Measuring Market Power in Network-Constrained Markets*

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Abstract

Producers in locational pricing markets have the ability to exercise market power by impacting the extent to which transport capacity constraints bind. We extend the single-location residual demand curve concept to a residual demand hypersurface that quantifies the impact of a supplier's output change at one location on prices at all locations. This concept improves our ability to explain the offers suppliers submit in the Italian locational pricing electricity market and demonstrates why the locations of a firm's generation capacity determines the size and direction of locational price changes associated with the divestment of a fixed amount of generation capacity.

Keywords: Locational pricing markets, Transmission network congestion, Unilateral market power

JEL Codes: L1, L9, Q4

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1 Introduction

Many products are physically delivered through pipelines, high-voltage transmission lines, transportation corridors, or telecommunications networks that are often subject to physical or operational constraints that limit the flow of the product between locations. When such constraints are present, the ability of a firm to influence locational prices can depend not only on its overall market share but also on the sizes and locations of its production capacity within the delivery network.

Wholesale electricity is transmitted through a network with finite capacity and the flows on this network are governed by the laws of physics.[1] The seven formal wholesale electricity markets in the United States—California (CAISO), Midcontinent (MISO), New England (ISO-NE), New York (NYISO), Pennsylvania-New Jersey-Maryland Interconnection (PJM), Texas (ERCOT), and Southwest Power Pool (SPP)—that serve more than two-thirds of the nation's electricity load and an increasing number of foreign markets, employ locational pricing mechanisms that explicitly account for the impact of capacity constraints between locations in the transmission network.

More granular pricing of electricity typically raises concerns about the exercise of local market power by suppliers that own one or more generation units taking advantage of their locations in the transmission network to increase their profits from selling energy.[2] This concern implies the need for methods to measure the market power of a supplier that owns multiple generation units at different locations in the transmission network in a locational pricing market.[3] The challenge of measuring the ability to exercise unilateral market power in network capacity-constrained settings extends beyond electricity and arises in other sectors as well, such as transportation, telecommunications, and natural gas.

We derive a general methodology for measuring the ability of a supplier that own generation units at multiple locations in the transmission grid to exercise unilateral market power in a lo-

[1] Wood et al. (2013) provides an introduction to electric power system operation.

[2] Local market power is not mitigated, and in many cases is amplified, by simplified market mechanisms that fail to account for the configuration transmission network and other relevant real-time operating constraints. This occurs because market participants recognize that these operating constraints must be respected in real time, and they anticipate compensation for resolving these constraints, as demonstrated in Graf et al. (2020b) for Italy and Daví-Arderius and Graf (2025) for Spain and Portugal.

[3] In regional transmission organization (RTO) markets in the United States, the Federal Energy Regulatory Commission (FERC) typically considers the RTO as the default relevant geographic market for market power analysis and evidence of smaller geographic markets is based on the historical frequency of binding transmission constraints (paragraphs 29–31 of 188 FERC ¶61,003, 2024).

cational pricing market. To this end, we extend the concept of a residual demand curve from a single-location market to a *residual demand system*, represented as a set of *residual demand hypersurfaces* that quantifies how a supplier that owns generation capacity at multiple locations can influence locational prices across the entire network.

We demonstrate the usefulness of our residual demand system concept for: (1) the modeling expected profit-maximizing offer prices for a supplier that owns generation units at multiple locations, (2) quantifying the impact of a large supplier divesting itself of a fixed quantity of generation capacity at different locations in the transmission network, and (3) developing own-location and cross-location measures of a supplier's ability to exercise unilateral market power at all locations in the grid. We also develop a stochastic equilibrium model of competition between two large firms setting locational quantities against the distribution of residual demand hypersurfaces determined by the offer curves of the remaining firms and use it to determine the equilibrium implications of different locational capacity divestment scenarios.

Computing the residual demand hypersurface faced by a supplier in a locational pricing market with finite transmission capacity across locations is significantly more challenging than computing a residual demand curve in a single price market with infinite transmission capacity across locations. First, it requires constructing a model of the actual price-setting process in the wholesale electricity market that replicates actual locational prices and output levels given the generation unit-specific offer curves submitted by all market participants. This typically requires solving a constrained optimization problem that yields locational quantities and prices for any set of locational offer curves consistent with the market rules submitted by all suppliers and any set of locational bid curves submitted by all demanders given the configuration of the transmission network. Points along a supplier's residual demand hypersurface are obtained by solving this optimization problem for a grid of inelastic locational output levels for that supplier using the offer curves of all other suppliers and the bid curves submitted by all demanders. The resulting vectors of locational prices and inelastic locational output level pairs are points along the supplier's residual demand hypersurface.

Computing an expected profit-maximizing offer curve for a supplier in a locational pricing market requires finding market-clearing prices and quantities for each possible realization of the distribution of residual demand hypersurfaces faced by the supplier for any offer curve consistent

with the market rules. The supplier's expected profit for a candidate set of locational offer curves is equal to the expected value of the realized profits earned for each possible residual demand hypersurface realization in this distribution. The set of locational offer curves consistent with the market rules that yields the highest expected value of these realized profits for each possible residual demand hypersurface realization is the solution to this optimization problem. We formulate and solve this problem as a Mathematical Program with Equilibrium Constraints (MPEC) as described in Luo et al. (1996).

Applying this expected profit-maximizing offer curve problem to a sample of 175 hourly market outcomes from the Italian day-ahead market, we find that our estimated expected-profit maximizing offer curves yield a 9.8% higher average profit for the largest supplier [3.6% higher for its main competitor] relative to the average profit using the actual offer curves submitted by both of these strategic suppliers. We then compute estimated profit-maximizing offer curves for these two suppliers assuming infinite transmission capacity between all locations in the Italian grid for the same distribution of residual demand curves faced by the supplier.[4] For the actual configuration of the transmission network in Italy, we compute the average profits that the two suppliers would earn in the Italian locational pricing market if they submitted their infinite transmission capacity optimal offer curve. The largest supplier's average profits would be only 5% higher versus 9.8% higher with optimal offer curves for the distribution of residual demand hypersurfaces. For the main competitor of the incumbent firm, the corresponding numbers are 1.5% higher versus 3.6% higher. These results illustrate the importance of accounting for the fact that firms compete against a distribution of transmission network-constrained residual demand hypersurfaces determined by the locational offer curves of their competitors and locational bid curves of all demanders, rather than simply a single aggregate offer curve of its competitors and a single aggregate bid curve of demanders as is implied by the assumption of infinite transfer capacity across locations in the transmission network.

Using our residual demand hypersurface framework to assess the competitive effects of generation capacity divestment from a supplier owning capacity at multiple locations, we find that

[4]Note that residual demand hypersurfaces become residual demand curves under the assumption of infinite transmission capacity between locations. Consequently, the market-clearing mechanism used to solve this infinite transmission capacity expected profit-maximizing offer curves always pays the same market-clearing price to all generation units as shown in Wolak (2000) and Wolak (2007).

divesting the same amount of capacity at different locations in the transmission network yields significantly different counterfactual locational prices. Using our expected profit-maximizing offer curve framework, we find that divesting 1.2 GW capacity from the largest firm in the center of Italy reduces the average price there by 6.7% and increases the average price in the north of Italy by 0.7%, both relative to the actual average prices at these locations. Divesting the same amount of capacity in the north of Italy increases the average price in the center of Italy by 0.3% and reduces the average price in the north of Italy by 8.1%.

Our residual demand hypersurfaces framework can be used to compute own- and cross-price inverse semi-elasticities of the residual demand hypersurface facing a supplier at each location in the transmission network that it owns generation capacity. These inverse semi-elasticities measure the ability of a supplier to exercise unilateral local market power at all locations that it owns generation capacity by withholding output at one location. These own- and cross-price inverse semi-elasticities can be used to design local market power mitigation (LMPM) mechanisms and define local markets for merger and antitrust analysis in locational pricing markets.[5] Developing a mechanism for using these inverse semi-elasticities to determine when a supplier's offer price at a location is worthy of mitigation or to define a local market for electricity generation is likely to require analysis by the relevant regulatory authority that is both context and region specific. Nevertheless, the empirical examples we provide for the Italian market are suggestive of the usefulness of these measures for these two tasks.

To assess the sensitivity of our capacity divestment analysis to the fact that a firm's offer behavior will impact its competitor's residual demand hypersurfaces, we develop a stochastic equilibrium model of transmission network-constrained competition between the two largest firms in Italy setting locational quantities against the distribution of residual demand hypersurfaces determined by the offer curves of their competitors and locational demand bid curves. This equilibrium analysis accounts for the fact that the two strategic suppliers' locational quantity choices jointly impact realized flows in the transmission network through smoothed versions of our residual demand hypersurfaces. This equilibrium model finds qualitatively similar locational price changes from the locational divestment scenarios from our expected profit-maximizing offer behavior anal-

[5] Graf et al. (2021) point out the necessity of automatic local market power mitigation mechanisms in all offer-based wholesale electricity markets and survey the range of existing designs in United States locational marginal pricing markets.

ysis, but smaller average price reductions to load. The expected profit-maximizing offer curve and the locational quantity-setting equilibrium results both demonstrate the importance of accounting for the location of generation capacity and demands as well as the configuration of the transmission network in assessing the competitive impacts of generation capacity divestment actions.

Competition in a wholesale electricity market is traditionally modeled using a single-location supply function equilibrium with single-location market demand uncertainty as described in Klemperer and Meyer (1989). However, the increasing share of energy from intermittent wind and solar units—sited according to resource availability—calls into question this approach to modeling competition among large firms with thermal generation across multiple locations. There are at least two reasons why this theoretical framework may not adequately represent actual outcomes in a locational pricing wholesale electricity market with significant wind and solar generation capacity at multiple locations throughout the transmission network which can increase the frequency and magnitude that transmission network constraints or other system operating constraints bind.

First, participants in these markets submit location-specific, non-decreasing step functions with a finite number of price and quantity steps. As noted in Wolak (2003a) and Wolak (2007), this requirement invalidates the approach used by Klemperer and Meyer (1989) to compute a firm's expected profit-maximizing offer curve as the envelope of best-response price-quantity pairs for all possible residual demand curves. Second, even with continuous and increasing supply functions,[6] transmission constraints cause expected profit-maximizing offer curves to depend on the probability distribution of random shocks to locational demands and transmission capacity, and the equations to be solved to compute the resulting offer curves are highly nonlinear, as shown in Wilson (2008).

The economics literature on expected profit-maximizing offer behavior in multi-unit auction markets, such as wholesale electricity markets, has largely ignored modeling the impact of transmission constraints on the pricing of energy.[7] We extend the model of expected profit-maximizing offer behavior by a supplier that owns multiple generation units in Wolak (2000) and Wolak (2007) to the case of a locational pricing market where generation units and demand centers are located at different points in a transmission network with finite transfer capacity between locations. The

[6] See, e.g., Green and Newbery (1992); Sioshansi and Oren (2007); Anderson and Hu (2008).
[7] See, e.g., Wolak (2000, 2007); Hortaçsu and Puller (2008); Reguant (2014).

increasing amount of wind and solar resources, often distant from major load centers, in virtually all wholesale electricity markets increases the importance of understanding the determinants of locational market power.

The remainder of the article proceeds as follows. In Section 2, we extend the residual demand curve measure of the ability of a supplier to exercise unilateral market power in a single-location market to the residual demand hypersurface for network-connected locational markets with finite transfer capacity. We then introduce residual demand hypersurface locational own- and cross-price inverse semi-elasticities and discusses how they might be used in the design of a local market power mitigation mechanism or to define a relevant antitrust market. Finally, we introduce our model of expected profit-maximizing offer behavior in a locational pricing market with finite transmission network based on the distribution of residual demand hypersurfaces faced by the supplier, as well as a locational quantity game using a distribution of smooth residual demand hypersurfaces. We describe institutional details, data requirements, and data curation in Section 3. In Section 4, we deploy our suite of models to the Italian wholesale electricity market. We show how expected profit-maximizing offer curves that ignore the potential for binding transmission network constraints yield lower expected profits than expected profit-maximizing offer curves that account for the configuration of the transmission network, location of demand bid curves, and location of generation capacity. In Section 5, we demonstrate how the expected profit-maximizing offer curves of a large supplier and the locational prices that result from these offer curves would change because of different locations of a divestment of the same total quantity of generation capacity. Section 6 concludes and suggests directions for future research.

2 Measuring Market Power in Locational Pricing Markets

This section introduces methods for measuring the ability to exercise unilateral market power in locational pricing markets. We first explain market clearing in a simple two-location market with finite transfer capacity. This market-clearing formulation provides the foundation for analyzing residual demand hypersurfaces,[8] which measure the potential for exercising unilateral market power in network-connected markets with finite transfer capacity. The hypersurfaces capture the

[8]The higher-dimensional analogues of curves (in $\mathbb{R}^2$) and surfaces (in $\mathbb{R}^3$) are called hypersurfaces which are regular submanifolds (Tu, 2011).

fact that an output choice at one location can influence prices in both locations, which is relevant for supplier operating units at both locations.

We then extend our residual demand hypersurface analysis to multi-location offer- and bid-based markets, as found in wholesale electricity markets. The residual demand hypersurfaces enable the computation of own- and cross-price inverse semi-elasticities, which may be used to measure the ability of the supplier to exercise unilateral market power. We also describe a more granular but computationally more challenging approach to measure unilateral market power: computing expected profit-maximizing offer curves. We conclude the section with a locational quantity game in which strategic suppliers compete using a distribution of smooth residual demand hypersurfaces.

These residual demand hypersurfaces capture all of the factors that allow a supplier, with generation units located across multiple points in the transmission network, to exercise unilateral market power: the configuration of the transmission network, the locational offer curves of all other suppliers, the locational bid curves of all demanders, and the specific market-clearing mechanism used to set locational prices and quantities. The own-price and cross-price inverse semi-elasticities of the residual demand hypersurfaces facing supplier can form the basis for the design of a local market power mitigation mechanism or the analysis of a proposed merger. However, the determination of how much of an ability to exercise unilateral market power and for how many hours during the year is too much and therefore worthy of mitigation is a decision made by the relevant regulatory authority based on input from a wide variety of stakeholder groups. Nevertheless, our residual demand hypersurface approach captures significantly more of the factors that enable a supplier to exercise unilateral market power in a locational pricing electricity market.

Two-Location Market with Finite Transfer Capacity

Assume two markets, $z = \{1, 2\}$, for a homogeneous good and a firm that owns production capacity in both markets that are connected by finite transfer capacity. For fixed locational demand functions and fixed locational aggregate outputs of firm i's competitors in market z, Q^z_{-i}, firm i's locational inverse residual demand function in market z can be written as $P^z(Q^1, Q^2)$ where

$Q^z = Q_i^z + Q_{-i}^z$ and Q_i^z is the output of firm i in market z and Q^z is the total output in market z.

Under the assumption of locational quantity-setting competition, each profit-maximizing firm i will solve the following optimization problem assuming the locational quantity choices of its competitors are fixed:

$$\max_{Q_i^1, Q_i^2} P^1(Q^1, Q^2)Q_i^1 + P^2(Q^1, Q^2)Q_i^2 - C_i^1(Q_i^1) - C_i^2(Q_i^2). \tag{1}$$

The transport capacity between the two markets determines the relationship between locational prices, P^1 and P^2, and locational outputs, Q^1 and Q^2. In a single integrated market, $P^1(Q^1, Q^2) = P^2(Q^1, Q^2) = P(Q)$ where $Q = Q^1 + Q^2$, which *implicitly* means all output is produced and sold at the same location.[9]

Before we derive the inverse residual demand surfaces $P^1(Q^1, Q^2)$ and $P^2(Q^1, Q^2)$, for our two-location model, we characterize how the transport capacity between the two locations impacts the partial derivatives of these functions with respect to the quantities at each location. If the transport capacity constraint is not binding for given levels of Q^1, Q^2, or equivalently, if there is infinite transport capacity between the two markets, $\frac{\partial P^1}{\partial Q_i^1} = \frac{\partial P^1}{\partial Q_i^2} = \frac{\partial P^2}{\partial Q_i^1} = \frac{\partial P^2}{\partial Q_i^2} = \frac{\partial P}{\partial Q_i}$, simply because $P^1 = P^2 = P$ and a change in the firm's output at either location will have the same effect on the single market-clearing price P. If the network is constrained, then $\frac{\partial P^1}{\partial Q_i^2} = \frac{\partial P^2}{\partial Q_i^1} = 0$ because a change in the firm's output in market 2 would not affect P^1 and a change in output in market 1 would not affect P^2, simply because the binding constraint separates the two markets. The partial derivatives, $\frac{\partial P^1}{\partial Q_i^1}$ and $\frac{\partial P^2}{\partial Q_i^2}$, would equal the slope of the locational inverse residual demand curve in market 1 and market 2, respectively. These properties of $P^1(Q^1, Q^2)$ and $P^2(Q^1, Q^2)$ are why we refer to them as inverse residual demand surfaces.

As shown in Wolak (2000), in a single-location market the residual demand function for any supplier has a closed form solution characterized by the market demand curve net of the aggregate willingness to supply curve for all remaining suppliers besides the one under consideration. In network-connected locational markets this solution is not possible. Locational prices are the result of solving a locational market-clearing optimization problem that explicitly takes into account the

[9]This single integrated market assumption is commonly employed in studies of market power in wholesale electricity markets, e.g., Ito and Reguant (2016), Puller (2007), and Bushnell et al. (2008). Mercadal (2022) treats locations as separate pre-determined markets based on transmission network characteristics. Ryan (2021) proposes an iterative method for modeling transmission capacity constraints in the Indian electricity market.

transport capacity constraint between the two markets.

To illustrate this mechanism, assume first that both markets can be described by the same linear inverse demand curve, $P^1(D^1) = P^2(D^2)$, as depicted in Figure 1. The price at location z, P^z, is a function of the demand served at location z, D^z, which corresponds to the total output in location z, Q^z, plus any imports or exports. Given a fixed aggregate output of firm i's competitors in each market, Q^1_{-i} and Q^2_{-i}, firm i may be able to cause the symmetric transport capacity between the two markets, $\overline{f}$, to bind by its choice of outputs, Q^1_i, Q^2_i. The price for market 1 is on the left vertical axis and the price for market 2 is on the right vertical axis in each of the two panels in Figure 1. The total output in market 1, Q^1, is on the horizontal axis read from the left to the right, and the total output in market 2, Q^2, is on the horizontal axis read from the right to the left.

Panels (a) and (b) of Figure 1 show how the two interconnected markets would clear given a fixed amount of transport capacity between the two markets and a fixed amount of total production of firm i's competitors in each market, Q^1_{-i} and Q^2_{-i}. The maximum transport capacity, $\overline{f}$, is indicated by the line between the equilibrium demand levels and the output levels in the two markets. Panel (a) shows that given firm i's locational outputs, the transport constraint will not bind because the resulting export from market 1 to market 2, f, or equivalently the resulting import of market 2 from market 1, $-f$, does not exceed the physical transport capacity limit, $\overline{f}$. Although the transport capacity between the two markets is unconstrained, some output in market 1 is used to serve demand in market 2. Holding the total amount of output of firm i in the two markets constant, there are many combinations of output produced in each market that would leave the transport capacity between the two markets unconstrained.

This outcome changes if firm i increases its output substantially in market 1 and reduces its output substantially in market 2, as depicted in Panel (b). Firm i's outputs in market 1 and market 2 lead to congestion of the transport capacity because not all the supply of market 1 can be exported to market 2 and still yield identical prices in the two markets. Prices in the two markets must differ to accommodate firm i's output choices in the two markets.

Whether the transport network will be congested for a given level of output in each market, inverse demand curves in each market, and fixed transport capacity connecting the two markets can be determined by the assumed locational market-clearing problem below:

$$f^*(Q^1, Q^2) = \arg\max_f \quad \int_0^{Q^1+f} P^1(\tau_1)\, d\tau_1 \; + \int_0^{Q^2-f} P^2(\tau_2)\, d\tau_2 \tag{2a}$$

$$\text{subject to} \quad -\overline{f} \leq f \leq \overline{f}, \tag{2b}$$

$$Q^i + f \geq 0, \quad i \in \{1, 2\}. \tag{2c}$$

where f^* is the transport flow that maximizes the sum of total surplus in both markets.

Problem (2) can be solved for any pair of market-level aggregate outputs, Q^1 and Q^2, resulting in quantities consumed in each market, locational prices, and the optimal transport or trade volume f^*, given the physical transport network and its constraints. (2b) limits the absolute transport flow to not exceed $\overline{f}$.[10] The prices in each market will be equal if the constraints in (2b) are not binding and will differ otherwise.[11]

This pricing model (2) yields a mapping from the total output in each market to prices in each market ($\mathbb{R}^2_+ \mapsto \mathbb{R}^2_+$). Holding Q^1_{-i} and Q^2_{-i} fixed, we can solve it for any vector of firm i's market-level outputs. In electricity markets, we assume transport between locations is costless, but the model is easily extendable to connected markets with a non-zero transport cost. For example, in the case of a per unit charge to move the product between markets equal to c, the term $c\,|f|$ must be added to the objective function (2a). The consequence of a transport cost is that less trade will occur.

Unlike the setting studied by Borenstein et al. (2000), we allow each firm to own production capacity in both locations. The firm's outputs in markets 1 and 2 will determine whether the transport capacity between the markets is congested. If the firm had production capacity in only one market, it could cause the transport capacity to bind in the manner discussed in Borenstein et al. (2000). However, having production capacity in both markets is likely to increase the firm's ability to cause the transport capacity constraint to bind because it can set output in both markets instead of a single market. This becomes evident from Panel (b) of Figure 1. The firm could find

[10] For simplicity, we assume that the upper limit of integration in each market will be greater or equal to the lower limit of integration in each market. This can be achieved by requiring market-level aggregate outputs, Q^1 and Q^2, to be greater or equal to the trade volume f, see (2c).

