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

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Abstract

We study the Colombian energy market, where diversified energy firms strategically substitute thermal generation for hydropower before droughts. This within-firm substitution, due to thermal generators internalizing the drop in hydropower supply during droughts, mitigates higher market prices. We show theoretically and empirically that these virtuous spillovers exist when thermal generators have market power but are severed when their residual demands are vertical or horizontal, which attenuates a firm's business stealing incentives. We conclude that industry consolidation can reduce prices if it promotes diversified production portfolios. Diversification can keep the green transition affordable by reducing the cost of renewable intermittencies.

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 ownership of the means of production has always been a hotly debated issue for transitioning economies (e.g., Blanchard and Kremer, 1997) and the green transition is no exception. Our current energy mix is the primary contributor to global emissions (IEA, 2023), calling for decarbonizing investments in the energy sector and pressuring energy firms to diversify their production technologies toward carbon-free renewable sources. These investments will likely pass on to consumers through higher electricity prices (Fabra and Reguant, 2014) and further exacerbate the societal costs of climate change (Köberle *et al.*, 2021, van Vuuren *et al.*, 2020) and its dire distributional consequences (Riahi *et al.*, 2021, Chancel *et al.*, 2023).[1] As a firm's generation capacity affects its ability to increase prices, the ownership of the means of "generation" arises as a new lever for transitioning policymakers beyond fiscal incentives (e.g., Acemoglu *et al.*, 2016, Barrage, 2020).

Surprisingly, we know little about how diversified firms make production decisions through the technologies in their portfolios (e.g., generators) as most economic models view units of capital as homogeneous (e.g., Solow, 1955, Sraffa, 1960). In reality, capital units are necessarily heterogeneous if a firm is diversified, as the same good can be produced at different costs by each of its technologies. This substitution can pose a threat to competition, as a diversified firm can shut down a generator to drive prices up while making profits with other generators, or it can increase energy security by hedging for tighter capacity constraints at one of its generators (e.g., low wind at a wind farm). Therefore, technology-specific production decisions are entangled with considerations about a firm's market power and extend beyond the energy sector to any industry where alternative processes produce the same good.[2] This question might not have received enough attention yet because our data are often at the level of firms rather than technologies.

How do diversified energy firms exert their market power? Consider a dam expecting a drought, tightening its capacity constraints and forcing it to decrease its supply. We show that if the dam belongs to a diversified firm – i.e., a firm that also owns thermal generators – with market power, its other generators will internalize that the firm's lower hydro supply will increase the market price and best respond by increasing their supplies, mitigating the price hike. This result requires both diversification, as the firm must have other generators to integrate production, and market power, as the firm's other generators must internalize the higher prices due to scarcity. We first derive this result theoretically in a simple oligopoly market that allows for closed-form solutions. Then, we document this mechanism in the Colombian wholesale energy market, where hydropower generation

[1] For instance, the regressivity of electricity prices (Reguant, 2019, Haar, 2020) might reveal a burden for low-income populations (Burgess *et al.*, 2017, 2020) and constrain firms' growth (Allcott *et al.*, 2016).

[2] These industries include both sectors with homogenous goods like the oil and gas (Fioretti *et al.*, 2022), coal extraction (Delabastita and Rubens, 2023), and commodities (Collard-Wexler and De Loecker, 2015), and sectors with multiproduct firms like manufacturing (Bassi *et al.*, 2022).

accounts for 70% of the total installed capacity, and diversified firms own dams. Through a structural model, we show that moving 10% of its rival's thermal capacity to the market leader can decrease prices by 5 to 10% during droughts. Our results have policy implications for the ownership of the means of production during the green transition, as most national energy markets impose divestitures if a firm's capacity exceeds a threshold that is the same for specialized and diversified firms and, more broadly, for the literature studying horizontal mergers by proposing a novel source of synergies (Nocke, 2022).

To understand the nature of synergies within diversified firms, consider a static homogeneous-good oligopoly game where firms are uncertain about the demand they face and have access to both low- and high-cost technologies, representing hydropower and thermal generation through fossil fuels, respectively. These technologies have capacity constraints, which shape a firm's cost curve as an increasing supply function, with vertical segments at capacity. The equilibrium price arises from firms submitting supply schedules detailing the quantity they are willing to produce at each potential market price according to the supply function equilibrium concept of Klemperer and Meyer (1989).[3] We show that the equilibrium markup does not only reflect the demand elasticity as in standard conduct models but also the extent of business stealing – the ratio of the slopes of a firm's supply to that of its rivals – making firms' strategies more aggressive if they expect that their rivals' strategic response will erode their market share at a given price.[4]

Assume that no firm is diversified and imagine reallocating high-cost capacity to the market leader, the firm with the most low-cost capacity. How will the price change? If the leader has abundant low-cost capacity, the main effect of the transfer is to reduce the ability of its rivals to compete: the price goes up. In contrast, if the leader faces scarcity, its best response is to employ the new high-cost capacity at high prices to steal market shares from rivals. Rivals will respond aggressively to defend their market shares by producing greater quantities for slightly lower prices. As this outbidding unravels at all price levels, each firm's best response is to expand its supply schedule. Hence, despite more concentration around the leader, the equilibrium price decreases because technology diversification provides the firm with business stealing incentives.

We provide empirical evidence of this mechanism in wholesale energy markets. Instead of exploiting mergers, which might have unobserved effects on generators' costs beyond moving capacity across ownership structures (e.g., David, 2021, Demirer and Karaduman,

[3]When marginal costs are increasing, agents in standard conduct models like Cournot and Bertrand would like to change their pricing strategies once uncertainty resolves, as they are forced to submit either vertical or horizontal schedules. Unlike them, supply function equilibria are ex-post optimal and subsume Cournot and Bertrand as extreme cases by allowing any non-negative slope at different market price.

[4]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).

2022), we focus on six years that have no mergers or entry and exit of generators and exploit time-variation in water inflows across dams to proxy for periods of abundance and scarcity. Consistent with our model, dams decrease their supplies ahead of a coming drought, and if they belong to a diversified firm, their thermal production compensates for the drop in hydro supply, mitigating the higher prices induced by scarcity.

To clarify the relationship between market power and diversified production, we structurally estimate and simulate an extended version of the supply function equilibrium game presented above. The structural model follows the main feature from the empirical analysis: thermal capacity is always available, while hydropower production today affects water availability tomorrow and, thus, future profits. We find that thermal generators internalize the dry spells occurring at a "sibling" dam only indirectly through the market clearing mechanism if they can influence prices – i.e., market power. If that is not the case, then the firm's supply is inframarginal and no spillovers across sibling generators are possible as none of its generators can affect prices and, thus, each other's production levels. A small increase in the firm's market power, all else equal, decreases market prices due to the mitigating effect of the increased sibling thermal supply. However, if market power increases further, making the firm's residual demand vertical, then the firm can drive prices up by reducing its entire supply. The data confirms this intuition, suggesting a U-shape pattern between market prices and the slope of generators' residual demands only during scarcity periods, as hydropower's cost advantage prevents using thermal during abundant periods. The business stealing effect drives this pattern.

To causally identify this U-shape in the data, we estimate the model and simulate prices in different scenarios where we exogenously endow the market-leading firm with increasing fractions of its competitors' thermal capacities. The model primitives – the marginal cost of thermal and hydropower generators and the value function – are identified from the first-order conditions.[5] We estimate the model on hourly markets between 2010 and 2015 and show that the model fits the data well. Our results indicate that average market prices decrease for small capacity reallocations. Expanding the reallocated capacity increases the leader's market power by raising the business stealing ratio, the mitigatory price effect diminishes until market prices increase again. The benefits of diversification are stronger when the leader faces dry spells as it cannot cover all its residual demand with its low-cost technology. In contrast, during wet spells, the reallocation decreases the ability of its rivals to compete, reducing the benefits of diversification.

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,

[5] Instead of following the production function literature, we build on the multi-unit auctions (e.g., Wolak, 2007, Reguant, 2014) and dynamic auctions literature (e.g., Jofre-Bonet and Pesendorfer, 2003), and focus on externalities across bidders (e.g., Fioretti, 2022), which are hidden in production functions.

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 is possible 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.[6]

We provide a unifying account featuring results from both streams of literature that allows us to discuss when diversification 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 (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).

Unlike other mechanisms to maintain energy prices low, no work for policymakers is required "to force" generators to compensate supply during scarcities. Beyond the standard tools available to policymakers (Abrell *et al.*, 2019, Ambec and Crampes, 2019, Schmalensee, 2019), our findings point to antitrust policies as a new lever to make the green transition affordable. For instance, no firm in Colombia can have more than 25% of the total installed capacity; this threshold aims to limit abuses of market power, but it also curbs the beneficial effects of diversified production. Although it is beyond the scope of this paper to determine the optimal threshold, we argue that it should vary based on a firm's technologies.[7] Potentially, optimal thresholds could also incentivize capacity buildups (e.g., De Frutos and Fabra, 2011, Elliott, 2022), a key policy for low energy prices along with improving transmissions and integration of generators in the network (e.g., Ryan, 2021, Gonzales *et al.*, 2023). In contrast, we find that forward contracts do not fully internalize capacity variations at sibling generators (Ausubel and Cramton, 2010), making ownership links preferable when market power is under control.

Our paper relates also to a growing literature studying market power. Probably because of data availability, 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,

[6]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.

[7]Relatedly, Nocke and Whinston (2022) propose that antitrust authorities diagnose the anti-competitivity of a merger through HHI thresholds that vary based on the merger-induced synergies.

Staiger and Wolak, 1992, Froeb *et al.*, 2003). In these models, concentration is a vicious force leading to higher prices, promoting empirical studies on concentration and markups (De Loecker *et al.*, 2020, Benkard *et al.*, 2021, Grieco *et al.*, 2023), which highlight the adverse effects of concentration on productivity (Gutiérrez and Philippon, 2017, Berger *et al.*, 2022) and the labor share (Autor *et al.*, 2020). Allowing for diversified production, our paper contributes to this literature by introducing a business stealing effect, pushing for more aggressive pricing depending on a firm's capacities.[8] Linking multiproduct firms with diversified production might be a promising avenue for future research.

In conclusion, interpreting our results as incentives for greater market power and less antitrust scrutiny would be flawed (e.g., Lancieri *et al.*, 2022, Babina *et al.*, 2023). Rather, the main contribution of this paper is to qualify what the optimal firm's size is in connection to market power and diversified technologies: we argue that disregarding a firm's technology portfolio can affect our ability to adequately judge the welfare implications of central economic phenomena and antitrust policies, such as entry, mergers, and divestitures/spin-offs.

The paper is structured as follows. Section 2 illustrates the simple theoretical framework that is the backbone of our empirical analysis. Section 3 introduces the Colombian wholesale market and describes the data. Section 4 provides empirical evidence of the impact of diversified production on market prices exploiting exogenous scarcity events. Sections 5 and 6 build and estimate a multi-unit auction model in this market and perform counterfactual experiments, respectively. Section 7 discusses our contributions for the green transition and antitrust policies and concludes.

2 Conceptual Framework

When firms have different technologies and capacities, a firm's market power depends on either its greater production efficiency or its larger capacity. When a firm dominates in capacities, it acts as a monopolist on the market unsatisfied by its competitors. In contrast, when a firm dominates in efficiency, it steals production from other firms by preventing the entry of its competitors. This section demonstrates that these two source of market power have opposing influences on market outcomes when firms are diversified.

Stylized framework. Consider a stylized oligopolistic market with N firms selling a homogeneous good, such as electricity. Three technologies are available: a low-, a high-, and a fringe-cost technology, with marginal costs c^l, c^h, and c^f, respectively, with

[8] This "synergy" is not to be confounded with more standard cost synergies where the marginal cost of the merged entity is equal to the minim marginal cost of the merging firms. Similar synergies are common in sectors such as energy (Verde, 2008, Demirer and Karaduman, 2022), meat packaging (Paul, 2001), broadcasting (Jeziorski, 2014), and alcoholic beverages (Miller *et al.*, 2021). The literature identifies in buyer concentration another source for lower consumer prices (Morlacco, 2019, Alviarez *et al.*, 2023).

$c^l < c^h < c^f$. Firm i's technology portfolio K_i is a vector detailing its capacity of low-, high- and fringe-cost technologies, namely, $K_i = (K_i^l, K_i^h, K_i^f)$.

The initial market has no diversified firm. There are 2 strategic firms and $N-2$ fringe firms.[9] 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-leading firm. 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 behave as price-takers. We first characterize the equilibrium with no diversified firm and then introduce diversification through a transfer of $\delta > 0$ high-cost units from Firm 2 to Firm 1, changing their portfolios to $\tilde{K}_1 = (K_1^l, \delta, 0)$ and $\tilde{K}_2 = (0, K_2^h - \delta, 0)$, respectively.

We postpone the full solution to Appendix A, and focus here on the more general take-aways. Figure 1 simulates market outcomes given the primitives presented in its top panel focusing on two scenarios. In the abundance scenario, left panel, Firm 1 has extensive low-cost capacity ($K_1^l = 9$). Under scarcity, right panel, Firm 2 has less low-cost capacity ($K_2^l = 5$). The other primitives are constant across scenarios: we normalize $c^l = 0$ without loss of generality, and set $c^h = 1$, $c^f = 2$, and $K_2^h = 4$. Each scenario illustrates the marginal cost curves of Firm 1 (red) and Firm 2 (blue) before and after the capacity reallocation. After the reallocation, a portion of Firm 1's cost curve is dotted, corresponding to the δ high-cost units reallocated from Firm 2 (shaded blue dotted line).

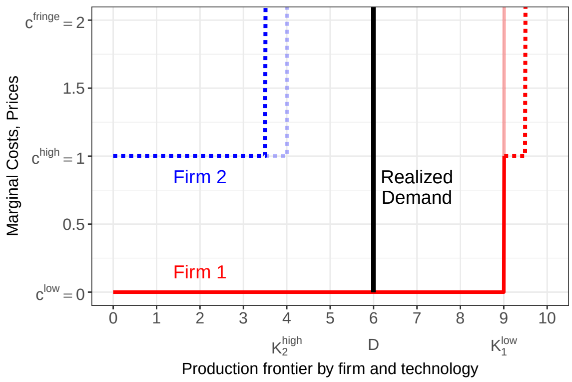
As standard in energy markets, the actual market demand is an unknown random variable, $D(\epsilon)$. Before demand is realized, firms commit to supply schedules detailing the quantity to be supplied as a function of the market price, $S_i(p)$. We examine the supply function equilibrium (SFE) of this game following Klemperer and Meyer (1989). Submitting a horizontal schedule – a price for all possible quantities – is consistent with Bertrand competition. A vertical schedule – a quantity for all prices – implies Cournot competition. By also allowing non-zero slopes, not only SFEs encompass standard competition models, but it also makes the equilibrium ex-post optimal: since agents must indicate their optimal production for each market price, they would never wish to change their strategy once the uncertainty regarding the market demand resolves, unlike in Cournot or Bertrand, which do not allow committing on multiple price-quantity pairs. This property of SFEs allows us to investigate the ex-post equilibrium with no assumption on the distribution of ϵ.

The middle panel of Figure 1 illustrates the equilibrium strategies from the point of view of Firm 1 *before* the capacity transfer. In each panel, Firm 1's supply, $S_1(p)$, is in

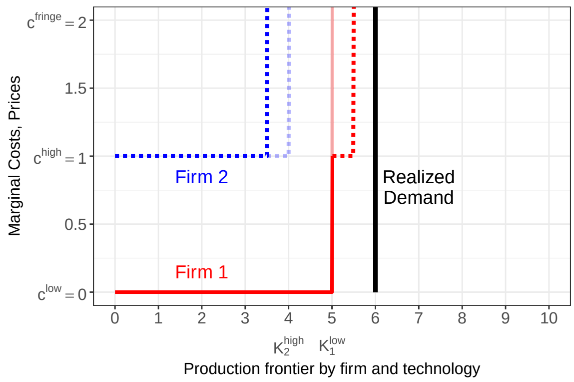
[9]We introduced fringe firms to ensure that the two strategic firms face decreasing residual demands. A price ceiling can replace this assumption as in Fabra and Llobet (2023), or we could assume that the market demand $D(p, \epsilon)$ decreases in p as in Klemperer and Meyer (1989).

Figure 1: Price-effect of diversified production under scarcity and abundance

Top panel: Marginal costs and realized market demand before and after the capacity transfer

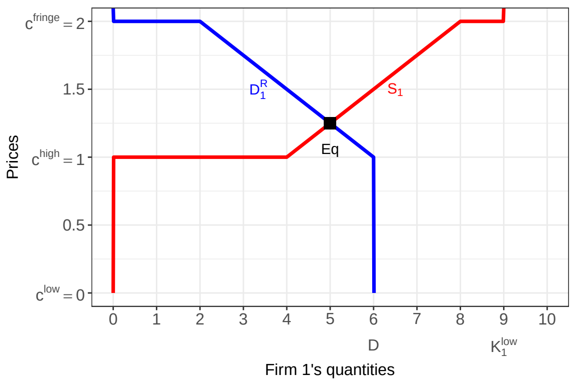


(a) Model primitives with abundance

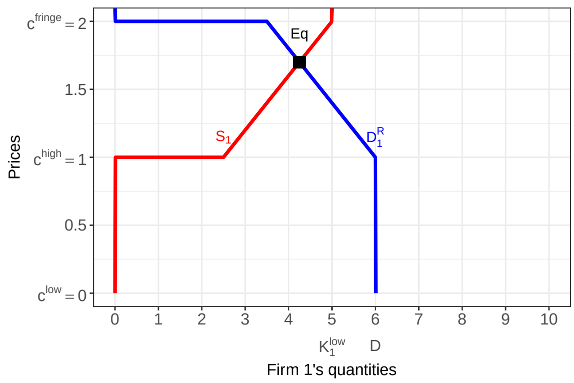


(b) Model primitives with scarcity

Middle panel: Realized equilibrium when Firm 1 is not diversified

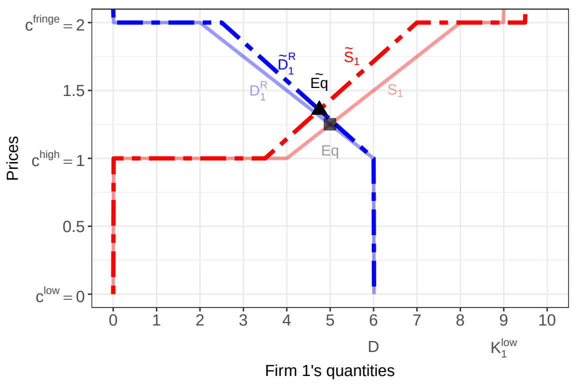


(c) Equilibrium with abundance

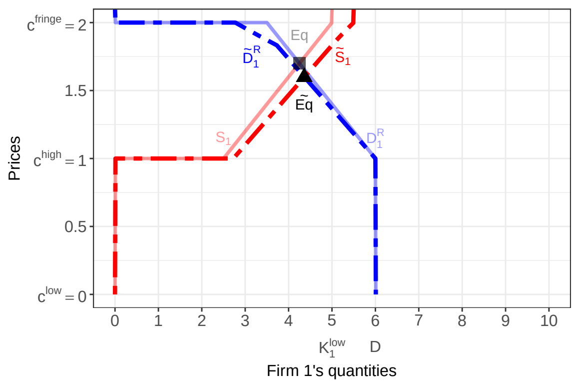


(d) Equilibrium with scarcity

Bottom panel: Realized equilibrium with Firm 1 diversified



(e) Eq. with abundance & diversified Firm 1



(f) Eq. with scarcity & diversified Firm 1

Notes: The top panel displays the cost curves of Firms 1 (blue) and 2 (red) before (shaded) and after (bold) the capacity transfer for either the case when Firm 1 faces abundance (left panels) or scarcity (right panels). The solid line displays the realized market demand, which is vertical. The middle panel shows the realized equilibrium when firms are not diversified. In the bottom panel, we transfer 0.5 units of capacity from Firm 2 to Firm 1, moving the market equilibrium from the square (Eq) to the triangle ($\tilde{Eq}$). Blue lines indicate firm 1's residual demands, $D_1^R(p) = D - \sum_{i \neq 1} S_i(p)$, while red lines indicate Firm 1's equilibrium supplies, $S_1(p)$. The superscripts $\sim$ indicate equilibrium objects after the capacity transfer in Panels (e) and (f), respectively. These simulations use the best response functions derived in Appendix A. The primitives are: the market demand is 6; marginal costs are 0, 1, and 2 for *low*-, *high*-, and *fringe*- technologies, respectively; Firm 2's *high*-cost capacity is 4. Finally, we vary Firm 1's *high*−cost capacities between 9 and 5 in Panels (c) and (d).

red and its residual demand, $D_1^R(p) = D - \sum_{j \neq 2} S_j(p)$, is in blue. In Panel (c), S_1 is initially flat at c^h: being more efficient than its competitors, Firm 1 extracts monopoly rents for demand realizations smaller than 4, covering the whole market by pricing at Firm 2's marginal cost. Firm 1 exhausts its capacity when it produces K_1^l units, after which $S_1(p)$ becomes vertical. Its residual demand, instead, is exactly the whole realized market demand for $p < c^h$ – i.e., 6 units – as none of its competitors is willing to produce below its marginal cost. As $\sum_{j \neq 1} S_j(p) > 0$ and increasing for $p \geq c^h$, D_1^R is downward sloping. Importantly, Firms 1 and 2 gain from producing their capacities before the price reaches $c^f = 2$, at which price all the non-strategic firms enters and the market clears. Therefore, in equilibrium, at least one of the two firms will exhaust its capacity in the limit $p \to c^f$. The firm that does not exhaust its capacity at this price has an advantage for high-demand realizations as it can sell more units at $p = c^f$. In Panel (c), Firm 2 exhausts its capacity first due to the large size of Firm 1's low-cost capacity. To see this, notice that $p \to c^f$ as $D_1^R \to 2$, at which value Firm 2 has already produced its entire capacity ($D - 2 = 4 = K_2^l$). In contrast, Firm 1 did not supply all its capacity as $p \to c^f$, and has one extra capacity for $p = c^f$, as indicated by S_1's horizontal segment for $p = 2$.

Panel (d) presents the opposite case, where Firm 1 exhausts its capacity as $p \to c^f$ instead of Firm 2 as in Panel (c). In this scenario, Firm 1's market power comes from its greater efficiency rather than its larger capacity: the firm uses 50% of its capacity to prevent Firm 2 from accessing the market by pricing $p = c^h$ for demand realizations smaller than 2.5 units. In contrast, Firm 1 uses only 4 out of its 9 units for foreclosure under abundance in Panel (c). Hence, foreclosure monopoly gains constrain the firm for high demand realizations. As Firm 1's supply is more inelastic in Panel (d), Firm 2 can drive prices up by committing to a more inelastic supply. As a result, Firm 2 only produces about 60% of its capacity in the limit as $p \to c^f$, leaving it with some idle capacity for high demand realizations.

Considerations about idle capacities matter when we diversify Firm 1 by reallocating δ units of K^h from Firm 2 to Firm 1, as shown in the bottom panel of Figure 1, which superimposes the new equilibrium strategies over those in the middle panel (shaded lines).

In Panel (e), Firm 2 will still exhaust its capacity before Firm 1 as $p \to c^f$ for any $\delta > 0$, leading Firm 2 to reduce its supply, $\tilde{S}_2$, at every price. Facing a more vertical residual demand, Firm 1 optimally decrease production. The new equilibrium has a higher price than in Panel (c). In this case, the standard textbook *marginal revenue effect* pushes the firms to produce less in more concentrated markets, driven by capacity differentials. In this case, there is no benefit from differentiation because the δ units were sold at prices below c^f by Firm 2 in Panel (c) but only at $p = c^f$ by Firm 1 in Panel (e) due to the merit order.[10]

[10] In the symmetric case where both Firm 1 and Firm 2 have identical technology profiles $K_1 = K_2 = (K^h, K^l, 0)$, with K^h and $K^l > 0$, a transfer of δ high-cost units from a firm to the other will lead to

Under scarcity, instead, Firm 1's supply was constrained at $p = c^f$ in the initial equilibrium in Panel (d). Importantly, notice that if Firm 1 were not constrained, it would have foreclosed Firm 2 for more units as it does under abundance. The transfer slacks Firm 1's marginal cost curve, allowing Firm 1 to expand $\tilde{S}_1$. Since the new high-cost capacity is profitable at prices greater than c^h ($\frac{p-c^h}{p}\big|_{p\to c^f} > 0$), Firm 1 has now the opportunity to take advantage of its more efficient technology by producing more at any price. For δ small, Firm 2 still has unused supply at $p = c^f$: Firm 2 best responds to Firm 1 by expanding its supply at any $p \in [c^h, c^f]$. Therefore, each firm engages in *business stealing*, and the market price drops, as shown in Panel (f). Effectively, the capacity transfer removes capacity that was originally sold at $p = c^f$ in Panel (d) by Firm 2 and put it in the market for prices below c^f. As the "employed" capacity increases for $p \leq c^f$, prices drop in Panel (f) compared to Panel (d). That is, having access to a new technology raises the value of the low-cost one.

