stock, two-by-two matrices

	(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: Generator, week-by-year, and hour	✓	✓	✓	✓	✓	✓	✓	✓
Clustered s.e., generator, 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 generator's current inflow (δ_{ijt}, unreported), and generator, week-by-year, and hour-fixed effects.

[13] 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 C1 shows that generators 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: Generator, week-by-year, and hour	✓	✓	✓	✓	✓	✓
Clustered s.e. by generator, 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

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

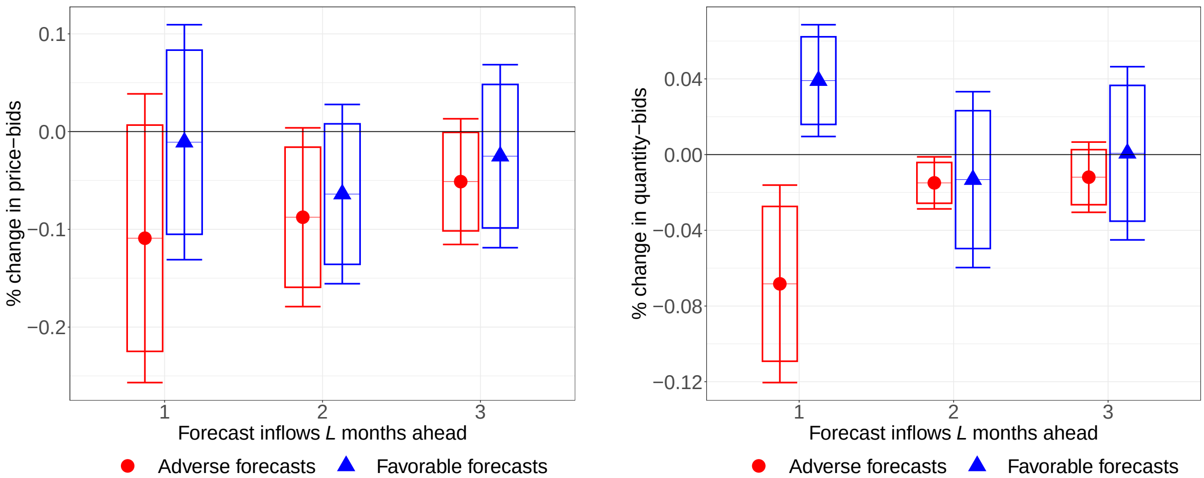
Notes: This table presents the coefficient estimates from the following regression

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

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.

C.2 Robustness

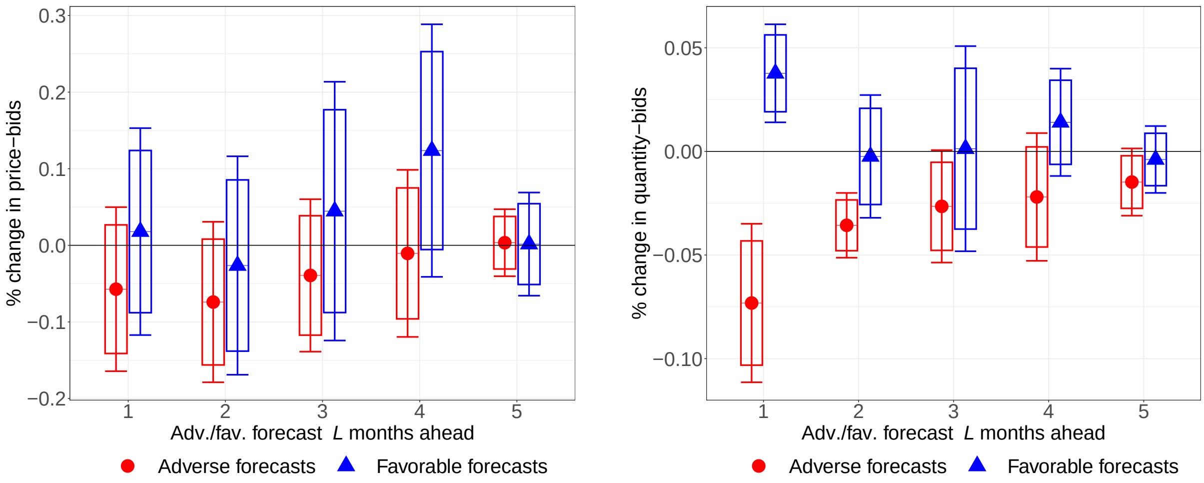
Figure C4: Hydropower generators' responses to inflow forecasts over 1, 2, and 3 months



(a) Price bids (b) Quantity bids

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts according to (1). Each plot reports estimates 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.

