# Measuring the Ability to Exercise Unilateral Market Power in Locational-Pricing Markets: An Application to the Italian Electricity Market*

Christoph Graf[†] Frank A. Wolak[‡]

September 5, 2022

**Abstract**

An increasing number of wholesale electricity markets employ locational pricing mechanisms that price aspects of the transmission network configuration. Suppliers that own generation capacity at one or more locations may have the ability to exercise unilateral local market power by impacting the extent to which these constraints bind. We extend the residual demand curve measure of the ability to exercise unilateral market power from a single location market to a residual demand hyper-surface that quantifies the impact of a supplier's unilateral output reduction at one location on all locational prices. Accounting for the fact that suppliers face residual demand hyper-surfaces improves our ability to explain the offer curves submitted by strategic suppliers and explains why the locations of a supplier's generation capacity is an key determinant of the size and direction of locational price changes associated with the divestment of a fixed amount of generation capacity. We develop a stochastic equilibrium model of competition between firms setting locational quantities against a distribution of residual demand hyper-surfaces to study these same questions.

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

**JEL Codes:** C6, C7, D4, L1, L9, Q4

*We thank Claudio Marcantonini for sharing his knowledge of the Italian electricity market and participants at a seminar at the Italian Regulatory Authority for Electricity, Gas and Water for their comments. Shmuel Oren and participants at the power seminar at UC Berkeley, and the participants at the European conference on Operational Research also provided helpful comments on a early version of this work. Finally, we thank Katja Seim and two anonymous referees for detailed comments on a previous draft.

[†]Institute for Policy Integrity, New York University, New York, NY 10012, United States and Program on Energy and Sustainable Development (PESD), Stanford University, Stanford, CA 94305-6072, christoph.graf@nyu.edu. Financial support from the Austrian Science Fund (FWF), J-3917, and the Anniversary Fund of the Oesterreichische Nationalbank (OeNB), 18306, is gratefully acknowledged.

[‡]Program on Energy and Sustainable Development (PESD) and Department of Economics, Stanford University, Stanford, CA 94305-6072, wolak@zia.stanford.edu

# 1 Introduction

All United States wholesale electricity markets, and an increasing number of foreign markets, employ mechanisms that explicitly incorporate the impact of transmission network constraints into the prices paid to specific generation units based on their location in the transmission network. More granular pricing of energy typically raises concerns about the exercise of local market power by suppliers that own one or more generation units taking advantage of their location in the transmission network to increase their profits from selling energy. This concern implies the need for methods for measuring the ability of a supplier that owns multiple generation units at different locations in the transmission network to exercise unilateral market power in a locational pricing market.

This paper derives a general methodology for measuring the ability of suppliers that own generation units at multiple locations in the transmission grid to exercise unilateral market power in a locational pricing market. To this end, we extend the concept of a residual demand curve from a single location market to a residual demand hyper-surface that accounts for the ability of a supplier that owns capacity at multiple locations to impact all locational prices from an output change at one location. We demonstrate the usefulness of residual demand hyper-surfaces for: (1) modeling expected profit-maximizing offer behavior by a supplier that own generation units a multiple locations, (2) quantifying the impact of this 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 local market power. We also develop a stochastic equilibrium model of competition between firms setting locational quantities against the distribution of residual demand hyper-surfaces and use it to determine the equilibrium implications of different locational capacity divestment scenarios.

Computing the residual demand hyper-surface 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 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 offer curves submitted by all market participants and any set of locational demands given the configuration of the transmission network. Solving this optimization problem for a grid of inelastic output levels from zero to the supplier's installed capacity at all locations that it owns generation units yields points along that supplier's residual demand hyper-surface.

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 hyper-surfaces faced by the supplier for any offer curve consistent with the market rules. An estimate of the supplier's expected profit for a candidate optimal offer curve is equal to the average of the realized profits earned for each possible residual demand hyper-surface realization in this distribution. The offer curve that respects the market rules that yields the highest average value of these realized profits is the solution to this problem. This expected profit-maximizing offer curve problem constrained by many market-clearing locational prices and quantities problems, one for each possible residual demand hyper-surface realization, can be merged into a single Mathematical Program with Equilibrium Constraints (MPEC) problem, the solution to which yields the supplier's expected profit-maximizing offer curve.

Applying this expected profit-maximizing offer curve problem to a sample of 175 hours market outcomes from the Italian day-ahead market, we find that our estimated expected-profit maximizing offer curves yield a 9.8% higher sample average profit for the largest supplier [3.6% higher for its main competitor] relative to the sample average profit using the actual offer curves of both of these strategic suppliers. We then compute best-response 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.[1] For the actual configuration of the transmission network in Italy, we compute the average profits that the two suppliers would earn in Italian locational pricing market if they submitted their infinite transmission capacity best response offer curve. The largest supplier's sample average profits would be only 5% higher versus 9.8% higher with best response offer curves for the distribution of residual demand hyper-surfaces. For the main competitor to the incumbent firm, the corresponding numbers are 1.5% higher versus 3.6% higher. These results demonstrate the importance of accounting for the fact that suppliers compete against the residual demand hyper-surfaces determined by the offers of their competitors, locational demands, and the configuration of the tranmission network, rather than simply an single aggregate offer curve of its competitors and a single system demand value implied by the assumption of infinite capacity across locations in transmission network.

Using our residual demand hyper-surface framework to assess the competition effects of generation capacity divestment from a supplier owning capacity at multiple locations, we find that divesting the same amount of capacity at different locations in the transmission network yields very different counterfactual locational prices. Using our best-response 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 the average actual 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%.

We also develop a stochastic equilibrium model of competition between firms setting locational quantities against the distribution of residual demand hyper-surfaces determined by the offer curves of their competitors and locational demands. This equilibrium analysis accounts for the fact that the strategic suppliers' locational quantity choices jointly

[1] Note that residual demand hyper-surfaces become residual demand curves under the assumption of infinite transmission capacity. Consequently.the market-clearing mechanism used to solve this infinite transmission capacity optimal best-reply offer curves always pays the same price to all generation units.

impact electricity flows in the transmission network through smoothed versions of our residual demand hyper-surfaces. This model finds qualitatively similar locational price changes from the divestment scenarios in both locations to our best-response offer behavior analysis, but smaller average price reductions to load. Our best-response offer curve and locational quantity-setting equilibrium results both demonstrate the importance of accounting for the location of generation capacity and demands and the configuration of the transmission network in assessing the competitive impacts of generation capacity divestments.

Our residual demand hyper-surfaces can be used to compute own- and cross-price inverse semi-elasticities of the residual demand hyper-surface facing a supplier at every location in the transmission network that it owns generation capacity that measures the ability of that supplier to exercise unilateral market power at that 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.[2] Although developing optimal the 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 beyond the scope of this paper, the examples we provide are suggestive of the usefulness of these measures for these two tasks.

The remainder of the paper is structured as follows. In Section 2, we extent the residual demand curve measure of the ability of supplier to exercise unilateral market power in a single-location market to the residual demand hyper-surface for multiple-location, spatially-connected markets. In Section 3, we focus on locational pricing electricity markets and introduce our of model of best-response offer behavior in a market with a potentially congested transmission network based on residual demand hyper-surfaces. Section 4 explains the mechanics of solving for the best-reply offer curve for a supplier that owns generation units at multiple locations and faces a distribution of residual demand hyper-surfaces de-

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

rived from the offer curves of its competitors, locational demands, given the configuration of transmission network. In Section 5, we show how best-response offer curves that ignore the potential for binding transmission network constraints yields lower expected profits than best-response offer curves that account for the configuration of the transmission network, locational demands, and location of generation units. In Section 6, we demonstrate how the best-response offer curves of a large supplier and the locational prices that result from these offer curves would change because of different locations of the divestment of a fixed quantity of generation capacity from the largest supplier in the Italian market. In Section 7, we consider this same problem using a locational quantity-setting equilibrium involving the two large firms competing against a distribution of residual demand hyper-surfaces. Section 8 introduces residual demand hyper-surface 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 an antitrust market. Section 9 concludes and suggests directions for future research.

# 2 Market Power in Locational Pricing Markets

This section introduces the residual demand hyper-surface as a measure of the ability to exercise unilateral market power in multiple spatially-connected markets. Assume two connected markets, $m = \{1, 2\}$, for a homogeneous good and a firm that owns production capacity in both markets. For fixed locational demand functions and fixed locational aggregate outputs of firm $i$'s competitors in market $m$, $Q^m_{-i}$, firm $i$'s locational inverse residual demand function in market $m$ can be written as $P^m(Q^1, Q^2)$ where $Q^m = Q^m_i + Q^m_{-i}$ and $Q^m_i$ is the output of firm $i$ in market $m$.