[11] Although we use the terms *residual demand hypersurface* and *residual demand system* interchangeably, the fact that prices in two or more locations can be equal because the transport constraint between them is not binding is an important distinction that makes *residual demand hypersurface* the more appropriate terminology.

it unilaterally profitable to set a high output in market 1 even when the firm may not be able to recover its market-level cost at such an output level. This action allows the firm to cause the transport capacity between the markets to bind which increases the price in market 2 and increases the firm's revenue from sales in market 2.[12]

The optimization problem in (2) can be solved for many locational output pairs for firm i to obtain the corresponding pairs of locational market-clearing prices. Hence, there is a functional relationship between the firm i's output vector and the market-clearing price vector, which can be used to construct a residual demand hypersurface, one for each of the two connected markets where the firm owns capacity. Visualizing the relationship between the price at one location and the firm's two locational outputs can be represented by a three-dimensional surface where the firm's locational outputs are on the horizontal axes (x, y-axes) and the locational price is on the vertical axis (z-axis). We refer to these graphs as the inverse residual demand hypersurface. For two connected markets, there are two of these three-dimensional surfaces.[13]

Figure 2 plots the inverse residual demand hypersurfaces corresponding to the example depicted in Figure 1. Panel (a) shows the three-dimensional surface for the price in market 1 and Panel (b) for the price in market 2. Remember that every point on the surfaces in Panel (a) and Panel (b) for the same level of Q_i^1 and Q_i^2 are the result of solving the optimization problem in (2). In Panel (c), we show the price difference as a function of the two locational output levels of firm i. This figure illustrates the unilateral ability of firm i to cause the transport capacity constraint to bind. For all output combinations leading to an unconstrained single market (all the points where $P^2(Q_i^1, Q_i^2) = P^1(Q_i^1, Q_i^2)$ in Figure 2, Panel c), the residual demand surface is effectively the residual demand curve for the unconstrained single price market. However, it is important to note that whether there is a binding transport constraint between the markets depends on the firm's output in each market, as is evident from Figure 2.[14]

[12] In Borenstein et al. (2000) the firm's locational residual demand curve can replaced by the market level residual demand curve for the output range that would lead to a nonbinding transport capacity constraint. Points where the slope of the firm's residual demand curve changes are solely determined by its locational output for a given transport capacity limit and the output of its competitor. This is no longer the case when firms own production capacity in the two local markets connected by finite transfer capacity.

[13] We follow the standard economic convention for demand curves of plotting price on the vertical axis (z-axis).

[14] In Figures O.3 and O.4 of the Online Appendix, we provide an example with asymmetric markets. Specifically, we lower the intercept of market 1 which makes it a lower-price market relative to market 2. As a result the uncongested market price, Figure O.3, Panel (a), will be lower than in the symmetric market case depicted in Figure 1, Panel (a). But the market-clearing price difference will be larger (Figure O.3, Panel b) when the transport constraint is binding for the same parameters used in Figure 1, Panel (b).

The residual demand hypersurface for firm i gives the demand for its output at each location for a pair of locational prices, or equivalently, the resulting pair of locational prices for a given pair of firm i's locational output levels. This concept allows us to incorporate a transport capacity constraint that connects markets in our measure of the ability of a supplier to exercise local market power. It also illustrates a potentially important avenue for exercising unilateral local market power by suppliers that own production capacity in two or more locationally distinct markets, which is particularly relevant to wholesale electricity markets.

Residual Demand Hypersurfaces for a Locational Pricing Electricity Market

This section generalizes the two-location logic to an arbitrary number of locations for a network-constrained offer- and bid-based market, as found in wholesale electricity markets around the world. The basic approach to constructing a residual demand hypersurface described above continues to hold, but solving for locational market-clearing prices requires finding the combination of feasible locational supply and demand quantities that maximizes the sum of as-offered producer surplus and as-bid consumer surplus, subject to aggregate demand equaling aggregate supply and accounting for transmission network constraints between locations. Computing the residual demand hypersurface a supplier faces for locational pricing markets requires solving this same market-clearing optimization problem for a grid of inelastic locational output levels for the supplier's generation units given the locational offer curves of all other suppliers, locational demand bids, and the configuration of the transmission network.

Computing Locational Market-Clearing Prices and Quantities

We first explain how locational offer- and bid-based markets are cleared and locational prices and quantities are determined from offer and bid curves submitted by all market participants. We then demonstrate how a simplified version of this market-clearing algorithm is used to construct points along the residual demand hypersurface in such a setting.

Suppliers in locational pricing wholesale electricity markets typically submit weakly increasing step functions giving their willingness to supply energy at each location as function of the price at that location. Demanders submit weakly decreasing step functions, given their willingness to

purchase energy at each location as a function of the price at that location.

Let $\mathbf{b}_i^{o,z}$ and $\mathbf{g}_i^{o,z}$ be supplier i's vectors of offer prices and corresponding offer quantities for location z and for all offer steps $k = 1, \ldots, K_i^{o,z}$, where $K_i^{o,z}$ is the number of offer price and quantity pairs submitted by supplier i in location z. Similarly, let $\mathbf{b}_j^{b,z}$ and $\mathbf{g}_j^{b,z}$ be demander j's vectors of bid prices and corresponding bid quantities for location z for all bid steps $m = 1, \ldots, M_j^{b,z}$, where $M_j^{b,z}$ is the number of bid price and quantity pairs submitted by demander j at location z.

A pair of offer price and corresponding offer quantity vectors $\mathbf{b}^o$ and $\mathbf{g}^o$ is the collection of offer curves for each supplier $i = 1, \ldots, I$ and each (pricing) location $z = 1, \ldots, Z$. A pair of bid price and corresponding bid quantity vectors $\mathbf{b}^b$ and $\mathbf{g}^b$ is the collection of each demander, $j = 1, \ldots, J$ and each (pricing) location $z = 1, \ldots, Z$.

The market operator determines two sets of decision variables. Let $x_{ik}^{o,z}$ denote the market-clearing quantity from increment k of supplier i at location z. We stack these awarded supply quantities across all suppliers, locations, and quantity increments into vector $\mathbf{x}^o \in \mathbb{R}^O$. Similarly, let $x_{jm}^{b,z}$ denote the market-clearing quantity from increment m of demander j at location z. We stack these awarded demand quantities across all demanders, locations, and quantity increments into vector $\mathbf{x}^b \in \mathbb{R}^B$. The market operator then solves the following linear program that maximizes total surplus—the difference between total as-bid consumer surplus and total as-offered producer surplus—subject to demand-supply balance and network transmission constraints:

$$\underset{\mathbf{x}^b, \mathbf{x}^o}{\text{maximize}} \quad (\mathbf{b}^b)^\top \mathbf{x}^b - (\mathbf{b}^o)^\top \mathbf{x}^o \tag{3a}$$

$$\text{subject to} \quad (\mathbf{1}_B)^\top \mathbf{x}^b - (\mathbf{1}_O)^\top \mathbf{x}^o = 0, \tag{3b}$$

$$\sum_{z=1}^{Z} A_{nl}^z \left((\mathbf{1}_{O^z})^\top \mathbf{x}^{o,z} - (\mathbf{1}_{B^z})^\top \mathbf{x}^{b,z} \right) \leq \overline{f}_{nl}, \quad (n,l) \in \mathcal{E}, \tag{3c}$$

$$\mathbf{0} \leq \mathbf{x}^o \leq \mathbf{g}^o, \;\; \mathbf{0} \leq \mathbf{x}^b \leq \mathbf{g}^b, \tag{3d}$$

where $\mathbf{1}_O$ is an O-dimensional vector of ones and $\mathbf{1}_B$ is a B-dimensional vector of ones. The vector $\mathbf{x}^{o,z}$ is composed of the elements of $\mathbf{x}^o$ for location z and $\mathbf{x}^{b,z}$ is composed of the elements of $\mathbf{x}^b$ for location z. $\mathbf{1}_{O^z}$ is a vector of ones of the same dimension as $\mathbf{x}^{o,z}$ and $\mathbf{1}_{B^z}$ is a vector of ones of the same dimension as $\mathbf{x}^{b,z}$.

The elements of the vectors $\mathbf{x}^b$ and $\mathbf{x}^o$ that maximize (3a) have to sum to the same value, i.e., system demand equals system supply (3b). Furthermore, these locational market-clearing quantities must satisfy the network feasibility constraints in (3c). Specifically, the resulting power flows should not exceed the nonnegative thermal limit $\overline{f}_{nl}$ of the transmission line from location n to location l. The coefficient A^z_{nl} in (3c) gives the contribution of a net injection at location z to the flow on transmission line $(n,l) \in \mathcal{E}$, where $\mathcal{E}$ contains all the transmission lines in the grid.[15] We treat transmission lines as directional, meaning that line (n,l) is different from line (l,n) and $\overline{f}_{nl}$ need not equal $\overline{f}_{ln}$.

Market-clearing quantity increments for suppliers, $\mathbf{x}^o$, must be nonnegative and less than or equal to their offered quantity increment levels ($\mathbf{g}^o$), and market-clearing quantity increments for demanders, $\mathbf{x}^b$, must be nonnegative and less their bid quantity increment levels for demanders ($\mathbf{g}^b$) as formulated in (3d). Let λ be the dual multiplier of the system balance constraint (3b) and μ_{nl} the dual multipliers of the transmission constraints in (3c). The locational market-clearing prices are:[16]

$$P^z = \lambda - \sum_{(n,l)\in\mathcal{E}} A^z_{nl}\mu_{nl}, \quad z = 1,\ldots,Z. \tag{4}$$

If all of the transmission capacity constraints in (3c) are not binding, their multipliers ($\mu_{nl}, (n,l) \in \mathcal{E}$) would be zero and hence the market-clearing price is the same in each location.

Computing Residual Demand Hypersurfaces for Multiple Locations

Computing the residual demand hypersurface of supplier i in a locational pricing electricity market requires solving the market-clearing optimization problem (3a)–(3d) for a grid of price inelastic locational output levels for firm i. Each vector of inelastic locational output levels, $\mathbf{Q}_i = \left(Q^1_i,\ldots,Q^Z_i\right)$, yields a corresponding vector of locational market-clearing prices, $\mathbf{P} = \left(P^1,\ldots,P^Z\right)$. These Z pairs of the locational outputs for firm i and corresponding locational prices are one point

[15] Matrix A is commonly denoted as the power transfer distribution factor (PTDF) matrix or shift factor matrix in the power system literature, see e.g., Kirschen and Strbac (2019). These PTDFs are typically derived from a direct current (DC) power flow model of the transmission network, which is a linear approximation to the alternating current (AC) power flow.

[16] Chapter 5 of Kirschen and Strbac (2019) and Chapters 7 and 8 of Wood et al. (2013) provide an introduction to locational marginal pricing in electricity markets with finite transmission capacity between locations. Note that we abstract away from pricing transmission losses which are accounted for in the determination of locational prices in US wholesale electricity markets but ignored in European markets.

on firm i's residual demand hypersurface. The vector of locational market-clearing prices associated with $\mathbf{Q}_i$ on firm i's residual demand hypersurface is the result of solving the following linear programming problem for the vector of locational outputs of firm i, $\mathbf{Q}_i$:

$$\underset{\mathbf{x}^b, \mathbf{x}^o_{-i}}{\text{maximize}} \quad (\mathbf{b}^b)^\top \mathbf{x}^b - (\mathbf{b}^o_{-i})^\top \mathbf{x}^o_{-i} \tag{5a}$$

$$\text{subject to} \quad (\mathbf{1}_B)^\top \mathbf{x}^b - (\mathbf{1}_{O_{-i}})^\top \mathbf{x}^o_{-i} - \sum_{z=1}^{Z} Q_i^z = 0, \tag{5b}$$

$$\sum_{z=1}^{Z} A^z_{nl} \left(Q_i^z + (\mathbf{1}_{O^z_{-i}})^\top \mathbf{x}^{o,z}_{-i} - (\mathbf{1}_{B^z})^\top \mathbf{x}^{b,z} \right) \leq \overline{f}_{nl}, \quad (n,l) \in \mathcal{E}, \tag{5c}$$

$$\mathbf{0} \leq \mathbf{x}^o_{-i} \leq \mathbf{g}^o_{-i}, \quad \mathbf{0} \leq \mathbf{x}^b \leq \mathbf{g}^b \,. \tag{5d}$$

The vectors $\mathbf{1}_{O_{-i}}, \mathbf{1}_{O^z_{-i}}, \mathbf{1}_B$, and $\mathbf{1}_{B^z}$ are vectors of 1's of the same dimension as $\mathbf{x}^o_{-i}, \mathbf{x}^{o,z}_{-i}, \mathbf{x}^b$, and $\mathbf{x}^{b,z}$. All other notation is as defined for the market-clearing optimization problem (3a)–(3d).

This optimization problem (5a)–(5d) is identical to the market-clearing problem (3a)–(3d) except the price-sensitive willingness to supply step functions of supplier i are replaced with price-inelastic locational quantities Q_i^z for $z = 1, \ldots, Z$ and $\mathbf{x}^b$ and $\mathbf{x}^o_{-i}$ are the choice variables. The vector of locational market-clearing prices $\mathbf{P}$ are derived from the optimal values of the dual variable of (5b), the energy balance constraint ($\lambda^{'}$), and the dual variables of (5c), the transmission constraints ($\mu^{'}_{nl}$), from solving (5a)–(5d). Specifically, the market-clearing price at location z for $\mathbf{Q}_i$, the vector of locational quantities for supplier i, is $P^z(\mathbf{Q}_i) = \lambda' - \sum_{(n,l)\in\mathcal{E}} A^z_{nl} \mu^{'}_{nl}$.[17] Solving this problem for a grid of values of the vector $\mathbf{Q}_i$ yields supplier i's residual demand hypersurface.[18]

Own- and Cross-Price Residual Demand Inverse Semi-Elasticities

The residual demand hypersurfaces can be used to compute own- and cross-price inverse semi-elasticities. These could be an input to the design of a local market power mitigation mechanism and be used to define local markets for merger and antitrust analyses. All locational marginal

[17] We add a "'" superscript to λ and the μ_{nl} to account for the fact that the dual multipliers that determine the $P^z(\mathbf{Q}_i)$ will differ from those that determine the P^z using firm i's locational offer curves.

[18] A residual demand hypersurface can show that the price at location z is unresponsive to changes in firm i's output at all locations. This residual demand hypersurface would be a horizontal plane implying that the firm i has no ability to change the price at location z from output changes at any location.

pricing electricity markets in the US have local market power mitigation mechanisms that limit the offer price a supplier can submit when it is deemed to have a substantial unilateral ability to exercise local market power (see, e.g., Graf et al., 2021). Withholding output at one location, impacts all locational prices by the same amount in an uncongested network. In a congested network, however, this is not always the case because binding transmission constraints segment the market. Hence, withholding output in one location may only increase the price in that location but not impact prices at other locations in the network by the same amount or at all.

Building on the inverse semi-elasticity measure of the ability of a supplier to exercise unilateral market power in a single-location market from McRae and Wolak (2014), we compute both inverse own- and cross-price semi-elasticities for each strategic supplier and each location. More precisely for each strategic supplier i we compute

$$\eta_i^{z,z'} = (Q_i^z/100)\frac{\partial P^{z'}(\mathbf{Q}_i)}{\partial Q_i^z}, \tag{6}$$

for any two locations z and z'. If $z = z'$ then $\eta_i^{z,z'}$ is the own-price inverse semi-elasticity, otherwise it is the cross-price inverse semi-elasticity of an output increase by firm i at location z on the price at location z'.

The own-price inverse semi-elasticity, $\eta_i^{z,z}$, measures the €/MWh change in the price at location z associated with supplier i increasing its output by 1 percent at that location. The cross-price inverse semi-elasticity $\eta_i^{z,z'}$ measures the €/MWh change in price at location z' associated with supplier i increasing its output by 1 percent at location z.

Expected Profit-Maximizing Offer Curves in a Locational Pricing Market

In this section, we present our model of expected profit-maximizing offer behavior in a locational pricing market that respects the market rules governing the set of allowable offer curves that all suppliers can submit, the allowable bid curves that all demanders can submit, and the actual market-clearing mechanism (3a)–(3d) used to compute the locational prices and quantities. When the supplier submits its offer curve, the locational offer curves of its competitors and the locational bid curves of demanders—both of which determine its residual demand hypersurface—are unknown. This is because all suppliers and demanders simultaneously submit their bid and of-

fer curves at the same time. An expected profit-maximizing supplier will therefore construct its offer curve to maximize the expected value of its realized profits, based on its beliefs about the distribution of the residual demand hypersurfaces it faces.

Let the vector of offer price and quantity pairs for supplier i at location z equal $\boldsymbol{\theta}_i^{o,z} = \{\mathbf{b}_i^{o,z}, \mathbf{g}_i^{o,z}\}$. It contains pairs of price steps and quantity increments for each offer step k at location z. Stacking firm i's locational offer curves across the Z locations yields $\boldsymbol{\theta}_i^{o} = (\boldsymbol{\theta}_i^{o,z})_{z \in Z}$.[19] A similar process can be followed for the locational offer curves of all other suppliers besides firm i at location z to construct $\boldsymbol{\theta}_{-i}^{o,z} = \left(\boldsymbol{\theta}_1^{o,z}, \ldots, \boldsymbol{\theta}_{i-1}^{o,z}, \boldsymbol{\theta}_{i+1}^{o,z}, \ldots, \boldsymbol{\theta}_I^{o,z}\right)$. Stacking the locational aggregate offer curves across the Z locations yields $\boldsymbol{\theta}_{-i}^{o} = \left(\boldsymbol{\theta}_{-i}^{o,z}\right)_{z \in Z}$.

Let the vector of bid price and quantity pairs for demander j at location z equal $\boldsymbol{\theta}_j^{b,z}$. It contains pairs of price steps and quantity increments m at location z. Stacking demander j's locational offer curves across the Z locations yields $\boldsymbol{\theta}_j^{b} = \left(\boldsymbol{\theta}_j^{b,z}\right)_{z \in Z}$. Stacking bid vectors for all J demanders yields $\boldsymbol{\theta}^{b} = \left(\boldsymbol{\theta}_j^{b}\right)_{j \in J}$.

Define all the market offers and bids as $\boldsymbol{\Theta} = \left(\boldsymbol{\theta}_i^{o}, \boldsymbol{\theta}_{-i}^{o}, \boldsymbol{\theta}^{b}\right)$, which represent the concatenation of firm i's offer curve, the offer curve of firm i's competitors, and the bid curves of all demanders. For each value of $\boldsymbol{\Theta}$, once the power transfer distribution factors matrix A and values of transmission limits $\overline{\mathbf{f}} = \left(\overline{f}_{nl}\right)_{(n,l) \in \mathcal{E}}$ have been specified, the locational pricing market-clearing problem (3a)–(3d) can be solved to compute the locational prices and quantities sold by each supplier and purchased by each demander. These magnitudes determine realized variable profit earned by each supplier for that value $\boldsymbol{\Theta}$.

Computing the expected profit maximizing value of $\boldsymbol{\theta}_i^{o}$ requires finding the offer price and quantity increments for firm i for each location z that yields the highest expected profit given power transfer distribution factors matrix A and values of transmission limits $\overline{\mathbf{f}}$. Because firm i does not know the value of $\boldsymbol{\theta}_{-i}^{o}$ or $\boldsymbol{\theta}^{b}$ when it submits the parameters of its locational offer curves, $\boldsymbol{\theta}_i^{o}$, it must choose the value of $\boldsymbol{\theta}_i^{o}$ to maximize the expectation of realized profits using an assumed distribution of $\boldsymbol{\theta}_{-i}^{o}$ and $\boldsymbol{\theta}^{b}$.

Computing the realized profit function of firm i in a locational pricing market requires the following notation. Let $S_i^z(P^z, \boldsymbol{\theta}_i^{o})$ equal the willingness-to-supply function of firm i at location z.

[19] Because we can represent the absence of capacity by setting maximum capacity to zero at any location z, we assume, without loss of generality, that firm i owns capacity at all Z locations.

This is a non-descreasing step function that depends on P^z, the price at location z and is parameterized by $\boldsymbol{\theta}_i^o$. Let $P^z(\boldsymbol{\Theta})$ be the short term price at location z and $\overline{P}(\boldsymbol{\Theta})$ the wholesale uniform purchase price for loads that results from solving the locational pricing market-clearing optimization problem (3a)–(3d) for the vector $\boldsymbol{\Theta}$.

We assume the uniform purchase price for demanders is the load-share-weighted average of the locational prices, because this uniform purchase price for demanders is a feature of the Italian market studied in Section 3.[20] In all locational pricing markets in the US, load-serving entities typically pay for energy according to similar quantity-weighted averages of locational prices.[21]

The vast majority of energy traded in short-term wholesale electricity markets is typically hedged through fixed-price forward market financial obligations signed in advance of the short-term market operation. These financial contracts are typically sold by generation unit owners to electricity retailers or large consumers to provide wholesale price certainty for a fixed quantity of energy during the hour and are settled financially through difference payments between the buyer and the seller (Wolak, 2000). For the case of Italy, they are typically settled against the uniform purchase price.[22]

Let P_i^C equal firm i's forward contract quantity-weighted average price of fixed-price forward contracts that settle against $\overline{P}(\boldsymbol{\Theta})$, the uniform purchase price, and Q_i^C is the net (sales less purchases) quantity of fixed-price forward contracts sold by firm i. In terms of this notation, the hourly realized variable profit function for firm i given $\boldsymbol{\theta}_{-i}^o$ and $\boldsymbol{\theta}^b$ is:

$$\Pi(\boldsymbol{\theta}_i^o; \boldsymbol{\theta}_{-i}^o, \boldsymbol{\theta}^b) = \sum_{z=1}^{Z} [S_i^z(P^z(\boldsymbol{\Theta}), \boldsymbol{\theta}_i^o) P^z(\boldsymbol{\Theta}) - C_i^z(S_i^z(P^z(\boldsymbol{\Theta}), \boldsymbol{\theta}_i^o))] - (\overline{P}(\boldsymbol{\Theta}) - P_i^C) Q_i^C. \quad (7)$$

The first term is the hourly variable profit firm i earns from short-term market sales at location z. $C_i^z(q)$ is the variable cost of firm i producing output level q at location z. The second term is the hourly total difference payments associated with financially settling firm i's fixed-price forward contract obligations. P_i^C is equal to $P_i^C = \frac{\sum_r P_{ir}^C Q_{ir}^C}{Q_i^C}$, where $Q_i^C = \sum_r Q_{ir}^C$, and P_{ir}^C is the price of forward contract r and Q_{ir}^C is the net forward position of contract r. A contract sold by the supplier

[20] See Section O.2.1 of the Online Appendix for a more detailed description of the uniform purchase price.

[21] Tangerås and Wolak (2018) demonstrate that this market rule can enhance the competitiveness of wholesale market outcomes.

[22] McRae and Wolak (2014) show that the quantity of fixed-price forward contract obligations has substantial impact on the incentive of a supplier with the ability to exercise unilateral market power to exploit it.

is a positive value of Q_{ir}^C and a contract purchased by the supplier is a negative value of Q_{ir}^C.

Firm i is assumed to maximize expected profits conditional on its beliefs about the distribution of its competitors' offers, $\boldsymbol{\theta}_{-i}^o$, and demands bids, $\boldsymbol{\theta}^b$, given the configuration of the transmission network as characterized by the power transfer distribution factor matrix A and transmission line limits $\overline{\mathbf{f}}$.