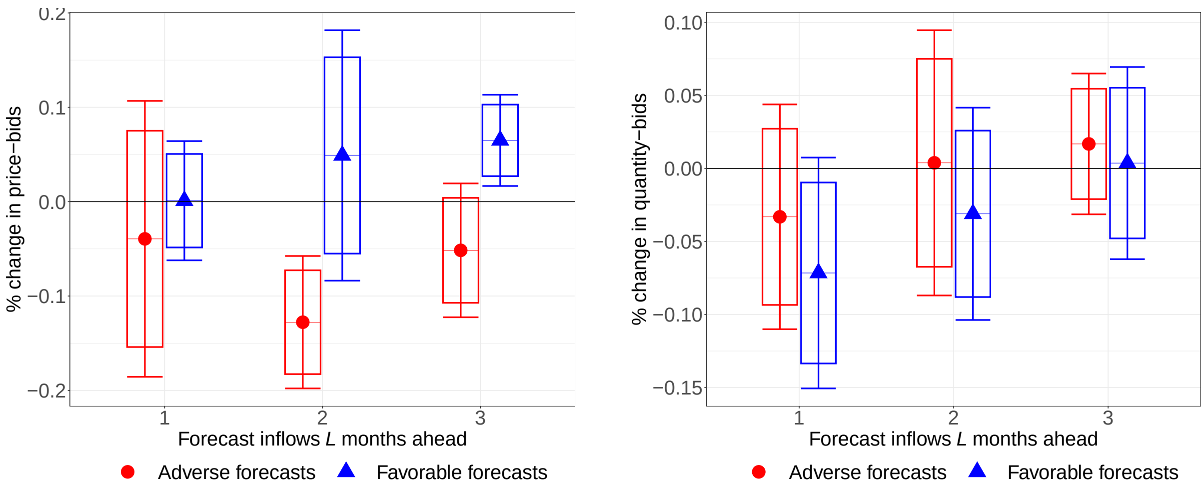
Figure C5: Hydropower generators' responses to inflow forecasts - separate regressions



(a) Price bids (b) Quantity bids

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts by running (1) five times – i.e., in each regression, we keep only one pair of adverse and favorable variable for each one of the five monthly forecasts reported in the figure. Each plot reports estimates 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.

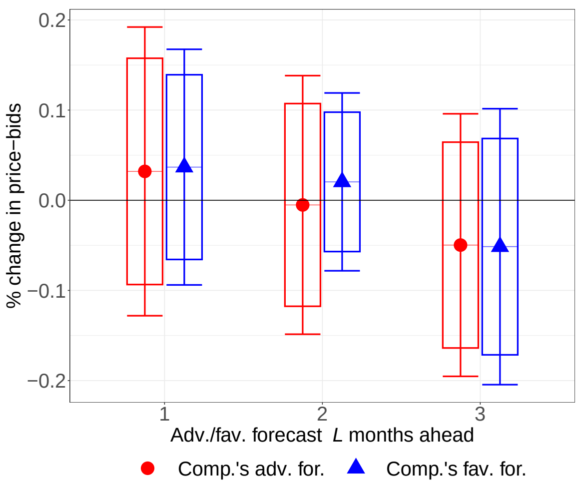
Figure C6: Sibling thermal generators' responses over 1, 2, and 3 months



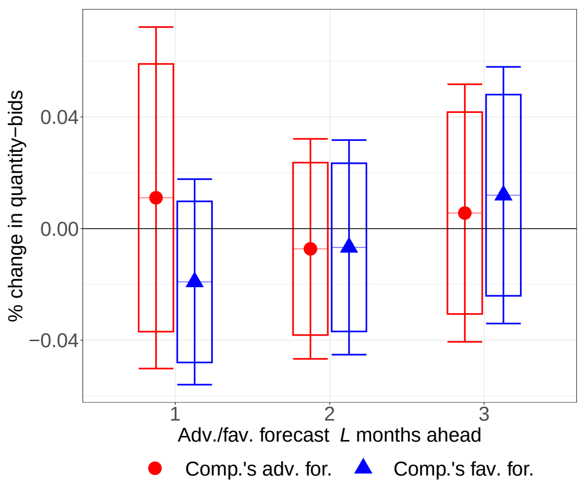
(a) Price bids (b) Quantity bids

Notes: The figure studies how sibling thermal generators respond to favorable or adverse future water forecasts according to (1). Each plot reports estimates 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.