In contrast, if the δ reallocation were large, prices might increase even under scarcity. To see this, imagine reallocating all the capacity of Firm 2 to Firm 1: Firm 1 becomes a de-facto monopolist for $p < c^f$, and will sell all its capacity at this price. In summary, for small δ reallocations, p decreases because Firm 1 employs generation capacity that was idle under Firm 2, but it increases for large δ, due to Firm 1's capacity dominance. This observation suggests a U-shape relationship between industry concentration and market prices, which we will later verify in the Colombian wholesale energy markets. Hence, going from abundance to scarcity, prices might go up as depicted by the difference in the market outcomes (triangles) in Panels (e) and (f); however, if the leader is adequately diversified, the price increase is mitigated, as suggested by the difference between the market outcomes before and after the reallocation in Panel (f).

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

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

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 "*business stealing*." This ratio is non-negative: if it is greater than one, i "steals" market shares from its rivals and "loses" to them when it is smaller than one, as p changes marginally. When

higher prices as in Garcia *et al.* (2001). In equilibrium, both firms exhaust their K^l capacity at the same market price: the larger firm will then exert its (capacity-driven) market power to drive prices up.

the residual demand is vertical ($D_i^{R'}(p) \to \infty$), (1) collapses to the standard Cournot case. Otherwise, the equilibrium supply will balance 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 $D_i^{R'}(p)$.

To gain intuition, imagine either plot in Figure 1 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 $S_i(p + h) - S_i(p) < D_i^R(p) - D_i^R(p + h)$.[11] In standard oligopoly games, firms only internalize that increasing production decreases prices through the price elasticity, (s_i/η),[12] but do not internalize the strategic response of their competitors through the slope of their supplies ($D_i^{R'}(p) = D'(p) - S'_{-i}(p)$). As a result, firms' equilibrium schedules in (1) are strategic complements.

In the remainder of the paper, we use the insights developed in this section to study the ownership of renewable technologies in the Colombian wholesale energy market.

3 The Colombian Wholesale Energy Market

This section outlines the energy market in Colombia and the available technologies.

3.1 Generation

Colombia produces about 170 GWh of energy daily.[13] Although the market counts about 190 generators owned by 50 firms between 2011 and 2015, it is quite concentrated around a few large diversified firms: the six firms with access to hydropower generation own more than half of all the generators and about 75% of all generation capacities. Most of the other firms own only one generator and have small available production capacities.

These large firms are diversified across *dams* and other types of generation, including *thermal* sources such as fossil fuel-based generators, such as coal and gas. Other available generation sources include renewables such as wind farms and run-of-river, which produces energy through turbines installed on a river with no ability to store water, unlike dams. Panel (a) of Figure 2, which reports hourly production capacities in MW for each

[11] Drawing a parallel with discrete choice models of entry games (e.g., Mankiw and Whinston, 1986, Berry *et al.*, 2016), at each price, firm i decides whether to "enter the market" by increasing its supply, $S_i'(p) > 0$, or "staying out" by keeping it constant, $S_i'(p) = 0$. In those games, i's market share decreases if consumers perceive new entrants as similar to incumbents, which resembles a downward sloping market demand, $D'(p) < 0$, or more aggressive competitors' pricing, $S'_{-i}(p) > 0$, which yield $D_i^{R'}(p) < 0$ in (1).

[12] 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 (1) 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 the homogeneous-good Bertrand models (Appendix A.2).

[13] For comparison across neighboring countries, energy production in 2022 was 227 GWh in Venezuela, 1,863 GWh in Brazil, 165 GWh in Peru, 91 GWh in Ecuador, and 33 in Panama. Outside this area, it was 11,870 GWh in US, 1,287 GWh in France, and 2,646 GWh in Japan.

technology between 2008 and 2016, shows that hydropower (blue) and thermal capacity (black) accounted for 60% and 30% of the industry capacity. Run-of-river (green) is the third production technology by size (less than 6%). Energy is also generated as a by-product of production processes like sugar and sold on the wholesale market and through solar and wind farms but these were minor sources before 2016.

The dominance of hydropower is even more striking in production, averaging about 75% of the total dispatched units. The remaining energy needs are compensated by thermal generation (about 20% of total production) and run-of-river (5%). Yet, there is variation over time: Panel (b) of the same figure contrasts production across technologies (left axis) with dry seasons, which we proxy by periods of high temperature or low rainfall at a dam (gray bars). Hydropower production decreases before and during a dry spell. In these periods, thermal production compensates for water scarcity.[14] Firms purchase and store fossil fuels like coal and gas in advance of expected dry spells (Joskow, 2011) and their price is closely linked to global commodity markets. In contrast, energy from run-of-rivers lacks storage, limiting its ability to compensate for the lack of hydropower.

Thermal generation has, on average, higher marginal costs than hydropower generation. Figure 3 reveals that wholesale energy prices more than double in scarcity periods.[15] Prices increased even more during the sustained dry spell caused by el Niño in 2016 and during the annual dry seasons (December to March).

3.2 Institutional Background

The 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.

Bidding in 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.[16] Quantity bids state the maximum amount (MWh) a generator is willing to produce in a given hour. A price bid indicates the minimum price

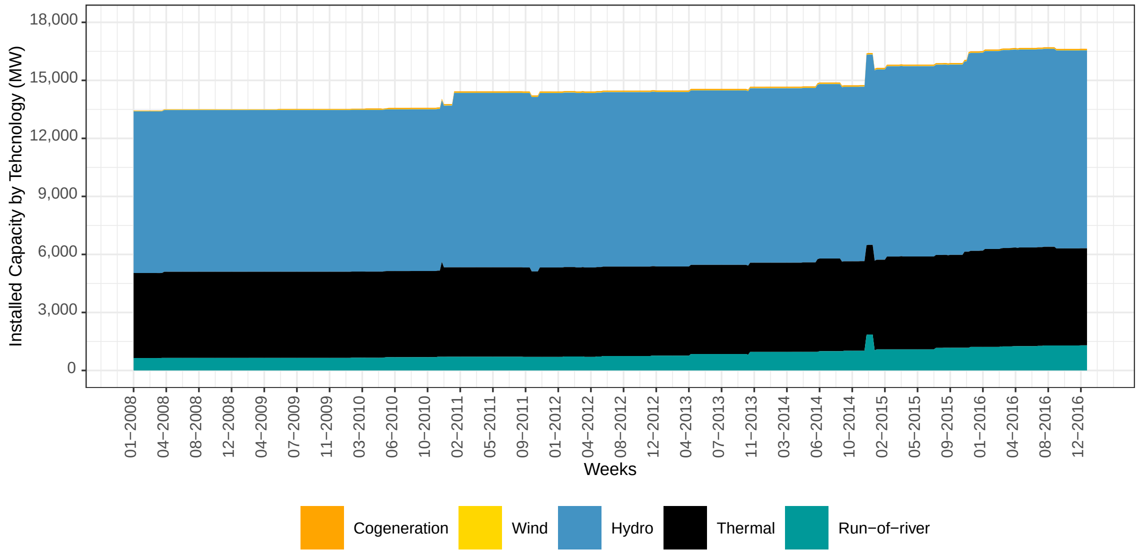
[14]This substitution pattern is visible in the data: the Spearman correlation between thermal production and a time-series recording the minimum rainfall at Colombian dams is -0.32 (p-value $\leq$ 0.01), while it is 0.27 (p-value $\leq$ 0.01) for hydropower generation.

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

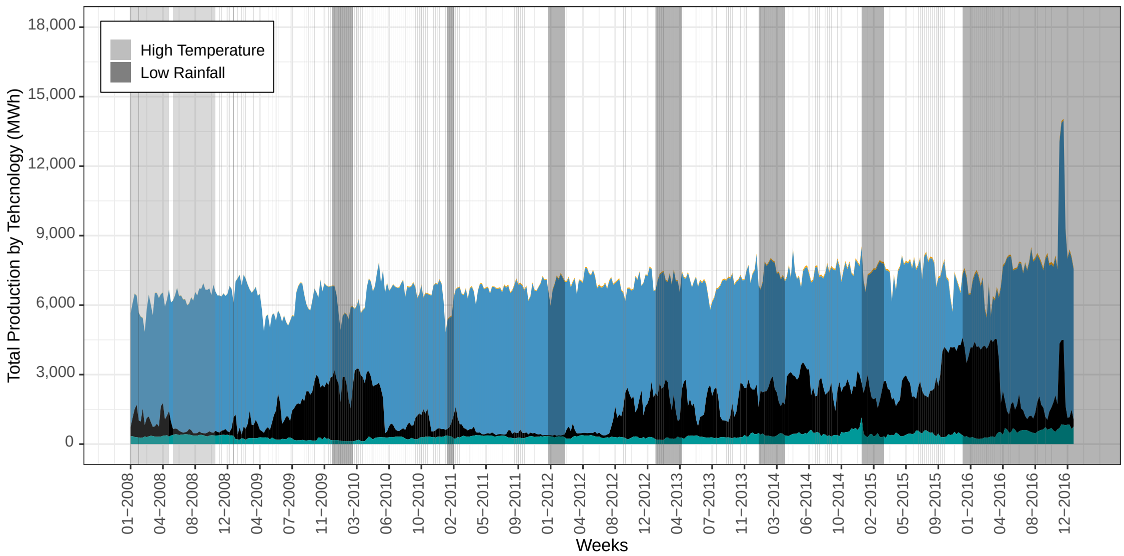
[16]Participation in the spot market is mandatory for large generators with capacity over 20MW.

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

(a) Total installed capacity by technology



(b) Total weekly production by technology

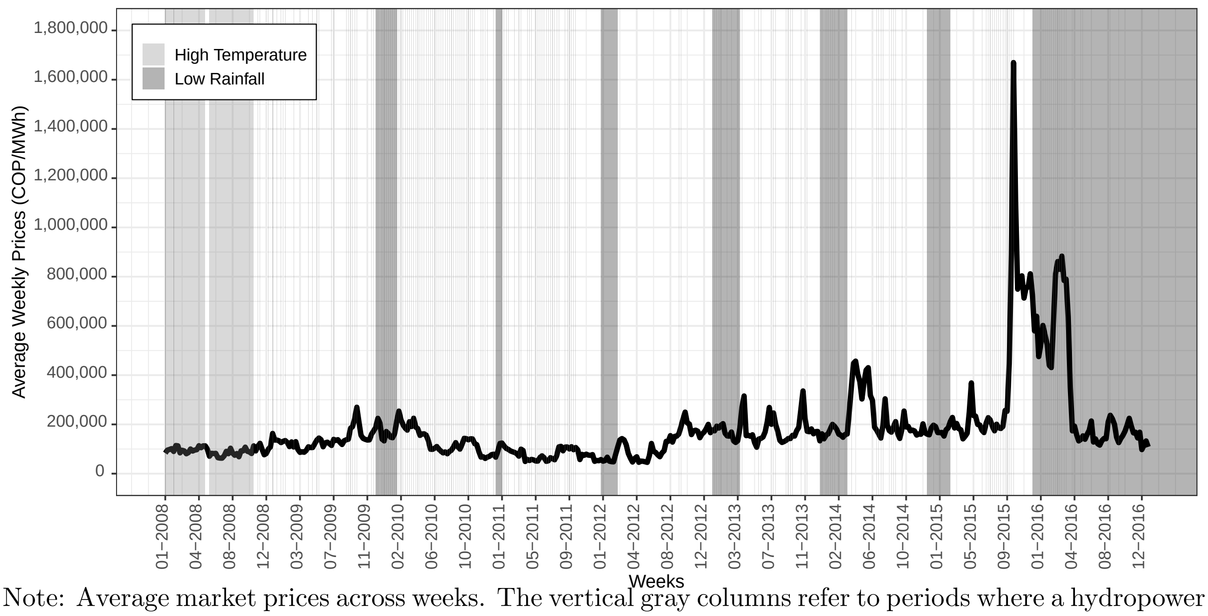


Note: Total installed capacity and production volumes by technology. The vertical gray columns in Panel (b) refer to periods where a hydropower generator experiences a temperature (rainfall) that is at least one standard deviation above (below) its long-run average.

(COP/MW) a generator is willing to accept to produce at each market hour. Each generator bids its own supply schedule, potentially taking into account the payoffs accruing to the other (*sibling*) generators owned by the same firm.

Spot market-clearing. Before bidding occurs in the day-ahead market, the agency responsible for the market (XM, the system operator) provides all generators with the estimated market demand for each hour of the following day. After the bidding, XM collects all bid schedules from the day-ahead market and ranks them from the least to

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$.

the most expensive to find the lowest price that satisfies demand in each hour. XM then informs all generators about the auction outcomes, or *despacho economico*. During the production day, the actual generation can differ from the depacho economico for several reasons, such as production constraints or transmission failures. The operator modifies the despacho economico to accommodate these issues during the production day. The spot hourly price is set at the value of the price bid of the marginal generator. All dispatched units are paid the same price.[17]

Forward market. The forward markets consist of bilateral contracts among pairs of agents. This market allows agents to decide the financial position of each of their power-generating units weeks in advance of the actual market. The purpose of these contracts is to hedge the uncertainty in the spot market prices. In our data, we observe a generator's overall contract position for each hourly market.

3.3 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

[17]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).

daily measures of rainfall and temperature from 303 measurement stations.[18]

To construct the rainfall forecasts, we use monthly summaries of the status of el Niño, la Niña, and the Southern Oscillation, or ENSO, based on the NINO3.4 index, provided by the *International Research Institute* (IRI) of Columbia University.[19] ENSO forecasts are published on the 19th of each month; each issue provides ENSO's probability forecast for the following nine months. These forecasts are a key data source used by dams to forecast inflows. We have monthly information from 2004 to 2017.

We integrate this dataset with daily prices of oil, gas, coal, liquid fuels, and ethanol. These commodities take part in energy production through either thermal (fossil fuel) or cogeneration (sugar manufacturing) generators.

4 Diversified Production: Empirical Evidence

How do Colombian energy firms employ their production technologies? Dams have low marginal cost compared to other technologies and we expect diversified firms to use only their *low*-cost technology in abundant periods. On the contrary, dry spells should steep up a firm's marginal cost curve, resulting in diversified production. Sections 4.1 and 4.2 test these hypotheses using variations in inflow forecasts. Section 4.3 addresses whether, consistent with the predictions in Figure 1, a greater thermal capacity for a firm experiencing a drought does, in fact, lead to lower price hikes through temporal variation in the size of the thermal capacity available to the firm expecting a dry spell.

4.1 Empirical Strategy

We build inflow forecasts for each hydropower generator using a flexible autoregressive distributed-lag or ARDL model (Pesaran and Shin, 1995). Loosely speaking, the inflow forecasts are obtained through OLS regressions of a generator's weekly average water inflow (including evaporation) on the water inflows in past weeks and past temperatures, rainfalls, and el Niño probability forecasts. We use a two-year moving window to produce 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.

[18]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 of the distance between that generator and the measurement stations. We account for the orography of the country (e.g., mountains) when computing the distance between generators and weather measurement stations, using information from the *Agustin Codazzi Geographic Institute* (IGAC).

[19]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.

We examine a generators' responses to future water inflows through,

$$y_{ij,th} = \sum_{l=1}^{L} \left(\beta_l^{low} \text{adverse}_{ij,t+l} + \beta_l^{high} \text{favorable}_{ij,t+l} \right) \\ + \mathbf{x}_{ij,t-1}\alpha + \mu_{j,m(t)} + \tau_t + \tau_h + \epsilon_{ij,th}, \tag{2}$$

which studies how generator j of firm i updates its current supply schedule $y_{ij,th}$ based on whether it expects favorable, favorable$_{ij,t+l}$, or adverse forecasts, adverse$_{ij,t+l}$, l months ahead compared to its average forecast. We collapse bids over weeks to reduce the extent of autocorrelation. For this reason, we exclude periods when a generator's quantity bid is below the 5^{th} percentile of the distribution of quantity bids placed by the generators of the same technology to avoid contamination from unobserved maintenance periods within a week. This truncation does not affect the results qualitatively.

We vary the variables $\{\text{adverse}_{ij,t+l}\}_l$ and $\{\text{favorable}_{ij,t+l}\}_l$ across analyses. If the focus is on hydropower, these variables are indicators that take the value one if dam j of firm i expects its l-month ahead forecast is either a standard deviation greater or lower than its long-run average (for the period 2008-2016) and zero otherwise, respectively. When instead we shift the analysis to *sibling* thermal generators – i.e., thermal generators owned by a firm that also has dams – we base these indicators on the sum of the l-month ahead inflow forecasts accruing to the dams owned by i.

We control for changes in market conditions in $\mathbf{x}_{ij,t-1,h}$ using weekly average market demand, water stocks, and forward contract position (in logs) for week $t-1$ and hour h. We capture all seasonal unobservables that could affect generators differently using fixed effects at the generator-by-month and firm-by-year levels ($\mu_{j,m(t)}$) and all macro unobservables (e.g., greater demand) using fixed effect at the week-by-year (τ_t), and hour levels (τ_h). The standard errors are clustered by generator, month, and year.[20]

Exclusion restriction. The identification of the parameters of interest in (2) relies on the exclusion restriction 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

[20] Alternatively, we could cluster the standard errors spatially. However, according to the hydrology literature (Lloyd, 1963), a river bed is a "fixed point" for all neighboring water flows (in surface and underground), making shocks at neighboring dams independent of each other. Furthermore, it is unclear what distance one should use for thermal generators. Therefore, we do not pursue this avenue.

forecast errors, that is, the observed inflow minus the forecasted inflow, are insignificant.

4.2 Results

4.2.1 Hydropower Generators

Figure 4 plots the main coefficient of interest from (2), $\{\beta_l^{low}, \beta_l^{high}\}$. The dependent variable is the log of hydropower generator j's price bid in Panel (a) and its quantity bids in Panel (b). We interpret the magnitude of the coefficient estimates as percentage changes when a hydropower generator faces an adverse forecast (red circles) or a favorable forecast (blue triangles) one, three, or five months ahead.[21]

As we would expect, dams steep up their supply schedules, $S_{ijth}(p)$, ahead of adverse events as current generations can engender future generations and thus require higher compensations (e.g., Balat *et al.*, 2015). In contrast, generators flatten their schedules ahead of favorable forecasts. In particular, while generators seem not to update their price bids to extreme events, Panel (b) finds greater absolute magnitudes for changes related to adverse rather than favorable forecasts. Generation drops by 7.1% for one-month adverse forecasts and 1.3% for two-month adverse forecasts, while it increases by about 3.7% one month ahead of a favorable forecast.[22]

4.2.2 "Sibling" Thermal Generators

Figure 5 estimates (2) on sibling thermal generators – i.e., thermal generators owned by firms with dams. In this case, as thermal generators do not have water stocks, we control for a firm's lagged total water stock in $\mathbf{x}_{ij,t-1}$. The results indicate that thermal generators have opposite responses to forecast inflows compared to hydropower generators: they steep up their supply schedule before favorable events (blue triangles) and flatten them out before adverse ones (red circles). Thermal generators respond mostly through their price bids and do so earlier than the hydropower generators in Figure 4. A potential reason is that this analysis focuses on more severe events due to its focus on firm-level instead of generator-level forecasts: their impact could be already apparent months earlier due to smaller cumulative inflows, leading to earlier responses.[23]

4.2.3 Competitors' Inflow Forecasts

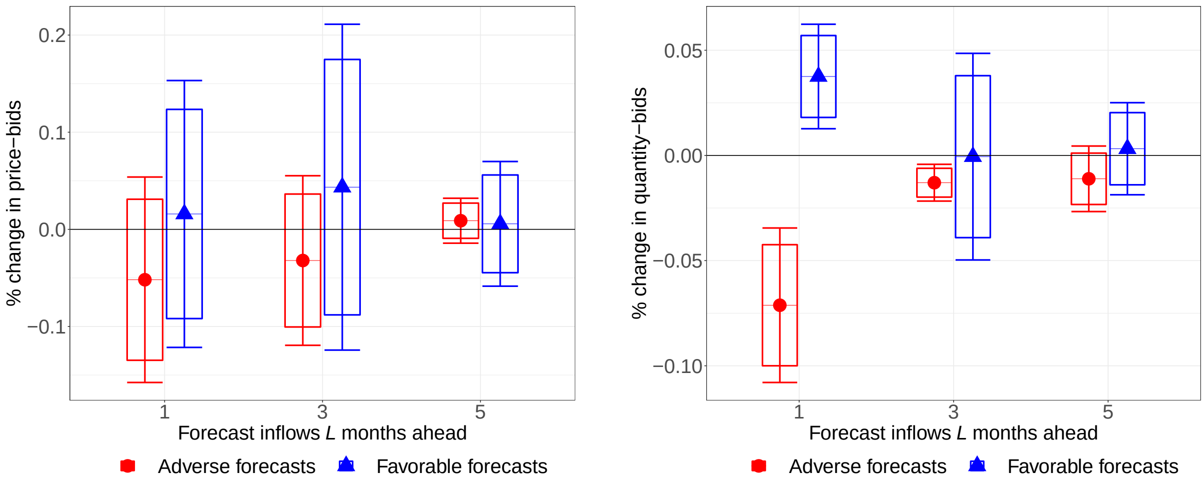
To have a complete picture of firms' behavior to future shocks, we also investigate whether hydropower generators internalize responses to competitors' forecasts. To this end, we let

[21] We pick this timing because the correlation across monthly inflow forecast is only 0.2 between forecasts that are two months apart and drops to 0 for forecasts further apart.

[22] The results are robust to different forecast horizons (Appendix Figure C4) and to running separate regressions (2) for each monthly forecast so to break any possible correlation across months (Figure C5).