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

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

where the capacity of transportation link between the two markets determines the relationship between $P^i$ $(i = 1, 2)$ and $Q^1$ and $Q^2$. In a single integrated market, $P^1 = P^2 = P(Q)$ where $Q = Q^1 + Q^2$, which *implicitly* means all output is produced and sold at the same location.[3]

Before we discuss how the inverse residual demand hyper-surfaces $P^1(Q^1, Q^2)$ and $P^2(Q^1, Q^2)$ are derived, we characterize how the capacity of the transportation link impacts the partial derivatives of these functions with respect to the quantities at each location. If the transportation link constraint is not binding, or equivalently, if there is infinite costless transportation 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 affect on the 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 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.

As shown in Wolak (2000), in a single location market the residual demand function for any supplier has a closed form solution as, $DR(p) = D(p) - SO(p)$, where $D(p)$ is the market demand curve and $SO(p)$ is the aggregate willingness to supply curve for all remaining suppliers besides the one under consideration. In multiple-location, spatially-connected markets this is not possible. Locational prices are the result of solving a spatial market-clearing optimization problem conditional on $Q_i^1$ and $Q_i^2$ for a given pair of locational demand functions and fixed pair of aggregate locational outputs from firm $i$'s competitors

[3]This assumption is commonly employed in studies of market power in wholesale electricity markets such as Ito and Reguant (2016), Bushnell et al. (2008), and Puller (2007). Mercadal (2022) treats $P^1(Q^1)$ and $P^1(Q^2)$ as separate pre-determined markets based on transmission network characteristics. Ryan (2021) proposed an iterative method to model network capacity effects starting with an uncongested market and then successively breaking off constrained areas and treating them as separate local markets.

that explicitly takes into account the transportation capacity constraints between the two markets.

To illustrate this mechanism, assume first that both markets can be described by the same linear inverse demand curve as depicted in Figure 1. 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 transportation capacity between the two markets, $K$, 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. The total output in market 1 is on the horizontal axis read from the left to the right and the total output in market 2 is on the horizontal axis read from the right to the left. The figures in Panel (a) and (b) 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 in each market, $Q^1$ and $Q^2$. The transportation capacity, $K$, is indicated by the line between the equilibrium demand levels and the output levels in the two markets. Panel (a) shows that given the zonal output of firm $i$, the network will be uncongested because the resulting export from market 1 to market 2, $r$, or equivalently the resulting import from market 2 to market 1, $-r$, does not exceed the physical transport capacity limit, $K$. 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 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 transportation network will be congested for a given level of outputs in each market, demand curves in each market, and fixed transport capacity connecting the two markets can be determined by the assumed spatial equilibrium market-clearing optimization problem which maximizes the sum of consumer surplus in both markets accounting for the transportation capacity between the two markets. The assumed spatial equilibrium market-clearing problem for two markets is:

$$J^*(Q^1, Q^2) = \arg\max_r \quad \int_0^{Q^1+r} P^1(\tau_1)\mathrm{d}\tau_1 + \int_0^{Q^2-r} P^2(\tau_2)\mathrm{d}\tau_2 \tag{2a}$$

$$\text{subject to} \quad -K \leq r \leq K, \tag{2b}$$

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

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 and locational prices. The prices in each market will be equal if the constraint in (2b) is not binding and will differ otherwise.

This pricing model (2) yields a mapping from the aggregate output in each market to prices in each market ($f\colon \mathbb{R}^2_+ \mapsto \mathbb{R}^2_+$). 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 is costless but the model is easily extendable to connected markets with a non-zero transportation cost. In the case of a per unit charge to move the product between markets equal to $c$, the term $c\,|r|$ must be added to the objective function (2a). The consequence of a transportation cost is that less trade will occur.

Note that unlike in the setting studied by Borenstein et al. (2000) we allow each firm to own production capacity in both locations. The firm's outputs in market 1 and market 2 will determine whether the transport capacity between the markets is congested. However, if the firm had productive capacity in only one market it could cause the transportation 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 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 transportation capacity between the markets to bind which increases the price in market 2 and increases the firm's revenue from sales in market 2.[4]

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 hyper-surface, 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 zonal 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 hyper-surface and for the case of two connected markets there will be two of these three-dimensional surfaces.[5]

Figure 2, plots the residual demand hyper-surfaces 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 transportation link to bind. For all output combinations leading to an unconstrained single market (all the points where $P^2(Q_i^1, Q_i^2) - P^1(Q_i^1, Q_i^2) = 0$ in Figure 2, Panel c), the residual

[4]In the case discussed in Borenstein et al. (2000), the firm's zonal residual demand curve is replaced by the market level residual demand curve for the output range that would lead to a non-binding transportation capacity constraint. Consequently, points where the slope of the firm's residual demand curve changes for the Borenstein et al. (2000) model will be solely determined by the firm's zonal output for a given transport capacity limit and the output of the firm's competitors. This is no longer the case when firms own capacity in two connected markets.

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

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 transportation constraint between the markets depends on the firm's output in each market, as is evident from Figure 2.[6]

We want to emphasize that the residual demand surface, as we define it, is simply the demand for the firm's output in each market at a pair of market prices, or equivalently, the resulting market prices for a given pair of the firm's market level outputs. This concept allows us to incorporate a transportation capacity constraint that connects markets in our measure of the ability of a supplier to exercise unilateral local market power. It also illustrates a potential important avenue for exercising unilateral local market power by suppliers that own production capacity in two spatially distinction markets that is particularly relevant to wholesale electricity markets. This is the ability change the output in one market in order to change the price in another connected market.

## 2.1 Residual Demand Hyper-Surface for an Electricity Market

This section generalizes the two-location logic of the previous section to an arbitrary number of locations for a wholesale electricity market. Computing the residual demand hyper-surface for a locational pricing electricity market requires solving the market-clearing optimization problem for a grid of locational output levels for the supplier's generation units given the offers of all other suppliers, locational demands, and the configuration of the transmission network.

**Definition 1** *Residual demand market-clearing for a locational pricing market given a vector of $Z$ locational outputs for firm $i$, $\mathbf{Q}_i = [Q_i^1, \ldots, Q_i^Z]$, using the power transfer distribution matrix $A$ to map locational net balances to power flows chooses the vector of demand bid quantities, $\mathbf{x}_b$ and offer quantities of suppliers besides firm $i$, $\mathbf{x}_{-i}$, to solve the following*

[6] Figures 3 and 4 provide an example with asymmetric markets.

*linear programming problem given* $\mathbf{Q}_i$*:*

$$\begin{aligned}
\underset{\mathbf{x}_b, \mathbf{x}_{-i}}{\text{maximize}} \quad & \mathbf{b}_b^\top \mathbf{x}_b - \mathbf{b}_{-i}^\top \mathbf{x}_{-i} \\
\text{subject to} \quad & \mathbf{1}^\top \mathbf{x}_b - \mathbf{1}^\top \mathbf{x}_{-i} - \sum_{z=1}^{Z} Q_i^z = 0 \quad [\lambda] \qquad (3) \\
& \sum_{z=1}^{Z} A_{kl}^z \left( Q_i^z + \mathbf{1}^\top \mathbf{x}_{-i}^z - \mathbf{1}^\top \mathbf{x}_b^z \right) - f_{kl} \leq 0 \quad [\mu_{kl}],\ (k,l) \in \mathcal{E} \qquad (4) \\
& \mathbf{x}_k \leq \mathbf{g}_k,\ k \in \{b, -i\} \\
& \mathbf{x}_k \in \mathbb{R}_0^+,\ k \in \{b, -i\},
\end{aligned}$$

*for a vector of transmission limits* $\mathbf{f}$*, and locational supply offer price and offer quantity pairs of firm i's competitors* $\left\{ \left( \mathbf{b}_{-i}^z, \mathbf{g}_{-i}^z \right) \right\}_{z=1}^{Z}$ *and locational demand bid price and demand quantity pairs* $\{(\mathbf{b}_b^z, \mathbf{g}_b^z)\}_{z=1}^{Z}$*. The corresponding locational market-clearing prices can be derived from the optimal values of the dual variables of* (3) *and* (4)*. Specifically,* $P^z(\mathbf{Q}_i) = \lambda^* - \sum_{(k,l)\in\mathcal{E}} A_{kl}^z \mu_{kl}^*,\ z = 1, \ldots, Z.$

The vector of locational prices and firm output quantities from each solution of this linear program yields a point on the supplier's residual demand hyper-surface.[7] Solving this problem for a grid of values of the vector $\mathbf{Q}_i$ from zero to the generation capacity owned by firm $i$ at each location $z$ yields the supplier's residual demand hyper-surface.

[Figure 1 about here.]