To operationalize the computation of the expected profit-maximizing value of $\boldsymbol{\theta}_i^o$ assume discrete distributions for $\boldsymbol{\theta}_{-i}^o$ and $\boldsymbol{\theta}^b$. Let $\boldsymbol{\theta}_{-ih}^o$ denote the vector of locational offer curves of all other suppliers besides firm i, and $\boldsymbol{\theta}_h^b$ the vector locational demand bids for all demanders for realization $h = 1, \ldots, H$. Together, $\boldsymbol{\Theta}_{ih}^{rd} = \left(\boldsymbol{\theta}_{-ih}^o, \boldsymbol{\theta}_h^b\right)$ and the configuration of the transmission network define a specific realization of the distribution of the set of inverse residual demand hypersurfaces, $\left(P_h^z\right)_{z \in Z}$, faced by firm i. The probability associated with each realization is denoted by by ω_h and $\sum_{h=1}^H \omega_h = 1$.[23]

Firm i's expected profit-maximization problem for this discrete distribution of offers of its competitors and the bids of all demanders is:

$$\underset{\boldsymbol{\theta}_i^o}{\text{maximize}} \quad \sum_{h=1}^{H} \omega_h \left[\sum_{z=1}^{Z} \left[P_h^z(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{ih}^{rd}) q_{ih}^z - C_i^z(q_{ih}^z) \right] - \left(\overline{P}_h(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{ih}^{rd}) - P_i^C \right) Q_i^C \right] \tag{8a}$$

subject to

$$S_{i1}^z(P_1^z(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{i1}^{rd}), \boldsymbol{\theta}_i^o) = q_{i1}^z, \text{ for } z = 1, \ldots, Z, \tag{8b}$$

$$S_{i2}^z(P_2^z(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{i2}^{rd}), \boldsymbol{\theta}_i^o) = q_{i2}^z, \text{ for } z = 1, \ldots, Z, \tag{8c}$$

$$\vdots$$

$$S_{iH}^z(P_H^z(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{iH}^{rd}), \boldsymbol{\theta}_i^o) = q_{iH}^z, \text{ for } z = 1, \ldots, Z, \tag{8d}$$

$$\mathbf{0} \leq \mathbf{b}_i^o \leq \hat{\mathbf{b}}, \tag{8e}$$

$$\hat{\mathbf{g}}_i \leq \mathbf{g}_i^o \leq \hat{\mathbf{g}}_i, \tag{8f}$$

where q_{ih}^z is the amount of energy produced by firm i at location z under realization h, given firm i's offer curve $\boldsymbol{\theta}_i^o$ and $\boldsymbol{\Theta}_{ih}^{rd}$.

The first set of inequality constraints (8e) requires offer prices to be greater than or equal to zero and less than or equal to the offer price cap $\hat{\mathbf{b}}$, a vector of regulatory price caps with each

[23] We assume $\omega_h = \frac{1}{H}$ for $h = 1, \ldots, H$ in our empirical analysis.

element equal to the regulatory price cap $\hat{b}$. The second set of inequality constraints (8f) require the offer quantity increments to be set at predefined levels $\hat{\mathbf{g}}_i$.[24]

For the same offer curve for firm i, each residual demand hypersurface realization gives rise to potentially different locational prices and a different uniform purchase price, $\overline{P}(\boldsymbol{\Theta}) = \overline{P}(\boldsymbol{\theta}_i^o, \boldsymbol{\theta}_i^{rd})$. For this reason, the term $\overline{P}(\boldsymbol{\Theta})Q_i^C$ in (7) and (8a) matters for determining firm i's expected profit-maximizing value of $\boldsymbol{\theta}_i^o$.

The locational market-clearing prices, $P^z(\boldsymbol{\Theta}) = P^z(\boldsymbol{\theta}_i^o, \boldsymbol{\Theta}_{ih}^{rd})$, and quantities for firm i and all other suppliers and all demanders for each residual demand hypersurface realization are determined by solving the transmission network-constrained market-clearing optimization problem in (3a)–(3d) with a uniform purchase price for demanders. As shown in Online Appendix O.2.1, this optimization problem can be solved as mathematical program with equilibrium constraints (MPEC) as discussed in Luo et al. (1996). The first-order conditions for each of the H locational market-clearing problems enter as constraints in the MPEC formulation. The computational complexity grows rapidly with H because each locational market-clearing problem introduces numerous first-order conditions. We refer to Online Appendix O.3 for additional details on how to reformulate the problem.

Our model is able to accommodate different firm and market structures. For example, if a firm is a vertically integrated, the variable profit function (7) would be augmented by the variable profit from retailing, $\sum_z (P^R - P^z - \tau_i)Q_i^{R,z}$, where P^R is the firm's fixed retail price,[25] $Q_i^{R,z}$ is the firm's retail load obligation at location z, and the marginal cost of electricity retailing for firm i is τ_i.[26] Finally, we note that if transmission constraints are never binding, and thus $P^z(\boldsymbol{\Theta}) = \overline{P}(\boldsymbol{\Theta}) = P(\boldsymbol{\Theta})$ for $z = 1, \ldots, Z$, the model simplifies to that described in Wolak (2000) and Wolak (2003b).[27]

[24]Relaxing this assumption and modeling the choice of offer quantity increments, requires replacing (8f) by new constraints. Specifically, all offer quantity increments at each location must be greater than or equal to zero and their sum must be less than or equal the capacity of the firm i at location z. Other physical constraints on the vector of offer quantity increments such as minimum safe operating levels of individual generation units and the capacity of individual generation units may also be important. See Wolak (2007) for more details on modeling the expected profit-maximizing choice of offer price and offer quantity increment choices in computing generation unit-level expected profit-maximizing offer curves.

[25]Retailers typically sign fixed-price long-term contracts with final consumers which implies retail prices are effectively fixed from the perspective of their offer behavior.

[26]Note, that although the demand side pays the uniform purchase price $\overline{P}$, if electricity is bought from the short-term market, a net selling vertically integrated firm can avoid to being exposed to the uniform purchase price risk if it sells and buys electricity at the same location.

[27]The model is capable of incorporating physical or financial transmission rights (FTRs), which can impact the incentive suppliers have to exercise local market power as discussed in Joskow and Tirole (2000), Cho (2003), or Gilbert et al. (2004). FTRs have existed in the Italian market (Duthaler and Finger, 2008), but our understanding is that there is

Expected Locational Quantity-Setting Equilibrium Model

The expected profit-maximizing offer curve framework for locational markets may overestimate the effect of a firm's market power because it does not account for the fact that their offer curve will impact its competitor's residual demand hypersurfaces.[28] We therefore construct an equilibrium model where large strategic firms make locational output choices instead of locational offer curves to impact locational prices through a potentially congested transmission network.

We assume that suppliers own production capacity in multiple locations and compete against each other in locational quantities through a distribution of smoothed versions of our residual demand hypersurfaces.[29] The smoothed residual demand hypersurfaces are created by the offers of the non-strategic firms, locational demands, and the configuration of the transmission network. In Figure 3, we show actual residual demand surfaces based on a finite grid of locational quantity vectors (Panel a) together with its smoothed versions (Panel b) using the multivariate smoothing approach outlined in Online Appendix O.4.1.

We assume that firms simultaneously choose locational quantities rather than offer curves to maximize expected profits given the locational quantity choices of their strategic competitor and the smoothed inverse residual demand hypersurfaces. Let the realized smoothed inverse residual demand hypersurface for location z, which is the function of the vector of aggregate locational quantities $\mathbf{Q} = \left(Q^1, \ldots, Q^Z\right)$, equal $\tilde{P}_h^z(\mathbf{Q})$ for each location $z = 1, \ldots, Z$, and the quantity-weighted average price equal $\overline{\tilde{P}}_h(\mathbf{Q})$. Each firm i's objective function is to maximize its expected profit as follows:

$$\underset{\mathbf{Q}_i}{\text{maximize}} \quad \sum_{h=1}^{H} \omega_h \left[\sum_{z=1}^{Z} \left[\tilde{P}_h^z(\mathbf{Q}) Q_i^z - C_i^z(Q_i^z) \right] \; - \; (\overline{\tilde{P}}_h(\mathbf{Q}) \; - \; P_i^C) Q_i^C \right] \tag{9a}$$

$$\text{subject to} \quad 0 \leq Q_i^z \leq \overline{Q}_i^z, \text{ for } z = 1, \ldots, Z. \tag{9b}$$

very little volume in these locational price hedging instruments during our sample period. If we had data on the FTRs holding of firm i we could account for their impact on firm i's offer behavior as discussed in Leslie (2021).

[28] An algorithm that iteratively updates offer curves could be employed; however, the significant computational burden of solving even a single expected profit-maximizing offer curve—combined with convergence challenges—makes this approach computationally infeasible at present.

[29] Quantity-setting models with producers behaving as price takers relative to the price of transmission can be found in Hobbs et al. (2005); Neuhoff et al. (2005); Hobbs and Pang (2007); Yao et al. (2008). Quantity-setting models where suppliers compete through a potentially constrained transmission network can be found in Oren (1997); Borenstein et al. (2000); Willems (2002); Gilbert et al. (2004).

The first order necessary conditions of (9) for each strategic firm i and assumed distribution of residual demand hypersurfaces using H smoothed residual demand hypersurface realizations are:

$$\text{for } i = 1, \ldots, I \text{ and } z = 1, \ldots, Z:$$

$$0 \leq Q_i^z \perp \sum_{h=1}^{H} \omega_h \left[\sum_{k=1}^{Z} \left[\frac{\partial \tilde{P}_h^k(\mathbf{Q})}{\partial Q_i^z} Q_i^k \right] + \tilde{P}_h^z(\mathbf{Q}) - \frac{\partial \overline{\tilde{P}}_h(\mathbf{Q})}{\partial Q_i^z} Q_i^c \right] - \frac{\mathrm{d}\, C_i^z(Q_i^z)}{\mathrm{d}\, Q_i^z} - \overline{\mu}_i^z \leq 0, \tag{10a}$$

$$0 \leq \overline{\mu}_i^z \perp Q_i^z \leq \overline{Q}_i^z. \tag{10b}$$

Solving the nonlinear complementary problem (10) should lead to stationarity points that are mutual best-responses. However, because residual demand hypersurfaces are smoothed but not shape constrained we cannot provide any guarantee that the resulting stationarity points are unique. Kolstad and Mathiesen (1987) show that quasi-concavity of the expected profit function is a necessary condition for a unique equilibrium in an unconstrained market. Note further that, even if locational (1-dimensional) residual demand functions are linear, our problem can have multiple or no pure strategy equilibria (Yao et al., 2008). We address this issue by doing an extensive pure strategy equilibria search along with different equilibrium selection procedures discussed in Online Appendix O.4.2.

3 Institutional Details and Data

In this section, we describe the Italian wholesale electricity market, general data requirements to implement the suite of models to measure the ability to exercise unilateral market power in network-constrained markets described in Section 2, and the data we used for our empirical analysis.

The Italian Wholesale Electricity Market

The Italian short-term market for wholesale electricity has been operating since 2004. It is organized in a sequential manner consisting of a day-ahead market, an adjustment market,[30] and an ancillary services market, also known as redispatch and real-time balancing market. After the day-ahead market has cleared, market participants have the opportunity to alter their day-ahead schedules in the adjustment market. Eventually, Terna, the Italian transmission system operator, builds up reserves, resolves congestion, and balances the grid in real-time in the so-called ancillary services or redispatch and real-time balancing market.

The day-ahead market is a crucial element in short-term wholesale markets because most of the energy consumed is sold in this market. The market splits into several market zones when congestion is present. In that case, producers receive a different price depending on the locations where they are selling energy. The demand side is pays a uniform purchase price. Retailers and large consumers submit a non-increasing piecewise constant demand curves. Suppliers submit non-decreasing piecewise constant energy offer curves that do not include a start-up or minimum load cost.[31] In the day-ahead market electricity is traded for the 24 hours of the next day ignoring any inter-temporal constraints, such as block bids,[32] or ramp rates to consider when clearing the market.

In 2007, the Italian day-ahead market consisted of seven domestic zones. Congestion between locations mostly took place between the North bidding zone and the rest of the mainland, as well as between the mainland and the islands of Sicily and Sardinia. During our sample period congestion between the North bidding zone and the rest of the mainland occurred over 80% of the hours. We refer to Online Appendices O.1.4–O.1.6 for more details on the transmission network and the prevalence of congestion.

The incumbent firm in the Italian market is Enel—the former state-owned monopolist. Its share of electricity generation was 31% in 2007. Enel's main competitor at the time was Edison with an electricity generation share of 22%. A detailed description of the Italian electricity supply

[30] The adjustment market has been replaced by a series of intra-day markets in later years. More details are provided by the Italian Power Exchange provides, see `http://www.mercatoelettrico.org/En/Mercati/MercatoElettrico/MPE.aspx`.

[31] In 2007 the maximum observed uniform purchase price was €242.4/MWh (Bosco et al., 2013).

[32] Although the Italian market does not have block bids, other European markets do. See Reguant (2014) for a description of block bids in the Spanish day-ahead market.

industry can be found in Online Appendices O.1.1 and O.1.2.

Locational market power in the Italian day-ahead market has been shown by Bigerna et al. (2016) who assess the ability of suppliers to exercise unilateral market power in the Italian day-ahead market using locational Lerner indices. Their results show that generators are only able to raise prices above competitive levels in specific congested locations. The importance of network considerations in the Italian day-ahead market is also confirmed by Fianu et al. (2022).

Although the day-ahead market is an important wholesale market segment during our sample period, because at that time virtually all of the expected real-time energy demand was traded there, there are several market interactions to consider. First, as emphasized by Wolak (2000) and McRae and Wolak (2014), the effect of fixed-price forward contract obligations on short-term market offer behavior must be accounted for. Second, the interaction with the redispatch and real-time balancing mechanism must be considered in regions with simplified market designs (see, e.g., Graf, 2025, for more details). Unlike in the United States, the Italian day-ahead market or other day-ahead markets across Europe do not fully incorporate all the relevant constraints necessary to securely operate the grid in real time. Therefore, market participants may have an incentive to withhold output from certain units behind a likely to be binding real-time constraint and to sell energy from a unit that is likely to be not needed in real-time. This behavior is called INC/DEC game where market participants offer into day-ahead market recognizing the probability of earning higher variable profits in redispatch and real-time balancing market as shown in Graf et al. (2020b,a, 2021). We discuss below how we estimate fixed-price forward contract positions and out-of-day-ahead market demand for specific units.

General Data Requirements

In order to compute residual demand hypersurfaces, market supply offer and bid offer data at the generation and consumption unit level with locational identifiers as well as a mapping from units to the firm is necessary. Furthermore, to replicate the market clearing, the transmission configuration including the power transfer distribution factors matrix and the transport limits between locations are necessary.

Computing expected profit-maximizing offer curves of a strategic supplier and expected lo-

cational equilibrium quantities in a game between quantity-setting suppliers requires additional data. Unit-level market offers need to be mapped to a firm because firms typically operate multiple units. Furthermore, generation unit-level heat rates as well as prices for fuel and CO_2 certificates are needed to construct aggregate short-term marginal curves and forward contract positions for each firm, location, and hour of the sample. For a fixed distribution of residual demand hypersurfaces, a supplier's expected profit-maximizing offer curve depends on its quantity of fixed-price forward contract obligations.[33]

Sample Curation and Assumptions

Our sample period is from September 1, 2007 to October 31, 2007 and we only consider the peak hours of the day—11, 12, 18, 19, and 20. We eliminated weekends and holidays from the sample.[34] In total, our sample is composed of 175 hourly day-ahead markets.

Our reasons for selecting this time period are the following: (i) hydro production usually peaks in spring after the snow-melt and thus its influence on the market is reduced; (ii) a relatively stable amount of imports exists from France and Switzerland; and (iii) electricity production from intermittent renewable sources, such as wind or solar was negligible at this time. This factors make the day-ahead market the relevant market segment with relatively minor redispatch in later market segments.

We have selected two strategic firms, Enel and Edison, which we refer to as the *incumbent* and the *main competitor*, respectively. We treat the remaining suppliers as competitive fringe. We calculate residual demand elasticities and expected profit-maximizing offer curves for each firm separately assuming that each firm maximizes expected profits given the distribution of residual demand hypersurfaces that it faces. In the locational equilibrium model we assume quantity competition between these two strategic firms.

We focus on the day-ahead market as this is by far the largest in terms of traded quantities. To reduce the computational complexity we aggregate locations to three locations or zones. These zones are North (N), Center (C), and Sicily (SI). We refer to Online Appendix O.2.5 for additional

[33] Wolak (2000) demonstrates this point empirically for a large supplier in the Australian electricity market.

[34] We remove the following set of days from our sample due to a significant restriction on transmission capacity between the North (N) and Central North (CN) bidding zones from Oct 22, 2007 to Oct 26, 2007 and between Calabria (CA) and Sicily (SI) from Oct 29, 2007 to Oct 31, 2007.

explanations around this simplification.

We use the weighted average day-ahead market-clearing price as the reference price for settling fixed-price forward contracts. Furthermore, we assume that non-convexities, e.g., start-up costs, as discussed in, e.g., Graf et al. (2020a) and Jha and Leslie (2025) are a minor concern for suppliers when formulating their offer curves. This implies that each hour of the day can be treated as independent from one another.

We calculate the short-term variable cost of production for each thermal generation unit using data on its heat rate and monthly prices for fuel and CO_2 emissions certificates. The firm's aggregate short-term marginal cost function is a non-decreasing step function with the quantity step equal to the available capacity of the unit and height equal to the short-term variable cost of the generation unit. For thermal plants that are not optimizing the offer prices of their units, we replace the marginal cost estimate by the actual offer price in the firm's aggregate short-term marginal cost function.

We optimize only over offer prices of relevant thermal units. The criteria we use to determine whether a unit is *relevant* is the unit's share of day-ahead market sales, relative to its real-time energy production. Thermal units below a 50% share or above a 150% share are treated as non-relevant for our analysis. Over- and under-selling in the day-ahead market can be related to the INC/DEC game where market participants offer into day-ahead market recognizing the probability earning higher profits in the redispatch market as shown in Graf et al. (2020b). We do not explicitly account for this incentive in our analysis but limit its impact by focusing on the units that optimize their offers to participate mainly in the day-ahead market. We do not remove offers from non-relevant units from the realized residual demand hypersurfaces. However, we include the actual energy sold by non-relevant units in the day-ahead market in each firm's objective function treating it as infra-marginal energy that is valued at the associated locational market-clearing price. This *relevant* unit criteria selects on average 55% of thermal capacity and 82% of energy sold in the day-ahead market by thermal units owned by our two strategic firms.

Our approach of fixing the offer quantities of relevant thermal units at their actual values and only optimizing offer prices would be problematic if significant physical capacity withholding were present in the Italian market. However, the coefficient of variation of total hourly offered quantity over the sample period is only 5% in the case of the incumbent and 10% in the case

of the main competitor. Because generation units are taken out of service for maintenance and unplanned outages, these numbers are consistent with our expectations for the impact of these outages and therefore increase our confidence that these market participants maximize expected profits by offering all of their available capacity to the short-term market and setting their offer prices in response to distribution of residual demand hypersurfaces they face.[35]

Fixed-price forward positions are typically only known to the firm. However, the price at which a firm offers its production capacity into the day-ahead market can reveal information about the quantity of fixed-price forward contract obligations it holds. As discussed in Wolak (2000), it would not be expected profit-maximizing for a supplier to offer capacity below its marginal cost if a supplier had zero fixed-price forward contract obligations, but it can be expected profit-maximizing to offer capacity beyond the supplier's forward contract obligation Q_i^C value above the unit's short-term marginal cost.[36]

For this reason, we set each firm's forward contract positions to the sum of offer quantity steps of thermal units offered below €30/MWh, which is the approximate marginal cost of a coal-fired unit. Offers at this price will be inframarginal almost with certainty because our analysis focuses on peak hours.[37] We elicit the forward contract positions for each firm and for each hour of the sample using this rule.[38]

Discrete Representation of Residual Demand Hypersurface Uncertainty

Both the locational expected profit-maximizing offer curves and the equilibrium locational quantities of a game between strategic suppliers are solved assuming uncertainty about residual demand hypersurfaces. In other words, each strategic supplier maximizes expected profits conditional on its estimate of the distribution of the residual demand hypersurfaces that it faces. Selecting a realistic residual demand hypersurface distribution is critical because it determines the distribution of variable profit realizations for each firm for the same offer curve. We represent the uncertainty

[35]Note that this logic implies that suppliers withhold capacity from the market by setting a high offer price. Endogenizing the quantity decision for each offer step could increase the firm's expected profit, but it would also massively increase the computational complexity of solving our optimal offer curve problem.

[36]Wolak (2003a) finds that this approach to estimating half-hourly values of Q_i^C matches the average pattern of the actual values of Q_i^C during the day and week for a large supplier in the Australian National Electricity Market.

[37]The minimum hourly price in the largest bidding zone (North) was €49/MWh during our sample period.

[38]The incumbent [main competitor] sells an average of 11.4 GWh [8.0 GWh] to the day-ahead market in each hour of our sample. Our estimate of the average hourly hedged quantity of energy, Q^C, for the incumbent is 8.1 GWh (71%) and 6.4 GWh (80%) for the main competitor.

a firm faces before submitting offers to the market (or before deciding how much locational quantities to sell) through discrete scenarios.

Specifically, we treat each hourly market in the sample as an independent event and, for each hourly period, select $H = 20$ representative markets from neighboring hours, assigning each with probability weight of $\omega_h = 1/20$. For instance, to compute the expected profit-maximizing offer curve for hour 12 of September 5, 2007, we sample residual demand hypersurface realizations from market instances at the same hour of the day across business days before and after September 5, 2007 including that day itself.

4 Model Results

This section presents the model results derived from applying the data and assumptions outlined in Section 3 to the models developed in Section 2. Specifically, we present the own-price and cross-price inverse residual demand semi-elasticities, expected profit-maximizing offer curves in a locational pricing market, and the equilibrium locational prices and quantities set two strategic firms competing by setting locational quantities in a transmission network with finite transfer capacity across locations.

Own- and Cross-Price Residual Demand Inverse Semi-Elasticities

There are three own-price inverse semi-elasticities and six cross-price inverse semi-elasticities, two for price changes at two locations with respect to a quantity change at the remaining location for three locations. We compute the inverse semi-elasticities for each of the 175 market outcomes using the step function residual demand hypersurfaces with discrete changes in the firm's locational output Q_i^z.

To obtain a non-zero own-price response for step function residual demand hypersurfaces, we vary each strategic firm's output at location z between zero and its maximum capacity at that location in 1 MWh steps upward from the firm i's actual output level and in 1 MWh steps downward from the firm's actual output until two different prices at location z are obtained. We then take ΔP^z as the difference between these two prices and ΔQ_i^z as the difference in the output levels associated with these two prices. We replace $\frac{\partial P^z(\mathbf{Q}_i)}{\partial Q_i^z}$ by $\frac{\Delta P^z}{\Delta Q_i^z}$ in (6). For $\Delta P^{z'}$ for the other

two locations we use the difference in prices at location z' associated with the two output levels at location z used to compute ΔQ_i^z. We replace $\frac{\partial P^{z'}(\mathbf{Q}_i)}{\partial Q_i^z}$ by $\frac{\Delta P^{z'}}{\Delta Q_i^z}$ in (6). This approach ensures that if the market is unconstrained $\eta_i^{z,z} = \eta_i^{z,z'}$ for $z' \neq z$. To estimate $\frac{\partial P^z}{\partial Q_i^z}$ and $\frac{\partial P^{z'}}{\partial Q_i^z}$ using the smoothed residual demand hypersurfaces these two partial derivatives are computed directly from the smoothed residual demand hypersurface functions.