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

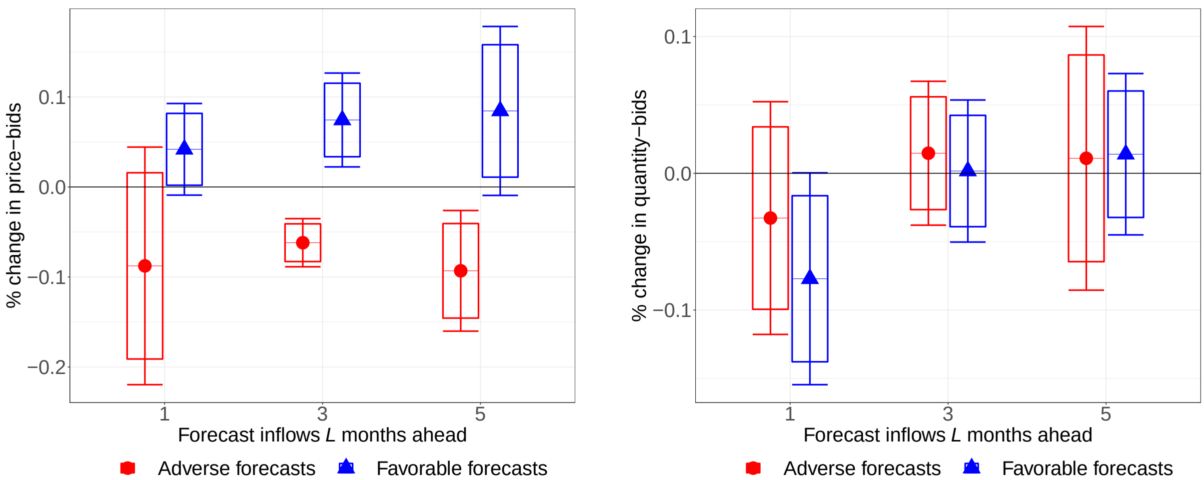
Figure 4: Hydropower generators' responses to inflow forecasts



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

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts according to (2). 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 5: Thermal generators responses to sibling hydro generators' inflow forecasts



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

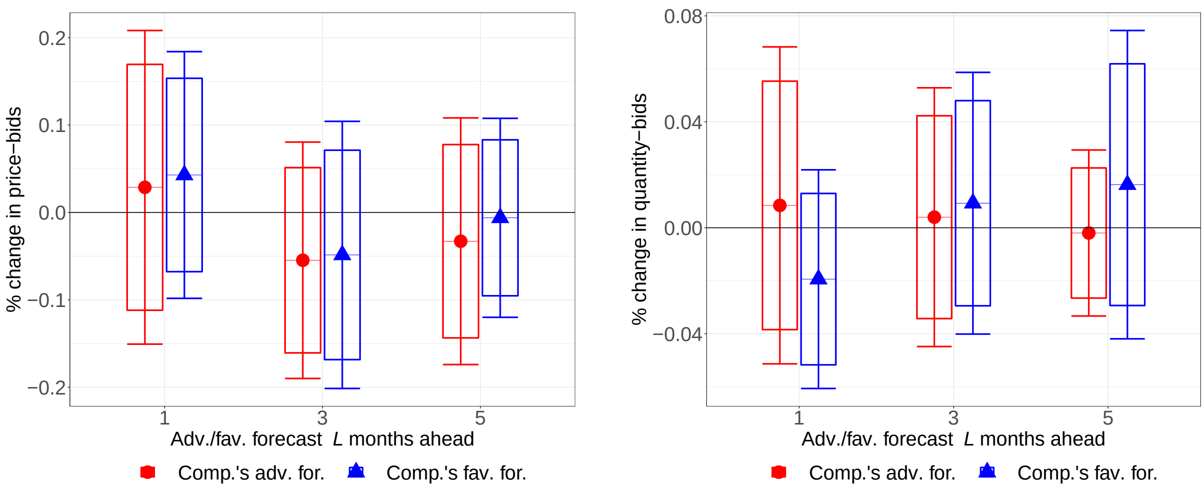
Notes: The figure studies how sibling thermal generators respond to favorable or adverse future water forecasts according to (2). Each plot reports estimates of $\{\beta_l^{low}\}$ in red and $\{\beta_l^{high}\}$ in blue for one, three, and five months ahead. Error bars (boxes) report the 95% (90%) CI.

adverse and favorable inflows in (2) be based on the sum of inflows at a firm's competitors while allowing for different slopes for each generator's water stock to adequately control in $\mathbf{x}_{ij,t-1}$ for the current water availability at different dams. Figure 6 indicates no movement of a firm's bid with respect to its competitors' forecasts: magnitude changes are small, generally within $\pm 1\%$ and not significant. We test for the joint significance of adverse and favorable forecasts and do not reject the null that they are zero at standard levels.[24]

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

Appendix C.1.3 expands this analysis in two directions. First, it shows that generators respond to their own inflow forecasts but not to the inflow forecasts of competitors. Second, although firms might find competitors' water stocks more informative than inflows, it provides suggestive evidence against this hypothesis. Therefore, generators do not seem to respond substantially to key potential state variables of their competitors. While this might seem at odds with competition, it is not unheard of in industrial organizations. For example, Hortaçsu *et al.* (2021) demonstrate that airline carriers use simple heuristics when it comes to pricing and do not take into account the pricing of other airline companies. Airline firms face similar problems to hydropower generators because they need to forecast seat (inflows) demand at multiple routes (dams). In both settings, focusing only on their own state variable while disregarding the state space faced by competitors, might simplify an otherwise hard-to-solve problem.

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 (2). 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.

4.3 Implications for Market Prices

Firms employ *high*-cost thermal technology in abundant (high water inflows) and scarce (low inflow) periods differently. We exploit the exogenous occurrence of dry periods at different firms with varying availability of thermal capacities to test whether a greater unshocked capacity (i.e., thermal) helps reduce the price hike due to the dry spell.

We base our analysis on the following regression model,

$$\begin{aligned}\ln(p_{th}) = &\sum_{l=1}^{L} \gamma_l^{low} \sum_i \Big(\text{adverse}_{i,t+l}\, K_{it}^T\Big) + \gamma_l^{high} \sum_i \Big(\text{favorable}_{i,t+l}\, K_{it}^T\Big) \\ &+ \sum_{l=1}^{L} \beta_l^{low} \sum_i \text{adverse}_{i,t+l} + \beta_l^{high} \sum_i \text{favorable}_{i,t+l} \\ &+ \gamma^{cap} \sum_i K_{it}^T + \mathbf{x}_{t-1,h} + \delta_{th} + \epsilon_t,\end{aligned} \tag{3}$$

where the logarithm of the hourly average weekly price is on the left-hand side. On the right-hand side, the first line of (3) features the interaction between whether a firm expects adverse or favorable forecasts l-months ahead – i.e., a generator's forecast inflow is one standard deviation below or above its long-run average – 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 ($\gamma_l^{low} < 0$), but no effect for favorable inflows ($\gamma_l^{high} \simeq 0$) if thermal generators do not operate in similar periods (cf. Figure 6). The remaining two lines of (3) 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 hour level.

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 (or month-by-year fixed effects) and earlier forecasts (e.g., one month ahead). Columns (1) and (2) control for current market conditions using lag demand and forward contract position and for the availability of hydropower using the total water stock. Fixed effects are at the hour and at the year-by-season (dry or rainy) level. Columns (3) and (4) use 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 other variables, are standardized; we present standard errors clustered at the month and year levels.

The first column excludes favorable inflows. The estimates indicate that a one standard deviation increase in the number of adverse inflows expected three to five months ahead increases current prices by 5 to 10% approximately. However, a contemporaneous one-standard-deviation increase in the sibling thermal capacity available partially compensates for these higher prices. Column (2) includes favorable inflows in the analysis, which are not found to affect spot prices when associated with greater thermal capacities.

We find qualitatively similar results in Columns (3) and (4). The sole difference is that the largest effect is now three months rather than five months ahead, which is consistent given the different set of controls – controlling for lagged water stocks in Columns (1)

Table 1: The impact of technology substitution on spot prices

	(1)	(2)	(3)	(4)
	Hourly average price across weeks (ln)			
Adverse inflows (3 months)	0.286	0.166	0.197**	0.210**
	(0.257)	(0.284)	(0.069)	(0.058)
Adverse inflows (5 months)	0.422*	0.413**	−0.115	−0.127
	(0.205)	(0.126)	(0.086)	(0.094)
Thermal cap. available to adv. inflows (3 months)	−2.370	−1.300	−1.670*	−1.750**
	(2.340)	(2.540)	(0.651)	(0.540)
Thermal cap. available to adv. inflows (5 months)	−3.590*	−3.508***	0.775	0.875
	(1.500)	(0.492)	(0.663)	(0.721)
Favorbale. inflows (3 months)		0.032		0.021
		(0.203)		(0.037)
Favorable. inflows (5 months)		0.374		0.001
		(0.195)		(0.083)
Thermal cap. available to fav. inflows (3 months)		−0.038		−0.045
		(1.654)		(0.249)
Thermal cap. available to fav. inflows (5 months)		−2.940		0.064
		(1.720)		(0.741)
Total sibling thermal capacity (GW)	−0.012*	−0.012**	−0.006***	−0.007***
	(0.005)	(0.004)	(0.001)	(0.001)
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			✓	✓
Clustered s.e. by	Year & month	Year & month	Year & month	Year & month
Median dep. variable (in ln)	11.946	11.946	11.946	11.946
Median dep. variable (in \$COP/MWh)	154,148	154,148	154,148	154,148
N	7,464	7,464	7,464	7,464
R2 Adj.	0.631	0.639	0.933	0.934

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

Notes: This table shows the estimated coefficients from (3). 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. The first two columns include fixed effects by year-by-season, while the last two columns have fixed effects by year-by-month. Standard errors clustered by year and month.

and (2) reduces the coefficient of adverse forecasts three months ahead due to greater correlations between these two variables than between the former and five-months ahead forecasts. Finally, as we would expect, greater (thermal) capacity always decreases market prices across all specifications, as it reduces bottlenecks.[25]

These empirical results support the industry dynamics discussed in Figure 1: here, we exploit variation in water inflows to compare market outcomes when the firm facing scarcity has more or less thermal capacity. However, thermal capacity is endogenous to firms' unobservable characteristics, which we cannot control in a time series regression. To this end, the next sections expand the model in Section 2 and run counterfactual exercises to shed light on the nexus between diversified firms and market power.

[25]Appendix Table C3 confirms these results by showing that the positive impact of sibling thermal capacity materializes especially during the dry seasons (March to December).

5 A Model of the Colombian Energy Market

This section extends the framework in Section 2 to match the Colombian wholesale market described in Section 3, including the renewable intertemporal tradeoff from Section 4.

There are N firms: each firm i has access to $J_i \geq 1$ generators that are either hydropower ($\tau_{ij} = H$) or thermal ($\tau_{ij} = T$). The set of hydropower generators of firm i is $\mathcal{H}_i$. A firm is diversified if it owns both generators of type H and T. Each firm submits daily price bids, b_{ijt}, and hourly quantity bids, q_{ijht}, for each of its generators.

We focus on the day-ahead market in day t, where each generator j of firm i submits a price-bid, b_{ijt}, and hourly quantity bids, $\{q_{ijht}\}_{j=0}^{23}$. As in Section 2, the hourly demand, $D_{ht}(\epsilon_{ht})$, is uncertain at the time of bidding, and it is known only up to a noise parameter, ϵ_{ht}, with mean zero and full support (Klemperer and Meyer, 1989). 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 demand, D_{ht}, to determine the lowest price so that demand equals supply:

$$D_{ht} = \sum_{i=1}^{N} S_{iht}(p_{ht}), \quad \text{for all } h = \{0, ..., 23\} \text{ and } t. \tag{4}$$

As in Section 2, a firm's profits in the spot markets in hour h of day t are the sum of the payoffs accruing to its generators. In addition, Colombian firms also participate in the forward market, which accounts for the firm's position in the forward contracts, and the reliability payment mechanism, which is a policy that forces generators to produce $\bar{q}_{ijt}$ anytime the spot price is above a scarcity price, $\bar{p}_t$.[26] Current profits are thus:

$$\pi_{iht}(\epsilon_{ht}) = \underbrace{D_{iht}^R(p_{ht}, \epsilon_{ht}) \cdot p_{ht} - C_{iht}}_{\text{Spot market}} + \underbrace{(PC_{iht} - p_{ht}) \cdot QC_{iht}}_{\text{Forward market}} + \underbrace{\mathbb{1}_{[p_{ht} > \bar{p}_t]}(\bar{p}_t - p_{ht}) \cdot \bar{q}_{ijt}}_{\text{Reliability payment}}, \tag{5}$$

where spot market profits are the difference between total hourly revenues and costs, C_{iht}. The former depends on the equilibrium quantity that firm i produces, namely i's residual demand at the prevailing market price, $D_{iht}^R(p_{ht}, \epsilon_{ht}) = D_{ht}(\epsilon_{ht}) - \sum_{l \neq i}^{N} S_{lht}(p_{ht})$. Marginal costs vary across hydro and thermal technologies so that the actual cost shouldered by firm i depends on its technology-specific supply of hydro, $S_{iht}^H(p_{ht})$, and thermal, $S_{iht}^T(p_{ht})$, power so that $S_{iht}(p_{ht}) = S_{iht}^H(p_{ht}) + S_{iht}^T(p_{ht})$. Finally, the firms make an economic loss (profits) if they sell QC_{iht} MWh at prices PC_{iht} lower than p_{ht} through their forward position and if they are forced to sell $\bar{q}_{ijt}$ according to the reliability mechanism.

One key aspect arising from the previous section is that current hydropower production today can endanger future hydropower production (see Figure C1). Drawing from the hydrology literature (Lloyd, 1963, Garcia *et al.*, 2001), a generator's water stock de-

[26] The scarcity price is updated monthly and computed as a heat rate times a gas/fuel index plus other (non-fuel) variable costs (Cramton and Stoft, 2007). Scarcity prices do not vary across generators, while scarcity quantities, $\bar{q}_{ijt}$, do. The latter is determined through yearly auctions (Cramton *et al.*, 2013).

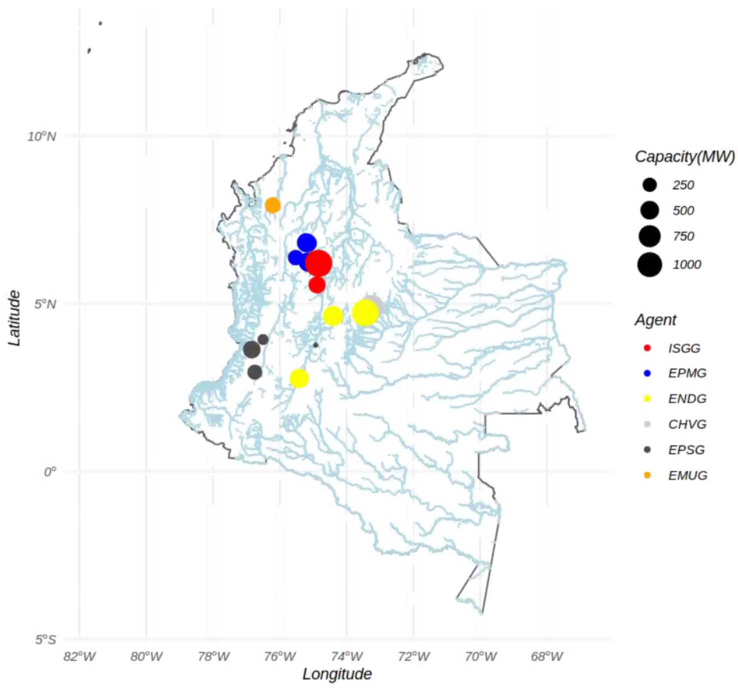
pends on the past water stock, the water inflow net of evaporation and other outflows, and the water used in production. At the firm level, the law of motion of a firm's overall water stock can be summarised through the following "water balance equation" as,

$$w_{it+1} = w_{it} - \underbrace{\sum_{h=0}^{23} S^H_{iht}(p_{ht})}_{\text{Water used in production}} + \underbrace{\sum_{j\in\mathcal{H}_i} \delta_{ijt}}_{\text{Water inflows}} , \tag{6}$$

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 GWh, $S^H_{iht}(p_{ht}) = \sum_{j\in\mathcal{H}_i} \mathbb{1}_{[b_{ijt}\leq p_{ht}]}\, q_{ijht}$ is the energy supplied by firm i's hydropower generators at the market price in each market hour, and δ_{ijt} is the daily water inflow of generator j.

Unlike the previous section which studied inflows at the level of dams, the law of motion in (6) is at the firm level for various reasons. First, our findings indicate that generators owned by the same firm respond to shock 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 7), 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, the rainfalls in a specific area accrue to just one firm, reducing the correlation across firms.

Figure 7: 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.

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

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

where the expectation is taken over the market demand uncertainty, ϵ_{ht}. Using a recursive formulation, a firm's objective function becomes

$$V(\mathbf{w}_t) = \mathbb{E}_\epsilon \left[\sum_{h=0}^{23} \pi_{iht} + \beta \int_{\mathbb{W}} V(\mathbf{u}) f\left(\mathbf{u} \middle| \boldsymbol{\Omega}_t\right) \, \mathrm{d}\mathbf{u} \right], \tag{7}$$

where the state variable is the vector of water stocks, $\mathbf{w}_t$ with domain $\mathbb{W} \equiv \{\mathcal{W}_i\}_i^N$, and $f(\cdot|\boldsymbol{\Omega}_t)$ describes its evolution according to the water balance equation, whose inputs in $\boldsymbol{\Omega}_t$ are the water stocks at time t and the realized hydropower productions and water inflows. Thus, when bidding, a strategic generator, whether hydro or thermal, considers its impact on future water stocks through the discount factor $\beta \in (0, 1)$.

Competitive fringe. As in Section 2, the supply schedule for fringe firms is zero for prices below their marginal cost and supply all their capacity only if they can break even.

5.1 Market Power and Market Prices with Diversified Firms

The large state space and large number of generators prevent us from solving for the supply function equilibrium analytically as we did in Section 2. Motivated by generators submitting hourly quantity bids but only daily price bids, which provides greater flexibility in selecting quantities than prices, we study the optimal quantity bids by taking first-order conditions (FOCs) of the objective function of firm i (7) with respect to the quantity supplied by generator j (whether thermal or hydro) in hour h at time t, q_{ijht}.

Notice that generators' supply schedules consist of a price and a quantity bid, which are not differentiable (e.g., Kastl, 2011). To take FOCs, we smooth these functions across the $\{\tau\}$ technologies owned by each firm (e.g., Wolak, 2007, Reguant, 2014). As a result, a firm submits a supply schedule for hydropower ($\tau = H$) and one for thermal ($\tau = T$) generators.[27] Omitting the expectation to ease the notation, the FOCs are:

[27] The smoothing procedure is outlined in Appendix E. To ease the notation, we do not index τ by j.

$$
\begin{aligned}
\frac{\partial V(\mathbf{w}_t)}{\partial q_{ijht}} = 0 \; : \; & \underbrace{\left(p_{ht}\frac{\partial D^R_{iht}}{\partial p_{ht}} + D^R_{iht}\right)\frac{\partial p_{ht}}{\partial q_{ijht}} - \frac{\partial p_{ht}}{\partial q_{ijht}}\left(QC_{ijht} + \mathbb{1}_{\{p_{ht}>\overline{p}\}}\overline{q}_{ijt}\right)}_{\text{Marginal revenue}} \\
& \underbrace{- \sum_{\tau\in\{H,T\}}\left(\frac{\partial S^\tau_{iht}}{\partial q_{ijht}} + \frac{\partial S^\tau_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\right)c^\tau_{it}}_{\text{Marginal cost}} \\
& + \underbrace{\left(\frac{\partial S^H_{iht}}{\partial q_{ijht}} + \frac{\partial S^H_{iht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\right)\int_{\mathbb{W}}\beta V(\mathbf{u})\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{iht}}\mathrm{d}\mathbf{u}}_{\text{Marginal value of holding water}} \\
& + \underbrace{\sum_{k\neq i}^{N}\frac{\partial S^H_{kht}}{\partial p_{ht}}\frac{\partial p_{ht}}{\partial q_{ijht}}\int_{\mathbb{W}}\beta V(\mathbf{u})\frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^H_{kht}}\mathrm{d}\mathbf{u}}_{\text{Marginal value from competitor } k\text{'s holding water}} \;=\; 0.
\end{aligned}
\tag{8}
$$

The derivative of firm i's current profits (5) in hour h, when q_{ijht} is submitted, is in the first two lines of (8). In the first line, the first term in parenthesis is the marginal revenue in the spot market, while the second term accounts for how the forward contract position and the reliability payment system affect bidding in the spot market. Market power affects marginal revenues by lowering $(p_{ht}\frac{\partial D^R_{iht}}{\partial p_{ht}} + D^R_{iht})\frac{\partial p_{ht}}{\partial q_{ijht}}$ below market prices, p_{ht}, when $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$. Otherwise, the firm is paid exactly p_{ht} on its marginal unit when it is price taker ($\frac{\partial p_{ht}}{\partial q_{ijht}} = 0$). This *marginal revenue effect* promotes the firm to reduce q_{ijht} for all its technologies when market power increases, as in standard competition models without differentiated producers. In Section 2, this mechanism is similar to large capacity transfers, which reduce the competitiveness of the competitors and benefit the receiver, leading to higher prices even under scarcity.

Market power affects equilibrium outcomes also through a *business stealing effect*, which relies on inflow-driven hydropower capacity changes through the intertemporal marginal value of holding water, acting like exogenous capacity transfers in Section 2. As a result, the actual cost of hydropower generation is the sum of its operational cost, c^H_{it}, in line two, and its intertemporal marginal value, in line three of (8). The latter intertemporal opportunity cost depends on i's current hydropower supply, $S^H_{iht}(p)$, which decreases i's future water stock and profits[28] through the transition matrix $f(\cdot|\mathbf{\Omega}_t)$, making the integral in line three of (8) non-positive. Since c^τ_{it} is constant over time, this opportunity cost moves i's marginal 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's market power modulates its response to scarcity. When j has no market power, $\frac{\partial p_{ht}}{\partial q_{ijht}} \to 0$, the firm suffers a future water loss of $\frac{\partial S^H_{iht}}{\partial q_{ijht}}$, which corresponds to the marginal change in hydro production from the FOCs. Market power, $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$, corrects this loss downward because the firm internalizes that for greater productions a smaller

[28] Occurrences of voluntary water spills are negligible in the data.

portion of its hydropower supply, $S^H_{iht}(p)$, is satisfied in equilibrium. The net effect (the term in parenthesis in line three) is positive: hydropower supply decreases ahead or during a drought as shown theoretically comparing Panels (c) and (d) of Figure 1 and empirically in Figure 4, but this drop declines with market power.

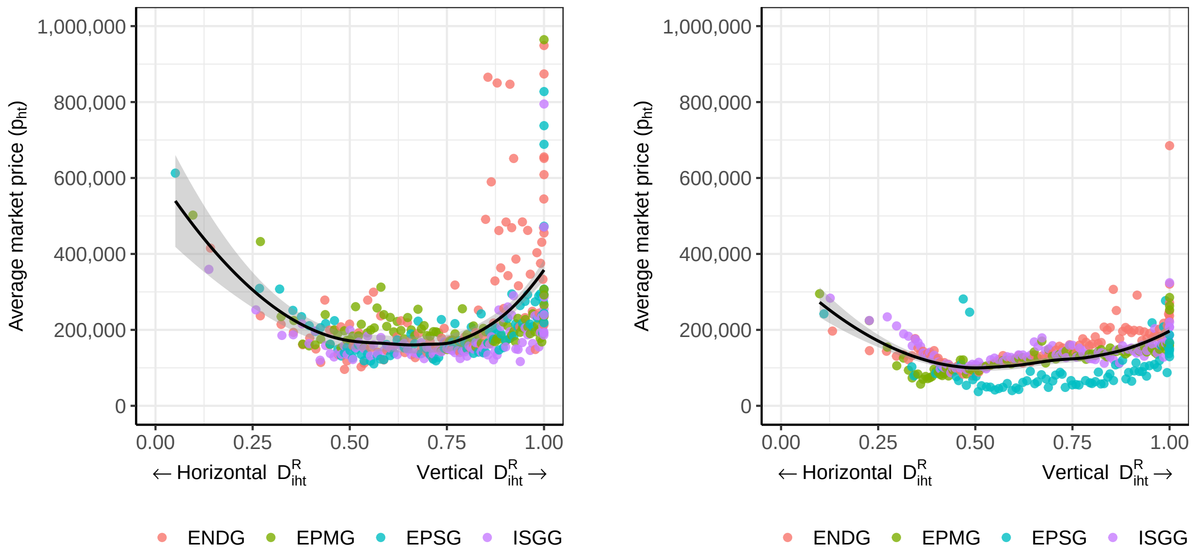
Investigating the supply decisions of sibling thermal generators clarifies the role played by market power in slacking the intertemporal opportunity cost created by hydropower. If j is thermal, q_{ijht} cannot affect S^H_{iht} directly ($\frac{\partial S^H_{iht}}{\partial q_{ijht}} = 0$), but only indirectly, through its price effect. That is, thermal generators internalize changes in water stocks only through $\frac{\partial S^H_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, which is negative. Accordingly, they increase production during scarcity, supporting the empirical evidence in Figure 5. Moreover, to save hydropower capacity, they increase their supply with their market power as it allows them to decrease p_{ht} and $S^H_{iht}(p)$. This mechanism also applies if j is hydropower, thereby reducing the intertemporal cost of holding water when $\frac{\partial p_{ht}}{\partial q_{ijht}} < 0$. Indeed, Panel (f) of Figure 1 indicates that a diversified firm supplies more (red dashed curve) than a non-diversified one (red shaded curve) also for production quantities below the low-cost capacity constraint (K^{low}_1).