[Figure 2 about here.]

[Figure 3 about here.]

[Figure 4 about here.]

Note that a inverse residual demand hyper-surface can show that the price in a local market is unresponsive to changes in firm $i$'s output at all locations. This residual demand

[7] Appendix C provides more technical details on the locational market-clearing process.

hyper-surface would be a horizontal plane implying that the firm has no ability to exercise unilateral market power in the local market associated with that price.

## 3 Optimal Offer Curve in a Locational Pricing Market

This section presents our model of optimal offer behavior in a locational pricing market. This model respects both, the market rules governing the set of allowable offer curves that all suppliers can submit and the actual market-clearing mechanism used to compute the locational prices and quantities that result from a given offer curve for each residual demand hyper-surface realization. Because a supplier does not know the offer curves of its competitors, the bid curves of demanders, and locational demands in the transmission network when it submits its offer curve, the supplier must construct its offer curve to maximize expected profits given its beliefs about the distribution of the residual demand hyper-surfaces that results from its uncertainty about these three unknowns.

Competition in a wholesale electricity market is typically modeled using supply functions with demand uncertainty as described in Klemperer and Meyer (1989). However, there are at least three reasons why this theoretical framework may not adequately represent actual outcomes in short-term wholesale electricity markets. First, participants in these markets actually submit non-decreasing step functions with a finite number of price and quantity steps. As noted in Wolak (2003b) 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-reply price-quantity pairs. The Klemperer and Meyer (1989) approach implies that the supplier's expected profit-maximizing supply curve does not depend on the shape of the distribution of residual demand uncertainty. However, as shown in Wolak (2003b) and Wolak (2007) for a single location market, under a market rule that requires suppliers to submit non-decreasing step functions, a supplier's expected profit-maximizing offer curve generally depends on the distribution of step-function residual demand curves that the supplier faces.

A second reason arises even if the supply functions are required to be continuous increasing functions as modeled in, for example Green and Newbery (1992); Sioshansi and Oren (2007); Anderson and Hu (2008): Transmission constraints cause expected profit-maximizing offer curves to depend on the probability distribution of random shocks to demand 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 optimal offer behavior in multi-unit auction markets, such as wholesale electricity markets, has largely ignored the impact of modeling the impact of transmission constraints in the pricing of energy (Wolak, 2000, 2007; Hortaçsu and Puller, 2008; Reguant, 2014). We extend the model in Wolak (2000) to the case of a locational pricing model with a potentially congested transmission network.[8]

We present our best-response offer curve model for a vertically-integrated firm $i$ operating in a locational marginal pricing market. We begin by introducing the notation necessary to present our model. Each firm $i = 1, \ldots, N$ operating in the market, offers a vector of price and quantity increments to the market at each location $z$, expressing its willingness to supply energy at location $z$ from its generation units. We assume there are $Z$ possible pricing locations in the transmission network.[9] Let $\boldsymbol{\theta}_i^z = \{\mathbf{b}_i^z, \mathbf{g}_i^z\} = (b_{i,11}^z, \ldots, b_{i,JK}^z, g_{i,11}^z \ldots, g_{i,JK}^z)$ be firm $i$'s vector of locational offer prices and quantities. It contains pairs of prices and quantities for each generator $j = 1, \ldots, J$ and each possible quantity and associated price step $k = 1, \ldots, K$ at location $z$. Stacking the firm's locational offer curves across the $Z$ locations yields $\boldsymbol{\theta}_i = \bigcup_{z=1}^{Z} \boldsymbol{\theta}_i^z$. Furthermore, define $\boldsymbol{\theta} = \boldsymbol{\theta}_i \cup \boldsymbol{\theta}_{-i} \cup \boldsymbol{\theta}_b$, the vector of offers

[8]We focus on a radial transmission network topology. 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). The market operator determines imports and exports between zones based on minimizing the as-offered costs to serve demand and subject to the physical capacity limits of the transmission lines.

[9]Because we can assume firm $i$ a maximum capacity at location $z$ equal to zero, without loss of generality, we assume firm $i$ owns capacity at all locations.

of all market participants, where the subscript $b$ denotes demand side bids and subscript $-i$ the supply offers of firm $i$'s competitors. For each location $z$, the elements of $\boldsymbol{\theta}_i^z$ make up a non-decreasing locational step function offer curve and the elements of $\boldsymbol{\theta}_b^z$ make up a non-increasing locational step function bid curve for demand.

Define $S_i^z(P^z, \boldsymbol{\theta}_i)$ as the willingness-to-supply function of firm $i$ at location $z$. This is a non-descreasing step function that depends on the price at location $z$ parameterized by $\boldsymbol{\theta}_i$. Let $P^z(\boldsymbol{\theta})$ be the short term price at location $z$ and $\overline{P}(\boldsymbol{\theta})$ the wholesale energy purchase price for loads that results from solving the locational pricing market-clearing optimization problem.[10] For the remainder of the paper, the purchase price for loads is assumed to be the load-share-weighted-average of the zonal prices. Load paying according to this price is a feature of the Italian market that is the focus of our empirical analysis.[11] Having loads pay the price in their congestion zone would be a straight forward modification of the model.

The variable cost of output level $q$ at location $z$ for firm $i$ is equal to $C_i^z(q)$. Furthermore, let $P_i^C$ equal firm $i$'s forward contract quantity-weighted average price of fixed-price forward contracts that settles against 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 $i$ is:

$$\Pi(\boldsymbol{\theta}_i) = \sum_z S_i^z(P^z(\boldsymbol{\theta}), \boldsymbol{\theta}_i) P^z(\boldsymbol{\theta}) - \sum_z C_i^z(S_i^z(P^z(\boldsymbol{\theta}), \boldsymbol{\theta}_i)) - (\overline{P}(\boldsymbol{\theta}) - P_i^C) Q_i^C. \tag{5}$$

The first term is the hourly revenue firm $i$ earns from wholesale electricity sales in the short-term market. The second term is the hourly variable cost of electricity sold in the short-term market and the third term is hourly total difference payments associated with settling the suppliers fixed-price forward contract obligations. $P_i^C$ is equal to $P_i^C = \frac{\sum_k P_{ik}^C Q_{ik}^C}{Q_i^C}$, where

[10] Note that prices at all locations and the purchase price for loads depend on the vector of offers of all suppliers and bids of all demanders through the locational pricing market-clearing optimization problem.

[11] See Appendix C.1 for a more detailed description on the computation of locational prices and the uniform purchase price. In all locational pricing markets in the US, load-serving entities typically pay for energy according to similar quantity-weighted averages of locational prices. Tangerås and Wolak (2018) demonstrate that this market rule can enhance the competitiveness of short-term market outcomes.

$Q_i^C = \sum_k Q_{ik}^C$, and $P_{ik}^C$ is the price of forward contract $k$ and $Q_{ik}^C$ is the net forward position of contract $k$. A contract sold by the supplier is a positive value of $Q_{ik}^C$ and a contract purchased by the supplier is a negative value of $Q_{ik}^C$.

Each firm in the market is assumed to maximize expected profits conditional on its distribution of beliefs about its competitors' offers, locational demands in the transmission network, and demand side bids, which along with configuration of the transmission network determine the distribution of residual demand hyper-surfaces the supplier faces. Market-clearing prices and quantities for each residual demand hyper-surface realization are determined by solving the transmission network-constrained market-clearing optimization problem with a uniform purchase price for loads but potentially different prices paid to generation units in each pricing zone.[12]

Firm $i$'s expected profit-maximization problem is:

$$\begin{aligned} \underset{\boldsymbol{\theta}_i}{\text{maximize}} \quad & \mathbb{E}\left[\Pi_i(\boldsymbol{\theta}_i)\right] \\ \text{subject to} \quad & \mathbf{0} \leq \mathbf{b}_i \leq \mathbf{1}\,\hat{b} \\ & 0 \leq \sum_k g_{i,jk} \leq \hat{g}_{i,j}, \ \forall j \end{aligned} \tag{6}$$

where $\mathbb{E}[\cdot]$ is the expectation taken with respect to the distribution of residual demand hyper-surfaces facing firm $i$, $\hat{b}$ is the scalar offer price cap set by the regulator and $\hat{g}_{i,j}$ is the maximum capacity of generation unit $j$ owned by firm $i$. The first set of inequality constraints require offer prices to be greater than zero and less than or equal to the offer cap. The second of inequality constraints require the sum of offer quantities for each generation unit to be less than or equal the capacity of the unit. For the same offer curve for firm $i$, each residual demand hyper-surface realization gives rise to potentially different locational prices and a different quantity-weighted average price, $\overline{P}(\boldsymbol{\theta})$. For this reason, the term $\overline{P}(\boldsymbol{\theta})Q_i^C$ in (5) matters for determining the firm $i$'s expected profit-maximizing value of $\boldsymbol{\theta}_i$.