Figures 4 and 5 present box and whiskers plots[39] for the 175 values of the own- and cross-price inverse semi-elasticities for the incumbent and main competitor for the step function and smoothed residual demand hypersurfaces, respectively. The inter-quartile range of values for both the own- and cross-price inverse semi-elasticities for both firms and both residual demand hypersurfaces are small relative the 90^{th} to 10^{th} range of values. Particularly for the own- and cross-price values based on the step function residual demand hypersurfaces there are a number of extremely large values. For example, for the North (N) zone and main competitor, the distribution of hourly values of the own-price inverse semi-elasticity in Figure 4 indicates a substantial ability to exercise unilateral market power during more than 25 percent of the hours in our sample. The absolute value of $\eta_i^{N,N}$ is greater than 2 for the vast majority of these hours, implying that one percent reduction of output in the North would increase the price by €2/MWh. The cross-price elasticities for the Center (C) and Sicily (SI) other locations, $\eta_i^{N,C}$ and $\eta_i^{N,SI}$, imply that prices in these two locations are largely unaffected by the main competitor or incumbent withholding output in the North.

The 10^{th} to 90^{th} percentile range of the own-price inverse semi-elasticities in Figure 4 contains values that are significantly larger in absolute value than the 10^{th} to 90^{th} range of cross-price inverse semi-elasticities. This is consistent with transmission congestion being prevalent during the hours of our sample, so that the ability of a supplier to exercise unilateral market power is confined to a local market. Nevertheless, many of the cross-price elasticities are significantly different from zero for the step function residual demand hypersurfaces and smoothed residual demand hypersurfaces.

The inverse semi-elasticities obtained by taking the partial derivative of the smoothed residual demand hypersurface, as shown in Figure 5, exhibit a narrower inter-quartile range and a substan-

[39] Average hourly values and standard deviations for these inverse semi-elasticities are displayed in Tables O.7 and O.8 of the Online Appendix.

tially smaller 10^{th} to 90^{th} percentile range compared to the corresponding inverse semi-elasticities in Figure 4.

A local market power mitigation mechanism could be designed around the selection of critical values of the hourly value of these own- and cross-price inverse semi-elasticities that would deem the supplier worthy of mitigation. For example, if the absolute value of the own-price inverse semi-elasticity exceeded a certain value, that supplier's offer price at that location would be mitigated. More sophisticated approaches could use functions of the own- and cross-price inverse semi-elasticities with respect to an output change at a location to determine when offer mitigation is appropriate. This approach to measuring the ability of a supplier to exercise unilateral market recognizes that output decisions at one location can impact locational prices throughout the transmission network. As the frequency and pattern of transmission congestion become less predictable because of the increasing amounts of intermittent renewable resources, understanding and mitigating local market power in locational pricing markets becomes increasingly important.

Scheffman and Spiller (1987) argue that own- and cross-price residual demand elasticities can be used to determine the geographic market definition for the purposes of merger analysis in spatial markets. Different from Scheffman and Spiller (1987), the own-price and cross-price inverse semi-elasticities are produced on an hourly basis, so any assessments of the extent of a geographic market can be made at an hourly level. This raises the question of how many hours of the year two regions are in the same geographic market.

If the hourly own-price inverse semi-elasticity is equal to the hourly cross-price inverse semi-elasticity at a location, then the market is unconstrained between these two locations because withholding output at that location raises prices at the two locations by the same amount. Building on this logic, one could argue that if for a specified set of hours, the mean of the hourly own-price inverse semi-elasticities is equal the mean of the hourly cross-price inverse semi-elasticities for another location, then these two locations are in the same market for that set of hours. Otherwise, these locations are in separate markets for that set of hours.

We perform a two-sample t-test for equality of two means assuming different variances for two samples for the own-price semi-elasticity for firm i in hourly market t at locational z, $\eta_{it}^{z,z}$, and the cross-price inverse semi-elasticity for firm i in hourly market t for an output change at location z for the price at location z', $\eta_{it}^{z,z'}$. In each case, our null hypothesis is that $\mathbb{E}[\eta_{it}^{z,z}]$ is equal

to $\mathbb{E}[\eta_{it}^{z,z'}]$. Applying this test to our sample of 175 hourly markets of own- and cross-price inverse semi-elasticities from out step residual demand hypersurfaces, Table O.9 of the Online Appendix reports one case where the null hypothesis that two locations are in the same market is not rejected. Specifically, the null hypothesis that the mean value of $\eta^{C,C}$ for the incumbent is equal to the mean of $\eta^{C,SI}$. For all other other cross-price inverse semi-elasticities in Table O.9, the null hypothesis is rejected. For the case of elasticities based on the smoothed residual demand hypersurfaces, the null hypothesis is always rejected, as shown in Table O.10 of the Online Appendix. These results suggest that, across the 175 hourly markets in our sample, all locations are separate local markets—except for Center and Sicily, in the case of the incumbent.

Expected Profit-Maximizing Offer Curves

In this section, we compare market outcomes using the computed expected profit-maximizing offer curves accounting for network constraints,[40] expected profit-maximizing offer curves assuming infinite transmission capacity, actual offer curves, and short-term marginal cost curves.

In Figure 6, we show the optimal expected profit-maximizing locational offer curves (green) for our assumed distribution of residual demand hypersurfaces for the incumbent for Hour 12 of September 5, 2007 and for our three locations—North (N), Center (C), and Sicily (SI). We also show the actual offer curves (blue), short-term marginal cost curves (orange), and the optimal locational offer curves under the assumption that there is infinite transmission capacity (red) for the same distribution of representative markets assumed to compute our optimal offer curves with the actual transmission network capacity. This figure shows that the optimal locational offer curves accounting for transmission constraints is different from the optimal offer curve assuming infinite transmission capacity, and generally appears to be closer to the actual offer curve.

In Table 1, we present average locational best-response prices as well as the average uniform purchase price and average profits for the incumbent firm and its main competitor across the 175 markets. Column (1) shows the result of market clearing when offer prices of the relevant units are replaced by our estimated marginal cost curves. Column (2) shows the market-clearing results using the actual offer curves. Column (3) shows the results of the expected profit-maximizing offer curves accounting for transmission constraints. Column (4) presents the results with the

[40] Computational details are provided in Section O.3.1 of the Online Appendix.

expected profit-maximizing offer curves computed assuming there is infinite transmission capacity between locations. Note that all four sets of locational offer curves are evaluated using the market-clearing mechanism that accounts for the configuration and capacity of the transmission network and actual offer curves of competitors and actual demand-bid curves for that hour of the sample. In Panel A, we present the average best-response prices, average best-response awarded quantities of the relevant units, as well as the average best-response profit for the incumbent. The same set of variables is presented for the main competitor in Panel B.

From columns (1) and (2), we are comforted to learn that offering at marginal cost would lead to a lower average profit compared to the average profit evaluated at actual offers. In case of the incumbent this difference is substantial. Comparing the actual offer curves to our optimal offer curves, the average profit using the expected profit-maximizing offer curves (column 3) is about 9.8% [3.6%] larger for the incumbent [main competitor] compared to the average profit using actual offer curves (column 2). In column (4), we show the result of market clearing assuming the firm uses the optimal offer curves computed assuming infinite transmission capacity. Comparing Columns 2 and 4, the expected profit-maximizing offer curve computed assuming infinite transmission capacity only increases average profits relative to average profits with the actual offer curve by 5% for the incumbent and 1.5% for the main competitor. From this we conclude that a significantly higher average profit increase is possible when accounting for transmission constraints in computing expected profit-maximizing offer curves than is achieved if infinite transmission capacity is assumed in computing the firm's optimal offer curve. This result emphasizes the importance accounting for the actual configuration transmission network when computing expected profit-maximizing offer curves for the day-ahead market.

Expected Locational Equilibrium Quantities

In this section, we present market outcomes using the computed expected profit-maximizing locational offer quantities accounting for network constraints and for the competition between the two strategic firms.[41]

In order to simplify the problem, we replace locational piece-wise constant short-term marginal cost curves by increasing and convex quadratic short-term marginal cost curves. The parameters

[41] Computational details are provided in Section O.4.2 of the Online Appendix.

of these functions are obtained through least squares fitting a curve to the piece-wise constant functions. In Figure 7, we plot the locational marginal cost functions and their fitted counterparts for the incumbent firm.

In Table 2, we present average locational equilibrium prices, average uniform purchase price, and the average profit for both strategic firms across the 175 markets. Column (1), Panel A and B,[42] shows the results of the expected profit-maximizing locational offer quantities accounting for transmission constraints. Note that all the locational quantities are treated as inframarginal (zero-offer price offers) and evaluated using the market-clearing mechanism that accounts for the configuration and capacity of the transmission network and actual offer curves of the non-strategic competitors and actual demand-bid curves for that hour of the sample.

The equilibrium analysis finds generally slightly lower average prices than the average prices resulting from actual offer curves (see Column 2 of Table 1) with the exception of Sicily. For example, the average uniform purchase price is €98.7/MWh compared to €103.1/MWh. Aggregate quantities are more similar to the actual aggregate cleared quantities, as are aggregate profits. This could be due to a number of factors: (1) our two-strategic firm equilibrium analysis, (2) the fact that strategic firms pick locational quantities rather than offer prices, and (3) our use of smoothed inverse residual demand hypersurfaces for each strategic firm's vector of locational quantities.

5 Counterfactual Divestment Analyses

This section analyzes how the same amount of capacity divestment, when implemented at different locations, affects (i) the incumbent's expected profit-maximizing offer curves and the resulting locational prices, and (ii) the expected locational equilibrium quantities of both strategic firms and the associated market outcomes. The specific locations in the transmission network where divestment occurs determine the extent of unilateral locational market power that the divesting supplier can exercise.

We focus on the incumbent because it owns a substantial amount of thermal capacity in all locations. We consider four scenarios, two where we divest about 1.2 GW of the incumbent's thermal capacity first in the North and then in the Center. That is about 8% of total capacity in

[42] The baseline values in Panel A and B are the same and duplicated only to improve readability of the table.

each of the two locations. In the remaining two scenarios, we divest about 2.4 GW in each of the two locations. In order to make the counterfactuals comparable to the baseline, we adjust the firm's forward positions using the procedure described in Section 3 for each modified generation portfolio. We also assume that the capacity is divested to a fringe supplier, meaning that the divested capacity is offered at marginal cost to the market. In order to make this exercise as realistic as possible, we divest whole units.[43]

Expected Profit-Maximizing Offer Curves

Table 3 presents our results for different levels of locational divestment. As expected, divesting the incumbent of thermal capacity leads to lower best-response prices. However, the locational configuration of the market turns out to be an important determinant of which divestment scenario lowers prices the most in which location. Divesting 1.2 GWs of the incumbent's thermal capacity in the North (Panel A) leads to a larger reduction in the uniform purchase price relative to divesting the same amount of capacity in the Center (Compare columns (2) and (5) to column (1) in Table 3). Although the channels leading to this result are slightly different; divestment in the North would lead to a lower average locational price at that location and a slightly higher price in the Center and Sicily. Hence, the incumbent's unilateral incentive to drive prices in these three locations apart would increase. Because the North zone is slightly larger than the Center zone (and much larger than Sicily), the decrease of the locational price in the North dominates the slight increase in the Center and hence the uniform purchase price would be lower. Divestment in the Center would lead to a price decrease at that location and a slightly higher price in the North and Sicily. However, the price decrease in the Center would dominate the price increases in the other locations and the best-response uniform purchase price would decline.

Applying a large divestment counterfactual scenario (2.4 GW) leads to even lower average best-response uniform purchase prices (Panel B of Table 3). The locational price dispersion is larger when divesting in the North than when divesting in the Center because congestion between the North and the Center would increase.

The change in deadweight loss relative to the baseline market outcome associated with each locational divestment scenario is the change in the total variable cost of serving locational de-

[43] We selected mostly coal plants and one economic gas plant to ensure that we are divesting inframarginal capacity.

mands throughout the transmission network, because these demands are completely price inelastic. However, a significant amount of generation capacity in the North does not have an incurred variable cost of production, as shown in Table O.1 of the Online Appendix. Consequently, the offer price times the amount of energy supplied by each generation unit is assumed to be its variable cost of production. This is one reason why the average hourly total variable cost falls slightly (to €721.8 K) relative to the baseline average hourly total variable cost (€723.1K) for the 1.2 GW divestment in the North. For the other three divestment scenarios, the average total variable cost increases slightly relative to the baseline value. Unlike in a single-location market, where divestment from a strategic supplier exercising unilateral market power to a price-taking supplier will always reduce the total variable cost of serving the same demand, in a potentially congested locational pricing market, where suppliers face distributions of residual demand hypersurfaces this need not always be the case.

These results demonstrate that the same number of MWs of divestment in different locations would yield different counterfactual prices, highlighting the importance of the location of demands, generation units owned by other firms and the divesting firm, and the configuration of the transmission network when assessing the competitive impact of a fixed GW divestment action.

Expected Locational Equilibrium Quantities

We perform the same two divestment analyses for two locations for the incumbent firm (1.2 GW and 2.4 GW in the Center and in the North) and analyze their effects on equilibrium prices, quantities, profits, and total costs. In Table 2, Panel A, we show that divesting about 1.2 GW of the incumbent's coal capacity in the Center (Columns 2–4) would reduce the average equilibrium price relevant for the demand side by 3.5% compared to the simulated baseline market outcomes (Column 1). The average locational price in the Center would decrease by 6.2% whereas locational prices in the North would only slightly decrease by 2.5%, and the price in Sicily would increase by 2.4%. Prices are averaged over all market instances and the market-clearing prices are computed using unsmoothed inverse residual demand surfaces for that market instance evaluated at the optimal quantities obtained from solving (10) for the two strategic firms. The total average output of

both strategic firms jointly is predicted to decrease by 7.9%—a result that is partially driven by our assumption that the divested capacity is purchased by a competitive fringe supplier and would be offered at short-term marginal cost. Average total profits of both firms would decrease by 10.1% and the total costs to serve demand would slightly decrease by 0.8%. A more aggressive divestment of about 2.4 GW of the incumbent's capacity in the Center (Panel B, Columns 2–4) would even further decrease the average equilibrium price relevant for demand by 4.7% compared to the simulated market outcomes under the baseline.

The second counterfactual deals with a divestment of the incumbent's capacity in the North (Columns 5–7). Although, for the small divestment (Panel A), as well as for the sizeable divestment (Panel B), the average equilibrium price in the North decreases by 3.1% and 6.9% respectively, the effect on the weighted average locational prices (relevant for the demand-side) decreases much less compared to when the divestment would take place in the Center. Comparing the average price dispersion between locational prices we find that divesting in the North would drive prices between the North and the Center further apart whereas the opposite effect is observed when divestment takes place in the Center.

Similar to the best-response divestment analysis the change in deadweight loss relative to the baseline market outcome is the change in the total variable cost of serving locational demands throughout the transmission network. The same problem with computing variable cost of non-thermal units arises here. In this case, the parametric locational marginal cost functions in Figure 7 are used instead of step function locational marginal cost functions. Under this specification, two divestment scenarios produce an increase in the average hourly total variable cost relative to the baseline average hourly total variable cost, while the other two lead to a decrease. Both decreases are associated divestment in the Center and the larger reduction in the average hourly total variable cost is associated with the larger capacity divestment of 2.4 GW. For the divestment in the North, the increase in the average hourly total variable cost is slightly larger for the 2.4 GW divestment scenario. These results reinforce our earlier point that different from the case of a single-location market, in a potentially congested locational pricing markets capacity divestment can increase the total variable cost of serving locational demands.

Our equilibrium analysis confirms the same quantitative results as in our best-response analysis, i.e., the largest percentage locational price reduction occurs at the location where the divest-

ment occurs, and there can be price decreases and even price increases in other locations.

6 Discussion and Conclusion

We have introduced residual demand hypersurfaces—a natural extension of the residual demand curve concept developed for single-location markets to interconnected locational markets with finite transmission capacity. These hypersurfaces allow us to analyze how a firm's quantity decisions at one location affect prices both locally and across the entire network. They also offer a framework for quantifying a supplier's potential to exercise unilateral market power at each location.

We have adapted the expected profit-maximizing offer curve model to incorporate these network-constrained residual demand hypersurfaces. We found that accounting for transmission constraints helps explain actual offer behavior in the Italian wholesale market better expected profit-maximizing offer curves constructed assuming infinite transmission capacity.

We have shown the importance of taking the location of a firm's capacity into account when assessing the impact of divestment scenarios to enhance market competitiveness in a locational pricing market with finite transmission capacity. We have developed a stochastic locational quantity-setting equilibrium model of competition that accounts for the fact that firms compete through a potential congested transmission network. Using this model, we confirmed the qualitative findings of our expected profit-maximizing offer curve model regarding the impact of various locational divestment actions on locational prices.

Finally, we have introduced quantitative measures of the supplier's unilateral ability to exercise locational market power. These own- and cross-price inverse semi-elasticities quantify the impact on prices at all locations of a supplier withholding a certain percentage of its output at one location. These measures are likely to be a useful input for designing local market power mitigation mechanisms and for defining relevant geographic markets in merger and antitrust analyses.

Our results rest on several assumptions that we hope to relax in future research. For instance, our analysis does not capture the repeated game nature of supplier interactions, as well as the market for fixed-price forward contracts, or the market for redispatch and real-time balancing. Finally, we do not account for non-convexities in the cost of operating thermal generation units.

References

Anderson, Edward J., and Xinmin Hu. 2008. "Finding Supply Function Equilibria with Asymmetric Firms." *Operations Research* 56(3): 697–711.

Bigerna, Simona, Carlo Andrea Bollino, and Paolo Polinori. 2016. "Market Power and Transmission Congestion in the Italian Electricity Market." *The Energy Journal* 37(2): 133–154.

Borenstein, Severin, James Bushnell, and Steven Stoft. 2000. "The Competitive Effects of Transmission Capacity in a Deregulated Electricity Industry." *The RAND Journal of Economics* 31(2): 294–325.

Bosco, Bruno, Lucia Parisio, and Matteo Pelagatti. 2013. "Price-capping in partially monopolistic electricity markets with an application to Italy." *Energy Policy* 54(0): 257–266.

Bushnell, James B., Erin T. Mansur, and Celeste Saravia. 2008. "Vertical Arrangements, Market Structure, and Competition: An Analysis of Restructured US Electricity Markets." *The American Economic Review* 98(1): 237–266.

Cho, In-Koo 2003. "Competitive Equilibrium in a Radial Network." *The RAND Journal of Economics* 34(3): 438–460.

Daví-Arderius, Daniel, and Christoph Graf. 2025. "Iberian Peninsula Blackout: A Trade-Off Between Operational Risk and Consumer Cost." Working paper, NYU Institute for Policy Integrity.

Duthaler, Christof, and Matthias Finger. 2008. "Financial Transmission Rights in Europe's Electricity Market." Conference Paper, International Conference on Competition and Regulation in Network Industries.

Fianu, Emmanuel Senyo, Daniel Felix Ahelegbey, and Luigi Grossi. 2022. "Modeling risk contagion in the Italian zonal electricity market." *European Journal of Operational Research* 298(2): 656–679.

Gilbert, Richard, Karsten Neuhoff, and David Newbery. 2004. "Allocating Transmission to Mitigate Market Power in Electricity Markets." *RAND Journal of Economics* 35(4): 691–709.

Graf, Christoph 2025. "Simplified Short-Term Electricity Market Designs: Evidence from Europe." . *The Electricity Journal*: 107486.

Graf, Christoph, Emilio La Pera, Federico Quaglia, and Frank A. Wolak. 2021. "Market Power Mitigation Mechanisms for Wholesale Electricity Markets: Status Quo and Challenges." Working paper, Program on Energy Sustainable Development, Stanford University.

Graf, Christoph, Federico Quaglia, and Frank A. Wolak. 2020a. "Market Performance Assessment in Locational Pricing Markets with Non-convexities." Working paper, Program on Energy Sustainable Development, Stanford University.

Graf, Christoph, Federico Quaglia, and Frank A. Wolak. 2020b. "Simplified Electricity Market Models with Significant Intermittent Renewable Capacity: Evidence from Italy." NBER Working Papers 27262, National Bureau of Economic Research.

Graf, Christoph, Federico Quaglia, and Frank A. Wolak. 2021. "(Machine) learning from the COVID-19 lockdown about electricity market performance with a large share of renewables." *Journal of Environmental Economics and Management* 105(0): 102398.

Green, Richard J., and David M. Newbery. 1992. "Competition in the British Electricity Spot Market." *Journal of Political Economy* 100(5): 929–53.

Hobbs, Benjamin F., and J. S. Pang. 2007. "Nash-Cournot Equilibria in Electric Power Markets with Piecewise Linear Demand Functions and Joint Constraints." *Operations Research* 55(1): 113–127.

Hobbs, Benjamin F., Fieke A.M. Rijkers, and Maroeska G. Boots. 2005. "The More Cooperation, The More Competition? A Cournot Analysis of the Benefits of Electric Market Coupling." *The Energy Journal* 26(4): 69–97.

Hortaçsu, Ali, and Steven L. Puller. 2008. "Understanding strategic bidding in multi-unit auctions: a case study of the Texas electricity spot market." *RAND Journal of Economics* 39(1): 86–114.

Ito, Koichiro, and Mar Reguant. 2016. "Sequential Markets, Market Power, and Arbitrage." *American Economic Review* 106(7): 1921–1957.

Jha, Akshaya, and Gordon Leslie. 2025. "Start-up Costs and Market Power: Lessons from the Renewable Energy Transition." *American Economic Review* 115(2): 690–724.

Joskow, Paul L., and Jean Tirole. 2000. "Transmission Rights and Market Power on Electric Power Networks." *RAND Journal of Economics* 31(3): 450–487.

Kirschen, Daniel S., and G. Strbac. 2019. *Fundamentals of Power System Economics*, Wiley.

Klemperer, Paul D., and Margaret A. Meyer. 1989. "Supply Function Equilibria in Oligopoly under Uncertainty." *Econometrica* 57(6): 1243–77.

Kolstad, Charles D., and Lars Mathiesen. 1987. "Necessary and Sufficient Conditions for Uniqueness of a Cournot Equilibrium." *The Review of Economic Studies* 54(4): 681–690.

Leslie, Gordon W 2021. "Who benefits from ratepayer-funded auctions of transmission congestion contracts? Evidence from New York." *Energy Economics* 93(0): 105025.

Luo, Zhi-Quan, Jong-Shi Pang, and Daniel Ralph. 1996. *Mathematical programs with equilibrium constraints*, Cambridge University Press.

McRae, Shaun D., and Frank A. Wolak. 2014. "How Do Firms Exercise Unilateral Market Power? Empirical Evidence from a Bid-Base Wholesale electricity Market." In *Manufacturing of Markets: Legal, Political and Economic Dynamics*, 390–420. Cambridge University Press.