Figure C7: Hydro generator's responses to competitors' forecasts over 1, 2, and 3 months



(a) Price bids

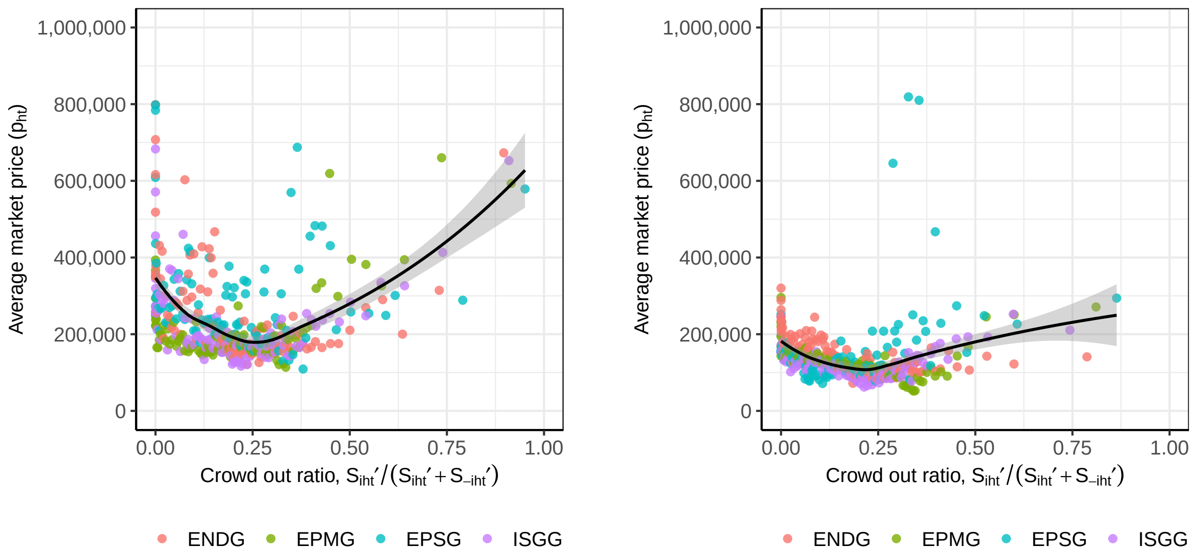


(b) Quantity bids

Notes: The figure studies how generators respond to favorable or adverse future water forecasts accruing to competitors according to (1). Error bars (boxes) report the 95% (90%) CI. Joint tests for $\{\beta_l^{low}\}_{l=1}^3$ and $\{\beta_l^{high}\}_{l=1}^3$ reject the null hypothesis that these coefficients are zero.

D Exhibits from the Structural Model

Figure D1: Relationship between prices and business stealing



(a) Scarcity periods (b) Abundant periods

Notes: The figure presents binned scatter plots (100 bins per firm) of the market prices (y-axis) for different levels of business stealing (x-axis). To avoid dividing by zero when $D_i^{R'} = 0$, we let the x-axis be $S'_{iht}(p)/(S'_{iht}(p) + S'_{-iht}(p))$. The denominator is the sum of $S'_{iht}(p) + S'_{-iht}(p)$ instead of just $S'_{-iht}(p) = {D^R_{iht}}'(p)$ as in (5) to account for ${D^R_{iht}}'(p) \simeq 0$ without truncating the data. Only diversified firms with a dam are considered. The black line fits the data through a spline (the 95% CI is in gray). Panel (a) focuses on markets where firm i has less than the 30^{th} percentile of its long-run water stock. Panel (b) focuses on periods where it has more than the 70^{th} percentile.