In conclusion, a diversified firm supplies more energy than a firm with specialized production for two reasons. First, if the thermal generators belonged to fringe firms, they would not internalize the drought. Second, combining the FOCs of hydropower and thermal generators, a firm's hydropower production increases in its thermal capacity, as we prove in Appendix A.3. Intuitively, the latter slacks future water needs, making holding water less valuable to the firm. Tracing this back to the conceptual framework of Section 2, Firm 1's supply schedule is flatter when it is diversified – Panel (f) of Figure 1 – than when it is not – Panel (d) – as its greater capacity reduces its marginal cost allowing it to expand its supply to steal market shares from its competitors.

These *marginal revenue* and the *business stealing* effects push quantities produced, and hence market prices, in opposite directions. Figure 8 examines the relationship between market prices (on the y-axis) and the slope of a firm's residual demand (on the x-axis), which is flat at 0 (i is price taker) and vertical at 1. Panel (a) focuses on scarcity periods – markets where firm i's water stock is below the 30^{th} percentile – while Panel (b) considers water-abundant periods where firm i's water stock is above the 70^{th} percentile. Each scatter plot averages hour-by-day markets with similar (x, y) coordinates over 100 points per firm. Although purely descriptive, a U-shape relationship between prices and market power is evident in Panel (a): business stealing dominates for cases of low market power, leading to an initial drop in market prices. As we exogenously raise market power, firms prefer to decrease production with all their technologies, increasing prices due to the marginal revenue effect. In contrast, the U-shape is less evident in Panel (b) of Figure 8, as in this case $\frac{\partial f(\cdot|\mathbf{\Omega}_t)}{\partial S^H_{iht}} \to 0$, making future profits less dependent on current production.

A similarly shaped relationship was found in Section 2 between market prices and concentration: in scarcity periods, small capacity transfers to the market leader decrease

Figure 8: 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 $\frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}}$, with 100 bins per firm. Only diversified firms with dams whose bids are dispatched 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.

market prices while larger transfers lead to higher prices as the leader faces an increasingly vertical residual demand. As in that case, business stealing incentives drive this U-shape relationship also in Figure 8, as documented in Appendix Figure D1 where we replace the x-axis with the business stealing ratio.[29]

Finally, the state space includes all firms' current water stocks, $\mathbf{w}_t$: the last line of (8) considers how a change in a competitor's hydropower generator impacts $\mathbf{w}_t$ and, thus, i's expected profits through the market clearing ($\frac{\partial S^H_{kht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \leq 0$). Because this channel does not affect firm i's thermal and hydro generators differently, it does not shed light on the implications of diversified technologies, on which this paper focuses.

5.2 Identification and Estimation

In this section, we provide conditions for identifying marginal costs and the value function from (8). First, note that all the derivatives of the residual demand and supply can be directly computed from the data upon smoothing price and quantity bids by technology and firm, as shown in Appendix E. Identifying the transition matrix, $f(\cdot|\cdot)$, is also trivial,

[29]Following Wolak (2007), an application of the envelope theorem to the market clearing yields that $\frac{\partial p_{ht}}{\partial q_{ijht}}$ can be rewritten as $\frac{\partial S_{iht}}{\partial q_{ijht}} / \left(\frac{\partial D^R_{iht}}{\partial p_{ht}} - \frac{\partial S_{iht}}{\partial p_{ht}} \right)$. With some algebra, we obtain that $\frac{\partial D^R_{iht}}{\partial p_{ht}} \frac{\partial p_{ht}}{\partial q_{ijht}} \propto (1 - S'_{iht}/{D^R_{iht}}')^{-1}$, which indicates that the slope of the residual demand w.r.t. a q_{ijht} is a decreasing function of the business stealing ratio introduced in Section 2.

as we observe net water inflows and stocks for all firms. Therefore, we can rewrite (8) as:

$$mr_{ijht} = \sum_{\tau \in \{H,T\}} X^{\tau}_{ijht} c^{\tau}_{it} - X^{H}_{ijht} \int_{\mathbb{W}} \beta V(\mathbf{u}) \frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^{H}_{iht}} \mathrm{d}\mathbf{u} - \sum_{k \neq i}^{N} \tilde{X}^{H}_{ijht} \int_{\mathbb{W}} \beta V(\mathbf{u}) \frac{\partial f(\mathbf{u}|\mathbf{\Omega}_t)}{\partial S^{H}_{kht}} \mathrm{d}\mathbf{u}, \quad (9)$$

where we grouped known terms into the following variables. The left-hand side, mr, is the marginal revenue or the first line of (8). 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 (8).

The only unknown terms are c^{τ}_{it} and $\beta V(\cdot)$, which we parameterize. We assume that technology-specific costs are a function of quantity produced, and we approximate $V(\cdot)$ nonparametrically – we provide more details in the next section. As a result of these assumptions, (9) is a linear function of these primitives and can be estimated by least-squares given adequate instruments. The advantage of this approach over numerically iterating the Bellman equation (7) is in being computationally lighter as a Colombian diversified firm has about 20 generators and thus submits 20 times 24 hourly $\{q_{ijht}, b_{ijt}\}$ combinations in each daily auction, which makes value function iterations expensive.

5.2.1 Estimation

We need to introduce some additional assumptions to estimate the primitives of interest. Flexible estimation of $V(\cdot)$ is troublesome because it requires a large number of parameters. Typically, a standard spline approximation of a univariate function requires five bases, or knots (e.g., Stone and Koo, 1985, Durrleman and Simon, 1989). Therefore, 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 instruments.

Our working assumption is that a firm only considers its future water stock when bidding, disregarding the future water stocks of its competitors. 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 only on firm i's future water stock and its law of motion (6) through $\mathbf{\Omega}_{it}$. This assumption resonates with the reduced form results in Section 4.2.3, showing a limited role of a firm's competitors' future states in explaining its bids.

We allow the transition matrix to vary across firms, $f_i(\cdot|\mathbf{\Omega}_{it})$. Its estimation mimics the estimation of inflow forecasts in Section 4. We model firm-level water inflows using an ARDL model (Pesaran and Shin, 1995); the portion of water inflows that the model does not explain – the 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 whose asymmetric tails help us investigate firms' behaviors during water-scarce and abundant periods – by maximum likelihood. Appendix B outlines the estimation of the transition matrix and discusses its goodness of fit.

We plug the smoothed derivatives of supply and demand and the estimated transition matrix in (9), which we can rewrite as follows

$$mr_{ijht} = \sum_{\tau \in \{H,T\}} \psi^{\tau} X^{\tau}_{ijht} - X^{H}_{ijht} \sum_{r=1}^{R} \gamma_r \int_{\underline{w}_i}^{\overline{w}_i} B_r(u) \frac{\partial f_i(u|\mathbf{\Omega}_{it})}{\partial S^{H}_{iht}} \mathrm{d}u + FE + \varepsilon_{ijht}, \tag{10}$$

where ψ^{τ} is the technology-specific marginal cost and $\sum_r \gamma_r B_r(u)$ are the spline bases that approximate $\beta V(u)$ over $R = 5$ knots and are known up to the γ_r coefficients.[30] We also assume that both the marginal costs and the value functions have a non-deterministic component, which gives rise to the error term ε_{ijht} in (10). Therefore, the estimation of $\{\psi^{\tau}\}_{\tau \in \{H,T\}}$ 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}, biasing the estimation. We employ variables shifting a generator's cost to control for endogeneity.[31] 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 substantially 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 estimate (10) on daily data between January 1, 2010, and December 31, 2015, by two-stage least squares and present the estimated primitives in Table 2 where we vary the set of fixed effects used in estimation across columns. In particular, Columns (1) and (2) use fixed effects by week, which we substitute with daily fixed effects in Columns (3) and (4). In addition to the fixed effects by firm, generator, and time, Columns (2) and (4) also account for month-by-technology fixed effects to control for time-varying factors affecting the production of some technology but not others (e.g., weather seasonality).[32]

The table has four panels. The first two panels show estimates for thermal ($\psi^{thermal}$) and hydro (ψ^{hydro}) marginal costs and for the five value function parameters (γ_r). The third panel indicates the fixed effects, and the latter displays test statistics for the IVs.

[30] An advantage of this approach is that we do not need to assume the discount factor.

[31] 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.

[32] The standard errors are clustered at the generator level. We find relatively similar results if we cluster standard errors at the level of firms, quartiles of capacity-by-technology (accounting for a generator's size), and weekdays to allow for correlation within similar generators owned by the same firm while accounting for demand differences (i.e., weekday vs. weekend electricity consumption).

Table 2: Estimated model primitives

	(1)	(2)	(3)	(4)
Marginal Costs (COP/MWh)				
Thermal ($\psi^{thermal}$)	203,677.62***	141,668.46***	221,304.18***	144,744.21***
	(27,089.82)	(25,973.12)	(30,676.82)	(24,760.50)
Hydropower (ψ^{hydro})	64,258.02	20,123.07	29,187.79	52,755.37
	(47,367.32)	(73,680.43)	(37,949.09)	(54,774.84)
Intertemporal Value of Water (COP/MWh)				
Spline 1 (γ_1)	–2,950.20	–6,812.77	–11,664.64*	–3,812.18
	(3,871.73)	(5,343.19)	(6,316.13)	(4,432.24)
Spline 2 (γ_2)	–2.301e-03	–1.546e-04	6.286e-04	–8.402e-04
	(1.417e-03)	(1.550e-03)	(2.151e-03)	(1.436e-03)
Spline 3 (γ_3)	–3.527e-09	1.919e-08*	–1.932e-08	1.712e-08*
	(6.771e-09)	(1.049e-08)	(1.835e-08)	(9.323e-09)
Spline 4 (γ_4)	3.246e-08*	–3.119e-08*	4.536e-08	–2.729e-08*
	(1.897e-08)	(1.667e-08)	(3.544e-08)	(1.487e-08)
Spline 5 (γ_5)	–1.414e-08	9.357e-08**	5.167e-08**	8.566e-08**
	(2.569e-08)	(4.023e-08)	(2.446e-08)	(3.565e-08)
Fixed Effects				
Firm	✓	✓	✓	✓
Generator	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
Date			✓	✓
Clustered s.e.	Generator	Generator	Generator	Generator
SW F ($\psi^{thermal}$)	194.34	162.86	1,919.25	168.62
SW F (ψ^{hydro})	497.69	422.00	634.45	1,321.92
SW F (γ_1)	540.51	1,469.70	291.62	157.63
SW F (γ_2)	496.05	1,332.65	459.68	143.17
SW F (γ_3)	218.39	121.81	1,070.14	162.82
SW F (γ_4)	73.20	63.96	804.80	51.49
SW F (γ_5)	160.13	159.37	291.35	102.47
Anderson Rubin F	10.30	111.61	70.19	106.90
KP Wald	20.62	16.49	12.08	35.80
Overid. p-value	0.14	0.29	0.25	0.23
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 (10) 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. The standard errors are clustered at the level of the generator. 2,900 COP $\simeq$ 1 US$.

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 we cannot compare our hydro cost and intertemporal value estimates with other papers (engineering estimates generally report the levelized cost of electricity, which is the discounted sum of investments and operations over the lifetime of a project), we can compare the thermal marginal costs with other papers. As a reference, the thermal marginal cost expressed in US dollars varies between 45.57$ and 70.44$ per MWh, where, given the large variation in the pesos - US dollar exchange rate, we take the exchange rates at the beginning and at the end of the sample period. This is in line with other papers and engineering estimates that assess the operating cost of coal- and gas-fired power plants between 20 and 40 $/MWh and 40 and 80 $/MWh, respectively (e.g., Blumsack, 2023).[33]

We present several robustness checks in the appendix. First, we show that changing the number of knots to approximate $V(\cdot)$ 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 with five or four knots (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 When Diversification Decreases Market Prices

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 2.

6.1 The Simulation Model

We base our simulation exercises on a firm's objective function (7) because the first-order conditions in (8) are not sufficient for optimality. 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. Thus, we follow Reguant (2014) and build a computational model based on (7) that solves numerically for a firm's best response given the other firms' strategies in each hourly market, using a mixed-linear integer programming solver.[34] That is, we assess the fit of the model by simulating the bids of EPMG, the

[33]For instance, Reguant (2014) estimates that thermal production in Spain costs between 30 and 36 euro per MWh in 2007 when oil and gas prices were considerably smaller than in the period we consider – the average yearly oil price was $72 per barrel in 2007, while the average price in 2010-2015 was $84.70, with peaks well above $100 per barrel.

[34]We use 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.

market-leading firm, taking the bids of its competitors as given.[35]

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 chooses the K-dimensional vector of hourly quantities $\{\mathbf{q}^{\tau}_{ht,k}\}_{h=0}^{23}$ for each technology τ (hydro or thermal) to solve

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

$$s.t.$$

$$\text{[Market-clearing:]}\quad D^R_{ht}(p_{ht}) = \sum_{\tau\in\{H,T\}}\sum_{k=1}^{K} q^{\tau}_{ht,k},\quad \forall\, h,\quad (11)$$

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

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

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

where we dropped the subscript i because the focus is on EPMG. The gross revenue function, $GR(D^R_{ht})$, is the discretized version of the static revenues in (5). It depends on $D^R_{ht}(p_{ht}) = \sum_{z=1}^{Z} \mathbb{1}_{[p_{ht,z}\le p_{ht}]} D^R_{ht,z}$, 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 (11) 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.[36]

Because our primary focus is on the intertemporal allocation of production capacity across technologies when firms face prolonged extreme events, we do not simulate each daily market between 2010 and 2015. We instead collapse the daily data across weeks and hours and solve for EPMG's best response using (11) for each hour-week pair. This approach reduces computation time without sacrificing precision, as we show next.

`r-project.org/web/packages/Rcplex/index.html`, and `https://www.ibm.com/it-it/products/ilog-cplex-optimization-studio`.

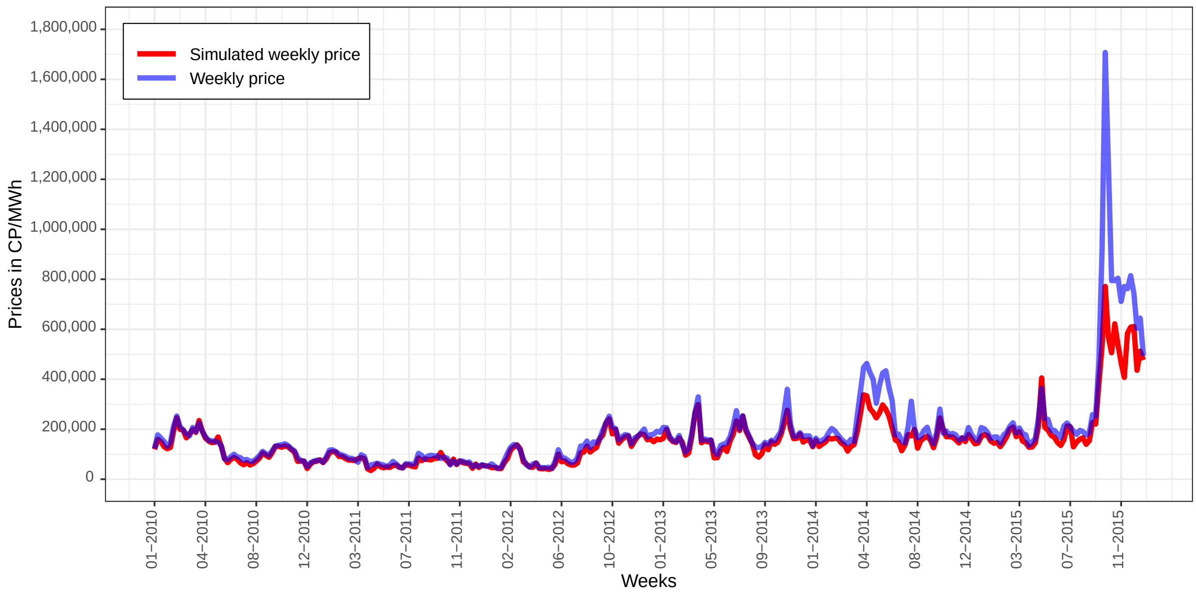
[35]EPMG has the largest semi-elasticity of demand in the time period under analysis (Appendix Figure F2). Hydropower generation is over than 80% of its total capacity (Figure F1).

[36]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).

6.2 Model Fit

Figure 9 compares the observed average weekly prices (red line) with the simulated ones (blue line). The model reproduces the price volatility remarkably well, especially over the first four years. The occurrence of El Niño in 2016, a drastic dry spell that has no precedent in our sample, surely impacted the transition matrix in late 2015, creating a gap between simulated and observed prices. Despite the model cannot deliver the enormous spike observed in late 2015, when prices increased by over ten times, it does predict that they are five to seven times higher. We also study price variation across hours in Appendix Table F1, showing a remarkable fit.[37] Overall, we conclude that despite being quite parsimonious – Table 2 only estimates seven parameters – the computational model can reproduce price volatility for Colombia over a rather long period.

Figure 9: Model fit: simulated vs. observed average weekly prices



Note: Comparison between observed (blue) and fitted (red) prices from solving EMPG's profit maximization problem (11). 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 causally test the model's predictions presented in Section 2, we simulate various policy scenarios where we vary the transferred capacity in January 2010 and compute market prices until December 2015. Transferring an equal fraction from all EPMG competitors, we increase the business stealing incentive, $\frac{-S'_{EPMG}(p)}{D^{R}_{EPMG}{}'(p)}$ in (1). Despite each technology in (11) has fixed capacity constraints over time, the intertemporal tradeoff modulates the

[37] 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).

perceived cost of using hydropower generation in each period, effectively creating periods where hydropower is abundant, as in Panel (c) of Figure 1, or scarce, as in Panel (d).[38]

Figure 10 summarises the results from the counterfactual exercises. In Panels (a) and (c), we move capacity from fringe firms (i.e., firms without 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. In contrast, in Panels (b) and (d), we transfer capacity from all firms, including the strategic competitors. Theoretically, we should update strategic firms' bids in every scenario according to (11), but it is computationally infeasible. Nonetheless, we focus on the effects of a small capacity transfer, which in practice will not cause the competitors' thermal capacities to become binding. Therefore, the counterfactual price drops are more conservative than if competitors also update their bids due to the strategic complementarity in bidding (Appendix A) as shown in Figure 1: the competitor's best response to a technology transfer is to increase (decrease) supply if the market leader increases (decreases) its supply.

Each panel shows a heatmap where we rank markets based on the extent of the drought experienced by EPMG on the x-axis and the size of the capacity transfer on the y-axis. The top (bottom) panel uses water inflows (stock) on the x-axis. Each cell of the heatmap presents the average difference between the counterfactual and the status quo market prices: darker blue (red) colors imply lower (higher) counterfactual prices.

Varying capacity transfers. Let's start from the first row of Panel (a), where EPMG is endowed with 10% of the fringe firms' thermal capacity. We find lower energy market prices on average across almost all periods (the deciles of EPMG's water inflow). The rows immediately above it are also mostly blue, indicating that moving 20% to 30% of the capacity available to EPMG's competitors also decreases market prices.[39] Zooming in on transfers lower than 50% to better appreciate the magnitude changes, Panel (a) 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).

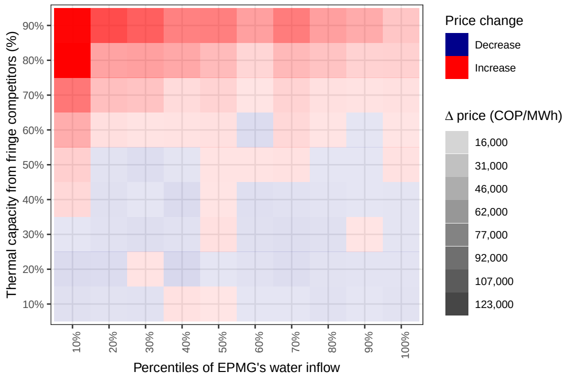
In contrast, counterfactual prices are mostly higher for large transfers, especially in the driest periods. During these periods, EPMG behaves as the standard textbook model would predict for a non-diversified firm that faces an increasingly vertical residual de-

[38] If we view the value function parameters ($\{\gamma_r\}_r^R$) estimated in (10) as equilibrium objects, they could vary under different industry configurations. 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 ($\{\gamma_r'\}_r^R$), we show in Appendix A.3 that the marginal benefit of holding water decreases with a firm's thermal capacity: we would expect EPMG to offload more water than our counterfactual predicts, meaning lower prices on average. An alternative interpretation of the value function parameters is that, since we estimate the model on the whole industry, they reflect the industry preference for holding water, which we assume to be constant across firms.

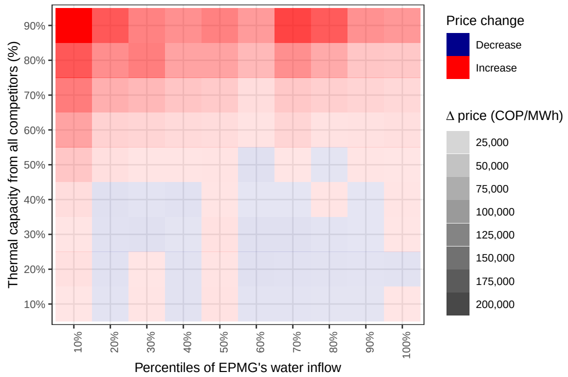
[39] To give an idea of the transfer, it would double EPMG's thermal capacity.

Figure 10: The price effect of a capacity transfer to the market leader (EPMG)

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

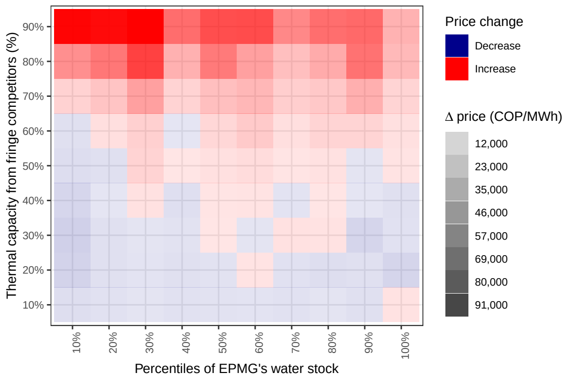


(a) Transferring $x\%$ from all fringe firms

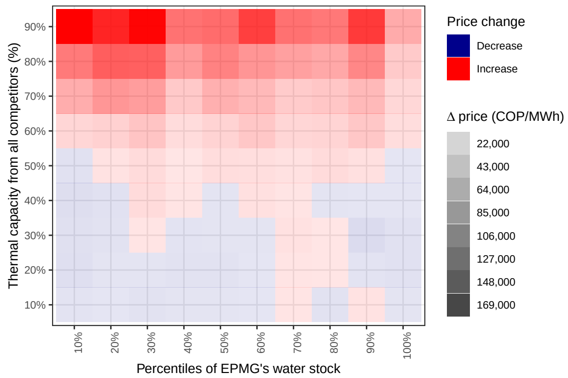


(b) Transferring $x\%$ from all firms

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 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$.

mand: 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 Figure 1 where small capacity transfers can decrease market prices if the market leader faces scarcity (Panel b) but a larger transfer provides it with *de facto* monopoly power, calling the market leader to raise prices.

Varying drought severity. The previous analyses studied counterfactual outcomes across different transfer levels given a scarcity level – i.e., across rows of the heatmap. Here, we compare outcomes across different scarcity levels given a specific transfer – i.e., across columns of the heatmap. Unlike the previous analysis, we prefer ranking markets using the deciles of the water stock on the x-axis rather than of water inflows. While the latter distribution is truly exogenous as firms cannot control daily water inflows, its distribution is much less persistent than that of water stocks. Therefore, markets in adjacent cells in Panel (a) of Figure 10 are much more heterogeneous than those in Panel (c), potentially biasing comparison across columns. Indeed, the cell colors across adjacent cells are more homogeneous in the bottom panels, which use the water stock distribution on the x-axis, than in the top ones, which use the water inflow distribution, instead.

We start our analysis from Panel (c) of Appendix Figure G1, which zooms on small transfers. 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 – a result consistent with the U-shape relationship observed between market prices and market power measures in Panel (a) of Figure 8, under scarcity, but not so evident in Panel (b), under abundance.

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. Clearly, there are no gains from transferring thermal capacity when the firm has a large amount of hydropower capacity, but there are gains from limited reallocation of capacity.