Mercadal, Ignacia 2022. "Dynamic Competition and Arbitrage in Electricity Markets: The Role of Financial Players." *American Economic Journal: Microeconomics* 14(3): 665–99.

Neuhoff, Karsten, Julian Barquin, Maroeska G. Boots, Andreas Ehrenmann, Benjamin F. Hobbs, Fieke A.M. Rijkers, and Miguel Vázquez. 2005. "Network-constrained Cournot models of liberalized electricity markets: the devil is in the details." *Energy Economics* 27(3): 495–525.

Oren, Shmuel S. 1997. "Economic Inefficiency of Passive Transmission Rights in Congested Electricity Systems with Competitive Generation." *The Energy Journal* 18(1): 63–83.

Puller, Steven L. 2007. "Pricing and Firm Conduct in California's Deregulated Electricity Market." *The Review of Economics and Statistics* 89(1): 75–87.

Reguant, Mar 2014. "Complementary Bidding Mechanisms and Startup Costs in Electricity Markets." *Review of Economic Studies* 81(4): 1708–1742.

Ryan, Nicholas 2021. "The Competitive Effects of Transmission Infrastructure in the Indian Electricity Market." *American Economic Journal: Microeconomics* 13(2): 202–42.

Scheffman, David T., and Pablo T. Spiller. 1987. "Geographic market definition under the US Department of Justice Merger Guidelines." *The Journal of Law and Economics* 30(1): 123–147.

Sioshansi, Ramteen, and Shmuel Oren. 2007. "How good are supply function equilibrium models: an empirical analysis of the ERCOT balancing market." *Journal of Regulatory Economics* 31(1): 1–35.

Tangerås, Thomas P., and Frank A. Wolak. 2018. "The Competitive Effects of Linking Electricity Markets Across Space and Time." Stanford university, program on energy and sustainable development working paper.

Tu, Loring W. 2011. *An Introduction to Manifolds*, Springer.

Willems, Bert 2002. "Modeling Cournot Competition in an Electricity Market with Transmission Constraints." *The Energy Journal* 23(3): 95–125.

Wilson, Robert 2008. "Supply Function Equilibrium in a Constrained Transmission System." *Operations Research* 56(2): 369–382.

Wolak, Frank A. 2000. "An Empirical Analysis of the Impact of Hedge Contracts on Bidding Behavior in a Competitive Electricity Market." *International Economic Journal* 14(2): 1–39.

Wolak, Frank A. 2003a. "Identification and estimation of cost functions using observed bid data." In *Advances in Economics and Econometrics: Theory and Applications, Eighth World Congress*, Vol 2, 133–169. Cambridge University Press.

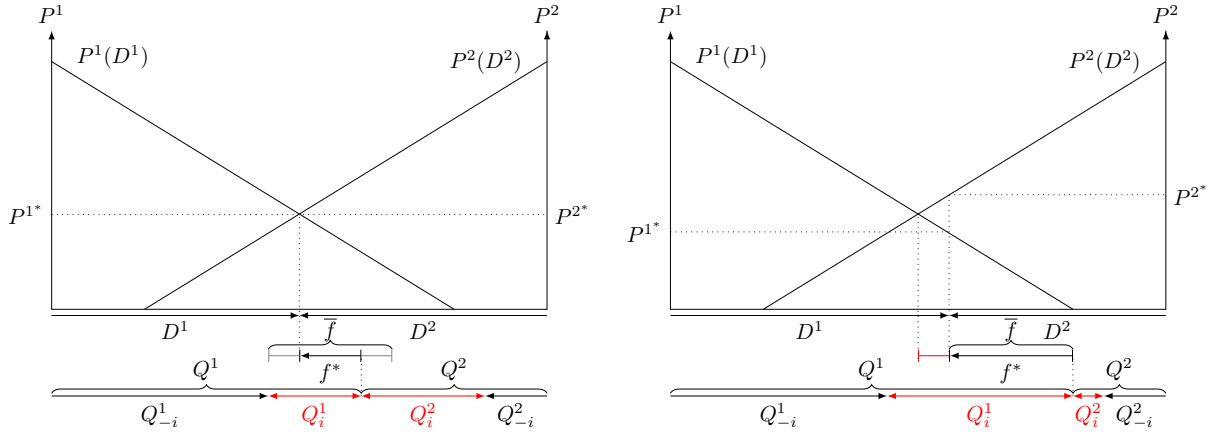
Wolak, Frank A. 2003b. "Measuring Unilateral Market Power in Wholesale Electricity Markets: The California Market, 1998–2000." *American Economic Review* 93(2): 425–430.

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

Wood, Allen J., Bruce F. Wollenberg, and Gerald B. Sheblé. 2013. *Power Generation, Operation, and Control*, John wiley & sons.

Yao, Jian, Ilan Adler, and Shmuel S. Oren. 2008. "Modeling and Computing Two-Settlement Oligopolistic Equilibrium in a Congested Electricity Network." *Operations Research* 56(1): 34–47.

Figure 1: Market-Clearing in Symmetric, Transport-Capacity-Constrained Markets

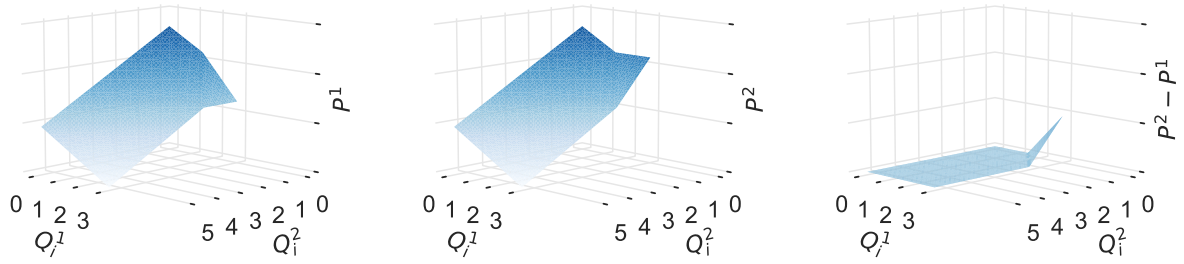


(a) Uncongested Markets

(b) Congested Markets

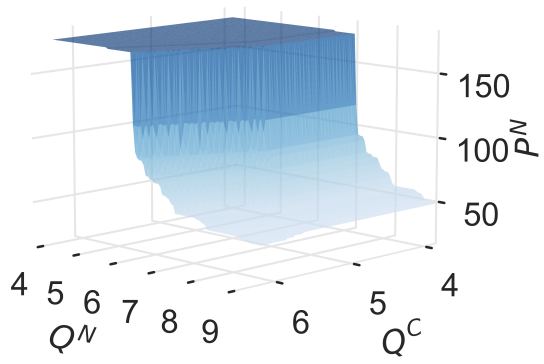
Notes: Panel (a): The resulting optimal export, f^*, given the inverse demand functions $P^1()$, $P^2()$ and total outputs Q^1, Q^2, does not exceed the transportation limit $\overline{f}$, equalizing locational prices P^1 and P^2. Although the transport capacity between the two markets is unconstrained, f^* output in market 1 is used to serve f^* demand in market 2. Panel (b): Firm i's choice to substantially increase it's output in location 1 and to reduce it in location 2, leads to a binding transport constraint ($f^* = \overline{f}$). This leads to different prices in the two markets.

Figure 2: Inverse Residual Demand Surfaces in Symmetric Markets

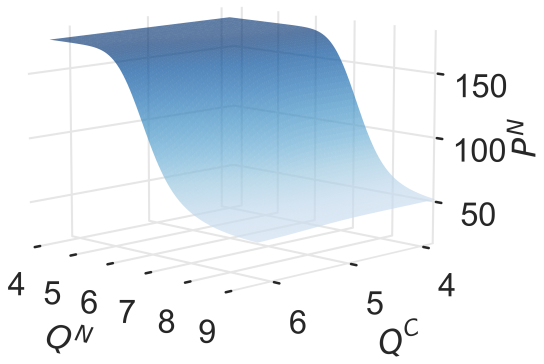


(a) Market 1 (b) Market 2 (c) Difference between (b) and (a)

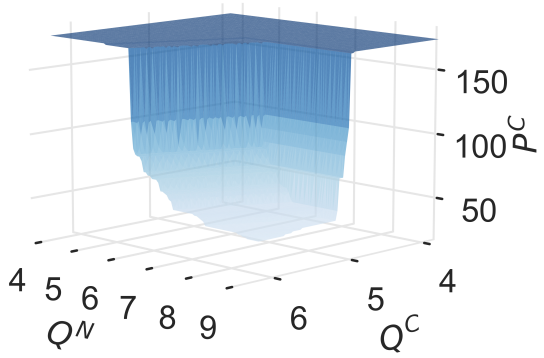
Figure 3: Actual versus Smoothed Residual Demand Surfaces



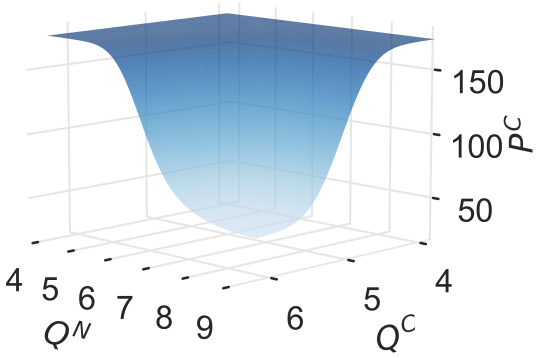
(a) North (N)



(b) North (N), Smoothed



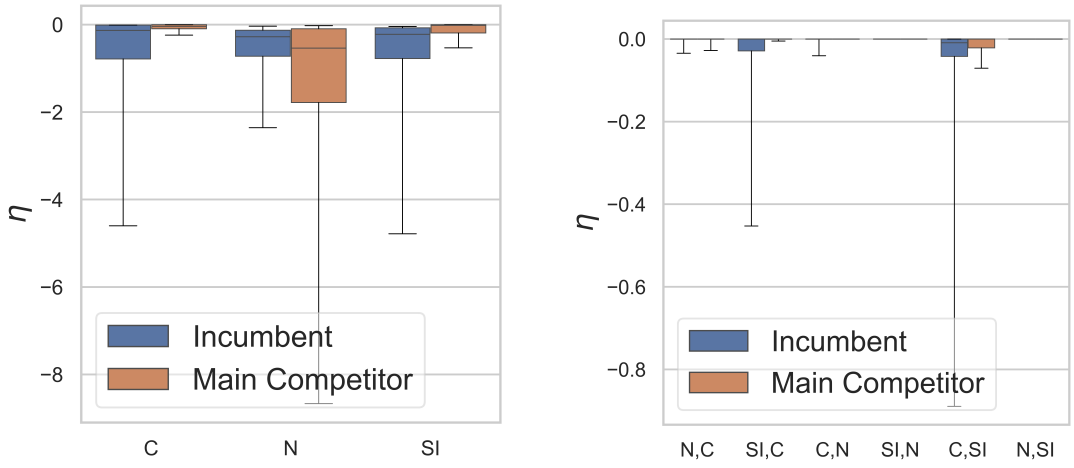
(c) Center (C)



(d) Center (C), Smoothed

Notes: Panel (a) and (c): Actual inverse residual demand surfaces on 2007-09-21, hour 11 for both strategic firms; Panel (b) and (d) Smoothed residual demand surfaces using normal kernel and bandwidth equals to 5% of total available capacity in each location. Supply in Sicily fixed to its actual level. Quantities are in GWh and prices in €/MWh.

Figure 4: Own- and Cross-Price Inverse Semi-Elasticities of Step-Function Residual Demand-Hyper Surfaces

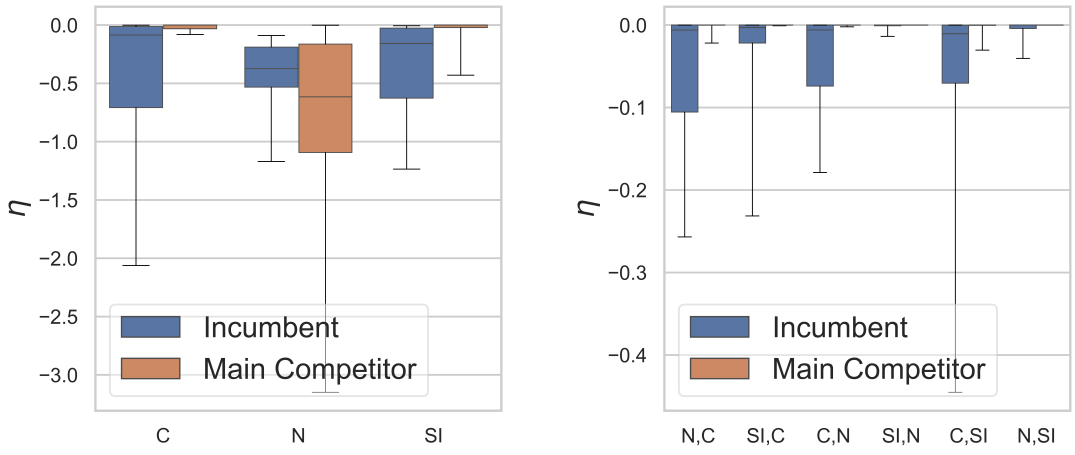


(a) Own-price inverse semi-elasticities

(b) Cross-price inverse semi-elasticities

Notes: Whiskers represent the 10th percentile and the 90th percentile of the data. Outliers falling outside this range are excluded from the plot.

Figure 5: Own- and Cross-Price Inverse Semi-Elasticities of Smoothed Residual Demand Hypersurfaces

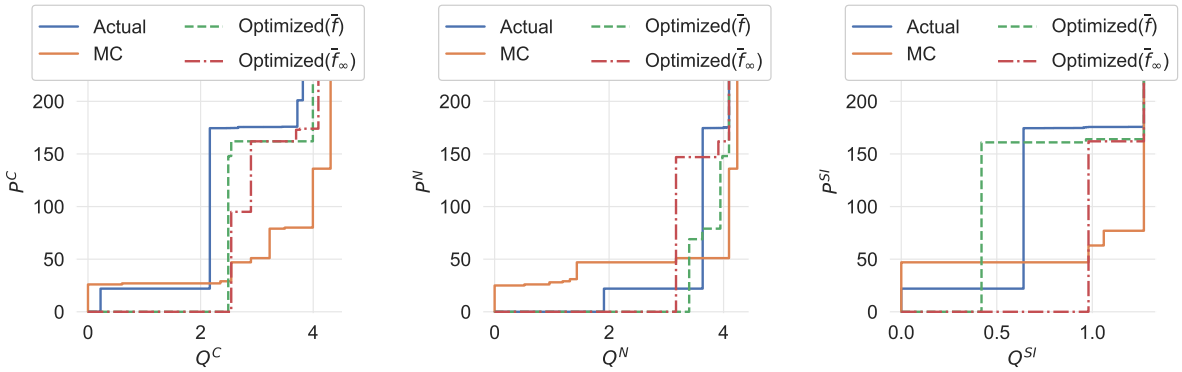


(a) Own-price inverse semi-elasticities

(b) Cross-price inverse semi-elasticities

Notes: Whiskers represent the 10th percentile and the 90th percentile of the data. Outliers falling outside this range are excluded from the plot.

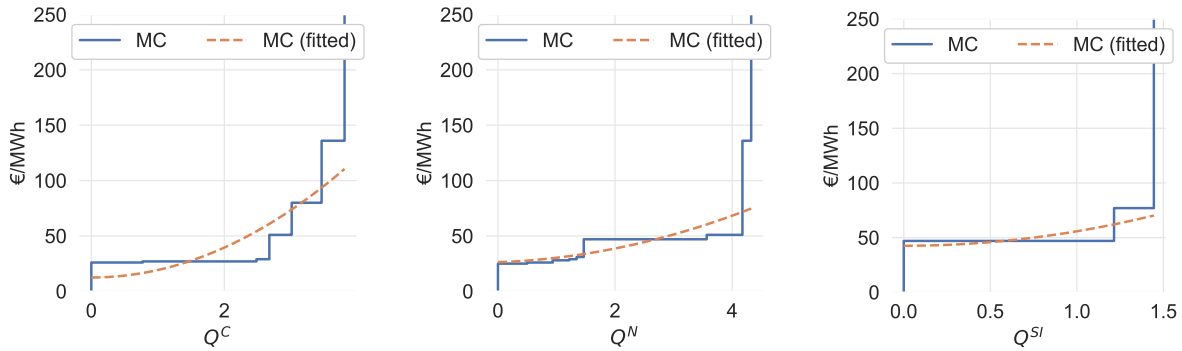
Figure 6: Incumbent's Optimized Locational Offer Curves



(a) Center (C) (b) North (N) (c) Sicily (SI)

Notes: September 5, Hour 12. Only relevant thermal units. Quantities are in GWh and prices in €/MWh.

Figure 7: Locational Short-Term Marginal Cost Functions



(a) Center (C) (b) North (N) (c) Sicily (SI)

Notes: Incumbent's piece-wise constant short-term marginal cost curves and fitted convex and increasing marginal cost curves in the Center (Panel a), North (Panel, b), and Sicily (Panel, c) for 2007-09-21, Hour 11. Quantities are in GWh and marginal costs in €/MWh.

Table 1: Expected Profit-Maximizing Offer Curve Results

	(1) MC	(2) Actual	(3) Optimized($\overline{f}$)	(4) Optimized($\overline{f}_\infty$)
		Panel A. Incumbent		
$\overline{P}$	78.9	103.1	105.5	102.7
P^C	82.5	119.8	115.3	111.9
P^N	74.5	90.1	92.8	94.6
P^{SI}	96.8	123.5	165.1	121.8
Q_i^C	3 134	2 348	2 805	2 740
Q_i^N	3 805	3 400	3 386	3 229
Q_i^{SI}	1 249	1 104	899	1 166
Q_i	8 189	6 853	7 091	7 136
Profit[1]	505.4	540.9	593.2	568.1
		Panel B. Main competitor		
$\overline{P}$	97.2	103.1	105.9	101.0
P^C	119.7	119.8	120.0	119.9
P^N	80.0	90.1	94.8	86.5
P^{SI}	121.3	123.5	122.7	121.7
Q_i^C	2 237	2 232	2 233	2 232
Q_i^N	4 302	3 893	3 917	4 129
Q_i^{SI}	461	311	462	453
Q_i	7 000	6 436	6 612	6 815
Profit[1]	370.1	370.4	383.6	376.1

Notes: Average market outcomes ($N = 175$). Prices in €/MWh, profits in €K, and quantities in MWh. Col (1): Market clearing evaluated at firm's short-term marginal cost estimates. Col (2): Market clearing evaluated at firm's observed offers. Col (3): Market clearing evaluated at firm's expected profit-maximizing offer curve. Col (4): Market clearing evaluated at firm's expected profit-maximizing offer curve computed under the assumption of infinite transmission capacity. Almost all solutions to compute expected profit-maximizing offer curves are proven global maxima (2 cases out of 350 cases have a MIP gap larger than 0.09% where the maximum value is 0.3%). The MIP gap is the difference in the objective function value between the current best integer solution and the optimal value of a linear program (LP) relaxation. If the gap is zero the resulting solution is the proven global optimum.

[1] Profits adjusted by $Q^C \cdot P^C$ with P^C set to the average actual uniform purchase price (€103/MWh) in our sample. Only relevant thermal units considered including adjustments for costs and revenues of non-relevant thermal units.

Table 2: Simulated Market Outcomes under Locational Quantity Competition

	(1) Baseline	(2) Divestment in the Center	(3) Δ	(4) Δ(%)	(5) Divestment in the North	(6) Δ	(7) Δ(%)
Panel A. Thermal capacity divestment of about 1.2 GW							
$\overline{P}$	98.7	95.2	−3.5	−3.5%	98.2	−0.5	−0.6%
P^C	105.6	99.1	−6.5	−6.2%	107.6	2.0	1.9%
P^N	87.7	85.5	−2.2	−2.5%	85.0	−2.7	−3.1%
P^{SI}	160.0	163.9	3.9	2.4%	164.5	4.5	2.8%
Q^C	4 892	3 939	−953	−19.5%	4 839	−53	−1.1%
Q^N	7 226	7 164	−61	−0.8%	6 402	−824	−11.4%
Q^{SI}	1 167	1 131	−36	−3.0%	1 136	−30	−2.6%
Q	13 285	12 235	−1 050	−7.9%	12 377	−908	−6.8%
Profit[1]	916	824	−92	−10.1%	851	−65	−7.1%
Total Cost[2]	945	938	−7	−0.8%	950	4	0.5%
Panel B. Thermal capacity divestment of about 2.4 GW							
$\overline{P}$	98.7	94.1	−4.6	−4.7%	96.9	−1.8	−1.9%
P^C	105.6	97.1	−8.5	−8.1%	108.7	3.1	3.0%
P^N	87.7	84.6	−3.1	−3.5%	81.7	−6.1	−6.9%
P^{SI}	160.0	166.3	6.3	3.9%	167.2	7.2	4.5%
Q^C	4 892	3 288	−1 604	−32.8%	4 787	−105	−2.1%
Q^N	7 226	7 145	−81	−1.1%	5 723	−1 502	−20.8%
Q^{SI}	1 167	1 111	−56	−4.8%	1 117	−50	−4.3%
Q	13 285	11 544	−1 740	−13.1%	11 627	−1 657	−12.5%
Profit[1]	916	769	−147	−16.0%	811	−105	−11.5%
Total Cost[2]	945	936	−9	−0.9%	951	6	0.6%

Notes: Average market outcomes ($N = 175$). Equilibrium selection criteria is maximized joint profits. Quantities and profits aggregated across both strategic firms. Prices in €/MWh, costs and profits in €K, and quantities in MWh.

[1] Profits adjusted by $Q^C \cdot P^C$ with P^C set to the average actual uniform purchase price (€103/MWh) in our sample. Only thermal units considered including adjustments for costs and revenues of non-relevant thermal units.

[2] Includes the variable costs of strategic firms computed using the assumed functional form as well as the costs of remaining firms including imports assuming that this energy is offered at marginal costs.