[12]Appendix C contains a detailed explanation on how the locational pricing market clears.

Our model is able to accommodate different firm and market structures. For example, if a firm is vertically integrated, the variable profit function (5) 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, $Q_i^{R,z}$ is the firm's retail load obligation at location $z$, and the marginal cost of electricity retailing for firm $i$ is $\tau_i$.[13] Finally, we note that if transmission constraints are never binding, and thus $P^z(\boldsymbol{\theta}) = \overline{P}(\boldsymbol{\theta}) = P()$ for $z = 1, 2, \ldots, Z$, the model simplifies to that described in Wolak (2000).[14]

# 4 Computing Expected Profit-Maximizing Offer Curves

In this section, we describe the mechanics of computing expected profit-maximizing offer curves given realizations from the distribution of residual demand hyper-surfaces faced by the firm. This requires choices for the main modeling inputs such as generation unit-level variable costs estimates, an estimated residual demand hyper-surface distribution, and the fixed-price forward contract positions held by suppliers. Given this information, we then describe the formulation of the MPEC problem solved to compute an expected profit-maximizing offer curve.

Our sample period is from September 1, 2007 to October 31, 2007.[15] We only optimize

[13] 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.

[14] The model is capable of incorporating physical or financial transmission rights, 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). The Italian market does not have financial transmission rights (FTRs) issued by the market operator and funded from the merchandising surplus similar to United States locational marginal pricing (LMP) markets. However, market participants can enter into bilateral locational price difference hedging instruments. Our understanding is that there is little, if any, volume in these locational price hedging instruments during our sample period. We have no data on the positions of any firms and therefore are unable to incorporate them into our model.

[15] We remove the following set of days from our sample due to a restriction on transmission capacity between the North (N) and Central North (CN) zones from Oct 22, 2007 to Oct 26, 2007. The sample average available line capacity between the two zones was approximately 2,500 MW, but it was below 1,700 MW on these days. We also remove Oct 29, 2007 to Oct 31, 2007, because we observed significantly reduced transmission capacity between Calabria (CA) and Sicily (SI) on these days. We believe that these transmission line de-rates would effect offer behavior because these transmission capacity limits are known to the market participants before they submit their offer curves to the day-ahead market and this would

over the peak hours of the day–11, 12, 18, 19, and 20. We eliminated weekends and holidays from the sample. In total, our sample is composed of 175 hourly 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 is negligible at this time.

We have selected two strategic firms, Enel and Edison, which we refer to as the *incumbent* and the *main competitor*, respectively. We calculate best-response offer curves for each firm separately assuming that each firm maximizes expected profits given the distribution of residual demand hyper-surfaces that it faces. We focus on the day-ahead market as this is by far the largest in terms of traded quantities and its weighted average clearing price is the reference price for clearing fixed-price forward contracts. A detailed description of the Italian electricity supply industry can be found in Appendices B.1 and B.2.

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 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 re-dispatch 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 hyper-surfaces. 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

impact the distribution of residual demand hyper-surfaces for the same assumed distribution of competitor offers curves, demand bids and locational demands. Hence, including scenarios with substantially different transmission capacity limits would likely bias our results.

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.

As pointed out previously, we focus on peak hours in which storage units are typically considered to be marginal suppliers. Furthermore, 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 hyper-surface 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 which suggests that storage units typically do not play a major role in determining day-ahead market outcomes during our sample period.

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 hyper-surfaces they face.[16]

## 4.1 Marginal Cost of Electricity Generation

We calculate the marginal cost of production for each thermal generation unit using data on its thermal efficiency and monthly prices for fuel and $CO_2$ certificates. The firm's aggregate 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 marginal 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 marginal cost function.

## 4.2 Eliciting Fixed-Price Forward Contract Positions

For a fixed distribution of residual demand hyper-surfaces, a supplier's best-reply offer curve depends on its quantity of fixed-price forward contract obligations.[17] Fixed-price forward positions are typically only known to the firm. However, the price at which a firm is 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 is expected profit-maximizing to offer capacity beyond a supplier's $QC_i$ value above the unit's marginal cost.[18] For this reason, we set $QC_i$ equal to the sum of offer quantity steps of thermal units offered below 30 EUR/MWh, which is the approximate marginal cost of a coal power plant. Offers at this price will be inframarginal almost with certainty because our analysis focuses on peak

[16]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 of our optimal offer curve problem.

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

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

hours.[19] We elicit the values of $QC_i$ for each firm for each hour in our sample using this rule.

The incumbent sells an average of 11.4 GWh and the main competitor sells an average of 8.0 GWh to the day-ahead market in each hour of our sample. Our estimate of the average hourly hedged quantity of energy for the incumbent is 8.1 GWh and 6.4 GWh for the main competitor. These estimates of $QC_i$ for each supplier mean that an average 71% of the incumbent's and 80% of the main competitor's production during our sample period is hedged in fixed-price forward contracts.

## 4.3 Scenario Selection

Each firm maximizes expected profits conditional on its estimate of the distribution of the residual demand hyper-surfaces that it faces. Selecting a reasonable residual demand hyper-surface distribution is critical because it determines the distribution of variable profit realizations for firm $i$ for the same offer curve. We select a sample of equally weighted "like-markets" for this estimated distribution.

The day-ahead market clears using the hourly offer curves and hourly demand curves submitted. Therefore, we treat every hour of the day for each weekday in our sample as independent events. We then select "like-markets" for a given hour of the day from these weekdays and that same hour of the day to obtain the residual demand hyper-surface realizations used to derive the best-reply offer curve. We cap the number of "like-markets" at 20, including the actual residual demand hyper-surface for that hour of our sample.[20]

## 4.4 Best-Response Offer Curve

We solve for the best-response offer curve that maximizes the twenty realized values of the profit function in Equation (5) for the twenty like-markets. A detailed technical description of

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

[20]Because the share of electricity generated from renewable sources was negligible in 2007, so we do not account for renewable energy production when selecting "like-markets."

the reformulation of the model into a mixed integer program can be found in Appendix D.[21]

We account for potential offer price and quantity indeterminacy by using the merit order number set by the market operator to guarantee uniqueness of each market-clearing outcome. The merit order number orders offers and bids in case of a tie—when their submitted offer prices are equal.[22] For the offer curve optimization problem we enforce a merit order of generation units at the zonal level according to our estimated short-run marginal costs.

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 the problem as it appears to firms participating in the day-ahead market. Furthermore, we are able to assess the quality of the solution indicated by the optimality gap (MIP gap) which 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.

The optimal best-response 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 hyper-surface realizations. For example, if it is optimal to withhold capacity, then any offer price larger than the maximum zonal 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.[23] Second, even

[21]Note that we are dealing with piece-wise constant residual demand hyper-surfaces to find a piece-wise constant offer curve and as such its derivatives with respect to the parameters of the offer curve are either zero or infinity. Hence, this rules out optimization techniques relying on derivatives.

[22]See Appendix C.3 for a more detailed description on this rule.

[23]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. Note that both ways to define best-response 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 best-response offer curve. 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

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 optimal offer curve intersects with the inverse residual demand hyper-surfaces. Moreover, it could be theoretically possible that a best-reply offer curve that will congest the network gives the same expected profit as a best-reply offer curve that does not congest the market. However, because we fix offer quantities at their actual values and use twenty "like markets" to estimate expected profits, and require offer prices to be greater than or equal to the unit's marginal cost, we limit the risk of non-unique solutions. Even though we are able to solve almost all instances to global optimality, we also re-run the optimization problem changing the random seed used to initialize the MIP solver to be reassured that our results are numerically stable.[24]

# 5 Best-Response Offer Curve Results

In this section, we compute market outcomes using the expected profit-maximizing offer curves, actual offer curves, and profit-maximizing offer curves assuming infinite transmission capacity. In Figure 5, we show the optimal locational offer curves (green) for our assumed distribution of residual demand hyper-surfaces for the incumbent for Hour 12 of September 5, 2007 for our three locations–North, Center, and Sicily. We also show the actual offer curves (blue), 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"like 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.

problem.

[24]All our models are implemented in Python 3.8 and use Gurobi 9.5 as a solver for the linear programs as well as the mixed integer programs. We run the mixed integer programs using four to ten cores for each market instance with a time limit of 20,000 seconds.

In order to demonstrate the importance of accounting for the configuration and capacity of the transmission network on offer behavior over a wide range of system conditions, we compute the absolute differences between the actual offer curves and the optimal offer curves as well as the absolute difference between the actual offer curves and the optimal offer curves assuming infinite transmission capacity across our 175 market instances.