Table D1: Estimated primitives – four spline parameters

	(1)	(2)	(3)	(4)
	Marginal costs (COP/MWh)			
Thermal ($\psi^{thermal}$)	204460.10***	151965.08***	213177.19***	149699.10***
	(1,880.65)	(1,840.22)	(1,626.95)	(1,624.97)
Hydropower (ψ^{hydro})	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	✓	✓	✓	✓
Generator				✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
Date			✓	✓
Clustered s.e.	Generator	Generator	Generator	Generator
SW F ($\psi^{thermal}$)	32.93	842.34	30.56	129.27
SW F ($\psi^{thermal}$)	2,314.39	760.89	3,458.28	700.41
SW F (ψ^{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 2), 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 ($\psi^{thermal}$)	204727.14***	143319.87***	220441.60***	146635.86***
	(1,803.36)	(1,843.71)	(1,644.41)	(1,529.32)
Hydropower (ψ^{hydro})	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	✓	✓	✓	✓
Generator	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
FE: Date			✓	✓
SW F ($\psi^{thermal}$)	3,129.14	1,257.31	2,991.60	1,097.29
SW F (ψ^{hydro})	443.62	272.74	883.91	367.55
SW F (ψ^{γ_1})	251.73	213.67	285.62	225.96
SW F (ψ^{γ_2})	219.64	273.32	270.25	300.83
SW F (ψ^{γ_3})	441.27	476.05	297.84	482.88
SW F (ψ^{γ_4})	522.38	550.59	296.71	553.52
SW F (ψ^{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
KP Wald	156.38	156.56	139.15	159.40
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 2), these estimates assume that the transition matrix is normally distributed. The top panels separate the marginal cost estimates and the value function parameters from the fixed effects used in estimation, which vary across columns. Our favorite specification is in Column (4), which includes day-fixed effects. The bottom panel provides diagnostic tests in the first stage. 2,900 COP ≃ 1 US$

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

	(1)	(2)	(3)	(4)
Marginal costs (COP/MWh)				
Thermal ($\psi^{thermal}$)	195271.35***	152621.02***	194831.41***	151112.79***
	(1,605.71)	(1,807.59)	(1,229.58)	(1,573.39)
Hydropower (ψ^{hydro})	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: Generator		✓		✓
FE: Month-by-technology		✓		✓
FE: Hour	✓	✓	✓	✓
FE: Week-by-year	✓	✓		
FE: Date			✓	✓
Clustered s.e.	Generator	Generator	Generator	Generator
SW F ($\psi^{thermal}$)	36.41	113.62	34.13	94.59
SW F (ψ^{hydro})	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
Overid. p-value	0.19	0.21	0.11	0.14
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 2), 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 the Variables

This section details the smoothing approach that allows interchanging differentiation and expectation after taking the first-order conditions of the value function (9) – that is, $\frac{\partial \int_\epsilon V(w,p(\epsilon)) f_\epsilon(\epsilon) \mathrm{d}\epsilon}{\partial p} = \int_\epsilon \frac{\partial V(w,p(\epsilon))}{\partial p} f_\epsilon(\epsilon) \mathrm{d}\epsilon$ – simplifying the interpretation and identification in Section 5. The smoothing procedure replaces indicators in supply and demand variables with their smoothed version.

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

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

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

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

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

$$\begin{aligned}
\frac{\partial \tilde{S}^\tau_{iht}}{\partial p_{ht}} &= \sum_{k \in \tau} q_{ikht} \frac{\partial \mathcal{K}\left(\frac{p - b_{ikt}}{bw}\right)}{\partial p_{ht}}, \\
\frac{\partial \tilde{S}^\tau_{iht}}{\partial q_{ijht}} &= \begin{cases} \mathcal{K}\left(\frac{p - b_{ijt}}{bw}\right) & \text{if } j \text{ has technology } \tau, \\ 0 & \text{otherwise,} \end{cases} \\
\frac{\partial \tilde{S}^\tau_{iht}}{\partial b_{ijt}} &= \begin{cases} -q_{ijht} \frac{\partial \mathcal{K}\left(\frac{p - b_{ijt}}{bw}\right)}{\partial b_{ijt}} & \text{if } j \text{ has technology } \tau, \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}$$