Reallocating from fringe or strategic firms? Finally, Panels (b) and (d) of Figure 10 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 Panels (a) and (c) 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

This paper studies a new factor affecting a firm's unilateral ability to influence market prices: diversified firms having access to multiple production technologies to produce the same good. We show through both new theory and empirics that the impact of a capacity transfer from followers to the market leader of a technology unavailable to the latter not only expands the leader's production frontier but also engenders strategic responses from both the senders and the receiver of the transfer. Surprisingly, these responses can result in lower prices despite the resulting increase in concentration. We inspect these responses within the Colombian wholesale energy market because it features diversified suppliers, which play an important role in the ongoing green transition and energy crisis. In this section, we discuss the main contributions of the paper and its policy implications.

7.1 Market Power, Synergies, and Divestitures

Our analysis focuses on markets for homogeneous goods like wholesale energy markets because regulations require firms to report the pricing strategies for each of their generators. However, our theoretical framework is general. We base our analysis on the supply function equilibrium proposed by Klemperer and Meyer (1989), where firms submit supply schedules detailing how much they are willing to produce for each quantity. Under perfect competition, these supply schedules mimic firms' marginal cost functions that are hockey-stick-shaped due to capacity constraints. Supply functions are instead detached from marginal costs under oligopolistic competition as firms exert their market power, in which case, Klemperer and Meyer (1989) show that the equilibrium spans Bertrand and Cournot models. Moreover, under increasing marginal costs and demand uncertainty, the supply function equilibrium is ex-post optimal, meaning that firms do not experience regret about their pricing strategy once uncertainty resolves, unlike the latter equilibrium concepts. Outside of commodity markets, similar games are played in business-to-business transactions where suppliers generally offer discounts to buyers willing to purchase greater quantities (Bornstein and Peter, 2022, Chao *et al.*, 2022).

Within this framework, we find that markups must balance a firm's unilateral ability to affect market prices – or a firm's demand elasticity – as in Bertrand and Cournot, with a business stealing effect (see Equation 1). The latter arises because, submitting a quantity for each market price, firms engage in a new entry game at each price level where a failure to update supply risks the loss of market shares if the realized demand is large enough. Indeed, when demand is vertical, the business stealing effect is a function of the ratio of a firm's market share to that of its competitors.

As a result, in our empirical application, transferring capacity of a different kind to the market leader does not necessarily result in higher prices; the final outcome depends on the *low*-cost capacity available to the capacity receiver, namely its water stock. When this capacity is large compared to its competitors' capacities, the market leader will not fear business stealing. Capacity transfers of any size will further exacerbate its competitive advantage, further stepping up its supply schedules. If, instead, its *low*-cost capacity is not so much greater than that of its competitors, transferring *high*-cost capacities – i.e., fossil fuel – from its competitors can help the leader steal market shares from them when demand is high, in which case it will expand its supply schedule. In response, competitors will optimally expand their supply schedules to protect their market shares. Thus, equilibrium prices can drop despite consolidation, a finding that we highlight theoretically in Panel (b) of Figure 1 and empirically in Figure 10. Figure 8 provides descriptive evidence of this effect, showing that it is mediated by a firm's ability to affect market prices.[40]

Standard synergies providing merging parties with either economies of scale or scope do not drive this result. For instance, it is common to model the marginal cost of the merger between two firms with costs c^a and c^b as the $\min\{c^a, c^b\}$ and to motivate it with better managerial practices (e.g., Braguinsky *et al.*, 2015, Demirer and Karaduman, 2022) or on efficiency grounds (e.g., Ashenfelter *et al.*, 2015, Miller and Weinberg, 2017). In our framework, synergies come from equilibrium responses from expanding a firm's marginal cost curve at the expense of others. These synergies are related to those studied in mergers of multiproduct firms in aggregative games (Nocke and Schutz, 2018a), where a firm's markup balances its demand elasticity with a self-cannibalization effect across its products (Nocke and Schutz, 2018b). Although we focus on homogeneous product markets, the business stealing we uncover relates to self-cannibalization in multiproduct markets, as it forces firms to internalize the change in their market shares beyond the elasticity of demand.

Our results have implications for horizontal mergers policies (Nocke and Whinston, 2022), which takes concentration as a primary measure of market distortions, as recent studies link it to declines in labor shares (Barkai, 2020, Autor *et al.*, 2020) and productivity growth (Gutiérrez and Philippon, 2017) and to greater markups (De Loecker *et al.*, 2020). We add to this literature by showing that the consequences of concentration also depend on production technologies. Our findings have consequences for standard tools that antitrust agencies use to limit concentration after a merger in diversified-product industries, such as divestitures (Compte *et al.*, 2002, Friberg and Romahn, 2015). To the extent that they do not simply reduce capacities but also make firms less diversified, forced divestiture can reduce a firm's ability to respond to scarcity events (i.e., high input cost periods), creating vicious market responses for competitors and potentially increasing market prices.

7.2 Who Should Own the Means of Production in the Green Transition?

Transitioning to a greener economy means changing our energy sources. Renewable sources are cheap but are intermittent and come with large fixed costs. Ultimately, the transition is likely to have distributional implications across consumers (Reguant, 2019, Haar, 2020) and regressive features for inelastic goods like electricity (Hortaçsu *et al.*, 2017, Enrich *et al.*, 2023, Leslie *et al.*, 2023). At the same time, high prices act as key incentives for firms to sustain the large investments needed to increase the renewable share of their technology portfolio (Elliott, 2022). Therefore, policies that are able to

[40]Prices cannot decrease with concentration without diversified production if we exclude buyer power (Alviarez *et al.*, 2023) or cost synergies (Ashenfelter *et al.*, 2015)

reduce energy prices during scarcity events by helping firms internalize their externality rather than forcing firms to lower prices (e.g., price caps) are key tools for policymakers to push the green transitions.

With large barriers to entry, national wholesale energy markets are far from perfectly competitive (e.g., Borenstein *et al.*, 1999). Market power arises based on the share of total capacity that a firm holds. While research has focused on energy sources at the national level, few papers examine how firms' energy portfolios affect market outcomes. Our paper shows that if firms have some market power, they internalize scarcity accruing at their renewable generators through non-shocked generators. More specifically, generation from the latter units increases as firms internalize that supply will drop at their sibling renewable generators, thereby increasing prices: adding non-renewable capacity to a firm expecting a drought can decrease price hikes by about 5 to 10% (Appendix Figure G2), a non-negligible amount. In concurrent work, Fabra and Llobet (2023) also find that diversified energy firms can result in lower prices than under specialization when firms compete á la Bertrand. Their work complements ours as they focus on solar and wind sources, whose availability can create information asymmetries between a resource owner and its rivals, and on allocation efficiency. These resources are not as central in Colombia and other equatorial and Scandinavian countries, where dams form most of the renewable capacity – due to dams' sizes compared to other generators, market power arises as the critical issue in these countries.

Our findings support modifying standard antitrust rules imposing capacity thresholds for firms – for instance, no firm can have more than 25% of the total installed capacity in Colombia. According to our results, these thresholds are important to avoid excessive market power but should vary across firms based on a firm's available technologies. Doing otherwise might preempt successful diversification attempts that provide firms with hedging opportunities. As firms can forecast scarcity events (Figure 4), forward contract markets can be viewed as another hedging opportunity (e.g., Anderson and Hu, 2008, Ausubel and Cramton, 2010, Bouckaert and Van Moer, 2017). However, their mitigation effect is only partial, as our model shows that firms internalize dry spells only through ownership linkages, and is further reduced by the evidence that forward prices follow the spot market prices (de Bragança and Daglish, 2016, Huisman *et al.*, 2021), which long-term contracts expensive when droughts are expected (McRae and Wolak, 2020).

In Colombia, hedging takes the form of fossil fuels; their usage increases CO_2 emissions, slowing the green transition. If dam ownership were not geographically concentrated (Figure 7), a heritage of the privatizations of the 90s, hedging could come from dams exposed to different inflow cycles. Hence, a different geographic distribution of dam ownership can increase welfare by reducing emissions compared to the status quo.

In 2023, Colombia still had only 1.5% of its installed capacity in solar and wind renewables. However, twelve wind projects totaling 2,072 MW and six solar projects totaling 908 MW were under construction at the end of 2022, and the Unidad de Planeación Minero Energética, the Colombian governmental agency managing the exploitation of natural resources, approved requests for several other solar and wind farm projects to start operating by 2027 (Arias-Gaviria *et al.*, 2019, Rueda-Bayona *et al.*, 2019, Moreno Rocha *et al.*, 2022). When operational, these projects will account for about 38% of Colombian installed capacity (SEI, 2023). With steady improvement in storage and drops in battery costs (Koohi-Fayegh and Rosen, 2020), renewables might substitute fossil fuels as a cheaper source of hedging for hydropower. Ultimately, to successfully internalize scarcity, diversified firms only need other generators experiencing abundance. Similar investments will ensure a speedy and affordable transition toward a greener economy.

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Online Appendix

A Theoretical Appendix

In this section, we analyze an oligopoly to illustrate the price effects of diversifying a firm's production portfolio by transferring capacity from high-cost followers to a low-cost market leader. Consider a general homogeneous good market with N strategic firms with access to production technologies $\tau \in \mathcal{T} = \{l, h\}$. l indicates the low-cost technology and h indicates the high-cost one, so that their marginal costs are $0 \le c^l < c^h$. The τ-technology capacity of firm i is $K_i^\tau \ge 0$. Its total output is the sum of its technology-specific supplies, $\sum_{\tau \in \mathcal{T}} S_i^\tau$, which costs the firm $C_i := \sum_{\tau \in \mathcal{T}} c^\tau S_i^\tau$. Naturally, the production of firm i with technology τ is constrained by its corresponding capacity, i.e., $S_i^\tau \in [0, K_i^\tau]$.

When firms compete in supply schedules, the quantity supplied is a function of price. Therefore, i's total quantity supplied is the function $S_i(p) := \sum_\tau S_i^\tau(p)$, where for each τ, $S_i^\tau(p)$ is the (right-continuous, non-decreasing) supply schedule of firm i with technology τ. Total demanded is a quantity $D(\epsilon)$ that depends on some exogenous variable ϵ with full support, which is unknown to the firm when their supply decisions are made.

The market clearing price is the smallest price at which the total quantity supplied in the market is no less than the total quantity demanded. To guarantee demand clearance, there is an infinite mass of competitive fringe producers who only enter the market when the price is at least their marginal cost, c^f. We consider the interesting case where $c^f > c^h$, in which, whenever the market price is at $p \ge c^f$, the fringe producers will enter and clear the market. Therefore the market clearing price is at most c^f. Without loss of generality, the fringe players' production is positive if and only if the realized demand, D is such that $D > \sum_i^N S_i(c^f)$, so that all the strategic firms have priority over the fringe firms. Hence, for any D, given the schedules S_i, the market clearing price is

$$p = \min \Big\{ c^f, \inf \big\{ x \big| \sum_i^N S_i(x) \ge D \big\} \Big\}. \tag{A1}$$

Supply function equilibrium (SFE). *Following Klemperer and Meyer (1989), firm i takes all the opponents' strategy S_j for $j \ne i$ as given, and chooses a supply schedule S_i^τ for each technology τ to maximize the ex-post profit*

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

at every realized level of $D(\epsilon)$ and for which the price p clears the market.

We first define for firm i its residual demand function

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

where $S_{-i} := \sum_{j \ne i} S_j$. Therefore, given the opponent's strategy, the profit of firm i with cost function C_i at the market clearing price is $D_i^R(p, \epsilon) \times p - C_i$.

When firms use continuous strategies on a price interval, the market clearing condition (A1) together with continuity implies $D_i^R(p,\epsilon) = S_i(p)$ whenever the market clears with a price on this interval. Since strategies are differentiable at the market clearing price, ex-post optimality implies the FOC for i [equivalent to the ex-ante Euler-Lagrange equation]:[1]

$$p\frac{\partial}{\partial p}D_i^R + D_i^R - \frac{d}{dS_i}C_i \times \frac{\partial}{\partial p}D_i^R = 0 \Leftrightarrow (p - c^\tau)\, S'_{-i}(p) = S_i(p). \tag{A2}$$

Two observations can be made readily. First, the firms' supply functions are *strategic complements*. To see this, differentiating (A2) again to obtain

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

Clearly, firms react by bidding more aggressively (increase S'_i) when opponents bid more aggressively. Second, i's markup at the market price depends on i's share of elasticity and its *business stealing*. To see this, denoting $S := S_i + S_{-i}$ and $s_i := \frac{S_i}{S}$, we have

$$S'_{-i}\,(p - c^\tau) = S_i(p) \Leftrightarrow \left(\frac{S'}{S}p\right)\frac{p - c^\tau}{p} = s_i \times \frac{S'}{-\frac{\partial}{\partial p}D_i^R}$$

where $\frac{S'}{-\frac{\partial}{\partial p}D_i^R}$ is the term for business stealing. At the market price, $S(p) = D$ implies $\frac{dS}{dp}\frac{dp}{dD} = 1$. Therefore, the elasticity is $\eta := \left(\frac{dp}{dD}\right)^{-1}\frac{p}{D} = \frac{dS}{dp}\frac{p}{S}$: the above equation is equivalent to Equation (1). The following proposition lists these findings.

Proposition A.1 *When firms' strategies are twice differentiable, then for all i,*

1. ***Strategic Complement****: firm i responds to a higher S'_{-i} with greater S'_i and S_i;*
2. ***Business Stealing****: i's markup satisfies $\frac{p-c_i(S_i(p))}{p} = \frac{s_i}{\eta} \times \frac{S'(p)}{-D_i^{R\prime}(p)}$.*

A.1 Solving for the Equilibrium Strategies Analytically

To solve for the equilibrium analysis, we focus on the case where $N = 2$ and $K_2^l = 0$. The following proposition characterizes the comparative static of relocating some h capacity of firm 2, to firm 1, the market leader, under two extreme scenarios.

Proposition A.2 *Let $K_2^l = 0$ and $N = 2$. For all small enough $\delta > 0$, consider the SFE comparative static that relocates δ units of production capacity from K_2^h to K_1^h.*

1. ***Approximate Monopoly****: the market price, p, increases in δ when $K_1^h, K_2^h > 0$, $K_1^l > \frac{c^f - c^l}{c^f - c^h}K_2^h$ and D is such that $S_2(p) > 0$;*
2. ***Under-diversified Duopoly****: the market price, p, decreases in δ when $K_1^l > K_2^h > \frac{c^f - c^h}{c^f - c^l}K_1^l$, K_1^h is small enough, and D is such that $S_2(p) > 0$;*
3. ***Business stealing****: in either scenario firm 1's threat of business stealing $\frac{dS_1}{dp}/\frac{dS_2}{dp}$ weakly increases in δ.*

[1] Indeed, it can be shown that the equilibrium strategies are continuous and piece-wise continuously differentiable on (c^h, c^f), and that $\frac{d}{dS_i}C_i = c^\tau$ for some $\tau \in \mathcal{T}$ in equilibrium.

This proposition can be interpreted as follows. When firm 1's low-cost capacity is large, reallocating δ h-technology units will increase the market price through the standard concentration effect [A.2.1]. However, when firm 1's capacity is only slightly larger than that of firm 2 (e.g., firm 1 faces scarcity), prices decrease after such a reallocation because the firms was under-diversified at baseline [A.2.2]. In both cases, the business stealing ratio increases as firm 1 has more ability to steal market share from competitors [A.2.3].

Proving Proposition A.2. *Proof.* From (A2) and the merit order, a simple optimization argument shows that $S_i^\tau(p) = 0$ for $p < c^\tau$, and that firms will use the higher-cost technology only when the low-cost one is exhausted. Therefore, $\forall p \in [c^h, c^f]$:

$$S_1(p) = \begin{cases} S_1^l(p) & = S_2' \times (p - c^l), \quad \text{if } S_1^l(p) < K_1^l, \\ S_1^h(p) + K_1^l & = S_2' \times (p - c^h), \quad \text{if } S_1^l(p) = K_1^l, \end{cases} \quad S_2(p) = \begin{cases} S_1^{l\prime} \times (p - c^h), & \text{if } S_1^l(p) < K_1^l, \\ S_1^{h\prime} \times (p - c^h), & \text{if } S_1^l(p) = K_1^l. \end{cases}$$

Solving this system of differential equations for S_1^l, S_1^h, and S_2 non-negative and non-decreasing, we find

$$S_1(p) = \begin{cases} c_1(p - c^l), & \text{if } S_1^l(p) < K_1^l, \\ c_3\left(p - c^h\right) + c_2\frac{1}{p - c^h}, & \text{if } S_1^l(p) = K_1^l, \end{cases} \quad S_2(p) = \begin{cases} c_1(p - c^h), & \text{if } S_1^l(p) < K_1^l, \\ c_3\left(p - c^h\right) - c_2\frac{1}{p - c^h}, & \text{if } S_1^l(p) = K_1^l, \end{cases}$$

for unknown coefficients c_1, c_2, c_3. A simple Bertrand-competition argument shows that both functions S_1 and S_2 have no discontinuity at $S_1(p) = K_1^l$. So we have

$$\begin{cases} K_1^l = c_1(p - c^l) = c_3(p - c^h) + c_2/(p - c^h) \\ c_1(p - c^h) = c_3(p - c^h) - c_2/(p - c^h) \end{cases} \Rightarrow \begin{cases} c_2 = \frac{(c^h - c^l)^2}{2}(\alpha - c_1) \\ c_3 = \frac{c_1}{2}\left(1 + \frac{\alpha}{\alpha - c_1}\right) \\ p - c^h = \frac{(c^h - c^l)}{c_1}(\alpha - c_1) \end{cases} \tag{A3}$$

where $\alpha := \frac{K_1^l}{c^h - c^l}$, and the last equality solves for the p at which $S_1^l(p) = K_1^l$. Notice that if such $p \geq c^f$, then firm 1 would not produce with high-cost capacity as the price approaches c^f from the left.[2]

It can be checked that the solution has $c_1 \in (0, \alpha)$. Lemmas A.1 and A.2 together imply that there is a unique SFE, which can be pinned down by monotonically increasing $c_1 \in (0, \alpha)$ until the first c_1 that solves $S_i(c^f) = \sum_\tau K_i^\tau$ for some $i \in \{1, 2\}$.

To prove Proposition A.2.1, given any $K_1^t, K_2^t > 0$, consider $c_1 = \frac{K_2^h}{c^f - c^h}$. By assumption $K_1^l \geq c_1(c^f - c^l)$, the equilibrium solution is given by

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

Now 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

[2] The marginal case where firm 1 is on the verge of supplying with high-cost at some price on (c^h, c^f) is given by the solution where $c_1 = \frac{K_1^l}{c^f - c^l}$.

holds. Therefore, c_1 decreases and the market-wide production

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

decreases at every price level as δ increases. Hence the market clearing price increases. Moreover, for all D such that $S_2 > 0$, the firm 1's business stealing measured by

$$\frac{dS_1}{dp} \Big/ \frac{dS_2}{dp} = \begin{cases} \infty, & \text{if } D(\epsilon) \geq \frac{K_2^h - \delta}{c^f - c^h}(2c^f - c^l - c^h), \\ 1, & \text{otherwise }, \end{cases}$$

at the market price is non-decreasing (increasing in δ), proving half of Proposition A.2.3

To prove Proposition A.2.2, we claim that firm 1 will produce with high-cost technology at some price $p < c^f$ under our assumption that $K_1^l > K_2^h > \frac{c^f - c^h}{c^f - c^l} K_1^l$. If the contrary were true, Lemma A.1 implies that firm 2 exhausts its capacity and $c_1(c^f - c^h) = K_2^h$. Therefore, as $p \to c^f$ the production of firm 1 approaches $c_1(c^f - c^l) = K_2^h \frac{c^f - c^l}{c^f - c^h} > K_1^l$, contradicting that firm 1 does not exhaust its low-cost capacity for $p \to c^f$.

Now we claim firm 1 exhausts all its capacity in the limit as $p \to c^f$ when K_1^h is small enough. Suppose on the contrary that in equilibrium firm 2 exhausts its capacity. By Lemma A.2, the production schedule of firm 2, $S_2(c^f) = c_3(c^f - c^h) - c_2/(c^f - c^h)$, is increasing in c_1 and so there is a unique $\tilde{c}_1$ such that $S_2(c^f) = K_2^h$. For $c_1 = \tilde{c}_1$, firm 1 exhausts K_1^l and produces with high-cost tech at some $p < c^f$, and $\tilde{c}_1 \geq \frac{K_1^l}{c^f - c^l}$. Denote by $\tilde{S}_1(c^f) = \tilde{c}_3(c^f - c^h) + \tilde{c}_2/(c^f - c^h)$, where $\tilde{c}_3$ and $\tilde{c}_2$ are the corresponding coefficients evaluated at $\tilde{c}_1$: since firm 1 is also producing with the h-technology, we have $\tilde{S}_1(c^f) - K_1^l > 0$. Now if 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 $K_2^h, K_1^l, c^h, c^l, c^f$ only, it implies that as $p \to c^f$, firm 1 will produce at infeasible levels, 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.2 then implies $c_1' < \tilde{c}_1$ and therefore firm 2 would have leftover capacity in the limit $p \to c^f$. Because of this lemma, the equilibrium parameter c_1' is uniquely solved for $\lim_{p \to c^f} S_1(p) = K_1^h + K_1^l$

$$c_3(c^f - c^h) + c_2/(c^f - c^h) = \frac{c_1'}{2}\left(2 + \frac{c_1'}{\alpha - c_1'}\right)(c^f - c^h) + \frac{(c^h - c^l)^2}{2} \frac{\alpha - c_1'}{c^f - c^h} = K_1^h + K_1^l.$$

Using this c_1', the equilibrium solution is given by

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

and

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

Now if we reduce K_2^h to $K_h^2 - \delta$ and increase K_1^h by $\delta > 0$ small enough, it will still hold that firm 1 just exhausts its capacity at $p \to c^f$ and 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.2 we have c_1' is increasing in δ. Therefore the market-wide production

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

is increasing at every price level as δ increases. Hence the market clearing price decreases. Moreover, for all D such that $S_2 > 0$ when market clears, firm 1's business stealing is

$$\frac{\frac{dS_1}{dp}}{\frac{dS_2}{dp}} = \begin{cases} 0, & \text{if } D(\epsilon) \geq A(c_1')(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{c^f - c^h} + K_1^h + \delta + K_1^l, \\ \frac{A(c_1') - B(c_1')}{A(c_1') + B(c_1')}, & \text{if } D(\epsilon) \in (K_1^h + (p^* - c^h)c_1', A(c_1')(c^f - c^h) - \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{c^f - c^h} + K_1^h + \delta + K_1^l), \\ 1, & \text{otherwise }, \end{cases}$$

where $A(c_1') := \frac{c_1'}{2}\frac{2\alpha - c_1'}{\alpha - c_1'}$ and $B(c_1') = \frac{(c^h - c^l)^2}{2}\frac{\alpha - c_1'}{(p - c^h)^2}$, and $p^* = c^h + \frac{c^h - c^l}{c_1'}(\alpha - c_1')$ is the price level at which firm 1 exhausts its l capacity. It can be checked that at every D, firm 1's business stealing is increasing as δ (and hence c_1') increases. □

A.1.1 Lemmas and Proofs

Lemma A.1 states that one of the two firms will exhaust its capacity as the market price reaches the $fringe-$ marginal cost. Lemma A.2 is a technical lemma used to prove that the equilibrium supply functions are unique.

Lemma A.1 *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 $D < \sum_{i,\tau} K_i^\tau$, 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.2 *Using c_2, c_3 solved in c_1 as in (A3), whenever $c_1 \geq \frac{K_1^l}{c^f - c^l}$ we have*

1. $c_3(c^f - c^h) - c_2/(c^f - c^h) \geq c_1(c^f - c^h)$ *where the equality holds iff* $c_1 = \frac{K_1^l}{c^f - c^l}$;

2. $c_3(c^f - c^h) + c_2/(c^f - c^h) \geq c_1(c^f - c^l)$ *where the equality holds iff* $c_1 = \frac{K_1^l}{c^f - c^l}$;

3. $c_3(c^f - c^h) - c_2/(c^f - c^h)$ *and* $c_3(c^f - c^h) + c_2/(c^f - c^h)$, *as functions in in* c_1, *are continuous and strictly increasing to* ∞.