We find the following inequality between the two metrics:

$$\sum_{i,z,t} w_{it}^z \left( \int_0^{\overline{q}_{it}^z} \left| \tilde{b}_{it}^z(\tau) - \tilde{b}_{it}^{z,*(f)}(\tau) \right| \, d\tau \right) < \sum_{i,z,t} w_{it}^z \left( \int_0^{\overline{q}_{it}^z} \left| \tilde{b}_{it}^z(\tau) - \tilde{b}_{it}^{z,*(f_\infty)}(\tau) \right| \, d\tau \right),$$

where $\tilde{b}_{it}^z(q), \tilde{b}_{it}^{z,*(f)}(q)$, and $\tilde{b}_{it}^{z,*(f_\infty)}(q)$ denote firm $i$' actual, optimal, and optimal offer curve assuming infinite transmission capacity, respectively, at location $z$ and hour of sample $t$. The weighting factor $w_{it}^z$ denotes the firm-location and hour-of-sample capacity share. Because the best-response offer curves are undefined for offers that are infra-marginal or extra-marginal under all scenarios we cap all offer curves at the maximum observed hourly locational price.

The above inequality for a fixed value of $i$, also holds for the main competitor but not for the incumbent because of its high best-reply offer prices in Sicily (see Table 1, Panel A, Row $P^{SI}$, Column 3). It turns out that the incumbent offers more aggressively than is unilaterally profitable. A potential explanation of restrained market power is regulatory threat that could be triggered if locational prices were raised too aggressively as discussed in (Hobbs et al., 2005).

In Table 1, we present average zonal 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 marginal cost estimate. Column (2) shows the market clearing results using the actual offer curve. Column (3) shows the results of the optimal best-response offer curve accounting for transmission constraints. Column (4) presents the results with the best-response offer curve computed assuming there is infinite transmission capacity between zones. 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, actual bid curves, and locational demand 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 optimal best-response 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 optimal best-response 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 largest competitor. From this we conclude that a significantly higher average profit increase is possible when accounting for transmission constraints in computing best response 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 offering computing optimal offer curves for the day-ahead market.

[Figure 5 about here.]

Table 1: Best-Response Offer Results

| | (1) $J(\{\mathbf{c}_i, \mathbf{g}_i\})$ | (2) $J(\boldsymbol{\theta}_i)$ | (3) $J(\boldsymbol{\theta}_i^*(f))$ | (4) $J(\boldsymbol{\theta}_i^*(f_\infty))$ |
|---|---|---|---|---|
| | *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 |
| $\Pi_i$[1] | 505,401 | 540,887 | 593,202 | 568,178 |
| | *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 |
| $\Pi_i$[1] | 370,080 | 370,438 | 383,644 | 376,081 |

*Notes:* Average market outcomes ($N = 175$). Prices in EUR/MWh, profits in EUR, and quantities in MWh. $J(\cdot)$ denotes the market clearing parametric on a firm's offer curve. Col (1): Firm's offer prices of relevant units replaced by their marginal cost estimate. Col (2): Firm's actual offer curve as observed in the data. Col (3): Firm's best-response offer curve. Col (4): Firm's best-response offer curve computed under the assumption of infinite transmission capacity. Almost all solutions of best reply offer curves supplied to $J(\cdot)$ 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%).

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

## 6 Location and the Price Effects of Divestment

This section analyzes how the same amount of capacity divestment in different zones would change the incumbent's optimal best-reply offer curves and resulting locational prices. The locations in the transmission network where the same number of megawatts (MWs) of generation capacity divestment takes place determines the extent of unilateral locational market power the divesting supplier is able to exercise.

We focus on the incumbent because it owns a substantial amount of thermal capacity in all zones. 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, respectively. In the remaining two scenarios, we divest about 2.4 GW in each of the two zones. In order to make the counterfactuals comparable to the status quo, we adjust the firm's forward positions using the procedure described in Section 4.2 for each modified generation portfolio. We also assume that the capacity is divested to a fringe player, 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.[25]

Table 2 presents our results. As expected, divesting the incumbent of thermal capacity leads to lower best-response prices. However, the zonal configuration of the market turns out to be a an important determinant of which divestment scenario lowers prices the most in which zone. Divesting 1.2 GWs of the incumbent's thermal capacity in the North or in the Center (Panel A) leads to a larger reduction in the uniform purchase price relative to the status quo relative to divesting the same amount of capacity in the North. Compare columns (2) and (5) to column (1) in Table 2). Although the channels leading to this result are slightly different, divestment in the North would lead to a lower average zonal price in this zone and a slightly higher price in the Center as well as a larger price in Sicily. Hence,

[25] We selected mostly coal plants and one economic gas plant to ensure that we are divesting inframarginal capacity. In the North, units 1 to 4 of the Fusina plant and unit 3 of the plant in La Spezia were divested. For the larger divestment we added units 3, 4, and 6 of the Genoa plant and units 3 and 4 of the Porto Corsini plant. In the Center we divested units 1 and 3 of the Brindisi plant, and for the large divestment we added unit 4 of the Brindisi plant and unit 3 of Sulcis plant.

the incumbent's unilateral incentive to drive prices in these three zones apart would increase. Because the North zone is larger than the Center zone (and much larger than Sicily), the decrease of the zonal price in the North dominates the slight increase in the Center and hence, the uniform purchase price would be lower. When divesting in the Center, the price in the Center would decrease, and so would the best-response uniform purchase price.

Applying a large divestment counterfactual scenario (2.4 GW) leads to even lower uniform purchase prices. We provide the average results of this exercise in Panel B of Table 2. Divesting a large amount of the incumbent's thermal capacity in the North leads to a smaller change in the uniform purchase price in comparison to the small divestment (compare row $\overline{P}$, column (5) in Panel A to the same row and column in Panel B in Table 2). Overall, the average effect on the uniform purchase price is about the same. The locational price dispersion is larger when divesting in the North than when divesting in the Center.

These results demonstrate that the same number of MWs of divestment in different zones 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. The finding that capacity location may be critical when measuring market power is in line with Bigerna et al. (2016) who assess the ability of suppliers to exercise unilateral market power in the Italian day-ahead market using zonal Lerner indices. Their results show that generators are only able raise prices above competitive levels in specific congestion zones. The importance of network considerations in the Italian day-ahead market is also confirmed by Fianu et al. (2022).

# 7 Locational Quantity-Setting Equilibrium Model

This section constructs an equilibrium model where strategic firms make locational output choices to impact locational prices through a potentially congested transmission network.

Table 2: Divestment of Incumbent's Capacity

| | (1) Baseline | (2) Divestment in the Center | (3) | (4) | (5) Divestment in the North | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | $J(\boldsymbol{\theta}_i^*)$ | $J(\boldsymbol{\theta}_i^*)$ | $\Delta$ | $\Delta(\%)$ | $J(\boldsymbol{\theta}_i^*)$ | $\Delta$ | $\Delta(\%)$ |
| | | | *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% |
| $\Pi_i$ | 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% |
| $\Pi_i$ | 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 EUR/MWh, costs and profits in k EUR. $J(\cdot)$ denotes the market clearing, parametric on a firm's offer curve. Col (1): Market clearing evaluated at incumbent's best response offer curve. Col (2): Market clearing evaluated at incumbent's best response 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 best response 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). All solutions of best reply offer curves supplied to $J(\cdot)$ are proven global maxima with the exception of 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%.

[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 run marginal costs.

Multiple suppliers own productive capacity in multiple locations and compete against one another through a smoothed version of our residual demand hyper-surfaces.[26] We use this model that to assess the impact of the same divestment actions by the incumbent firm considered in the previous section assuming that the two large strategic firms each set their vector of locational quantities to maximize expected profits given the locational quantity

[26] 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).

choices of their competitors and the distribution of smoothed residual demand hyper-surfaces created by the offers of the remaining firms, locational demands, and the configuration of the transmission network.

We begin by describing the multivariate Nadaraya-Watson (N-W) estimator that we use to smooth the residual demand hyper surfaces. For that purpose we briefly 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

$$\hat{m}(\mathbf{x}) = \frac{\sum_{i=1}^{n} \left( \prod_{j=1}^{p} \left[ k \left( \frac{x_j - X_{ij}}{h_j} \right) \right] y_i \right)}{\sum_{i=1}^{n} \left( \prod_{j=1}^{p} \left[ k \left( \frac{x_j - X_{ij}}{h_j} \right) \right] \right)}, \tag{7}$$

where $k(t)$ is a univariate kernel function, $\mathbf{h} = (h_1, h_2, ..., h_p)'$ 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 bandwiths used for smoothing. In Figure 6, 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 above.

[Figure 6 about here.]