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

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

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

F Model Fit

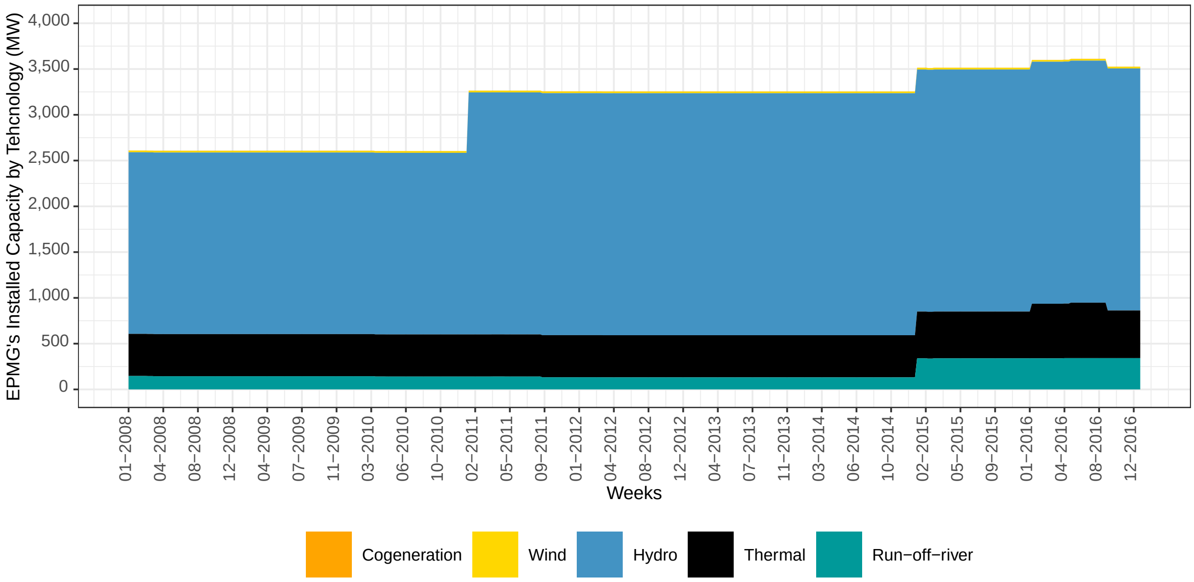
Table F1: Hourly prices across simulations

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

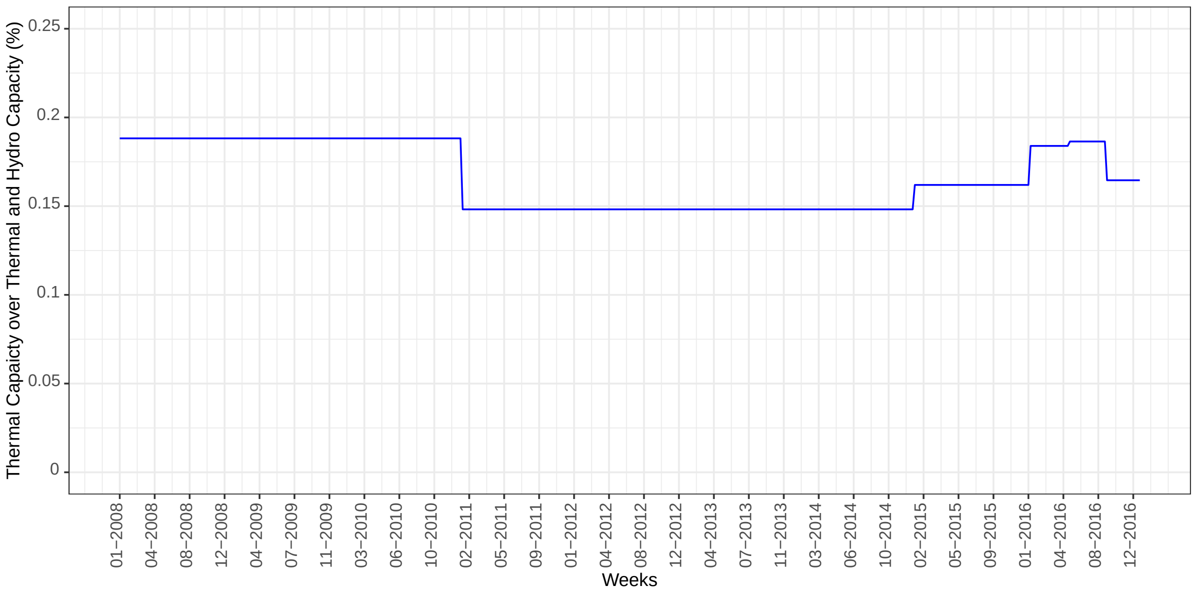
Notes: The table compares average hourly prices across the simulated and actual data. The simulation model is described in Section 6.2. The simulations in this table employ a different number of steps in the first and second panels. 2,900 COP $\simeq$ 1 US$.