The proof is elementary and is skipped for brevity.

A.2 Lerner Index With Standard Conduct Models

Cournot. Assume that two firms compete à la Cournot. The demand function is $p(Q) = a - b \cdot Q$, where $Q = q_A + q_B$. Firms A and B face marginal costs $c_A < c_B$. A firm maximizes its profit, $\Pi_i^{Cournot} = p(Q) \cdot q_i - c_i \cdot q_i$. The optimal quantity for firm i is found as:

$$a - 2b \cdot q_i - b \cdot q_{-i} - c_i = 0.$$

Denote the elasticity of the market demand by $\tilde{\eta} = -\frac{\partial Q}{\partial p}\frac{p}{Q}$, then we have that

$$\begin{aligned} p - c_i &= \frac{1}{\eta} \cdot \frac{-p}{b \cdot Q} \cdot b \cdot q_i \\ \frac{p - c_i}{p} &= \frac{s_i}{\tilde{\eta}}, \end{aligned} \tag{A4}$$

where s_i is i's market share, q_i/Q. The latter equation also holds for $N > 2$ firms. When $N = 1$, $s_i = 1$: the oligopolist markup equation collapses to the monopolist one.

Drawing a parallel between (A4) and (1) from the main text, the share of i's price elasticity of demand in the second line of (A4) is $\frac{s_i}{\tilde{\eta}} = \frac{q_i/Q}{\tilde{\eta}} = (-\partial \ln p/\partial \ln Q) \cdot q_i/Q$. Under the supply function equilibrium studied in Section 2, demand D is vertical and firm i best-responds to its residual demand, $D^R(p) = D - S_{-i}(p)$. Thus, in this game, the share of i's price elasticity of demand is no longer with respect to Q, but with respect to D according to $(-\partial \ln p/\partial \ln D) \cdot S_i/D = \frac{S_i/D}{\eta} = \frac{s_i}{\eta}$, which is remarkably similar to the right-hand side in (A4). Hence, the two types of conduct in (1) and (A4) present the same variables, besides for the market power term, $\frac{S_i'(p)}{S_{-i}'(p)}$.

Bertrand. Bertrand competition is generally studied for multi-product firms. Since we study homogenous goods, this section focuses on single-product firms. Consider an industry with N firms; each firm i has marginal cost c_i. A firm chooses prices for all its products by maximizing $\Pi_i^{Bertrand} = (p_i - c_i) \cdot s_i$, where s_i is the market share of brand k sold by firm i. The FOCs of the problems with respect to the choice of price p_i are:

$$\begin{aligned} s_i + (p_i - c_i)\frac{\partial s_i}{\partial p_i} &= 0 \\ \frac{(p_i - c_i)}{p_i} \underbrace{\frac{\partial s_i}{\partial p_i}\frac{p_i}{s_i}}_{-\eta_i} \frac{p_i}{p_i} &= -1 \\ \frac{(p_i - c_i)}{p_i} &= \frac{1}{\eta_i}, \end{aligned} \tag{A5}$$

which results in a similar relation between elasticities and markups as (A4). Once again, the main difference between this equation and that in the main text (1) is the absence of the ratio of the supply derivatives of firm i and its competitors $(-i)$.

A.3 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 ψ^t and ψ^h the marginal costs for thermal and hydro respectively, then we have the profit function for each period t

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

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

$$V(w_0, K) := \mathbb{E}_\delta \left[\max_{\substack{w_{t+1}(w_t+\delta_t,K) \\ q_t(w_t+\delta_t,K)}} \sum_{t=0}^{\infty} \beta^t \Pi(w_t + \delta_t - w_{t+1}, q_t) \right] \tag{A6}$$

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

$$V(w_0, K) = \mathbb{E}_{\delta_0} \left[\max_{\substack{w_1 \le w_0 + \delta_0 \\ q_0 \le K}} \{\Pi(w_0 + \delta_0 - w_1, q_0) + \beta V(w_1, K)\} \right] \tag{A7}$$

Proposition A.3 *When $GR(.)$ is a strictly concave and twice differentiable function, the marginal benefit of holding water decreases in thermal capacity K, i.e. $V_{21} < 0$.*

Proof. Since the gross revenue GR is strictly concave, it follows from standard arguments that V is also strictly concave.

Consider formulation (A7) 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

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

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 (A6). 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

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

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

Therefore, we have

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

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. □

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:

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

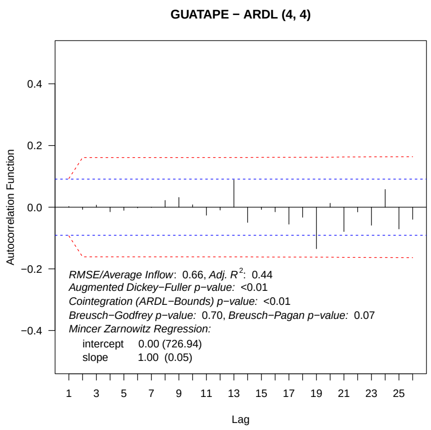
where K denotes the number of control variables in $\mathbf{x}_{j,t-q}$.

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.

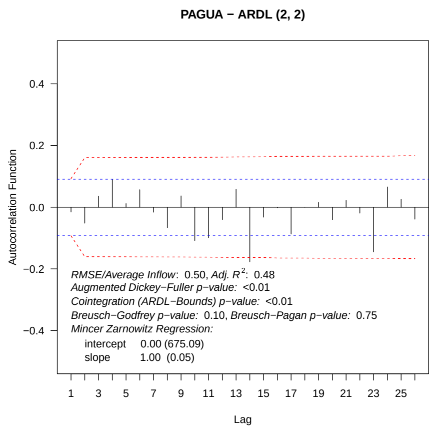
Quality of the fit. Figures B1 and B2 report the autocorrelation function and the Ljung-box test for the error term ϵ_t in (B2) for the largest dams in Colombia in the period we consider. The p-values of Ljung-box test never reject the null of autocorrelation.

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.

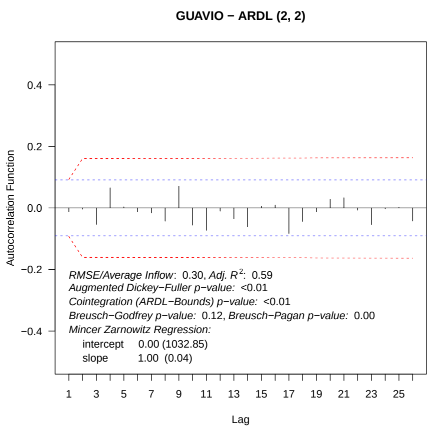
Figure B1: ARDL model diagnostics for some of the largest dams in Colombia in our sample period



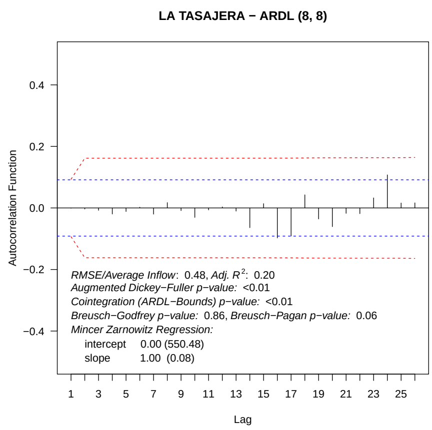
(a) Guatape



(b) Pagua



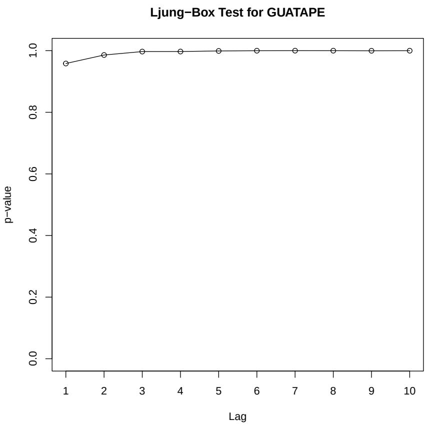
(c) Guavio



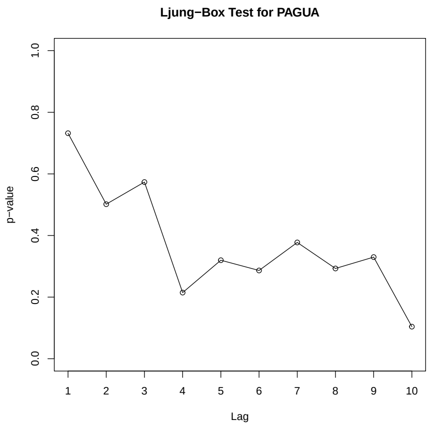
(d) La Tasajera

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.

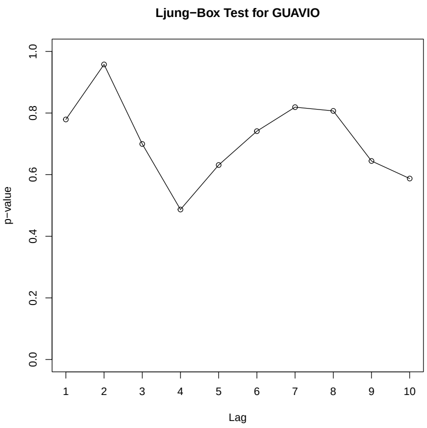
Figure B2: Ljung boxes for some of the largest dams in Colombia



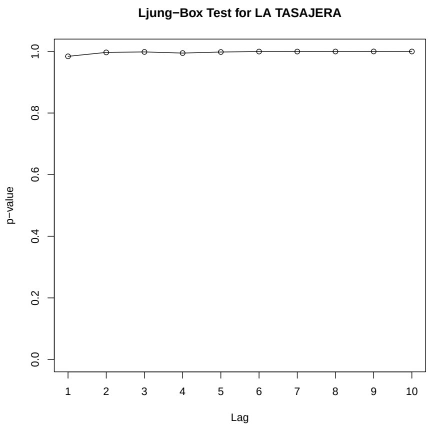
(a) Guatape



(b) Pagua



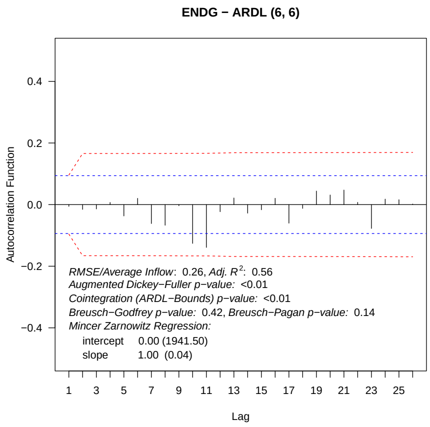
(c) Guavio



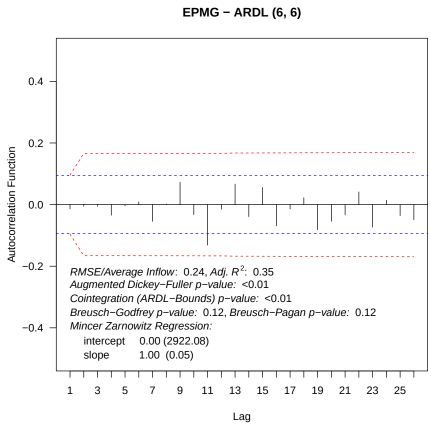
(d) La Tasajera

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.

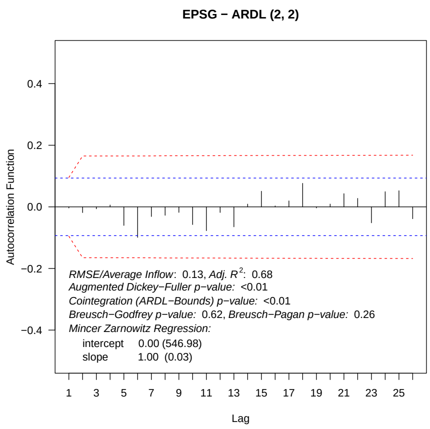
Figure B3: ARDL model diagnostics at firm level



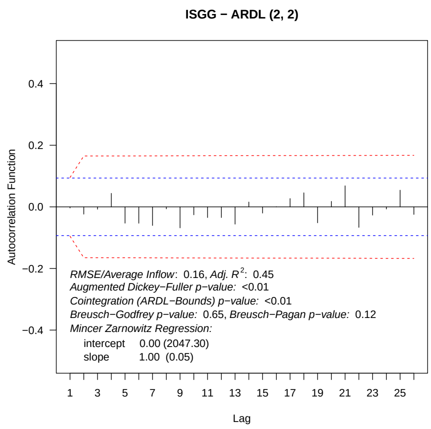
(a) ENDG



(b) EPMG



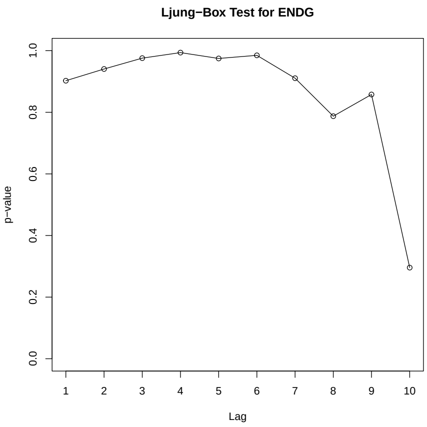
(c) EPSG



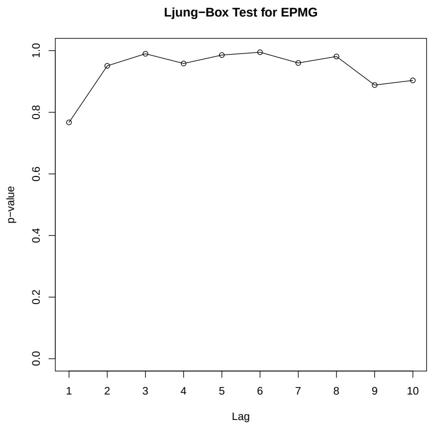
(d) ISGG

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.

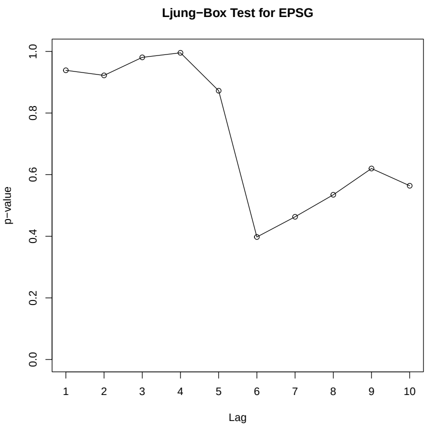
Figure B4: Ljung boxes at the firm level



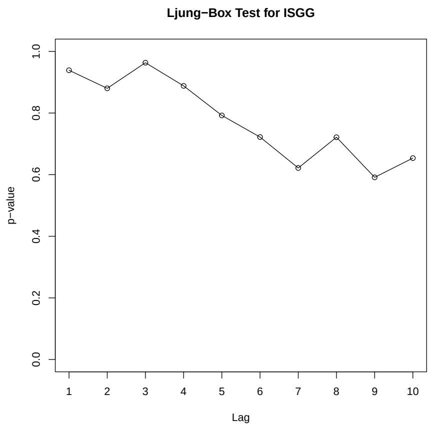
(a) ENDG



(b) Pagua



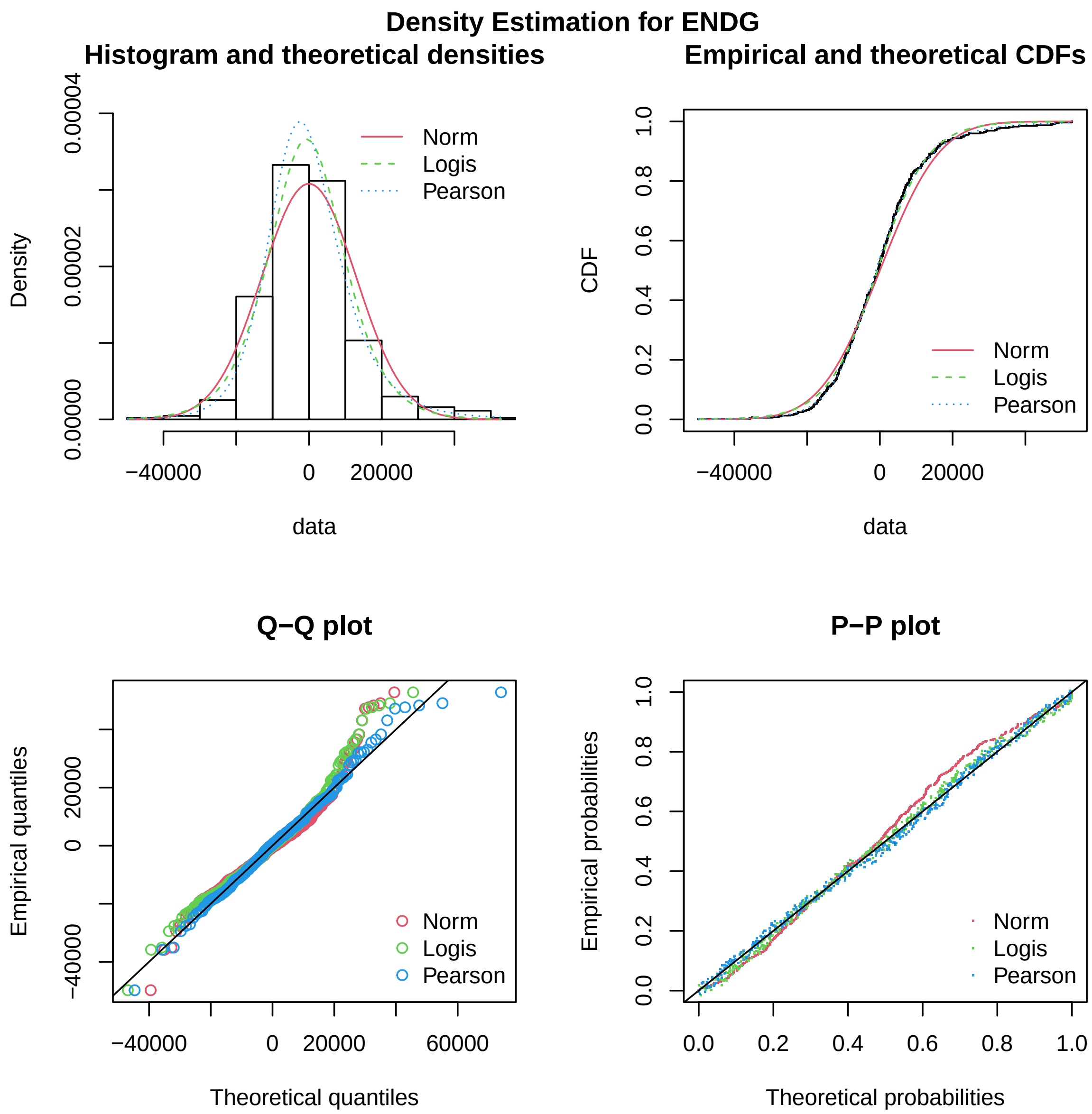
(c) EPSG



(d) ISGG

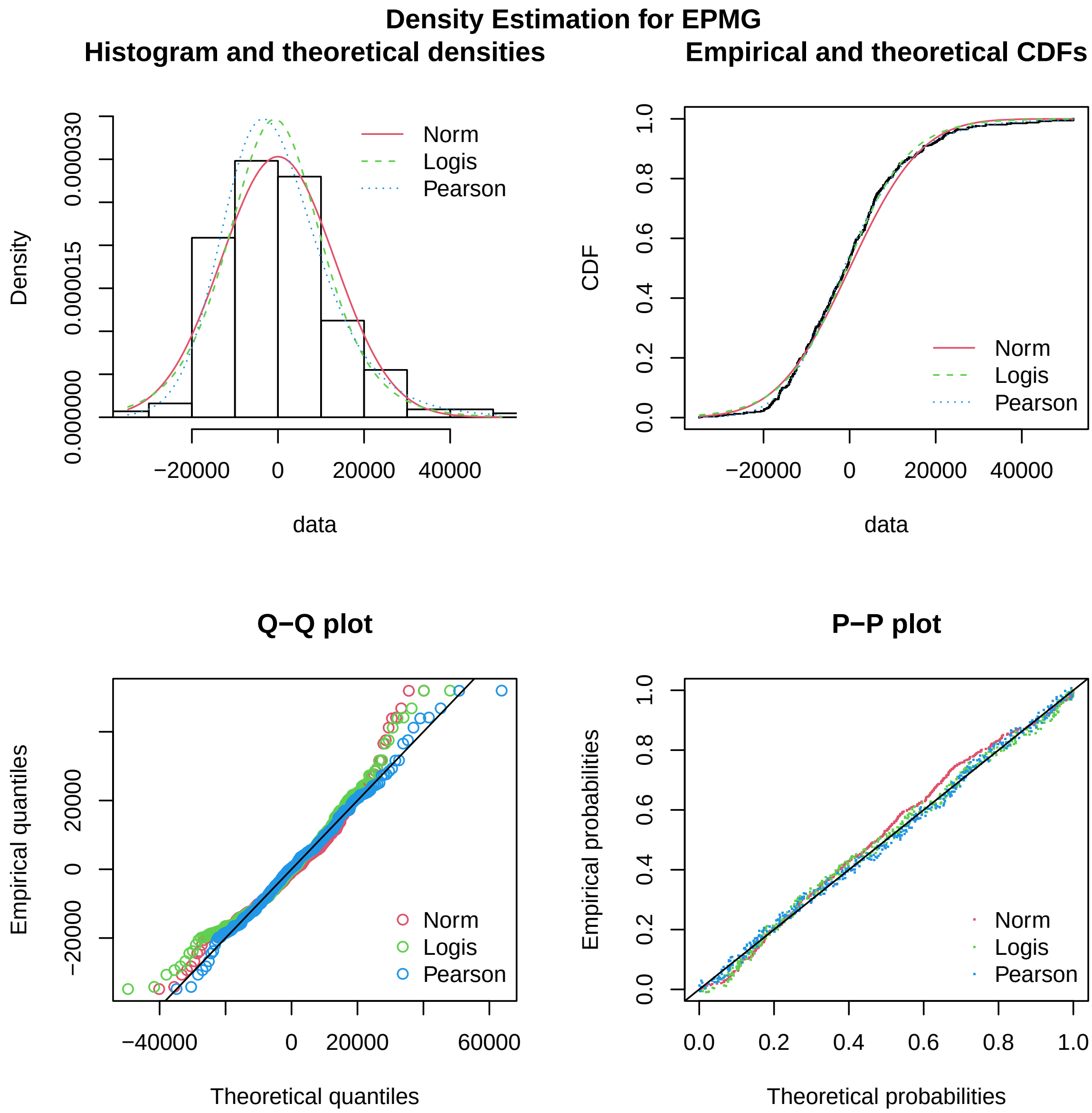
Notes: The plot shows the p-values of Ljung-box tests of whether any of a group of autocorrelations of a time series are different from zero.