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 hyper-surfaces created by offers of the remaining competitors, locational demands, and the configuration of the transmission network. Let the realized smoothed inverse residual demand hyper-surface for zone $z$ which is the function of the vector of aggregate locational quantities $\mathbf{Q}$ equal $\tilde{P}^z(\mathbf{Q}, \epsilon)$ and the quantity-weighted average price equal $\overline{\tilde{P}}(\mathbf{Q},\epsilon)$. Each firm $i$'s objective function is:

$$\underset{\mathbf{Q}_i}{\text{maximize}} \quad \mathbb{E}_\epsilon \left[ \sum_{z=1}^{Z} \tilde{P}^z(\mathbf{Q},\epsilon) Q_i^z - C_i^z(Q_i^z) \; - \; (\overline{\tilde{P}}(\mathbf{Q},\epsilon) \; - \; P_i^C) Q_i^C \right] \tag{8a}$$

$$\text{subject to} \quad 0 \le Q_i^z \le \overline{Q}_i^z, \quad \forall z \in \mathcal{V}(i), \tag{8b}$$

where $\epsilon$ parameterizes the distribution of residual demand uncertainty.

The first order necessary conditions of (8) for each strategic firm $i$ and assumed distribution of residual demand hyper-surfaces using $S$ smoothed residual demand hyper-surface realizations are:

$$Q_i^z \ge 0 \perp S^{-1} \sum_{s=1}^{S} \left( \sum_{k=1}^{Z} \left( \frac{\partial \tilde{P}_s^k(\mathbf{Q})}{\partial Q_i^z} Q_i^k \right) + \tilde{P}_s^z(\mathbf{Q}) - \frac{\partial \overline{P}_s(\mathbf{Q})}{\partial Q_i^z} Q_i^c \right) - \frac{\mathrm{d}\, C_i^z(Q_i^z)}{\mathrm{d}\, Q_i^z} - \overline{\mu}_i^z \le 0, \quad \forall i, z = 1, \ldots, Z. \tag{9a}$$

$$0 \le \overline{\mu}_i^z \perp Q_i^z \le \overline{Q}_i^z, \quad \forall i, z = 1, \ldots, Z. \tag{9b}$$

Solving the nonlinear complementary problem (9) should lead to stationarity points that are mutual best-responses. However, because residual demand hyper-surfaces 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 the single zone case. Note further that even if zonal (1-dimensional) residual demand functions are linear our problem can have multiple or no pure strategy equilibria (Yao et al., 2008).

To circumvent the issue of uniqueness, we deploy an extensive search strategy using different starting value combinations to trace out potentially multiple stationarity points.[27]

[27] 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 zones ($Z = 3$). Inspecting the computational solutions, we find that 99% of runs in the baseline case 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 market instances converged to the same stationarity point. The proportions are similar for the counterfactual runs where we divest capacity in different locations analogous to Section 6.

We compute the inverse residual demand hyper-surfaces on a grid of locational quantity values. For each zone 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 zones, $Z = 3$, this implies $20^3 = 8{,}000$ market-clearing solutions per market instance to obtain a smoothed inverse residual demand hyper-surface. For the $S = 20$ "like markets" used to model distribution of the inverse residual demand hyper-surfaces, 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 zone $z$, $h_z = 0.05 \sum_i \overline{Q}_i^z$, that is 5% of the maximum of output quantities of the two firms in zone $z$.[28] In order to simplify the problem, we replace zonal piece-wise constant short run marginal cost curves by increasing and convex quadratic short run marginal cost curves. The parameters of these functions are obtained through least squares fitting a curve to the piece-wise constant functions. In Figure 7, we plot the zonal marginal cost functions and their fitted counterparts for the incumbent firm.[29]

[Figure 7 about here.]

[28]In Table 9, we present equilibrium results using $h_z = 0.1 \sum_i \overline{Q}_i^z$ 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 3. We find that a more smoothing leads to average prices that are lower and that deviate more from actual observed prices. However, the average price differences between zones before versus after divestment are preserved.

[29]We solve the nonlinear complementarity problem (9) using the solver *PATH* (version 5.0.05; Dirkse and Ferris, 1995) with its default parameter settings.

We perform the same two divestment analyses for two locations for the incumbent firm described in Section 6, 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 3,[30] 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 zonal price in the Center would decrease by 6.2% while zonal 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 are the market-clearing prices computed using unsmoothed inverse residual demand surfaces for that market instance evaluated at the optimal quantities obtained from solving (9) for the two strategic firms. The total average output of both strategic firms 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 firm and would be offered at marginal cost. Average 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 coal capacity in the Center (Panel B) would even further decrease the average equilibrium price relevant for demand by 4.7% compared to the simulated market outcomes under the status quo.

The second counter-factual 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 zonal 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 zonal prices we find that divesting in the North would drive prices between the North and the Center further apart while the

[30] We do find a few instances with multiple stationarity points and we select those with the largest joint expected profits. However, we also employed a different equilibrium selection criterion, where expected consumer surplus is maximized. These results are presented in Table 8. The results are almost indistinguishable and the qualitative interpretation of the results is independent of the two equilibrium selection methods.

opposite effect is observed when divestment takes place in the Center.

Discussion of DWL In terms of the average cost to serve load we find an even slight increase relative to the simulated status quo outcome.

Our equilibrium analysis confirms the same quantitative results as our best response analysis that the largest percentage zonal price reduction occurs in the zone where the divestment occurs, and there can be price decreases and even price increases in other zones. However, equilibrium analysis finds smaller quantitative results in terms of the percentage price effects relative to the best response analysis. 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 hyper-surfaces for each strategic firm's vector of locational quantities.

# 8 Own- and Cross-Price Residual Demand Elasticities

This section describes how the residual demand hyper-surfaces can be used to compute own- and cross-price inverse semi-elasticities that could be an input to the design of a local market power mitigation mechanism and used to define local markets for merger and antitrust analysis. All United States locational pricing markets 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. In an uncongested market withholding output at one location impacts all locational prices by the same amount as discussed in Section 2. In a congested network 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

Table 3: Simulated Market Outcomes under Quantity Competition

| | (1) Baseline | (2) Divestment in the Center | (3) | (4) | (5) Divestment in the North | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | $J(\{\mathbf{0},\mathbf{Q}_i^*\})$ | $J(\{\mathbf{0},\mathbf{Q}_i^*\})$ | $\Delta$ | $\Delta(\%)$ | $J(\{\mathbf{0},\mathbf{Q}_i^*\})$ | $\Delta$ | $\Delta(\%)$ |
| *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% |
| $Q^C$(Strategic Firms) | 4,892 | 3,939 | −953 | −19.5% | 4,839 | −53 | −1.1% |
| $Q^N$(Strategic Firms) | 7,226 | 7,164 | −61 | −0.8% | 6,402 | −824 | −11.4% |
| $Q^{SI}$(Strategic Firms) | 1,167 | 1,131 | −36 | −3.0% | 1,136 | −30 | −2.6% |
| *Q (Strategic Firms)* | 13,285 | 12,235 | −1,050 | −7.9% | 12,377 | −908 | −6.8% |
| Profit(Strategic Firms)[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% |
| $Q^C$(Strategic Firms) | 4,892 | 3,288 | −1,604 | −32.8% | 4,787 | −105 | −2.1% |
| $Q^N$(Strategic Firms) | 7,226 | 7,145 | −81 | −1.1% | 5,723 | −1,502 | −20.8% |
| $Q^{SI}$(Strategic Firms) | 1,167 | 1,111 | −56 | −4.8% | 1,117 | −50 | −4.3% |
| *Q (Strategic Firms)* | 13,285 | 11,544 | −1,740 | −13.1% | 11,627 | −1,657 | −12.5% |
| Profit(Strategic Firms)[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. Prices in EUR/MWh, costs and profits in k EUR, and quantities in MWh.

[1] Profits adjusted by $QC \cdot PC$ with $PC$ set to the average actual uniform purchase price (103 EUR/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 short run marginal costs.

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

$$\eta_{z,z'}(i) = (Q_i^z/100)\frac{\partial P^{z'}(\mathbf{Q}_i)}{\partial Q_i^z}, \tag{10}$$

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

$z'$.

The own-price inverse semi-elasticity, $\eta_{z,z}(i)$, measures the EUR/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 $\eta_{z,z'}(i)$ measures the EUR/MWh change in price at location $z'$ associated with supplier $i$ increasing its output by 1 percent at location $z$.