Figure F1: EPMG's total installed capacity by technology

(a) EPMG's installed capacity over time

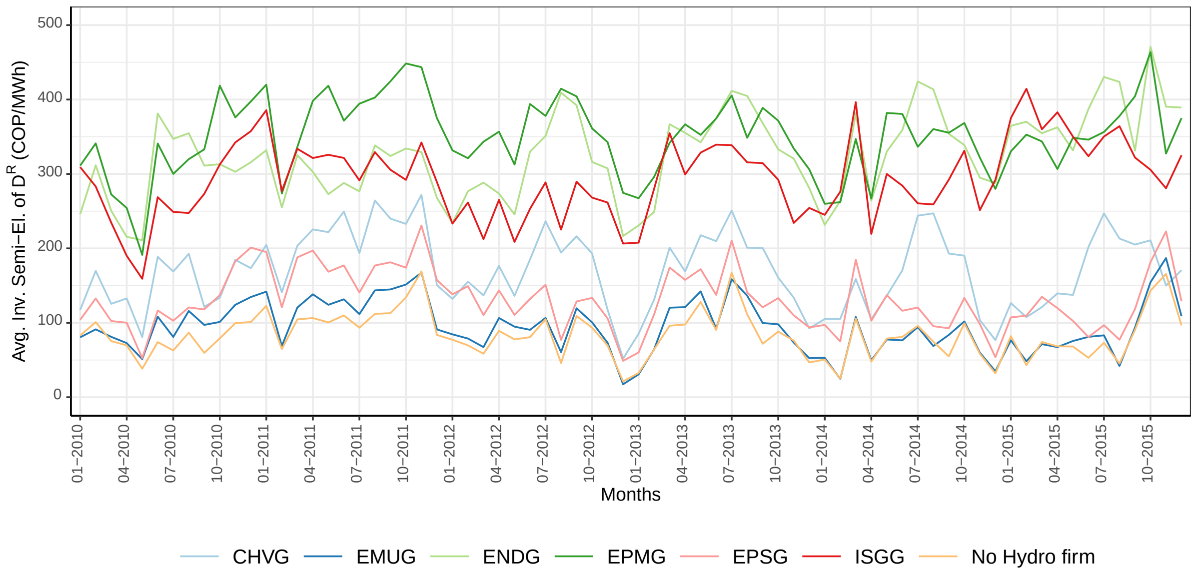


(b) Thermal capacity as a percentage of EPMG's thermal and hydro capacity



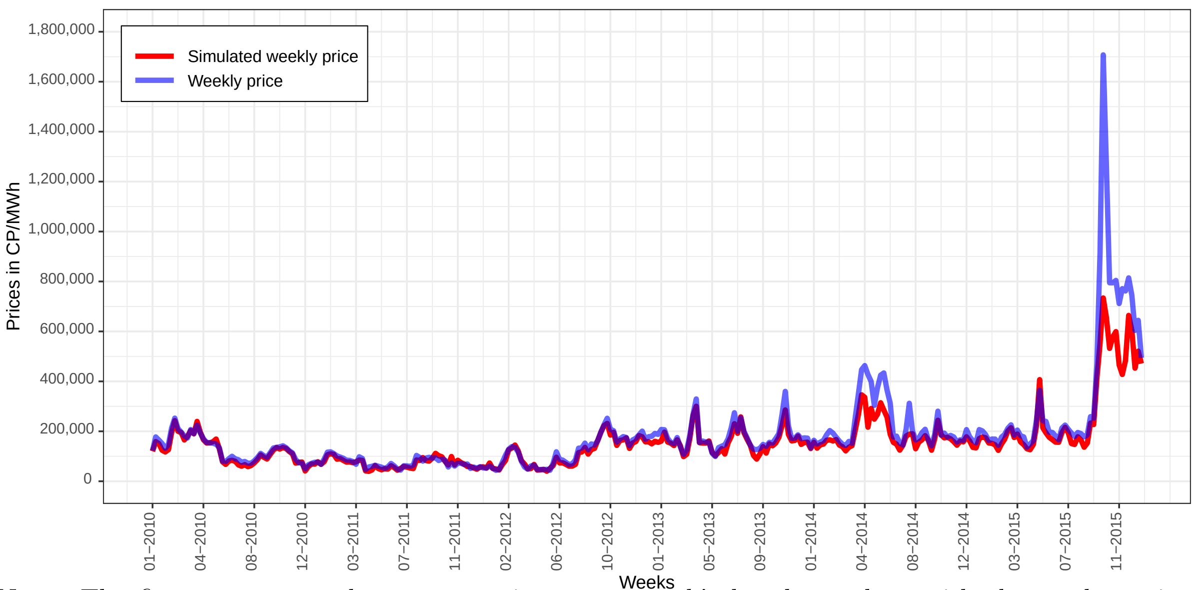
Note: The relative contribution of different technologies to EPMG's installed capacity over time.

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 generators (orange). The semi-elasticity is equal to the COP/MWh increase in the market-clearing price that would result from a supplier reducing the amount of energy it sells in the short-term market during hour h by one percent. 2,900 COP $\simeq$ 1US$.