Table 3: Divestment of Incumbent's Capacity

	(1) Baseline	(2) Divestment in the Center	(3)	(4)	(5) Divestment in the North	(6)	(7)
			Δ	$\Delta(\%)$		Δ	$\Delta(\%)$
Panel A. Thermal capacity divestment of about 1.2 GW							
$\overline{P}$	105.5	103.5	-2.0	-1.9%	101.9	-3.6	-3.4%
P^C	115.3	107.6	-7.7	-6.7%	115.7	0.4	0.3%
P^N	92.8	93.4	0.7	0.7%	85.2	-7.6	-8.1%
P^{SI}	165.1	172.7	7.6	4.6%	174.7	9.6	5.8%
Profit	593.2	495.6	-97.6	-16.4%	533.3	-59.9	-10.1%
Total Cost[1]	723.1	725.9	2.7	0.4%	721.8	-1.3	-0.2%
Panel B. Thermal capacity divestment of about 2.4 GW							
$\overline{P}$	105.5	101.1	-4.4	-4.2%	100.8	-4.7	-4.4%
P^C	115.3	103.4	-11.8	-10.3%	115.9	0.6	0.6%
P^N	92.8	91.6	-1.2	-1.3%	82.5	-10.2	-11.0%
P^{SI}	165.1	176.3	11.1	6.7%	180.5	15.4	9.3%
Profit	593.2	438.6	-154.6	-26.1%	499.8	-93.4	-15.7%
Total Cost[1]	723.1	725.8	2.7	0.4%	723.7	0.6	0.1%

Notes: Average market outcomes ($N = 175$). Prices in €/MWh, costs and profits in €K. Col (1): Market clearing evaluated at incumbent's expected profit-maximizing offer curve. Col (2): Market clearing evaluated at incumbent's expected profit-maximizing offer curve assuming that coal capacity in the Center was divested. Col (3): Actual change between Col (1) and Col (2). Col (4): Relative change between Col (1) and Col (2). Col (5): Market clearing evaluated at incumbent's expected profit-maximizing offer curve assuming that coal capacity in the North was divested. Col (6): Actual change between Col (1) and Col (5). Col (7): Relative change between Col (1) and Col (5). Almost all solutions to compute expected profit-maximizing offer curves are proven global maxima (3 cases out of 1,050 with MIP gap larger than 0.09%. Maximum MIP gap of these 7 cases is equal to 0.38%). The MIP gap is the difference in the objective function value between the current best integer solution and the optimal value of a linear program (LP) relaxation. If the gap is zero the resulting solution is the proven global optimum.

[1] Includes costs of explicitly modeled thermal units as well as costs of remaining supply capacity (including imports) assuming that this capacity is offered at short-term marginal costs.

ONLINE APPENDIX

"Measuring Market Power in Network-Constrained Markets"

Christoph Graf and Frank A. Wolak

September 10, 2025

This Online Appendix is organized as follows. In Section O.1, we give a detailed description of the Italian electricity market. Section O.2 describes the locational pricing market-clearing engine used by the market operator and presents the computation of the uniform market-clearing price paid by loads. In Section O.3, we show how to reformulate the expected profit-maximizing offer curve problem into a mixed integer program and solve for expected profit-maximizing offer curves in a locational pricing market. In Section O.4, we provide additional details on how to smooth kinky residual demand hypersurfaces used to compute locational equilibrium quantities. Furthermore, we provide additional details on how we deal with potential non-unique solutions in our locational quantity-setting equilibrium model. Additional figures and tables are presented in Section O.5.

O.1 Market Description and Market Structure

In this section, we provide additional context and details on the Italian electricity market and its market structure. Furthermore, we provide descriptive statistics and market outcomes during our sample period.

O.1.1 The Italian Electricity Market

The Italian short-term market for wholesale electricity has been operating since April 2004. It consists of a day-ahead market, an adjustment market,[1] and an ancillary services market, also known as the re-dispatch and real-time balancing market. After the day-ahead market has cleared, market participants have the opportunity to alter their day-ahead schedules in the adjustment market. Eventually, Terna, the Italian transmission system operator, builds up reserves, resolves congestion, and balances the grid in real-time in the so-called ancillary services or redispatch and real-time balancing market.

The Italian day-ahead market for electricity is a non-compulsory net-pool locational market administrated by the market operator. The market splits into several submarkets when tranmission congestion is present. In that case, producers receive a different price depending on where they are injecting energy. The demand side pays a uniform purchase price. Retailers and large consumers bid a non-increasing demand curve at their location. Suppliers submit non-decreasing energy offer curves that do not include a start-up or minimum load cost. Demand bid and supply offer prices are floored at zero and capped at 500 EUR which was lifted to 3 000 EUR in 2008. In 2007 the maximum observed uniform purchase price was €242.4/MWh (Bosco et al., 2013). For each production or consumption unit a maximum of four offer steps is allowed. In the day-ahead market electricity is traded for the 24 hours of the next day and there are no inter-temporal constraints, such as block bids,[2] or ramp rates to consider when clearing the market. Assuming that non-convexities as discussed in Graf et al. (2020) are a minor concern for suppliers when formulating their offer curves implies that we can treat each hour of the day as independent from one another.

Many market participants have fixed-price long-term contract obligations to supply and purchase electricity. In the day-ahead market, participants may self-schedule (a part of) their bilateral commitments. Self-scheduled demand and supply enter the day-ahead market as price inelastic

[1] The adjustment market has been replaced by a series of intra-day markets in later years. The Italian Power Exchange provides a detailed description on their website, see `http://www.mercatoelettrico.org/En/Mercati/MercatoElettrico/MPE.aspx`.

[2] See, e.g., Reguant (2014), for a description of block bids in the Spanish day-ahead market.

bids.[3] In case of transmission congestion, an explicit transmission capacity fee (CCT)[4] is due for the self-schedules. The CCT is defined as the difference between the hourly purchase price in the withdrawal zones of the contract and the hourly electricity selling price in the injection zones of the contract. Hence, the CCT translates into a cost for injections into exporting zones, because it contributes to increasing congestion; and it translates into a subsidy for injection into importing zones, as it contributes to relieving congestion. The CCT is zero if no congestion is present. Note that regular day-ahead market transactions pay/receive an implicit congestion fees based on the zonal price difference (for further details see Ardian et al., 2018).[5]

In 2007, the Italian market consisted of seven domestic bidding zones, five limited production bidding zones, and six foreign virtual bidding zones to organize imports and exports. The network structure relevant for the day-ahead market clearing at the time was assumed to be radial.[6] Congestion between bidding zones mostly took place between the North bidding zone and the rest of the mainland as well as between the mainland and the islands of Sicily and Sardinia. During our sample period congestion between the North bidding zone and the rest of the mainland occurred over 80% of the hours. We refer to Sections O.1.4–O.1.6 for more details on the transmission network and the prevalence of congestion. The Italian market operator publishes day-ahead market offers and bids, clearing quantities and prices, as well as day-ahead market transmission limits between bidding zones for each hour of the sample.[7]

O.1.2 Market Structure

In 2007, annual electricity demand reached about 340 TWh net of energy for pumping and before transmission line losses. Peak demand was in December with about 56.8 GW. Available installed capacity was 77.6 GW. The demand in the day-ahead market reached 330 TWh, whereas about

[3] There is the theoretical possibility to self-schedule demand or supply at a positive price but this option is hardly ever used by market participants.

[4] Those charges are called Corrispettivo per l'assegnazione dei diritti di utilizzo della capacit'a di trasporto (CCT). See `http://www.mercatoelettrico.org/en/tools/glossario.aspx`.

[5] For more details on the market we refer to `http://www.mercatoelettrico.org/En/MenuBiblioteca/documenti/20111216Annual_Report_2010.pdf`.

[6] In such a network loops are absent, meaning that there is a unique path between every two nodes in the network. In a radial transmission network the effect of congestion on a transmission link is to separate the system into zones at either end of the link, each zone having its own price for energy. This implies that each zone has an induced net demand for energy—the original zonal demand plus prescribed exports minus prescribed imports as shown in Wilson (2008).

[7] See `https://www.mercatoelettrico.org/`.

two-thirds of the demand was fulfilled through market transactions and the remainder through self-schedules.

All customers have the right to choose their electricity supplier since July 2007. However, most domestic consumers had not opted for this option at the time. For those households and small companies, the single buyer—a state controlled entity—is in charge for procuring electricity from the day-ahead market and reselling it to retailers (ARERA, 2008a).

In 2007, 85% of gross electricity production came from thermal plants and 13% from hydro (including some pumped-hydro storage units). The remaining share came from geothermal sources and wind power. In terms of thermal capacity, the majority uses natural gas followed by coal and fuel oil. See Graf and Marcantonini (2017) for more details. Compared to Italy's neighbors in the North—with nuclear power as the dominant source in France and hydro power in Switzerland—this is a rather expensive power production mix which explains the large amount of imports.

The incumbent firm in the Italian market is Enel—the former state-owned monopolist. Its share of electricity generation was about 31% in 2007. Enel's main competitor at the time was Edison. It was controlled by Aem—a Milan based utility and Edf—the French state-owned company. Furthermore, Edison controlled half of Edipower's capacity via a tolling agreement. Edipower is a generation company with capacity in the North bidding zone as well as in Sicily. Furthermore, Aem controlled 20% of Edipower. We decided to model Edison, Aem, Edf, Edipower as one company construct, which we refer to as Edison in the article.[8] Edison's market share in generated electricity was about 13.7% in 2007 and Edipower's 8%.

Both the incumbent (Enel) and main competitor (Edison) operate hydro plants for other firms in the north of the country. However, in most of the cases the two firms hold also shares of these other firms. We therefore decided to add this hydro capacity to each of these firms' generation capacity.

Some thermal plants in the Italian market are operated by a state-owned entity due to a special regime called CIP-6/92.[9] The state-owned entity signed contracts for differences with the owners

[8]See the European Commission's merger case "COMP/M.3729–EDF/AEM/EDISON" for more details on the firm construct including the tolling agreement.

[9]This is a controversial resolution put in place before the market liberalization, with the purpose to subsidize the production of electricity from renewable and "assimilated" sources. In practice, many thermal plants, such as cogeneration plants, managed to benefit from the CIP-6 subsidy by claiming to be "assimilated" to renewables. The electricity produced from "assimilated" sources under the CIP-6 agreement is not negligible as it comprised approximately 15% of the domestic thermoelectric production in 2007, (see, e.g., ARERA, 2008b). Note that this law is in stark

of these thermal plants and in exchange offered the capacity at zero to the market. This leaves the state-owned entity with the price risk of the short-term market. If reselling of contracts were forbidden, CIP-6 contracts would enter the firms' objective function. However, only the net-position of contracted quantity matters when offering to the short-term market and therefore, we do only implicitly account for the contracts signed with the state-owned entity.

In Table O.1, we show the zonal distribution of production capacity by generation type, location, and firm.[10] The data in the table reveals that the incumbent has a dominant position in the Center bidding zone. Capacity shares of both firms are more balanced in the North bidding zone. Market concentration is particularly high in Sicily.

O.1.3 Day-Ahead Market Offers and Transactions

Table O.2 shows market offers and transactions for the sample period. A large share of domestic supply offers is price inelastic and domestic demand bids are almost entirely inelastic. Imports play a significant role in the Italian market as 14% of electricity consumed is imported. The amount of electricity from pumped storage units is negligible because our sample is restricted to peak hours only.[11]

O.1.4 Transmission Network

Figure O.1 shows the transmission network structure in 2007 relevant for the day-ahead market clearing. It is a radial representation where nodes are aggregated to bidding zones. The bidding

contrast to EU law and was therefore phased out.

[10] We elicit capacity data from the day-ahead offer data by taking the maximum offer quantity per unit, day, and hour during our sample period. This method yields a total supply capacity of 70.7 GW. This value is slightly lower than the reported number of total net capacity of 77.6 GW reported by ARERA (2008a) for the whole year of 2007. Possible explanations for the difference are that we derive capacity value estimates only by using offer data from the fall 2007 and not the whole year. Typically, available hydro capacity peaks in the spring after the snow melt and therefore a reduced value of available capacity in the fall is credible. Furthermore, the value provided by the regulator does not account for planned outages during our sample period.

[11] Storage units are typically assumed to offer based on an opportunity cost logic. Modeling independent storage units would have their offer behavior depend on expected future electricity prices as discussed in (Graf and Wozabal, 2013). Endogenizing storage unit offer decisions in this manner would severely complicate our model. Therefore, we leave actual storage offers in the residual demand hypersurface and include the actual energy sold in the day-ahead market in the firm's objective function treating it as infra-marginal capacity that is valued at the relevant zonal market-clearing price. However, we emphasize that storage units not only transfer energy from low price periods to high price periods, but they also provide operating reserves or real-time balancing services because of their flexibility. The average day-ahead quantity of energy sold by storage units is 0.8 GWh, which is about 13% of the total storage generation capacity and only 1% of the total generation capacity.

Table O.1: Capacity and Peak Demand

Type/Zone	C[1]	N[2]	SI[1]	Total
Panel A. Incumbent				
Thermal	11.0	6.9	2.1	20.0
Storage[3]	1.6	4.0	0.4	6.0
Other[4]	1.7	3.8	0.2	5.7
Total	14.3	14.7	2.7	31.7
Panel B. Main competitor				
Thermal	3.7	7.6	1.2	12.5
Storage[3]		0.3		0.3
Other[4]	0.3	2.3		2.6
Total	4.0	10.2	1.2	15.4
Panel C. Fringe				
Total	9.6	13.2	1.1	23.9
Panel D. Market				
Total	27.8	38.1	4.8	70.7

Notes: Capacity values in GW are derived by aggregating maximum offered quantities in the day-ahead market during our sample period. Capacity estimates include capacity contracted under the CIP-6 regime.

[1] Center (C) zone includes bidding zones CN, CS, CA, S, and SA and limited production bidding zones therein.

[2] Includes capacity in limited production zones.

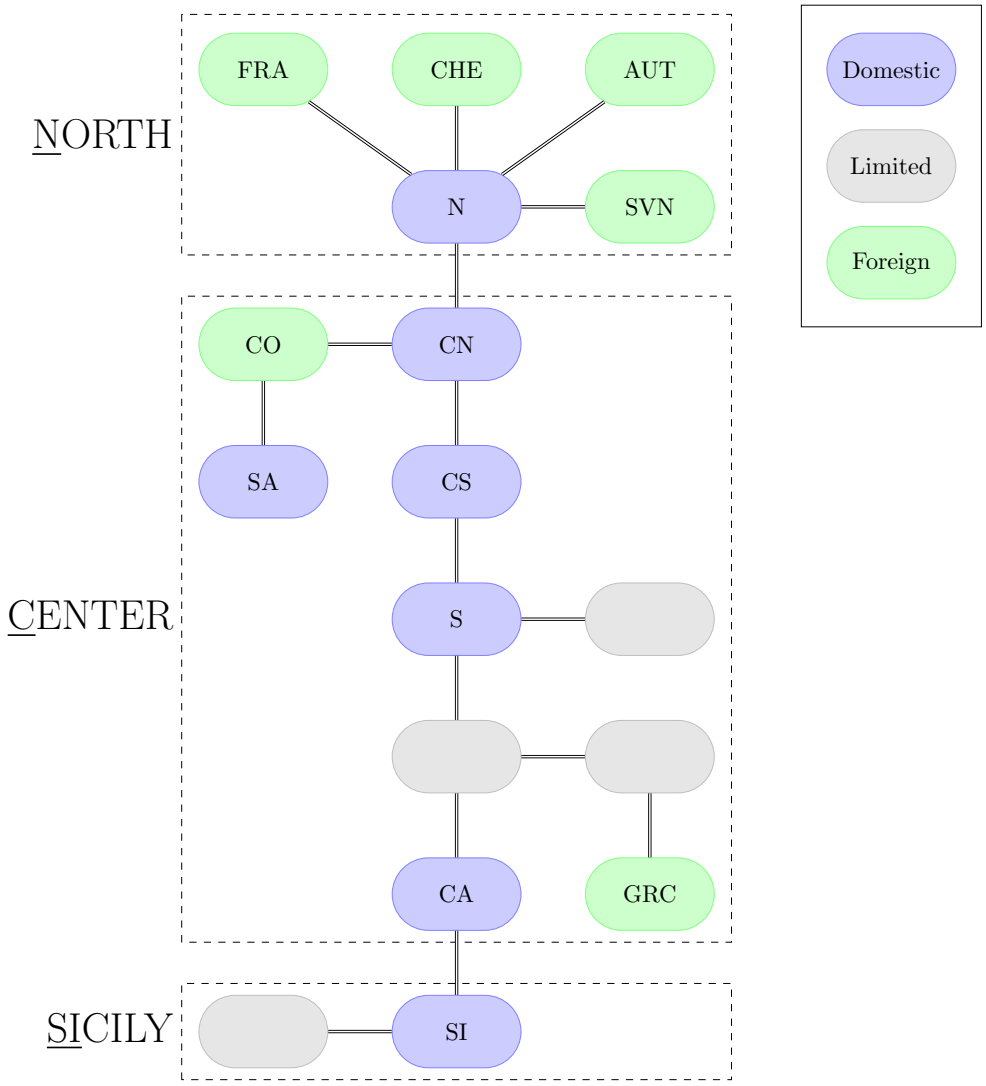
[3] Production capacity of largest pumped-hydro storage plants.

[4] Includes run-off the river plants, hydro systems with dams and reservoirs, capacity from geothermal, wind, and photovoltaics, and capacity from small and unmatched thermal power plants.

zones can be subdivided into domestic bidding zones, limited production bidding zones, and virtual foreign bidding zones.[12] Domestic bidding zones contain generation as well as load whereas limited production bidding zones only contain generation. The Italian power system is highly interconnected with its neighboring countries in the North, especially, France (FRA) and Switzerland (CHE). Italian as well as foreign market participants can make sale offers or purchase bids for electricity in the foreign virtual bidding zones.

[12]Domestic bidding zones are: North (N), Center-North (CN), Center-South (CS), Sardinia (SA), South (S), Calabria (CA), and Sicily (SI); Limited production bidding zones are Brindisi, Foggia, Monfalcone, Priolo Gargallo, Rossano, Turbigo-Ronco; and virtual foreign bidding zones are: Mainland France (FRA), Corsica (CO), Switzerland (CHE), Austria (AUT), Slovenia (SVN), and Greece (GRC). A detailed list of bidding zones can be found here: `http://www.mercatoelettrico.org/en/mercati/mercatoelettrico/zone.aspx`.

Figure O.1: Bidding Zone Configuration



Domestic, limited (production), and foreign bidding zones and transfer capacities between them were used to clear the day-ahead market in 2007. Dashed rectangles represent the simplified topology used for our quantitative analysis.

Table O.2: Day-Ahead Market Offers, Bids, and Transactions

	GWh	Share	Count
Panel A. Market Offers and Bids			
Domestic supply offers	54.0	1.00	194 506
Price inelastic	23.9	0.44	83 587
Import offers	6.8	1.00	23 637
Price inelastic	5.9	0.86	20 469
Pumping bids	0.1	1.00	7
Price inelastic			0
Export bids	0.8	1.00	1 825
Price inelastic	0.2	0.22	334
Domestic demand bids	44.9	1.00	72 933
Price inelastic	44.9	1.00	72 274
Panel B. Transactions			
Domestic Sales	39.0	0.87	147 488
Imports	6.2	0.14	21 744
Pumping	−0.1	0.00	7
Exports	−0.2	0.00	553
Domestic Purchases	44.9	1.00	72 274

Notes: Average offer and bid quantities, average transactions, and aggregate number of observations. Aggregate number of observations (N).

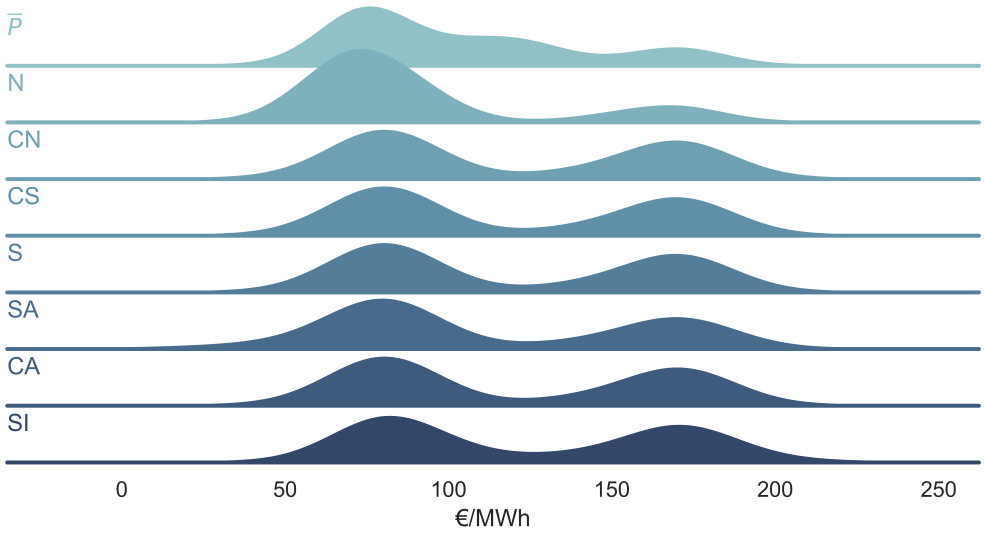
O.1.5 Zonal Prices

Figure O.2 shows the distributions of zonal day-ahead market prices during our sample. Two things are notable from this figure: (i) the zonal prices appear to follow a bimodal distribution that is less pronounced in the North bidding zone (N) and (ii) the uniform purchase price does a good job in absorbing the high prices frequently observed in all the bidding zones south of the North bidding zone.

O.1.6 Prevalence of Congestion

Table O.3 shows the zonal price differences and occurrences of congestion during our sample period. The data in the table reveals that in about 80% of the cases, the price in the mainland bidding zones except North (CN, CS, S, CA) is higher than in the North bidding zone (N). Conditional on observing a higher price in all other bidding zones except the North bidding zone, the price

Figure O.2: Zonal Day-Ahead Market Price Distributions



difference is relative to other bidding zones is about €35/MWh.

O.2 Locational Market Clearing

In this section, we provide additional details on how locational market-clearing prices and quantities are computed in the Italian day-ahead market. The market-clearing problem in Equation (3) is implemented analogue to how the Italian day-ahead market is cleared. We discuss features that guarantee uniqueness of the market-clearing solutions as well as how we deal with the uniform purchase price rule and how we reduce model complexity.

O.2.1 Uniform Purchase Price

The Italian day-ahead market for electricity has demand side bidders face a uniform purchase price. The historical reason for this rule is that consumers on remote islands or the less economically developed South should not be disadvantaged. From a modeling perspective this implies that the following additional constraint needs to hold:

$$\overline{P} \sum_{r \in \boldsymbol{\theta}^{b,r}} x^r = \sum_{z=1}^{Z} \sum_{r \in \boldsymbol{\theta}^{b,r,z}} P^z x^r, \tag{O.1}$$

Table O.3: Prevalence of Congestion

	N	CN	CS	S	SA	CA	SI
Panel A. Row price higher than column (share)							
N	0.00	0.00	0.00	0.00	0.06	0.00	0.00
CN	0.80	0.00	0.00	0.01	0.18	0.01	0.01
CS	0.80	0.00	0.00	0.01	0.18	0.01	0.01
S	0.80	0.00	0.00	0.00	0.18	0.00	0.00
SA	0.76	0.03	0.03	0.05	0.00	0.04	0.03
CA	0.80	0.01	0.01	0.01	0.19	0.00	0.00
SI	0.97	0.60	0.60	0.61	0.73	0.59	0.00
Panel B. Row price less column price, conditional on being higher							
N					26.95		
CN	36.87			1.11	45.44	1.11	0.61
CS	36.87			1.11	45.44	1.11	0.61
S	36.85				45.44		
SA	30.27	0.67	0.67	0.78		0.73	0.64
CA	37.06	14.31	14.31	14.86	43.55		
SI	34.28	6.36	6.36	6.31	16.34	6.15	

where $\boldsymbol{\theta}^{b,r}$ is the subsets of demand bids containing only regular demand bids. Regular demand bids originate from a domestic bidding zone and are not from a pumped-hydro storage unit. Equation (O.1) can be interpreted as money conservation law.[13] However, incorporating (O.1) into Problem (3) renders the problem non-linear because clearing prices are a function of clearing quantities. There are three possibilities for computing the uniform purchase price $\overline{P}$: (i) Search for an optimal solution that fulfills (O.1) by solving problem (3) for different uniform purchase price candidates,[14] (ii) set-up the problem as a bi-level problem which can be translated into a single level problem and solved with off-the shelf mixed integer programming solvers (see, e.g., Savelli et al., 2017), or, (iii) calculate the uniform purchase price as the demand quantity weighted zonal price. We employ the third option because of its simplicity and high accuracy for our problems (see ection O.2.4 for more details).