Because we model the Italian market with three locations, the Center (C), North (N), and Sicily (SI), there are three inverse own-price semi-elasticities and six inverse cross-price 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 hyper-surfaces with discrete changes in $Q_i^z$. To obtain a non-zero own-price response for step function residual demand hyper-surfaces, 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'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 $\Delta P^z$ as the difference between these two prices and $\Delta Q_i^z$ 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 (10). 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 $\Delta Q_i^z$. We replace $\frac{\partial P^{z'}(\mathbf{Q}_i)}{\partial Q_i^z}$ by $\frac{\Delta P^{z'}}{\Delta Q_i^z}$ in (10). This approach ensures that if market is unconstrained $\eta_{z,z}(i) = \eta_{z,z'}$ 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 hyper-surfaces these two partial derivatives are computed directly from the smoothed residual demand hyper-surface functions.

Figures 8 and 9 present box and whiskers plots[31] for the 175 values of the own- and cross-price inverse semi-elasticites for the incumbent and main competitor for the step function and smoothed residual demand hyper-surfaces, respectively. The inter-quartile range of values

[31]Sample average hourly values and standard deviations for these inverse semi-elasticities are displayed in Tables 10 and 11.

for both the own- and cross-price inverse semi-elasticites for both firms and both residual demand hyper-surfaces 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 hyper-surfaces there are number of extremely large values. For example, for the North zone and main competitor, the distribution of hourly values of the own-price inverse semi-elasticity in Figure 8 indicates a substantial ability to exercise unilateral market power during more than 25 percent of the hours in our sample. The absolute value of $\eta_{N,N}(i)$ 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 Euros per MWH. The cross-price elasticities for the other two zones. $\eta_{N,C}$ and $\eta_{N,S}$, imply that prices in these two zones are largely unaffected by the main competitor or incumbent withholding output in the North.

[Figure 8 about here.]

[Figure 9 about here.]

The $10^{th}$ to $90^{th}$ percentile range of the own-price inverse semi-elasticites in Figure 8 contains values that are significantly larger in absolute value than the $10^{th}$ to $90^{th}$ range of cross-price inverse semi-elasticites. 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 hyper-surfaces and smoothed residual demand hyper-surfaces. For example, a value of 0.1 EUR/MWh for the cross-price semi-elasticity of an output in change in the Center zone on the price in Sicily for the incumbent implies that a 10% decrease in this supplier's output in the Center increases the price in Sicily by 1 EUR/MWh.

Consistent with the fact they are derived from taking the partial derivative of a smoothed residual demand hyper-surface, the inverse semi-elasticies in Figure 9 tend to have a smaller inter-quartile range and significantly smaller $10^{th}$ to $90^{th}$ percentile range that the corresponding inverse semi-elasticities in Figure 8. However, similar to Figure 8, the own-price inverse semi-elasticities in Figure 9 have significantly larger $10^{th}$ to $90^{th}$ range than any of the cross-price inverse semi-elasticities.

A local market power mitigation mechanism could be designed around the selection of critical values the hourly value of these own- and cross-price inverse semi-elasticities that would deem supplier worthy of mitigation. For example, if the absolute value of the own-price inverse semi-elasticity exceeded certain value, that suppliers 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.

Following the logic of Scheffman and Spiller (1987) these own- and cross-price residual demand hyper-surface elasticities can be used to determine the geographic market definition for the purposes of merger analysis in a wholesale electricity market. Different from Scheffman and Spiller (1987), these measures are produced on an hourly basis, so assessments on the extent of the geographic market following their approach can be made on a hourly basis. The cross-price residual demand hyper-surface elasticities also provide additional information on frequency that the entire market separates across locations.

# 9 Discussion and Conclusion

We have introduced residual demand hyper-surfaces, which are the natural extension of the residual demand curve concept developed for single location markets for locational markets connected with finite transmission capacity. These hyper-surfaces make it possible to infer the effect of a firm's locational quantity choice on the price at that location and the price at all other locations. Residual demand hyper-surfaces provide measures of the ability of a supplier to exercise unilateral market power at each location.

We have adapted the best-response offer curve model to incorporate these transmission-constrained residual demand hyper-surfaces. We found that taking transmission constraints into account helps explain actual offer behavior in the Italian wholesale market better than 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 locational pricing market with finite transmission capacity. We 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 features of the results our best response offer model of the impact of different locational divestment actions on locational prices.

Finally, we introduced quantitative measures of the unilateral ability of supplier to exercise locational market power. These own-price 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 to a design of a local market power mitigation mechanism and the process of geographic market definition for merger and antitrust analysis.

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

# References

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

_ **, Xinin Hu, and Donald Winchester**, "Forward contracts in electricity markets: The Australian experience," *Energy Policy*, 2007, *35* (5), 3089–3103.

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

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

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

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

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

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

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

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

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

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

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

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

**_ , Emilio La Pera, Federico Quaglia, and Frank A. Wolak**, "Market Power Mitigation Mechanisms for Wholesale Electricity Markets: Status Quo and Challenges," Working Paper 2021.

**_ , Federico Quaglia, and Frank A. Wolak**, "Market Performance Assessment in Locational Markets with Non-convexities," Working Paper 2020.

**_ , _ , and _** , "Simplified Electricity Market Models with Significant Intermittent Renewable Capacity: Evidence from Italy," NBER Working Papers 27262, National Bureau of Economic Research 2020.

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

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

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

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

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

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

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

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

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

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

**McRae, Shaun D. and Frank A. Wolak**, "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," Cambridge University Press, 2014, pp. 390–420.

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

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

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

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

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

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

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

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

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

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

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

**Tangerås, Thomas P. and Frank A. Wolak**, "The Competitive Effects of Linking Electricity Markets Across Space and Time," Stanford University, Program on Energy and Sustainable Development Working Paper 2018. `web.stanford.edu/group/fwolak/cgi-bin/sites/default/files/competitive-effects-linking_tangeras_wolak.pdf`.

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

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

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

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

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

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

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

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

# Online Appendix

## A Introduction

This appendix is organized as follows. In Section B, we give a detailed description of the Italian electricity market. Section C describes the zonal market-clearing engine used by the market operator. In Section D, we show how to reformulate the best-response offer curve problem into a mixed integer program and solve for best-response offer curves in a locational pricing market.

## B Market Description

### B.1 The Italian Electricity Market

The Italian spot market for electricity began operation in April 2004. It is organized in a sequential manner, similar to the Spanish power market described in Ito and Reguant (2016). More precisely, it consists of a day-ahead market, an adjustment market,[32] and an ancillary services market, also known as re-dispatch 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 and resolves congestion in the so-called ancillary services or re-dispatch market.

The Italian day-ahead market for electricity is a non-compulsory net-pool zonal market administrated by the market operator. The market splits into several market zones when congestion is present. In that case, producers receive a different price depending on the zones where they are producing energy. The demand side is paid a uniform purchase price (UPP). Retailers and large consumers bid a non-increasing demand curve. Suppliers submit

[32]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`.

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 UPP was 242.4 EUR/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,[33] or ramp rates to consider when clearing the market. Assuming that non-convexities as discussed in Graf et al. (2020a) 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 bids.[34] Following the definition in Anderson et al. (2007), the day-ahead market can therefore be described as a "net-pool". In case of transmission congestion, an explicit transmission capacity fee (CCT)[35] 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).[36]

In 2007, the Italian market consisted of seven domestic zones, five limited production

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

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

[35] 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.

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

zones and six foreign virtual zones to organize imports and exports. The network structure relevant for the day-ahead market-clearing was radial. Congestion between 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 and the rest of the mainland occurred over 80% of the hours. We refer to Appendices B.4–B.6 for more details on the transmission network and the prevalence of congestion.

## B.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 2/3 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 **??** 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 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 paper.[37] 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.[38] The state-owned entity signed contracts for differences with the owners 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. We explain how we elicit the net contract position from a firm's offer data in Section 4.2.

In Table 4, we show the zonal distribution of production capacity by generation type, location, and firm.[39] The data in the table reveals that the incumbent has a very dominant

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

[38] 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 co-generation 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 contrast to EU law and was therefore phased out.

[39] We elicit capacity data from the day-ahead offer data by taking the maximum offers 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.

position in the Center zone. Capacity shares of both firms are more balanced in the North zone. Market concentration is particularly high in Sicily.

Table 4: 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 zones CN, CS, CA, S, and SA and limited production poles therein.
[2] Includes capacity in limited production poles.
[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.

## B.3 Day-Ahead Market Offers and Transactions

Table 5 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.

Furthermore, the value provided by the regulator does not account for planned outages during our sample period.

Imports play a considerable 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.

Table 5: Day-Ahead Market Offers, Bids, and Transactions

| | GWh | Share | $N$ |
|---|---|---|---|
| *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, and average transactions per market instance (hour of a day) in our sample. Aggregate number of observations ($N$).