Figure B5: Transition matrix for ENDG



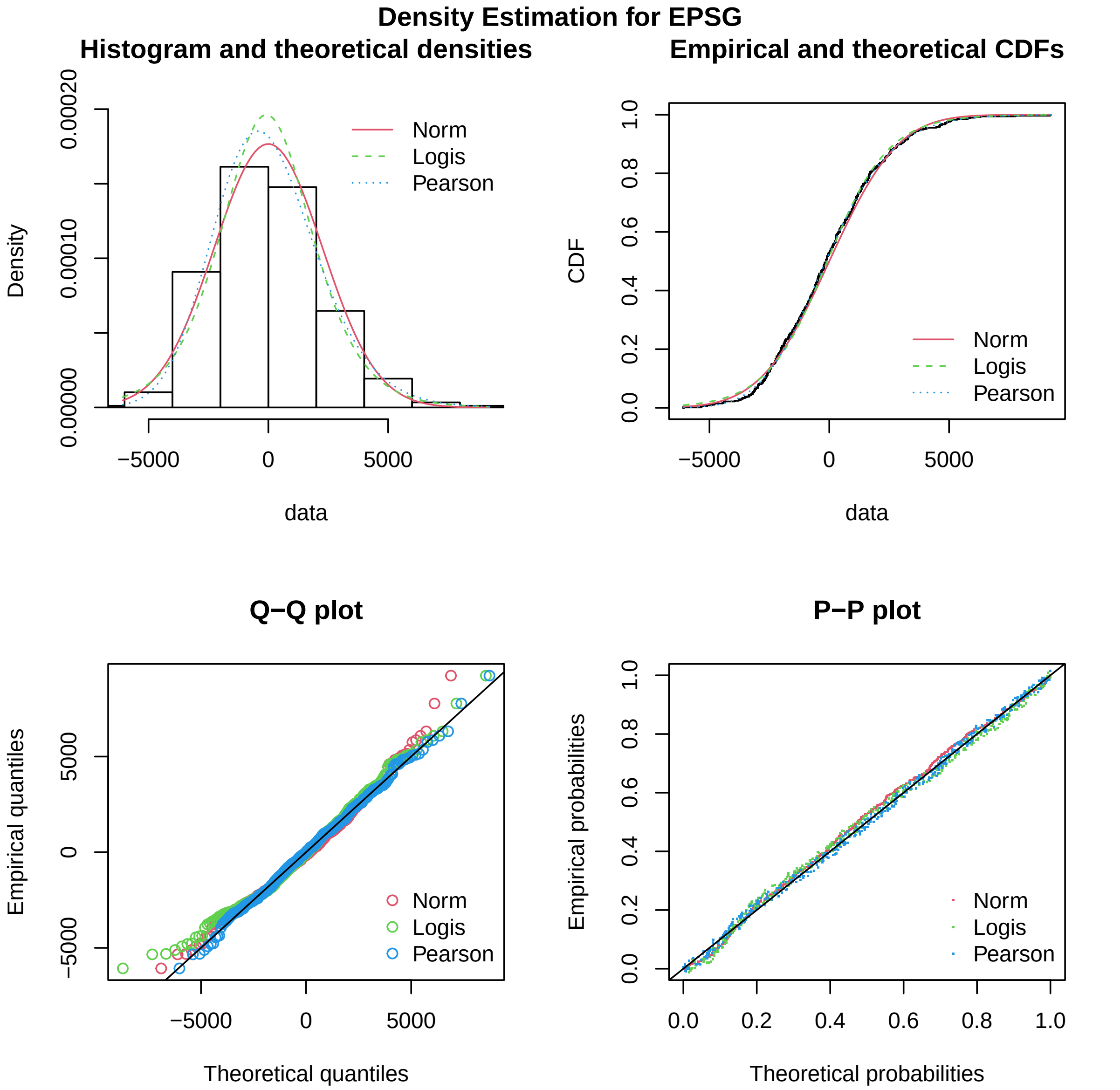
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

Figure B6: Transition matrix for EPMG



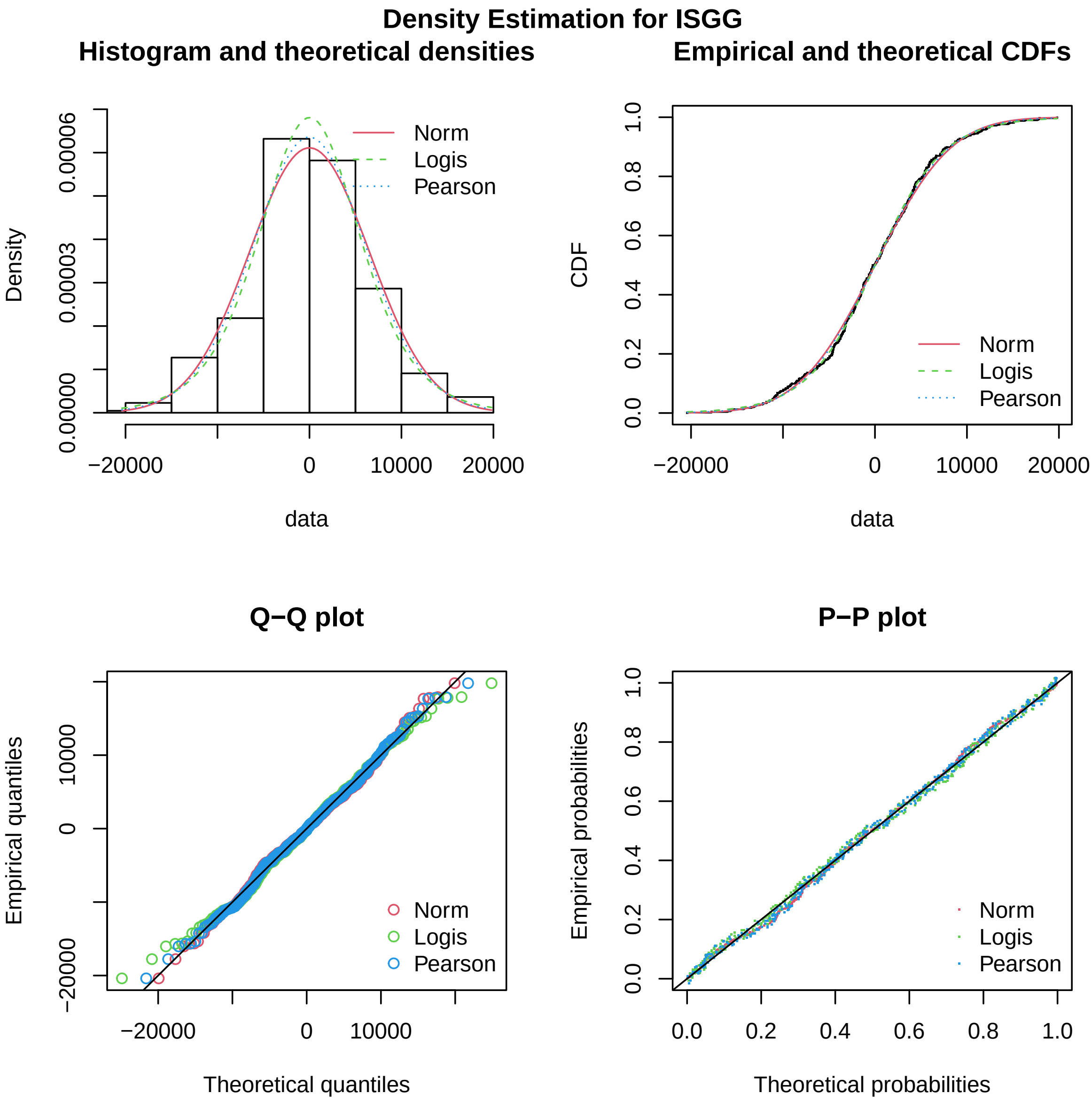
Note: The plots show the quality of the fit of the normal, logistic, and Pearson Type IV distribution to the error term from the ARDL model.

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 (2) 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 4.2.2. 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.[3]

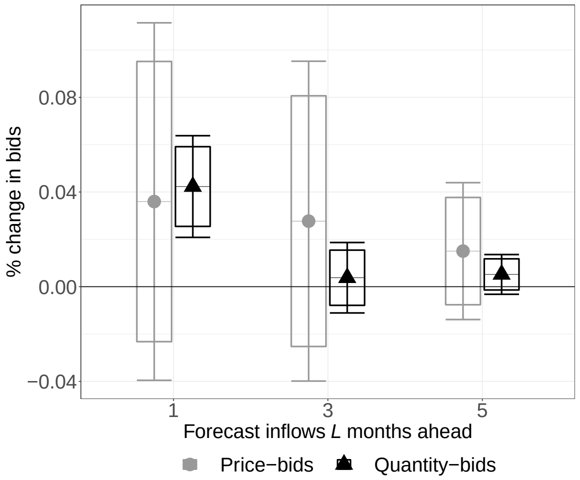
C.1.2 The Response of "Sibling" Thermal Generators

The coefficient estimates are in Figure C2. As in Section 4.2.2, 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.

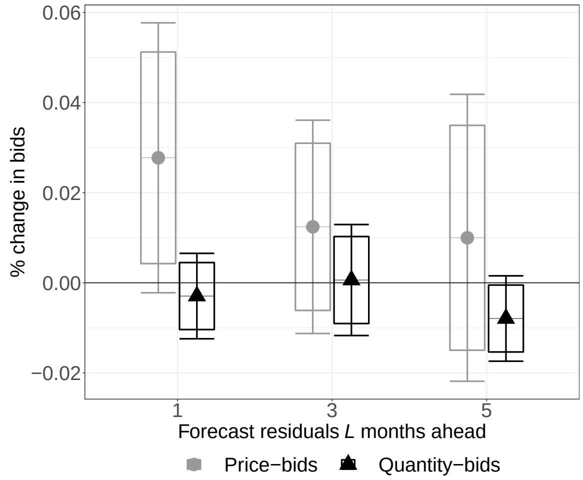
[3]Some price-bid coefficients are positive in Panel (a). However, this result is rather noisy, as suggested by the slightly higher response of price bids to the one-month forecast in Panel (b). The rationale is that generators submit only one price bid per day but multiple quantity bids; thus, there is less variation in price bids. Controlling for lagged quantities (in logs) in the price-bids regressions (B3) and (2) 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*

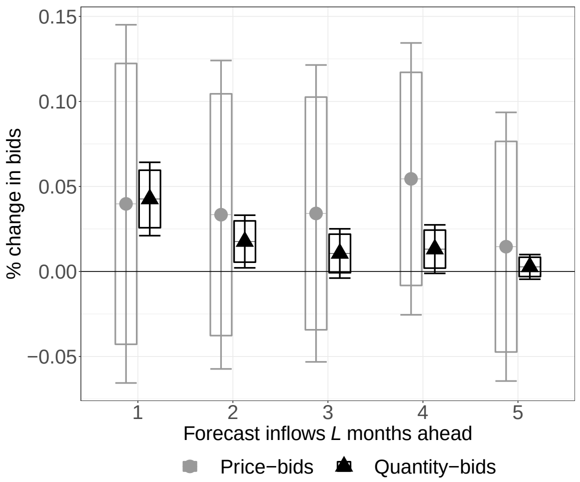


(a) Expected inflows (standardized forecasts)

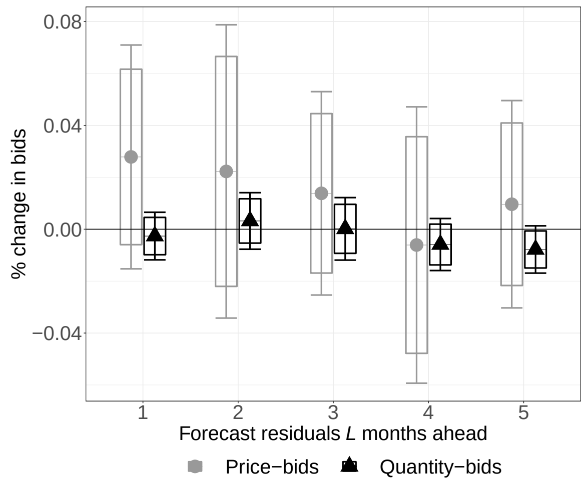


(b) Unexpected inflows (forecast residuals)

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



(c) Expected inflows (standardized forecasts)



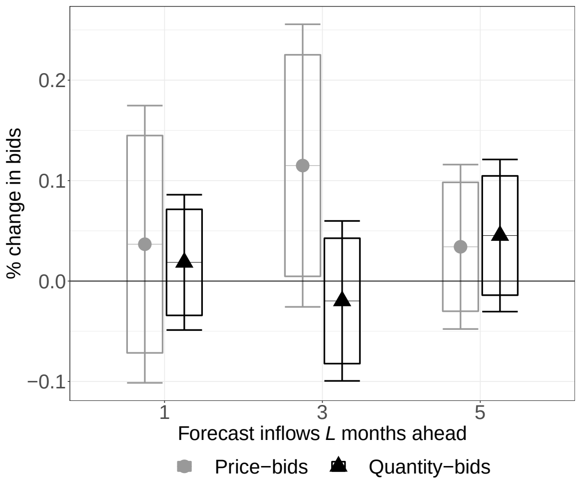
(d) Unexpected inflows (forecast residuals)

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.

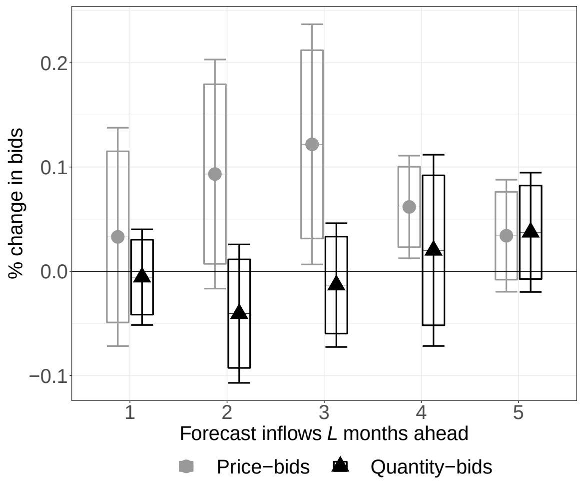
C.1.3 The Response to Competitors' Inflow Forecasts

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



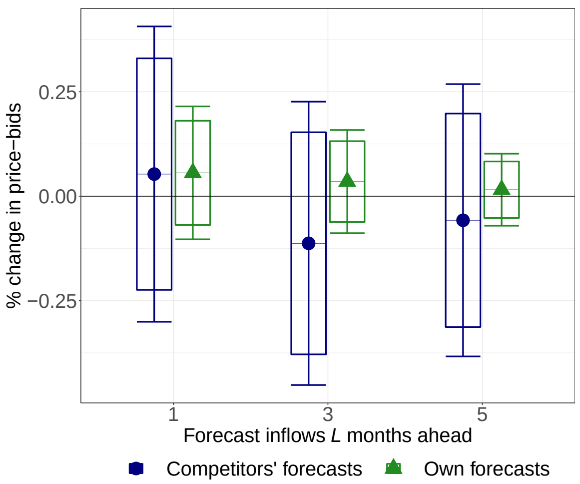
(a) Single regression



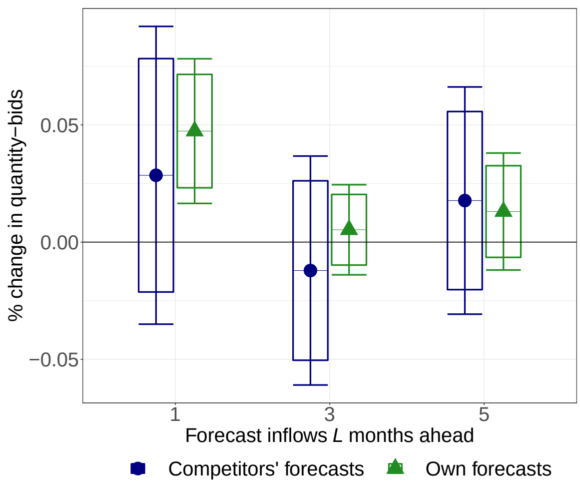
(b) Separate regressions

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.[4]

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.

[4] 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

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

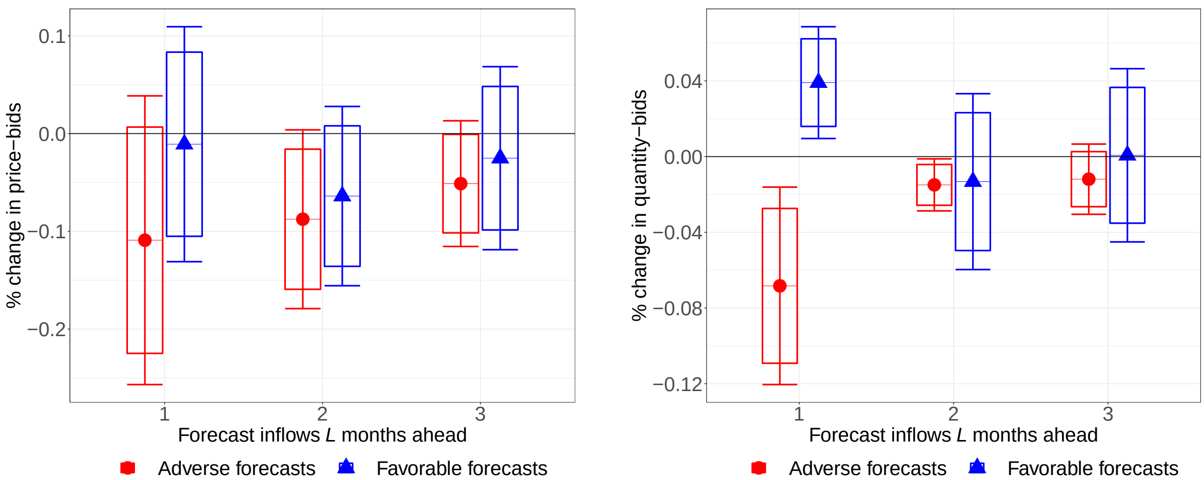
Notes: This table presents the coefficient estimates from the following regression

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

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

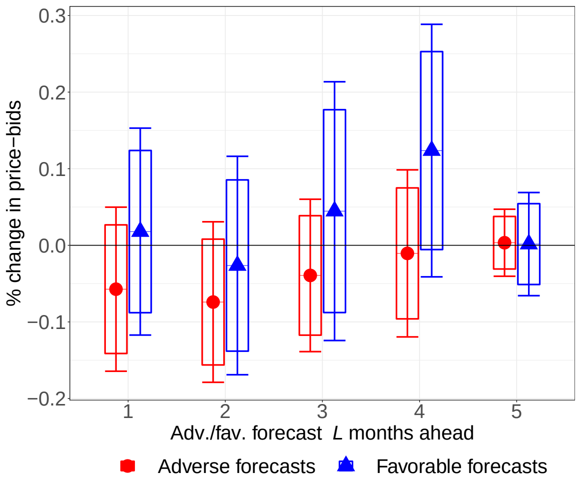
Figure C4: Hydropower generators' responses to inflow forecasts over 1, 2, and 3 months



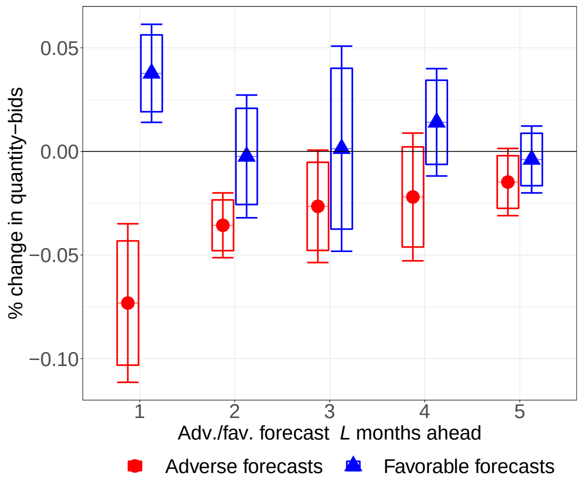
(a) Price-bids (b) Quantity-bids

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts according to (2). 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



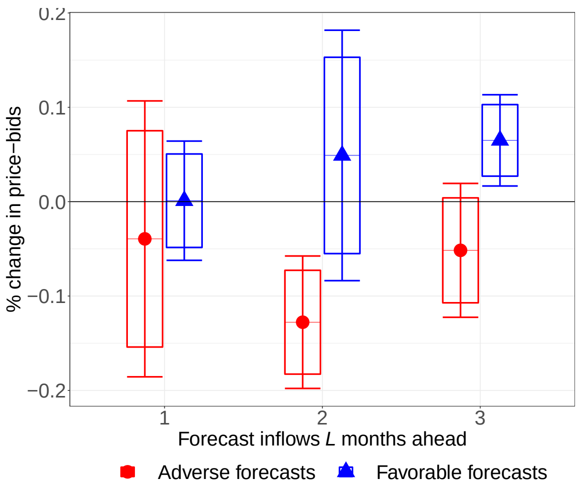
(a) Price-bids



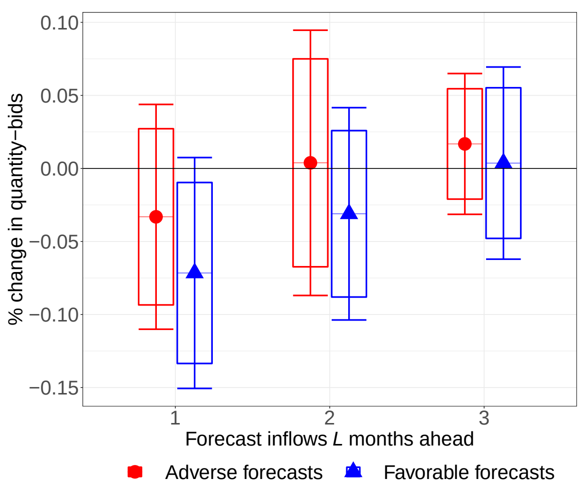
(b) Quantity-bids

Notes: The figure studies how hydropower generators respond to favorable or adverse future water forecasts by running (2) 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



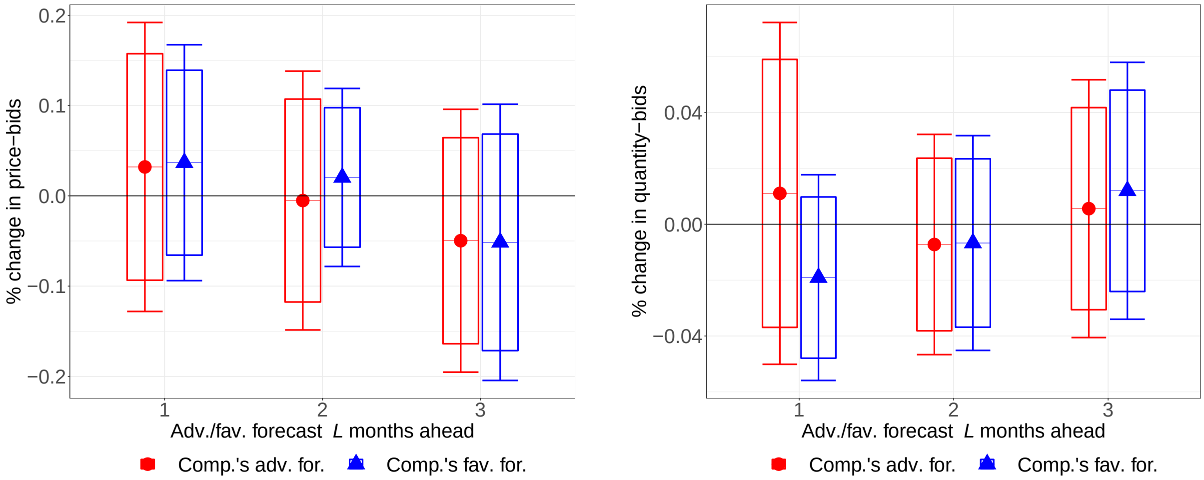
(a) Price-bids



(b) Quantity-bids

Notes: The figure studies how sibling thermal generators respond to favorable or adverse future water forecasts according to (2). 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 (2). 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.