[13] On the right hand side of (O.1) we could also sum over all offers.

[14] This iterative approach is the method used by the Italian market operator. A more detailed description of the algorithm can be found here: `http://www.mercatoelettrico.org/En/MenuBiblioteca/Documenti/20041206UniformPurchase.pdf`.

O.2.2 Price/Quantity Indeterminacy

Market participants submit step-functions. Hence, rules that define what to do when aggregated supply and demand step-functions overlap are necessary. The rules applied by market operator are the following: In case supply and demand curves intersect at a horizontal portion of both curves, the market-clearing solution is where allocated quantity is maximized. In case supply and demand curves intersect at a vertical portion of both curves the market-clearing solution is where the price is minimal. Practically this is achieved by shifting the curves by a small amount.[15]

O.2.3 Uniqueness

The offer data come with a merit order number which is used to prioritize among the marginal supply and demand bids. For equal marginal supply/demand bid prices, the merit order number acts as a tie breaking rule that is necessary to guarantee unique solutions of the market clearing in the setting of piece-wise constant offer/bid curves.[16] According to the Decision 111/06, Article 30.7, published by the Italian Regulatory Authority for Electricity Gas and Water, the following priority is considered in case the same price is offered: offers from essential units, offers from non-programmable renewables, combined heat and power plants, incentivized power plants (e.g., CIP-6/92), power plants using national fuels, and then all other plants. In cases where offers/bids have equal priority, the chronological order of receipt of bids and offers acts as a tie-breaker (first in, first out).

O.2.4 Accuracy

We are able to solve the Italian day-ahead market for electricity with perfect accuracy for all market instances in our sample. Table O.4 shows the mean absolute deviation between the actual zonal prices and the replicated zonal prices in the national bidding zones and the mean absolute deviation between the actual and replicated uniform purchase price ($\overline{P}$).

[15] More details can be found under: `http://www.mercatoelettrico.org/En/MenuBiblioteca/Documenti/20100429MarketSplitting.pdf` and Tribbia (2015).

[16] See Kastl (2011) on the importance of tie-breaking rules in obtaining a unique equilibrium with discrete bids

Table O.4: Mean Absolute Deviation between Actual and Replicated Prices

Hour	Count	$\overline{P}$	CA	CN	CS	N	SA	SI	S
11	35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
12	35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
18	35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
19	35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	35	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Total	175								

O.2.5 Simplifications to Reduce Model Complexity

We make two modifications of the original data and setting that greatly reduce the complexity of solving our expected profit-maximizing offer curve model as well as our locational quantity equilibrium model. First, we use a simpler transmission network configuration. Second, we restrict best-response offer prices to be multiples of one Euro rather than multiples of one Euro cent which is the restriction on offer prices set by the market platform.

Regarding the simpler network configuration, we conclude from Figure O.2 and Table O.3 that congestion is mainly a concern between the North bidding zone and the Center-North bidding zone, as well as between the Calabrian bidding zone and the Sicily bidding zone. This inspired us to reduce the complexity of the problem by replacing the actual transmission configuration relevant for the day-ahead market by a simpler three-national-zone network model.

Italy is importing electricity in almost all cases in our sample (see Table O.2). We also find instances where the transmission constraint between the North bidding zone and Switzerland is binding. We therefore cap all imports offers at the level of the actual quantity dispatched to avoid situations where more electricity would be imported than is actually possible. To sum up, the simplified transmission network configuration consists of: (i) the North zone which includes virtual foreign trading bidding zones, (ii) the Center zones which covers all national bidding zones on the mainland except the North zone plus Sardinia and the virtual trading bidding zone with Greece, and (iii) Sicily including the virtual trading bidding zone with Malta. We refer to these zones as North (N), Center (C), and Sicily (SI). These three-national-zone network model is used for all our quantitative analyses. In Figure O.1 we show the actual topology used to clear the day-ahead market and how it relates to the three-national-zone network model.

Clearing the market with the underlying simpler network configuration captures the clearing prices and quantities sufficiently well. The patterns congestion for the relevant period does not appear to change and the average uniform purchase price is €103.0/MWh as compared to the average actual uniform purchase price of €102.9/MWh. Rounding the original offer price data to the nearest euro and using the three-zone network configuration leads to an average uniform purchase price of €103.1/MWh.

O.3 Expected Profit-Maximizing Offer Curves

We adapted the expected profit-maximizing bidding problem for a generation company as in locational pricing market described in Ruiz and Conejo (2009). The expected profit-maximizing offer problem for supplier i is to find $\boldsymbol{\theta}_i^o$—the vector of offer prices and quantities for all generation units owned by the firm i—that maximizes the expected value of the firm's variable profit function given in (7). The expectation of this variable profit function is taken with respect to the distribution of residual demand hyper surfaces faced by firm i. Specifically, we assume a discrete distribution of for $\boldsymbol{\theta}_{-i}^o$ and $\boldsymbol{\theta}^b$, where $\boldsymbol{\theta}_{-ih}^o$ is the vector of locational offer curves of all other suppliers besides firm i and $\boldsymbol{\theta}_h^b$ is the vector locational demand bids for all demanders for realization $h = 1, \ldots, H$. In the case of infinite transmission capacity between locations in the market the supplier's problem reduces to that described in Wolak (2000).

Each possible residual demand hyper surface realization for a given value $\boldsymbol{\theta}_i^o$ gives rise to a set of zonal prices and generation unit-level dispatch quantities for all generation units through the locational market-clearing mechanism. For the case of Italy, the market-clearing mechanism takes the bid and offer curves of market participants and solves the optimization problem described in Section O.2.

The resulting prices and dispatch levels from the market-clearing optimization problem for each residual demand hypersurface realization are substituted into (7) to obtain the realized variable profit function for that residual demand surface realization. Repeating this process for all possible residual demand surface realizations for fixed value of $\boldsymbol{\theta}_i^o$ and averaging these realized variable profit values yields our expected profit for firm i at $\boldsymbol{\theta}_i^o$. Finding the value of $\boldsymbol{\theta}_i^o$ that maximizes this function (8) yields firm i's expected profit-maximizing offer curves for all of its

generation units.

For our choice of 20 residual demand surface realizations, this logic implies that we would need to solve 20 market-clearing problems each time we compute the expected profit function for firm i for given value of $\boldsymbol{\theta}_i^o$. The solutions to these 20 market-clearing problems are formulated in terms of Karush-Kuhn-Tucker (KKT) conditions of the market-clearing problem defined in (3). The KKT conditions are added as constraints to the firm's expected profit maximizing offer curve problem. Hence the problem is a mathematical program with equilibrium constraints (MPEC).

Before we derive the KKT conditions of the market-clearing problem we convert (3) into its standard form splitting $\boldsymbol{\theta}^o = \{\mathbf{b}^o, \mathbf{g}^o\}$ into $\boldsymbol{\theta}_i^o = \{\mathbf{b}_i^o, \mathbf{g}_i^o\}$ and $\boldsymbol{\theta}_{-i}^o = \left\{\mathbf{b}_{-i}^o, \mathbf{g}_{-i}^o\right\}$ and adding index h to capture that the market problem needs to be solved for each residual demand surface scenario $h = 1, \ldots, 20$. For given market offers and bids and transmission topology and limits the reformulated problem (O.2) yields the same equilibrium prices and quantities than (3). Note that we also add the corresponding dual variables or dual vectors in parentheses next to each equation in (O.2).

$$\underset{\mathbf{x}^b, \mathbf{x}^o}{\text{minimize}} \quad (\mathbf{b}_i^o)^\top \mathbf{x}_{ih}^o + (\mathbf{b}_{-ih}^o)^\top \mathbf{x}_{-ih}^o - (\mathbf{b}_h^b)^\top \mathbf{x}_h^b \tag{O.2a}$$

$$\text{subject to} \quad (\mathbf{1}_{B_h})^\top \mathbf{x}_h^b - (\mathbf{1}_{O_i})^\top \mathbf{x}_{ih}^o - (\mathbf{1}_{O_{-ih}})^\top \mathbf{x}_{-ih}^o = 0, \qquad : (\lambda_h) \tag{O.2b}$$

$$\forall (n,l) \in \mathcal{E} : \tag{O.2c}$$

$$\sum_{z=1}^{Z} A_{nl}^z \left((\mathbf{1}_{O_i^z})^\top \mathbf{x}_{ih}^{o,z} + (\mathbf{1}_{O_{-ih}^z})^\top \mathbf{x}_{-ih}^{o,z} - (\mathbf{1}_{B_h^z})^\top \mathbf{x}_h^{b,z} \right) - \overline{f}_{nl} \leq 0, \quad : (\mu_{nl,h}) \tag{O.2d}$$

$$-\mathbf{x}_{ih}^o \leq \mathbf{0}, \qquad : (\underline{\boldsymbol{\rho}}_{ih}^o) \tag{O.2e}$$

$$\mathbf{x}_{ih}^o - \mathbf{g}_i^o \leq \mathbf{0}, \qquad : (\overline{\boldsymbol{\rho}}_{ih}^o) \tag{O.2f}$$

$$-\mathbf{x}_{-ih}^o \leq \mathbf{0}, \qquad : (\underline{\boldsymbol{\rho}}_{-ih}^o) \tag{O.2g}$$

$$\mathbf{x}_{-ih}^o - \mathbf{g}_{-ih}^o \leq \mathbf{0}, \qquad : (\overline{\boldsymbol{\rho}}_{-ih}^o) \tag{O.2h}$$

$$-\mathbf{x}_h^b \leq \mathbf{0}, \qquad : (\underline{\boldsymbol{\rho}}_h^b) \tag{O.2i}$$

$$\mathbf{x}_h^b - \mathbf{g}_h^b \leq \mathbf{0}, \qquad : (\overline{\boldsymbol{\rho}}_h^b) \tag{O.2j}$$

In (O.3) we derive the Lagrangian, $\mathcal{L}_h$, corresponding to (O.2).

$$\mathcal{L}_h = (\mathbf{b}_i^o)^\top \mathbf{x}_{ih}^o + (\mathbf{b}_{-ih}^o)^\top \mathbf{x}_{-ih}^o - (\mathbf{b}_h^b)^\top \mathbf{x}_h^b + \tag{O.3}$$

$$\lambda_h \left((\mathbf{1}_{B_h})^\top \mathbf{x}_h^b - (\mathbf{1}_{O_i})^\top \mathbf{x}_{ih}^o - (\mathbf{1}_{O_{-ih}})^\top \mathbf{x}_{-ih}^o \right) +$$

$$\sum_{(n,l)\in\mathcal{E}} \mu_{nl,h} \left(\sum_{z=1}^{Z} A_{nl}^z \left((\mathbf{1}_{O_i^z})^\top \mathbf{x}_{ih}^{o,z} + (\mathbf{1}_{O_{-ih}^z})^\top \mathbf{x}_{-ih}^{o,z} - (\mathbf{1}_{B_h^z})^\top \mathbf{x}_h^{b,z} \right) - \overline{f}_{nl} \right) +$$

$$\underline{\boldsymbol{\rho}}_{ih}^o (-\mathbf{x}_{ih}^o) + \overline{\boldsymbol{\rho}}_{ih}^o (\mathbf{x}_{ih}^o - \mathbf{g}_i^o) + \underline{\boldsymbol{\rho}}_{-ih}^o (-\mathbf{x}_{-ih}^o) + \overline{\boldsymbol{\rho}}_{-ih}^o (\mathbf{x}_{-ih}^o - \mathbf{g}_{-ih}^o) +$$

$$\underline{\boldsymbol{\rho}}_h^b \left(-\mathbf{x}_h^b \right) + \overline{\boldsymbol{\rho}}_h^b \left(\mathbf{x}_h^b - \mathbf{g}_h^b \right).$$

The first order necessary conditions of the market operator's market-clearing problem defined in (3) yields the following Karush-Kuhn-Tucker (KKT) conditions for each $h = 1, \ldots, H$:[17]

[17] Note that we minimize the negative sum of consumer and producer surpluses instead of maximizing the sum of consumer and producer surpluses. We also account for the fact that demand side is effectively paying the demand weighted zonal price as discussed in Section O.2.1.

Stationarity conditions

$$\mathbf{b}_i^o - W_{ih}^o \mathbf{P}_h - \underline{\boldsymbol{\rho}}_{ih}^o + \overline{\boldsymbol{\rho}}_{ih}^o = \mathbf{0}, \tag{O.4a}$$

$$\mathbf{b}_{-ih}^o - W_{-ih}^o \mathbf{P}_h - \underline{\boldsymbol{\rho}}_{-ih}^o + \overline{\boldsymbol{\rho}}_{-ih}^o = \mathbf{0}, \tag{O.4b}$$

$$-\mathbf{b}_h^b + \overline{P}_h - \underline{\boldsymbol{\rho}}_h^b + \overline{\boldsymbol{\rho}}_h^b = \mathbf{0}, \tag{O.4c}$$

Primal feasibility, dual feasibility, and complementary slackness conditions

$$(\mathbf{1}_{B_h})^\top \mathbf{x}_h^b - (\mathbf{1}_{O_i})^\top \mathbf{x}_{ih}^o - (\mathbf{1}_{O_{-ih}})^\top \mathbf{x}_{-ih}^o = 0, \tag{O.4d}$$

$$\mathbf{0} \leq \mathbf{x}_{ih}^o \perp \underline{\boldsymbol{\rho}}_{ih}^o \geq \mathbf{0}, \tag{O.4e}$$

$$\mathbf{0} \leq \mathbf{g}_i^o - \mathbf{x}_{ih}^o \perp \overline{\boldsymbol{\rho}}_{ih}^o \geq \mathbf{0}, \tag{O.4f}$$

$$\mathbf{0} \leq \mathbf{x}_{-ih}^o \perp \underline{\boldsymbol{\rho}}_{-ih}^o \geq \mathbf{0}, \tag{O.4g}$$

$$\mathbf{0} \leq \mathbf{g}_{-ih}^o - \mathbf{x}_{-ih}^o \perp \overline{\boldsymbol{\rho}}_{-ih}^o \geq \mathbf{0}, \tag{O.4h}$$

$$\mathbf{0} \leq \mathbf{x}_h^b \perp \underline{\boldsymbol{\rho}}_h^b \geq \mathbf{0}, \tag{O.4i}$$

$$\mathbf{0} \leq \mathbf{g}_h^b - \mathbf{x}_h^b \perp \overline{\boldsymbol{\rho}}_h^b \geq \mathbf{0}, \tag{O.4j}$$

$$\mathbf{0} \leq \overline{f}_{nl} - \sum_{z=1}^{Z} A_{nl}^z \left((\mathbf{1}_{O_i^z})^\top \mathbf{x}_{ih}^{o,z} + (\mathbf{1}_{O_{-ih}^z})^\top \mathbf{x}_{-ih}^{o,z} - (\mathbf{1}_{B_h^z})^\top \mathbf{x}_h^{b,z} \right) \perp \mu_{nl,h} \geq \mathbf{0}, \ \forall (n,l) \in \mathcal{E}, \tag{O.4k}$$

Auxiliary variables

$$\mathbf{P}_h = (P_h^z)_{z \in Z} = \left(\lambda_h - \sum_{(n,l) \in \mathcal{E}} A_{nl}^z \mu_{nl,h} \right)_{z \in Z}, \tag{O.4l}$$

$$\overline{P}_h = \mathbf{w}_h^\top \mathbf{P}_h, \tag{O.4m}$$

whereas the matrix W maps supply offers and demand bids to zones and $\mathbf{w}$ is the vector of zonal demand weights. The market-clearing problem (O.2) is a convex optimization problem, so the KKT conditions are also sufficient.[18]

Equations (O.4a)–(O.4c) are the stationarity conditions, i.e., the partial derivatives of the Lagrangian, (O.3), with respect to $\mathbf{x}_{ih}^o$, $\mathbf{x}_{-ih}^o$, and $\mathbf{x}_h^b$, making use of auxiliary variables in (O.4l) and (O.4m), which define market-clearing prices.

[18]Note that we have implemented all mathematical programs accounting for uniqueness as described in Sections O.2.2 and O.2.3. We decided to omit these additional constants in the notation to make it easier to follow.

Equations (O.4d)–(O.4k) are the primal feasibility, dual feasibility, and complementary slackness conditions. (O.4d) and the left part of (O.4k), i.e., the partial derivatives of the Lagrangian, (O.3), with respect to λ_h and $\boldsymbol{\mu}_h$, are the primal feasibility conditions. The dual feasibility conditions require all elements of the dual vectors corresponding to the inequality constraints, i.e., $\underline{\boldsymbol{\rho}}^o_{ih}$, $\overline{\boldsymbol{\rho}}^o_{ih}$, $\underline{\boldsymbol{\rho}}^o_{-ih}$, $\overline{\boldsymbol{\rho}}^o_{-ih}$, $\underline{\boldsymbol{\rho}}^b_h$, $\overline{\boldsymbol{\rho}}^b_h$, and $\boldsymbol{\mu}_h$, to be non-negative. The complementary slackness conditions needed require the product of the inequality constraint functions and the corresponding duals to be zero.

The problem (O.4) can be formulated as a mixed integer linear program by introducing additional binary variables able to deal with the either/or nature of the complementarity slackness constraints (O.4e)–(O.4k). Because we are dealing with piece-wise constant residual demand hypersurfaces to find a piece-wise constant offer curve, derivatives with respect to the parameters of the offer curve are either zero or infinity. Hence, this rules out optimization techniques relying on derivatives.

Finally, we rewrite the firm's expected profit-maximization offer curve problem and include the $H = 20$ sets of KKT conditions above as constraints:

$$\underset{\mathcal{X},\mathcal{Y}}{\text{minimize}} \sum_{h=1}^{H} \omega_h \left[\overline{P}_h Q_i^C + \sum_{z=1}^{Z} \left(\mathbf{c}_i^z\right)^\top \mathbf{x}_{ih}^{o,z} - \sum_{z=1}^{Z} \left(\left(\mathbf{1}_{O_i^z}\right)^\top \mathbf{x}_{ih}^{o,z} \right) P_h^z \right] \tag{O.5a}$$

$$\text{subject to} \quad \mathbf{0} \leq \mathbf{b}_i^o \leq \hat{\mathbf{b}}_i, \tag{O.5b}$$

$$\hat{\mathbf{g}}_i \leq \mathbf{g}_i^o \leq \hat{\mathbf{g}}_i, \tag{O.5c}$$

$$\text{(O.4a)–(O.4m), for } h = 1, \ldots, H, \tag{O.5d}$$

$$\mathcal{X} = \left(\mathbf{b}_i^o, \mathbf{g}_i^o, \left(\mathbf{x}_{ih}^o\right)_{h\in H}, \left(\mathbf{x}_{-ih}^o\right)_{h\in H}, \left(\mathbf{x}_h^b\right)_{h\in H} \right), \tag{O.5e}$$

$$\mathcal{Y} = \left(\left(\lambda_h\right)_{h\in H}, \left(\boldsymbol{\mu}_h\right)_{h\in H}, \left(\overline{\boldsymbol{\rho}}_h\right)_{h\in H}, \left(\underline{\boldsymbol{\rho}}_h\right)_{h\in H} \right). \tag{O.5f}$$

where $\omega_h = \frac{1}{H}$ for $h = 1, 2..., H$.

The objective function (O.5a) consists of three terms; the value of fixed-price forward contracts, the short-term production costs,[19] and the revenue from selling energy. This objective function is equivalent to (8a) when dropping the sunk term $-P_i^C Q_i^C$, although the notation slightly differs

[19]The short-term marginal cost of production c_i^z are assumed to be constant for each unit.

to better accommodate the discrete nature of bids and offers submitted to the market. Note that maximizing expected profits is equivalent to minimizing negative expected profits. The constraint (O.5b) restricts firm i's offer price vector entries in $\mathbf{b}_i^o$ to be between the market operator's price floor (zero) and price cap ($\hat{\mathbf{b}}$). We only optimize over the unit-level offer prices and hold unit-level offer quantities fix. Therefore, we fix the unit-level offer quantities to predefined levels ($\hat{\mathbf{g}}_i$) in constraint (O.5c).[20] In (O.5d) we add the sets of KKT conditions that determine the market-clearing solution for each realization h. We minimize over all primal variables in (O.5e), which includes the unit-level offer price, and over all dual variables in (O.5f), whereas $\overline{\boldsymbol{\rho}}_h = \left(\overline{\boldsymbol{\rho}}_{ih}^o, \overline{\boldsymbol{\rho}}_{-ih}^o, \overline{\boldsymbol{\rho}}_h^b\right)$ and $\underline{\boldsymbol{\rho}}_h = \left(\underline{\boldsymbol{\rho}}_{ih}^o, \underline{\boldsymbol{\rho}}_{-ih}^o, \underline{\boldsymbol{\rho}}_h^b\right)$.