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

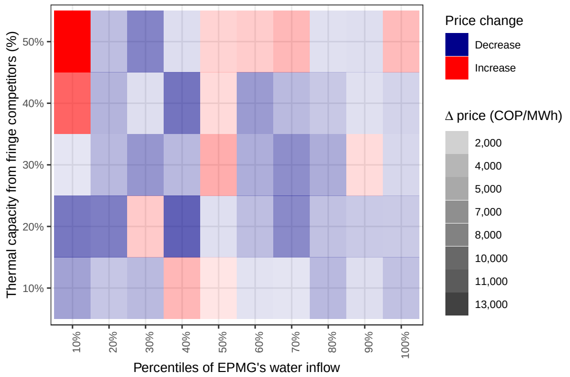


Note: The figure compares the average price over a week's hourly markets with the market prices obtained from solving EMPG's profit maximization problem (13) for each hourly market. The solver employs thirty steps to discretize the demand and the value function and 10 steps for each technology-specific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

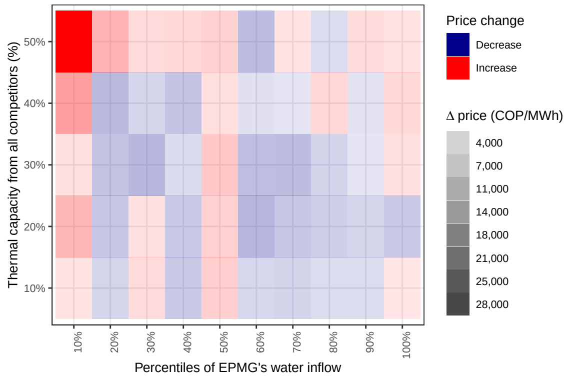
G Counterfactual Analyses: Tables and Figures