Table C3: The impact of technology substitution on spot prices across seasons

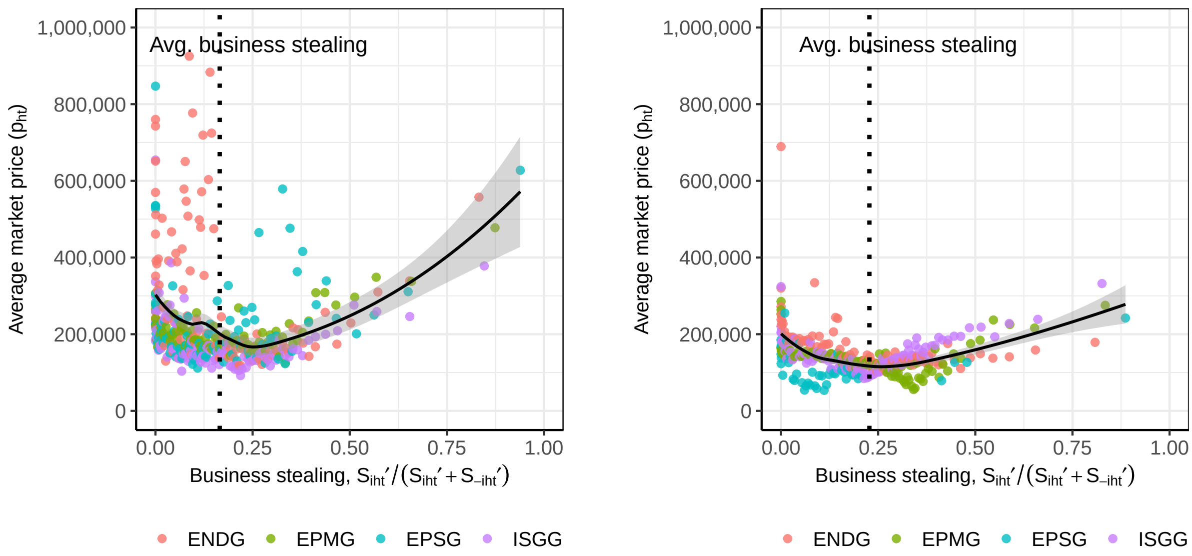
	(1)	(2)
	Hourly average price across weeks (ln)	
Total sibling thermal capacity (GW)	−0.007 85	−0.005 454***
	(0.007 04)	(0.000 799)
Adverse inflows (3 months)	0.0229	0.3343**
	(0.0842)	(0.0765)
Adverse inflows (5 months)	0.120	−0.241
	(0.214)	(0.117)
Thermal cap. available to adv. inflows (3 months)	−0.162	−2.769**
	(0.812)	(0.747)
Thermal cap. available to adv. inflows (5 months)	−1.10	1.979
	(1.75)	(0.944)
Lag demand (ln)	1.869**	1.66*
	(0.633)	(0.64)
Lag contract position (ln)	−0.542*	−0.543
	(0.233)	(0.561)
FE: Year-by-month	✓	✓
FE: Hour	✓	✓
Median dep. variable (in ln)	11.934	11.958
Median dep. variable (in $COP/MWh)	152,401	156,120
Clustered s.e. by	Year & month	Year & month
Subset	Wet season	Dry season
N	5.040	2.424
R2 Adj.	0.914	0.920

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

Notes: This table shows the estimated coefficients from (3). The dependent variable is the hourly wholesale price (in logs) so that the coefficients can be interpreted as percentage changes. Unlike Table 1, this table estimates (3) on different seasons: the first column focuses on the wet season (from April to November) and the second column focuses on the dry season (from December to March). Standard errors are clustered by year and month.

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). Since demand is vertical $D_i^{R'} = -S_i'$: hence to avoid dividing by zeros, 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 $S'_{-iht}(p)$ as in (1) to account for $S'_{-iht}(p) \simeq 0$ 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 ($\psi^{thermal}$)	194897.17***	157783.19***	194739.39***	149699.10***
	(23,815.33)	(30,285.54)	(23,816.43)	(31,060.26)
Hydropower (ψ^{hydro})	117918.58***	68,920.91	127323.61***	51,297.15
	(15,763.87)	(109793.29)	(15,236.51)	(66,230.75)
	Intertemporal value of water (COP/MWh)			
Spline 1 (γ_1)	–4,172.94	3,466.69	555.13	10,797.46
	(5,199.93)	(4,433.25)	(2,860.60)	(6,706.77)
Spline 2 (γ_2)	–1.914e-03	–2.502e-03	–2.985e-03*	–3.576e-03*
	(1.431e-03)	(2.011e-03)	(1.493e-03)	(1.961e-03)
Spline 3 (γ_3)	6.524e-09*	1.599e-08*	9.504e-09*	1.382e-08*
	(3.325e-09)	(8.588e-09)	(4.730e-09)	(7.090e-09)
Spline 4 (γ_4)	1.470e-08	–2.310e-08	–4.796e-09	–1.996e-08
	(9.490e-09)	(2.091e-08)	(9.418e-09)	(1.420e-08)
	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 (ψ^{hydro})	147.35	192.14	130.37	1,628.33
SW F (γ_1)	469.69	869.78	568.03	249.90
SW F (γ_2)	664.20	415.03	233.01	370.99
SW F (γ_3)	65.98	80.57	537.50	172.45
SW F (γ_4)	26.91	15.47	752.78	55.22
Anderson Rubin F	19.74	43.46	196.42	106.90
KP Wald	5.74	9.41	8.47	21.39
Overid. p-value	0.15	0.13	0.10	0.16
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 (10) 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. The standard errors are clustered at the level of the generator. 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 ($\psi^{thermal}$)	204,727.14***	143,319.87***	220,441.60***	146,635.86***
	(28,325.54)	(25,840.50)	(30,818.24)	(24,543.39)
Hydropower (ψ^{hydro})	46,491.28	28,163.59	28,458.10	60,353.00
	(52,823.03)	(69,216.84)	(37,397.66)	(51,818.25)
Intertemporal value of water (COP/MWh)				
Spline 1 (γ_1)	–797.45	–6,751.10	–9,712.11*	–3,744.90
	(3,944.05)	(5,278.98)	(5,659.04)	(4,094.15)
Spline 2 (γ_2)	–3.346e-03*	–3.154e-04	–2.173e-04	–1.064e-03
	(1.695e-03)	(1.657e-03)	(2.093e-03)	(1.500e-03)
Spline 3 (γ_3)	–4.894e-09	2.009e-08*	–1.621e-08	1.837e-08*
	(8.692e-09)	(1.091e-08)	(1.744e-08)	(9.650e-09)
Spline 4 (γ_4)	4.070e-08	–3.179e-08*	4.205e-08	–2.848e-08*
	(2.422e-08)	(1.698e-08)	(3.381e-08)	(1.501e-08)
Spline 5 (γ_5)	–2.216e-08	8.949e-08**	4.422e-08*	8.251e-08**
	(2.844e-08)	(3.901e-08)	(2.212e-08)	(3.421e-08)
Fixed Effects				
Firm	✓	✓	✓	✓
Generator	✓	✓	✓	✓
Month-by-technology		✓		✓
Hour	✓	✓	✓	✓
Week-by-year	✓	✓		
FE: Date			✓	✓
Clustered s.e.	Generator	Generator	Generator	Generator
SW F ($\psi^{thermal}$)	154.12	224.24	1,529.34	130.50
SW F (ψ^{hydro})	516.90	378.63	715.46	1,885.82
SW F (γ_1)	995.28	2,977.43	344.76	266.18
SW F (γ_2)	125.25	1,159.14	533.56	166.11
SW F (γ_3)	310.90	130.10	423.58	228.60
SW F (γ_4)	83.29	57.88	998.67	62.75
SW F (γ_5)	181.17	98.96	298.75	124.10
Anderson Rubin F	10.30	111.61	70.19	106.90
KP Wald	24.47	13.34	12.20	26.58
Overid. p-value	0.13	0.29	0.26	0.22
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 (10) 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. The standard errors are clustered at the level of the generator. 2,900 COP $\simeq$ 1 US$

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

	(1)	(2)	(3)	(4)
	Marginal costs (COP/MWh)			
Thermal ($\psi^{thermal}$)	195,271.35***	152,621.02***	194,831.41***	151,112.79***
	(23,993.80)	(30,884.62)	(23,621.62)	(30,492.26)
Hydropower (ψ^{hydro})	120408.48***	32,919.28	128840.47***	59,085.78
	(16,258.70)	(78,427.99)	(15,439.79)	(63,782.79)
	Intertemporal value of water (COP/MWh)			
Spline 1 (γ_1)	–2,720.98	6,297.20	1,569.04	10,291.14
	(5,204.24)	(5,100.84)	(3,059.75)	(6,504.18)
Spline 2 (γ_2)	–2.752e-03*	–2.829e-03	–3.485e-03**	–3.836e-03*
	(1.534e-03)	(2.031e-03)	(1.649e-03)	(2.136e-03)
Spline 3 (γ_3)	7.278e-09*	1.527e-08*	1.025e-08*	1.538e-08*
	(3.639e-09)	(8.119e-09)	(5.077e-09)	(7.788e-09)
Spline 4 (γ_4)	1.844e-08	–2.010e-08	–4.491e-09	–2.165e-08
	(1.183e-08)	(1.624e-08)	(1.016e-08)	(1.494e-08)
	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 (10) 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. The standard errors are clustered at the level of the generator. 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 (7) – 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.[5] 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 (7) are computed using the envelop theorem. Their smoothed versions are

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

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

F Model Fit

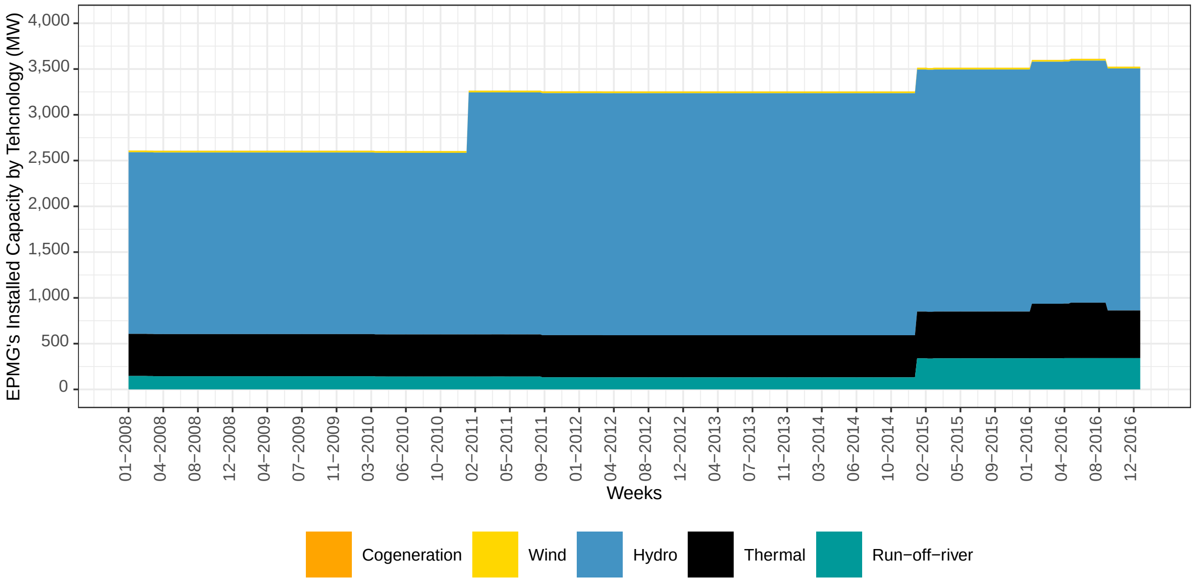
Table F1: Hourly prices across simulations

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

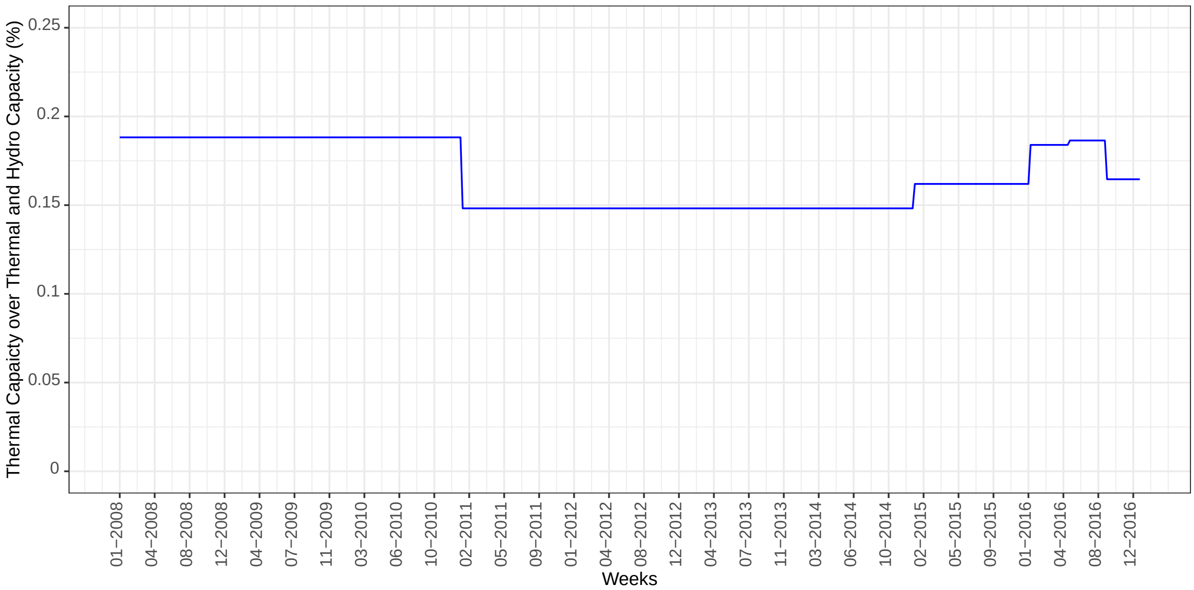
Notes: The table compares average hourly prices across the simulated and actual data. The simulation model is described in Section 6.2. The simulations in this table employ a different number of steps in the first and second panels. 2,900 COP $\simeq$ 1 US$.

Figure F1: EPMG's total installed capacity by technology

(a) EPMG's installed capacity over time

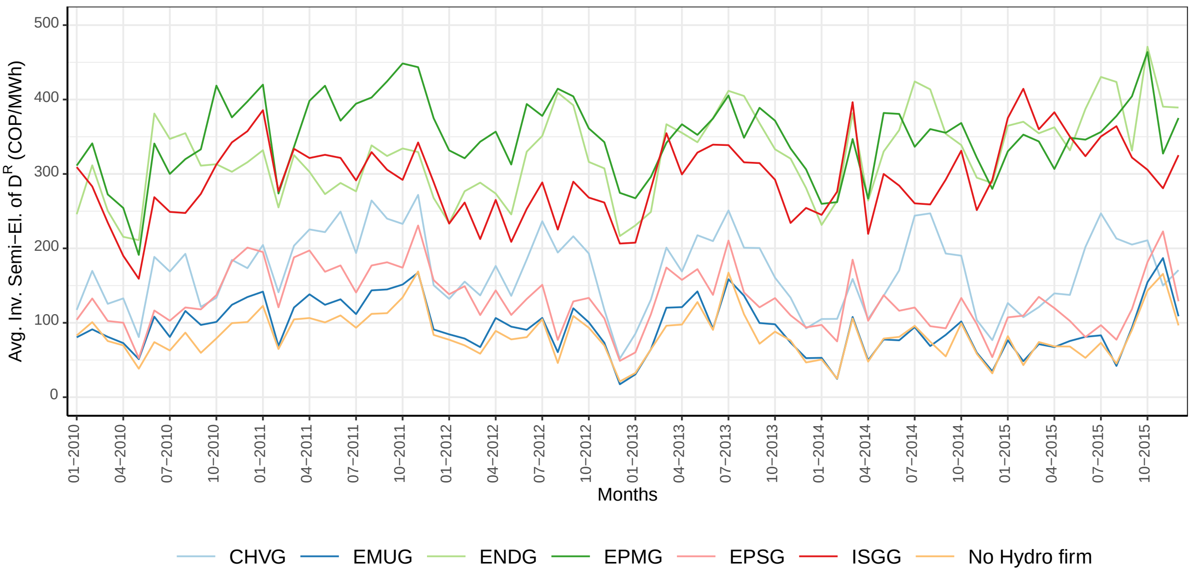


(b) Thermal capacity as a percentage of EPMG's thermal and hydro capacity



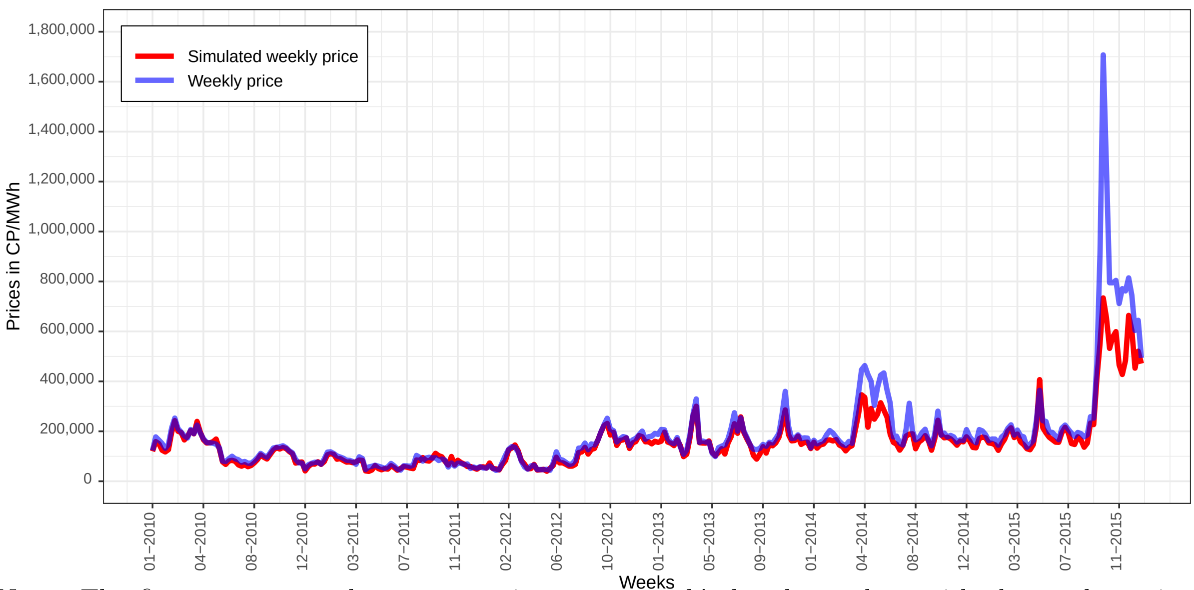
Note: The relative contribution of different technologies to EPMG's installed capacity over time.

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

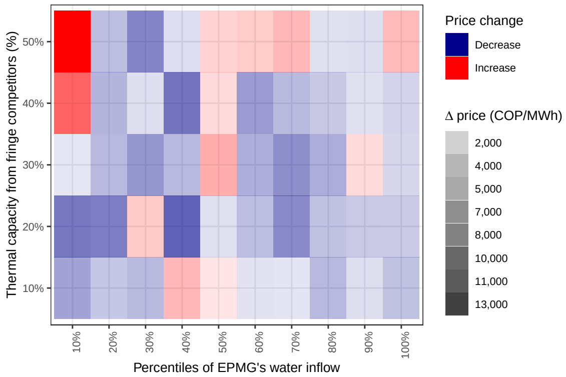


Note: The figure compares the average price over a week's hourly markets with the market prices obtained from solving EMPG's profit maximization problem (11) for each hourly market. The solver employs thirty steps to discretize the demand and the value function and 10 steps for each technology-specific supply ($M = Z = 30$, $K = 10$). 2,900 COP $\simeq$ 1 US$.

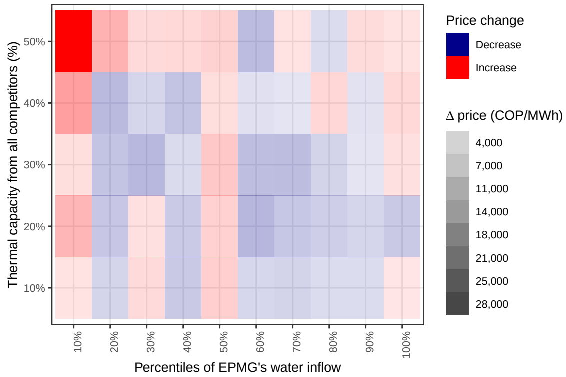
G Counterfactual Analyses: Tables and Figures

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

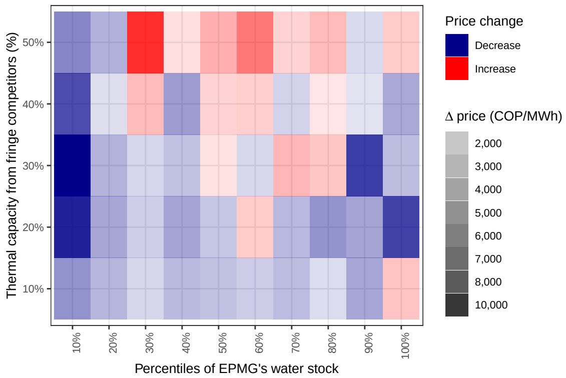


(a) Transferring $x\%$ from all fringe firms

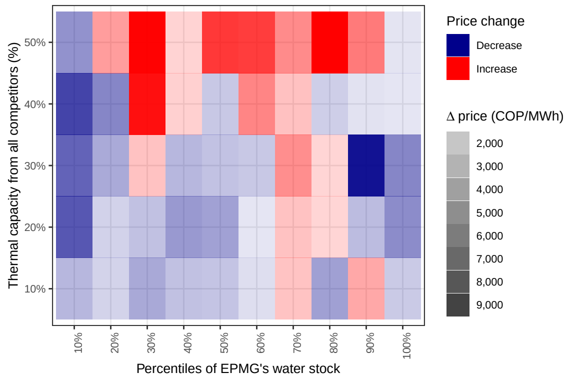


(b) Transferring $x\%$ from all firms

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



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

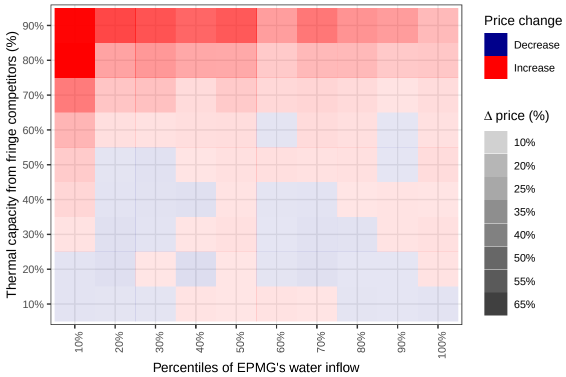


(d) Transferring $x\%$ from all firms

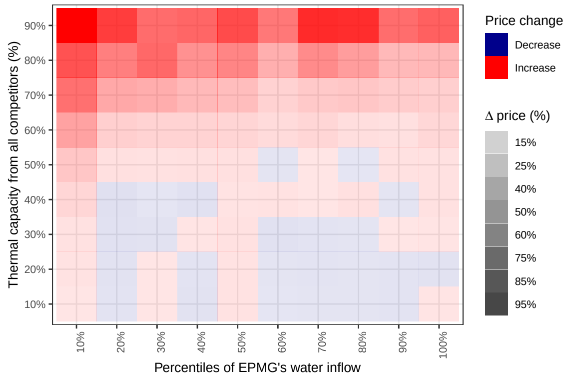
Notes: The figure presents the results from the counterfactual exercises discussed comparing observed prices with counterfactual market prices as we endow the market leading firm with a fraction of its competitors' thermal capacities (y-axis) for varying levels of scarcity (x-axis). Top (bottom) panels 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 10, 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

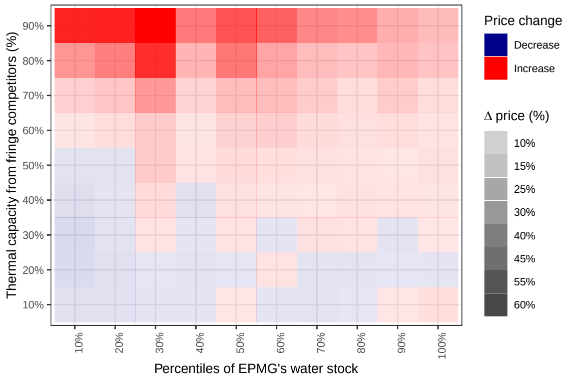


(a) Transferring $x\%$ from all fringe firms

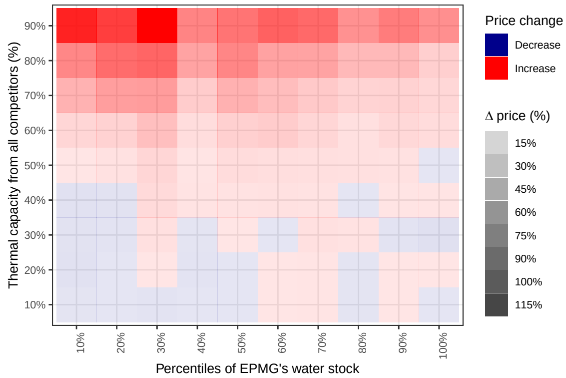


(b) Transferring $x\%$ from all firms

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

References in the Online Appendix

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

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