Given that Q_i^C, $\mathbf{c}_i^z$, and $\mathbf{w}$—the vector of zonal demand weights that determine $\overline{P}$—are exogenous, the only nonlinear term in (O.5a) is the revenue from selling energy into different market zones, $\sum_{z=1}^{Z}\left(\left(\mathbf{1}_{O_i^z}\right)^\top \mathbf{x}_{ih}^{o,z}\right) P_h^z$, because both cleared quantities $\mathbf{x}_{ih}^{o,z}$ as well as zonal market-clearing prices $\mathbf{P}_h = \left(P_h^z\right)_{z\in Z}$, are endogenous. We make use of the strong duality theorem to eliminate this non-linear term. Because the market operator's problem (O.2) is convex the strong dual theorem tells us that the function value of the dual problem is equal to the function value of the primal problem at the optimum. Hence, we can equalize the objective function of the primal problem with the objective function of the dual problem, which for all $h = 1, \ldots, H$ results in

$$(\mathbf{b}_i^o)^\top \mathbf{x}_{ih}^o + (\mathbf{b}_{-ih}^o)^\top \mathbf{x}_{-ih}^o - (\mathbf{b}_h^b)^\top \mathbf{x}_h^b = -(\overline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{g}_i^o - (\overline{\boldsymbol{\rho}}_{-ih}^o)^\top \mathbf{g}_{-ih}^o - (\overline{\boldsymbol{\rho}}_h^b)^\top \mathbf{g}_h^b - (\boldsymbol{\mu}_h)^\top \overline{\mathbf{f}}. \tag{O.6}$$

Furthermore, we take the inner product between (O.4a) and $\mathbf{x}_{ih}^o$ for all $h = 1, \ldots, H$, which yields

$$(\mathbf{b}_i^o)^\top \mathbf{x}_{ih}^o - (W_{ih}^o \mathbf{P}_h)^\top \mathbf{x}_{ih}^o - (\underline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{x}_{ih}^o + (\overline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{x}_{ih}^o = 0. \tag{O.7}$$

From (O.4e) we know that $(\underline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{x}_{ih}^o = 0$ and according to (O.4f), $(\overline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{x}_{ih}^o = (\overline{\boldsymbol{\rho}}_{ih}^o)^\top \mathbf{g}_i^o$. Using this, and plugging (O.7) into (O.6) gives us for all $h = 1, \ldots, H$:

[20] Constraint (O.5c) can also easily be replaced by capping the production of a unit by its maximum available capacity as we defined it in Equation (8a). However, optimizing also over step-wise unit-level offer quantities would require additional ordering assumptions, because there are many ways to subdivide a unit's available capacity into discrete steps. Note also that we enforce a merit order of the firm's generation units at the zonal level according to our estimated short-term marginal costs.

$$(W^o_{ih}\mathbf{P}_h)^\top \mathbf{x}^o_{ih} = (\mathbf{b}^b_h)^\top \mathbf{x}^b_h - (\mathbf{b}^o_{-ih})^\top \mathbf{x}^o_{-ih} - (\overline{\boldsymbol{\rho}}^o_{-ih})^\top \mathbf{g}^o_{-ih} - (\overline{\boldsymbol{\rho}}^b_h)^\top \mathbf{g}^b_h - \boldsymbol{\mu}_h^\top \overline{\mathbf{f}}. \tag{O.8}$$

Finally, we can replace the non-linear term $\sum_{z=1}^{Z}\left(\left(\mathbf{1}_{O_i^z}\right)^\top \mathbf{x}^{o,z}_{ih}\right) P^z_h$ in (O.5a) with its linear equivalent defined in (O.8). Note that $\sum_{z=1}^{Z}\left(\left(\mathbf{1}_{O_i^z}\right)^\top \mathbf{x}^{o,z}_{ih}\right) P^z_h$ and $(W^o_{ih}\mathbf{P}_h)^\top \mathbf{x}^o_{ih}$ are equivalent.

O.3.1 Computation

We solve for the expected profit-maximizing offer curve by integrating over 20 representative market instances.

The advantage of the mixed integer problem formulation is that we are not required to smooth the problem or make any assumptions about the functional form of the residual demand. This allows us to model the optimal step function offer curve problem as it appears to firms participating in the day-ahead market.

The expected profit-maximizing offer curve may not be unique for several reasons. First, optimal offer prices are undefined for offers that are infra-marginal or extra-marginal for all residual demand hypersurface realizations. For example, if it is optimal to withhold capacity, then any offer price larger than the maximum locational price and smaller than the price cap is optimal. Likewise, if an offer is accepted in all scenarios, the offer price can be between the minimal locational price and the offer price floor. We set the prices of extramarginal offers to the price cap and prices of inframarginal offers to the price floor. A different but also plausible approach would be to set the offer prices of inframarginal [extramarginal] offers epsilon below [above] the lowest [highest] realization of locational best-response prices. Both ways to define expected profit-maximizing offer curves will lead to the same best-response market-clearing results. However, the choice of how to deal with inframarginal and extramarginal offers can lead to different best-response market-clearing results when we compute the offer curves where the firm ignores its impact on transmission constraints when determining its expected profit-maximizing offer curve.[21] Second, even for marginal units there can be several combinations of optimal offer prices that lead to the same expected profits. This can be the case if there are large gaps in the offer prices where the op-

[21] We tried both ways to deal with inframarginal and extramarginal offers and find that in both cases the firm's best-response expected profits are significantly higher when network effects are accounted for in the firm's optimal offer curve optimization problem.

timal offer curve intersects with the inverse residual demand hypersurfaces. Moreover, it could be theoretically possible that a expected profit-maximizing offer curve that will congest the network gives the same expected profit as a expected profit-maximizing offer curve that does not congest the network. However, because we fix offer quantities at their actual values, use 20 representative market instances to estimate expected profits, and require offer prices to be greater than or equal to the unit's short-term variable cost, we limit the risk of non-unique solutions.

O.4 Locational Quantity-Setting Equilibrium Model

In this section, we provide additional details how to solve the smooth locational quantity-setting equilibrium model introduced in Section 2 of the article. In Section O.4.1, we describe how we smooth the residual demand hypersurfaces and in Section O.4.2 we discuss computational aspects including uniqueness and equilibrium selection.

O.4.1 Kernel Smoothing

We begin by describing the multivariate Nadaraya-Watson (N-W) estimator that we use to smooth the residual demand hypersurfaces. For that purpose we switch notation and detail the estimator in the common kernel regression analysis notation (see, e.g., Liu and Yang, 2008; Racine, 2008). Consider an $n \times p$ matrix of continuous covariates, X, and a $n \times 1$ vector of dependent variables, Y. The N-W estimator is defined as

$$\hat{m}(\mathbf{x}) = \frac{\sum_{i=1}^{n} \left(\prod_{j=1}^{p} \left[k\left(\frac{x_j - X_{ij}}{h_j} \right) \right] y_i \right)}{\sum_{i=1}^{n} \left(\prod_{j=1}^{p} \left[k\left(\frac{x_j - X_{ij}}{h_j} \right) \right] \right)}, \tag{O.9}$$

where $k(t)$ is a univariate kernel function, $\mathbf{h} = (h_1, \ldots, h_p)'$ a vector of bandwidths, X_{ij} is the j^{th} element of the i^{th} row of X, and y_i is the i^{th} row of Y. We assume a standard Gaussian kernel $k(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}$.

In the context of residual demand hyper surfaces, the rows of X are locational quantity values on a grid and the rows of Y are the corresponding locational prices P^z. The spacing of the grid will be a parameter of the model and so will be the bandwidths used for smoothing.

O.4.2 Computation

We solve the smooth nonlinear complementarity problem (10) to derive expected locational equilibrium quantities using the solver *PATH* (version 5.0.05; Dirkse and Ferris, 1995) with its default parameter settings.

We compute the inverse residual demand hypersurfaces on a grid of locational quantity values. For each location we select 20 points equally spaced between zero and 110% of joint maximum available capacity of the two strategic firms. The rationale behind using a value that is larger than the joint maximum available capacity is that kernel smoothing typically underperforms at the border of the support of the function so that extending the maximum values is a way to avoid this behavior for the economically relevant range of output values.

Because two strategic firms compete in three locations, $Z = 3$, this implies $20^3 = 8\,000$ market-clearing solutions per market instance to obtain a smoothed inverse residual demand hypersurface. For the $H = 20$ representative markets used to approximate the distribution of the inverse residual demand hypersurfaces, our approach requires clearing the market $8\,000 \cdot 20 = 160\,000$ times to solve for a stochastic equilibrium in quantities for one market instance. We choose the smoothing parameters that enters the kernel for location z, $\delta_z = 0.05 \sum_i \overline{Q}_i^z$, that is 5% of the maximum of output quantities of the two firms in location z.[22]

A potential concern of solving the nonlinear complementary problem (10) is uniqueness. To circumvent this issue, we deploy an extensive search strategy using different starting value combinations to trace out potentially multiple stationarity points. Specifically, we derive all permutations of an aggressive quantity choice (80% of a firm's available capacity) and an defensive quantity choice (20% of a firm's available capacity). We permute over locations as well as firms which yields $2^{Z \times N} = 64$ combinations in our setting with two strategic firms ($N = 2$) and both firms controlling capacity in each of the three market zones ($Z = 3$). Inspecting the computational baseline solutions, we find that 99% of runs converge. Excluding the solutions that did not converge, 82% of all 175 market instances in our sample converged to the same stationarity point. Dropping solutions that are dominated in terms of expected profits of both firms, we find that 95% of all

[22] In Table O.6, we present equilibrium results using $\delta_z = 0.1 \sum_i \overline{Q}_i^z$ as a smoothing factor to check the sensitivity of our approach with respect to this parameter choice. The entries in this table should be compared to values in Column (1) in Table 2. We find that more smoothing leads to lower average prices that deviate more from actual observed prices. However, the average price differences between locations before versus after divestment are preserved.

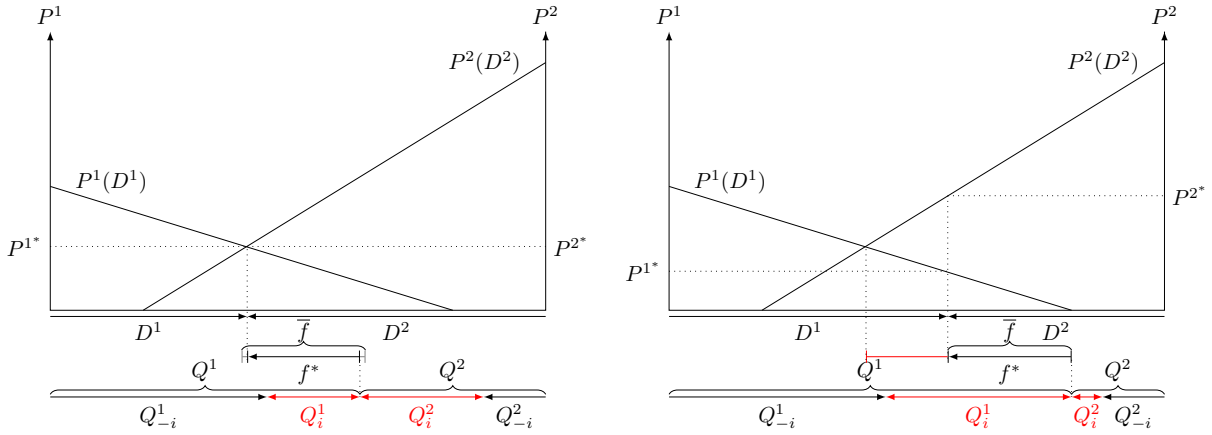
market instances converged to the same stationarity point. The proportions are similar for the counterfactual runs where we divest capacity in different locations.

By using the extensive search strategy described above, we do find a few instances with multiple stationarity points. Our default equilibrium selection criterion is to select those with the largest joint expected profits (see Table 2). However, we also employed a different equilibrium selection criterion, where expected consumer surplus is maximized. These results are presented in Table O.5. The results are almost indistinguishable and the qualitative interpretation of the results is independent of the two equilibrium selection methods.

O.5 Additional Figures and Tables

In this section, we provide additional figures and tables that are referenced in the article.

Figure O.3: Market-Clearing in Asymmetric, Transport-Capacity-Constrained Markets

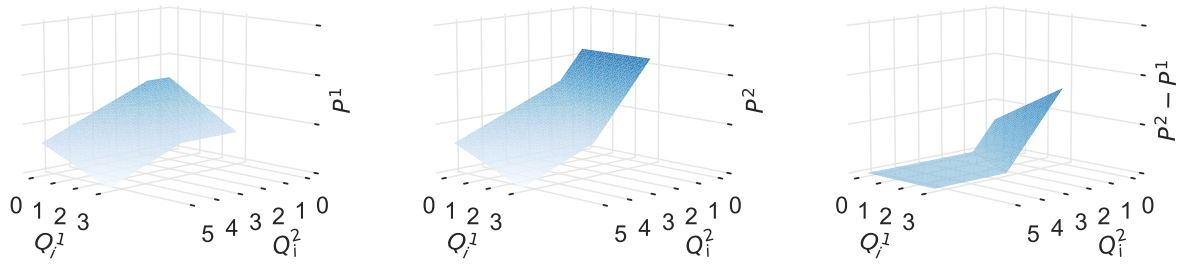


(a) Uncongested Markets

(b) Congested Markets

Notes: Panel (a): The resulting optimal export, f^*, given the inverse demand functions $P^1()$, $P^2()$ and total outputs Q^1, Q^2, does not exceed the transportation limit $\overline{f}$, equalizing locational prices P^1 and P^2. Although the transport capacity between the two markets is unconstrained, f^* output in market 1 is used to serve f^* demand in market 2. Panel (b): Congested markets. Firm i's choice to substantially increase it's output in location 1 and to reduce it in location 2, leads to a binding transport constraint ($f^* = \overline{f}$). This leads to different prices in the two markets.

Figure O.4: Inverse Residual Demand Surfaces in Asymmetric Markets



(a) Market 1 (b) Market 2 (c) Difference between (b) and (a)

Table O.5: Simulated Market Outcomes under Quantity Competition (Maximized Expected Consumer Surplus)

	(1) Baseline	(2) Divestment in the Center	(3) Δ	(4) Δ(%)	(5) Divestment in the North	(6) Δ	(7) Δ(%)
Panel A. Thermal capacity divestment of about 1.2 GW							
$\overline{P}$	98.6	95.2	−3.4	−3.5%	98.1	−0.6	−0.6%
P^C	105.6	99.1	−6.5	−6.2%	107.4	1.8	1.7%
P^N	87.7	85.5	−2.2	−2.5%	85.0	−2.7	−3.1%
P^{SI}	158.5	163.2	4.7	3.0%	163.9	5.4	3.4%
Q^C	4 884	3 929	−955	−19.5%	4 832	−52	−1.1%
Q^N	7 225	7 163	−62	−0.9%	6 401	−823	−11.4%
Q^{SI}	1 192	1 161	−31	−2.6%	1 154	−39	−3.2%
Q	13 301	12 253	−1 048	−7.9%	12 388	−914	−6.9%
Profit[1]	916	825	−91	−9.9%	851	−65	−7.1%
Total Cost[2]	944	936	−8	−0.8%	949	5	0.5%
Panel B. Thermal capacity divestment of about 2.4 GW							
$\overline{P}$	98.6	94.0	−4.6	−4.6%	96.9	−1.8	−1.8%
P^C	105.6	97.0	−8.6	−8.1%	108.7	3.1	3.0%
P^N	87.7	84.7	−3.1	−3.5%	81.7	−6.1	−6.9%
P^{SI}	158.5	165.4	6.9	4.4%	166.8	8.3	5.3%
Q^C	4 884	3 280	−1 605	−32.9%	4 782	−102	−2.1%
Q^N	7 225	7 143	−82	−1.1%	5 723	−1 502	−20.8%
Q^{SI}	1 192	1 136	−56	−4.7%	1 131	−61	−5.1%
Q	13 301	11 559	−1 742	−13.1%	11 636	−1 665	−12.5%
Profit[1]	916	770	−146	−16.0%	811	−105	−11.4%
Total Cost[2]	944	935	−9	−1.0%	950	7	0.7%

Notes: Average market outcomes ($N = 175$). Equilibrium selection criteria is maximized joint profits. Quantities and profits aggregated across both strategic firms. Prices in €/MWh, costs and profits in €K, and quantities in MWh.

[1] Profits adjusted by $Q^C \cdot P^C$ with P^C set to the average actual uniform purchase price (€103/MWh) in our sample. Only thermal units considered including adjustments for costs and revenues of non-relevant thermal units.

[2] Includes costs of explicitly modeled thermal units as well as costs of remaining supply capacity (including imports) assuming that this capacity is offered at short-term marginal costs.

Table O.6: Simulated Market Outcomes under Quantity Competition with a Larger Smoothing Parameter Value

	Baseline
$\overline{P}$	94.9
P^C	102.4
P^N	84.0
P^{SI}	151.5
Q^C	4 911
Q^N	7 282
Q^{SI}	1 188
Q	13 381
Profit[1]	903
Total Cost[2]	938

Notes: Average market outcomes ($N = 175$). Relative smoothing parameter is set to 10% of maximum domain value in each location. Equilibrium selection criteria is maximized joint profits. Quantities and profits aggregated across both strategic firms. Prices in €/MWh, costs and profits in €K, and quantities in MWh.

[1] Profits adjusted by $Q^C \cdot P^C$ with P^C set to the average actual uniform purchase price (€103/MWh) in our sample. Only thermal units considered including adjustments for costs and revenues of non-relevant thermal units.

[2] Includes costs of explicitly modeled thermal units as well as costs of remaining supply capacity (including imports) assuming that this capacity is offered at short-term marginal costs.

Table O.7: Average Own- and Cross-Price Inverse Semi-Elasticities of Residual Demand Surfaces

	(1) C	(2) N	(3) SI
Panel A. Incumbent			
$\eta^{C,col}$	-17.76	-0.04	-10.07
	(86.32)	(0.27)	(66.81)
$\eta^{N,col}$	-0.05	-0.86	-0.00
	(0.33)	(1.65)	(0.02)
$\eta^{SI,col}$	-5.28	-0.00	-6.47
	(34.78)	(0.02)	(35.05)
Panel B. Main competitor			
$\eta^{C,col}$	-0.27	-0.05	-0.07
	(1.10)	(0.62)	(0.62)
$\eta^{N,col}$	-0.02	-5.90	-0.00
	(0.14)	(22.05)	(0.01)
$\eta^{SI,col}$	-0.00	-0.00	-0.42
	(0.01)	(0.00)	(2.21)

Notes: Averages taken over the sample ($N = 175$). Standard deviations below in parentheses.

Table O.8: Average Own- and Cross-Price Inverse Semi-Elasticities of Smoothed Residual Demand Surfaces

	(1) C	(2) N	(3) SI
Panel A. Incumbent			
$\eta^{C,col}$	-0.63	-0.09	-0.23
	(1.12)	(0.29)	(0.69)
$\eta^{N,col}$	-0.15	-0.55	-0.02
	(0.47)	(0.67)	(0.10)
$\eta^{SI,col}$	-0.11	-0.01	-0.48
	(0.03)	(0.05)	(0.71)
Panel B. Main competitor			
$\eta^{C,col}$	-0.06	-0.01	-0.01
	(0.23)	(0.07)	(0.06)
$\eta^{N,col}$	-0.02	-1.08	-0.00
	(0.14)	(1.53)	(0.00)
$\eta^{SI,col}$	-0.00	-0.00	-0.14
	(0.01)	(0.00)	(0.53)

Notes: Averages taken over the sample ($N = 175$). Standard deviations below in parentheses.

Table O.9: Paired Sample Test of Mean Own- and Cross-Price Inverse Semi-Elasticities of Residual Demand Hypersurfaces

	(1) C	(2) N	(3) SI
Panel A. Incumbent			
$\eta^{C,col}$		-2.71	-0.93
$\eta^{N,col}$	-6.32		-6.84
$\eta^{SI,col}$	-0.32	-2.44	
Panel B. Main competitor			
$\eta^{C,col}$		-2.25	-2.07
$\eta^{N,col}$	-3.52		-3.53
$\eta^{SI,col}$	-2.47	-2.48	

Notes: Two-sided Welch t-test assuming unequal standard deviations.

Table O.10: Paired Sample Test of Mean Own- and Cross-Price Inverse Semi-Elasticities of Smoothed Residual Demand Hypersurfaces

	(1) C	(2) N	(3) SI
Panel A. Incumbent			
$\eta^{C,col}$		-6.09	-3.95
$\eta^{N,col}$	-6.40		-10.26
$\eta^{SI,col}$	-6.06	-8.61	
Panel B. Main competitor			
$\eta^{C,col}$		-2.49	-2.53
$\eta^{N,col}$	-9.09		-9.32
$\eta^{SI,col}$	-3.49	-3.53	

Notes: Two-sided Welch t-test assuming unequal standard deviations.

References

Ardian, Faddy, Silvia Concettini, and Anna Creti. 2018. "Renewable Generation and Network Congestion: An Empirical Analysis of the Italian Power Market." *The Energy Journal* 39(2): 3–39.

ARERA 2008a. "Annual report to the European Commission on the regulatory activities and the state of services in the electricity and gas sectors." , Italian Regulatory Authority for Energy, Networks and Environment. https://www.autorita.energia.it/allegati/relaz_ann/08/E08_NR_Italy-EN.pdf.

ARERA 2008b. "Annual report to the state of services and the regulatory activities." , Italian Regulatory Authority for Energy, Networks and Environment. https://www.arera.it/allegati/inglese/annual_report/relann2008english.pdf.

Bosco, Bruno, Lucia Parisio, and Matteo Pelagatti. 2013. "Price-capping in partially monopolistic electricity markets with an application to Italy." *Energy Policy* 54(0): 257–266.

Dirkse, Steven P., and Michael C. Ferris. 1995. "The path solver: a nommonotone stabilization scheme for mixed complementarity problems." *Optimization Methods and Software* 5(2): 123–156.

Graf, Christoph, and Claudio Marcantonini. 2017. "Renewable energy and its impact on thermal generation." *Energy Economics* 66(0): 421–430.

Graf, Christoph, Federico Quaglia, and Frank A. Wolak. 2020. "Market Performance Assessment in Locational Pricing Markets with Non-convexities." Working paper, Program on Energy Sustainable Development, Stanford University.

Graf, Christoph, and David Wozabal. 2013. "Measuring competitiveness of the EPEX spot market for electricity." *Energy Policy* 62(0): 948–958.

Kastl, Jakub 2011. "Discrete Bids and Empirical Inference in Divisible Good Auctions." *The Review of Economic Studies* 78(3): 974–1014.

Liu, Rong, and Lijian Yang. 2008. "Kernel estimation of multivariate cumulative distribution function." *Journal of Nonparametric Statistics* 20(8): 661–677.

Racine, Jeffrey S. 2008. "Nonparametric Econometrics: A Primer." *Foundations and Trends in Econometrics* 3(1): 1–88.

Reguant, Mar 2014. "Complementary Bidding Mechanisms and Startup Costs in Electricity Markets." *Review of Economic Studies* 81(4): 1708–1742.

Ruiz, Cesar, and Antonio J. Conejo. 2009. "Pool Strategy of a Producer with Endogenous Formation of Locational Marginal Prices." *IEEE Transactions on Power Systems* 24(4): 1855–1866.

Savelli, Iacopo, Antonio Giannitrapani, Simone Paoletti, and Antonio Vicino. 2017. "An Optimization Model for the Electricity Market Clearing Problem with Uniform Purchase Price and Zonal Selling Prices." *IEEE Transactions on Power Systems* 33(3): 2864–2873.

Tribbia, Claudio 2015. "Solving the Italian Electricity Power Exchange." , Politecnico Milano.

Wilson, Robert 2008. "Supply Function Equilibrium in a Constrained Transmission System." *Operations Research* 56(2): 369–382.

Wolak, Frank A. 2000. "An Empirical Analysis of the Impact of Hedge Contracts on Bidding Behavior in a Competitive Electricity Market." *International Economic Journal* 14(2): 1–39.