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

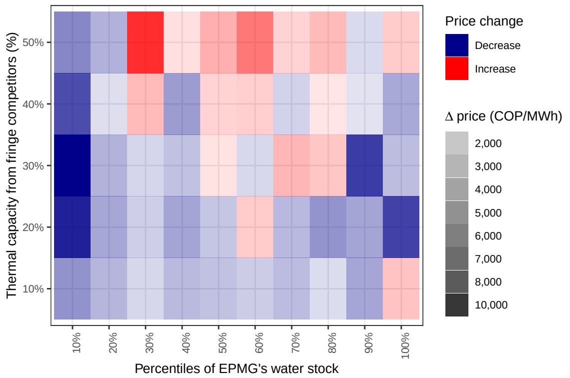


(a) Transferring x% from all fringe firms

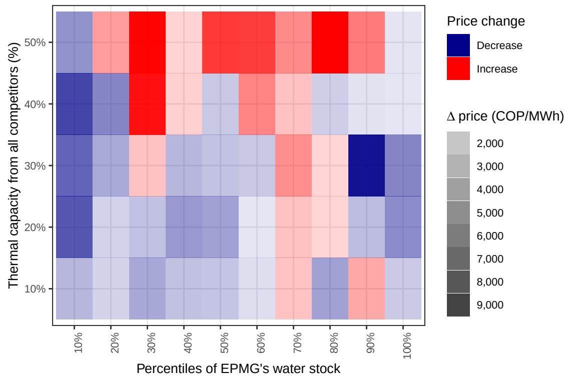


(b) Transferring x% from all firms

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



(c) Transferring x% from all fringe firms

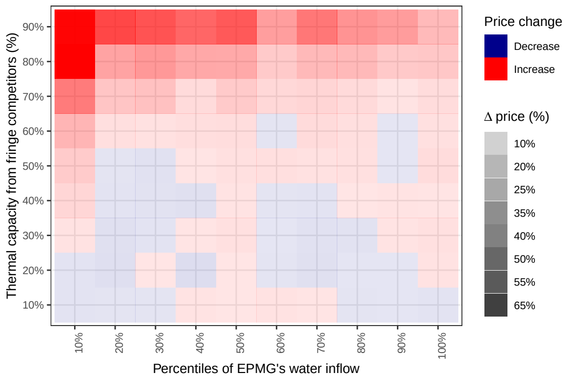


(d) Transferring x% from all firms

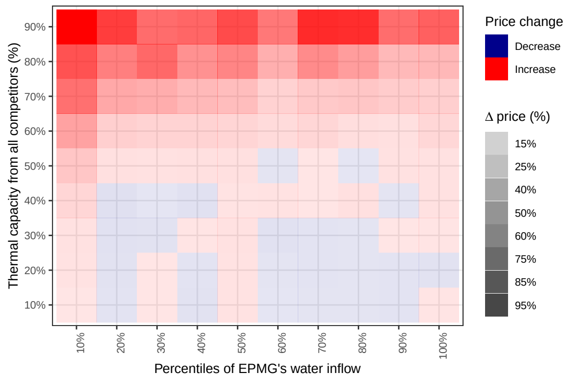
Notes: The figure presents the results from the counterfactual exercises discussed comparing observed prices with counterfactual market prices as we endow the market leading firm with a fraction of its competitors' thermal capacities (y-axis) for varying levels of scarcity (x-axis). Top (bottom) panels 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 11, 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

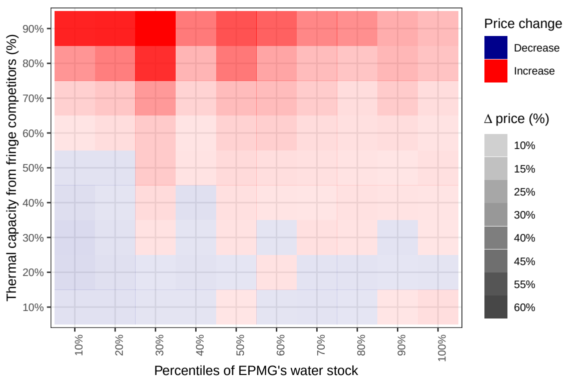


(a) Transferring $x\%$ from all fringe firms

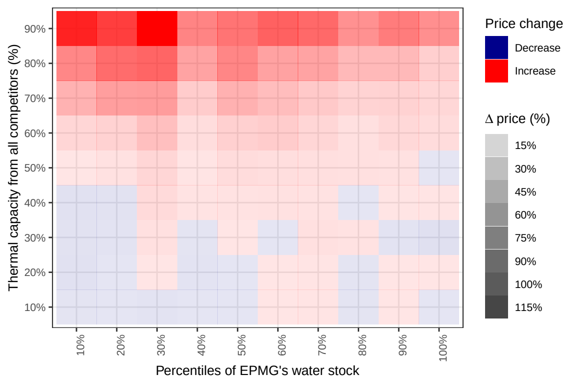


(b) Transferring $x\%$ from all firms

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



(c) Transferring $x\%$ from all fringe firms



(d) Transferring $x\%$ 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 11, which compares absolute price differences, this analysis compares percentage price differences by dividing each price difference by the baseline simulated market price ($x\% = 0$).