## B.4 Transmission Network

Figure 10 shows the transmission network structure in 2007 relevant for the day-ahead market clearing. It is a radial representation where nodes are aggregated to zones. The zones can be subdivided into domestic zones, limited production zones and foreign zones.[40] Do-

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

mestic zones contain generation as well as load while limited production 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 players can make sale offers or purchase bids for electricity in the foreign virtual zones.

[Figure 10 about here.]

### B.5 Zonal Prices

Figure 11 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 zone (N) and (ii) the uniform purchase price (UPP) does a good job in absorbing the high prices frequently observed in all the zones south of the North zone.

[Figure 11 about here.]

### B.6 Prevalence of Congestion

Table 6 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 zones except North (CN, CS, S, CA) is higher than in the North zone (N). Conditional on observing a higher price in all other zones except the North zone, the price difference is relative to other zones is about 35 EUR/MWh.

## C Market Clearing

The market operator's objective function is to maximize the sum of as offered and as bid consumer and producer surplus accounting for transmission grid constraints.[41] Market par-

[41]As offered and as bid means that supply offer curves are treated as marginal cost curves and demand bids are treated as true demands in optimization problem.

Table 6: 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 | |

ticipants submit an offer curve and/or a demand curve, respectively. Given an aggregate supply function $\boldsymbol{\theta}_o = (\mathbf{b}_o, \mathbf{g}_o)$ and an aggregate demand function $\boldsymbol{\theta}_b = (\mathbf{b}_b, \mathbf{g}_b)$, the market operator solves the following linear program

$$\begin{aligned}
\underset{\mathbf{x}_b, \mathbf{x}_o}{\text{maximize}} \quad & \mathbf{b}_b^\top \mathbf{x}_b - \mathbf{b}_o^\top \mathbf{x}_o && \text{(11a)} \\
\text{subject to} \quad & \mathbf{1}^\top \mathbf{x}_b = \mathbf{1}^\top \mathbf{x}_o && \text{(11b)} \\
& \sum_{z=1}^{Z} A_{kl}^z \left( \mathbf{1}^\top \mathbf{x}_o^z - \mathbf{1}^\top \mathbf{x}_b^z \right) \leq f_{kl}, \ (k,l) \in \mathcal{E} && \text{(11c)} \\
& \mathbf{x}_k \leq \mathbf{g}_k, \ k \in \{b, o\} && \text{(11d)} \\
& \mathbf{x}_k \in \mathbb{R}_0^+, \ k \in \{b, o\}\,. && \text{(11e)}
\end{aligned}$$

The values of $\mathbf{x}$ that maximize (11a) have to be balanced, i.e., demand equals supply (Equation 11b). Furthermore, these quantities must satisfy the network feasibility constraints, that is, the resulting power flows should not exceed the thermal limits $f_{kl}$ of the transmission lines. The matrix $A$ in Equation 11c gives the contribution of a net injection in zone $z$ to transmission line $(k,l) \in \mathcal{E}$, where the $\mathcal{E}$ contains all transmission lines of the system. Market-clearing quantities $\mathbf{x}$ must be non-negative and less than or equal to their offered quantity levels ($\mathbf{g}$). Let $\lambda$ be the dual multiplier of the balance constraint (11b) and $\mu_{ij}$ the duals of the transmission constraints in (11c). The optimal zonal prices are given as

$$P^z = \lambda - \sum_{(k,l)\in\mathcal{E}} A^z_{kl}\mu_{kl}, \quad z = 1, 2, \dots, Z. \tag{12}$$

If all of the constraints in (11c) are not binding, their multipliers $(\mu_{kl}, (k,l) \in \mathcal{E})$ would be zero and hence the market clearing price is the same in each zone.

## C.1 Uniform Purchase Price

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

$$\overline{P} \sum_{r\in B_R} x_r = \sum_{z=1}^{Z} \sum_{r\in B_r(z)} P^z x_r, \tag{13}$$

where $B_R$ is the subsets of demand bids containing only regular demand bids. Regular demand bids originate from a domestic zone and are not from a pumped-hydro storage unit. Equation (13) can be interpreted as money conservation law. On the ride hand side of (13) we could also sum over all offers. However, incorporating (13) into Problem 11 renders the problem non-linear. There are three possibilities for computing a UPP: (i) Search for an optimal solution that fulfills (13) by solving the problem for different UPP candidates,[42] (ii)

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

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 UPP as the demand quantity weighted zonal price. In this paper, we went for the last option because of its simplicity and high accuracy (see Section C.4).

## C.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.[43]

## C.3 Uniqueness

The offer data come with a merit order number which is used to prioritize amongst 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.[44]. 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

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

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

of receipt of bids and offers acts as a tie-breaker (first in, first out).

## C.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 7 shows the mean absolute deviation between the actual zonal prices and the replicated zonal prices in the domestic demand zones and the mean absolute deviation between the actual and replicated uniform purchase price (UPP).

Table 7: Mean Absolute Deviation between Actual and Replicated Prices

| Hour | Count | UPP | 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 | | | | | | | | |

## C.5 Simplifications to Reduce Model Complexity

We make two modifications of the original data and setting that greatly reduce the complexity of solving our best-response offer curve 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 11 and Table 6 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 5). 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 zones, (ii) the Center zones which covers all national zones on the mainland except the North zone plus Sardinia and the virtual trading zone with Greece, and (iii) Sicily. We refer to these bidding zones as North (N), Center (C), and Sicily (SI).

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 EUR/MWh as compared to the average actual uniform purchase price of 102.9 EUR/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 EUR/MWh.

# D Best-Response Offer Function Calculation

We adapted the best-response bidding problem for a generation company as described in Ruiz and Conejo (2009). The best-response offer problem for supplier $i$ is to find the value of $\boldsymbol{\theta}_i$, 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 (5). The expectation of this variable profit function is taken with respect to the distribution of residual demand hyper surfaces faced by firm $i$. Each possible residual demand hyper surface realization for a given value $\boldsymbol{\theta}_i$ 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 C.

The resulting prices and dispatch levels from the market-clearing optimization problem for each residual demand hyper-surface realization are substituted into (5) 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 $\boldsymbol{\theta}_i$ and averaging these realized variable profit values yields our expected profit for firm $i$ at $\boldsymbol{\theta}_i$. Finding the value of $\boldsymbol{\theta}_i$ that maximizes this function yields firm $i$'s expected profit-maximizing offer curves for all of its generation units.

In order to facilitate readability of the mathematical presentation of the solution to this problem we omit the fact that for each value of $\boldsymbol{\theta}_i$ the market-clearing problem must be solved for each residual demand hyper-surface realization in order to determine the zonal prices and generation unit-level dispatch quantities necessary to compute the realized variable profit of firm $i$ for that residual demand surface realization. For our choice of 20 residual demand surface realizations, this logic implies that we must solve 20 market-clearing problems each time we compute the expected profit function for firm $i$ for given value of $\boldsymbol{\theta}_i$. The solutions to these 20 market-clearing problems are formulated in terms of Karush-Kuhn-Tucker (KKT) conditions, which implies that the firm's expected profit offer curve problem is a mathematical program with equilibrium constraints (MPEC).

The market operator's necessary Karush-Kuhn-Tucker (KKT) conditions are[45]

[45]Note that we minimize the negative sum of consumer and producer surpluses instead of maximizing the sum of consumer and producer surpluses.

$$\mathbf{b}_i - W_i\mathbf{P} - \underline{\boldsymbol{\mu}}_i + \overline{\boldsymbol{\mu}}_i = \mathbf{0}, \tag{14a}$$

$$\mathbf{b}_{-i} - W_{-i}\mathbf{P} - \underline{\boldsymbol{\mu}}_{-i} + \overline{\boldsymbol{\mu}}_{-i} = \mathbf{0}, \tag{14b}$$

$$-\mathbf{b}_b + W_b\mathbf{P} - \underline{\boldsymbol{\mu}}_b + \overline{\boldsymbol{\mu}}_b = \mathbf{0}, \tag{14c}$$

$$\mathbf{1}^\top \mathbf{x}_b - \mathbf{1}^\top \mathbf{x}_{-i} - \mathbf{1}^\top \mathbf{x}_i = 0, \tag{14d}$$

$$0 \le \mathbf{x}_i \perp \underline{\boldsymbol{\mu}}_i \ge 0, \tag{14e}$$

$$0 \le \mathbf{g}_i - \mathbf{x}_i \perp \overline{\boldsymbol{\mu}}_i \ge 0, \tag{14f}$$

$$0 \le \mathbf{x}_{-i} \perp \underline{\boldsymbol{\mu}}_{-i} \ge 0, \tag{14g}$$

$$0 \le \mathbf{g}_{-i} - \mathbf{x}_{-i} \perp \overline{\boldsymbol{\mu}}_{-i} \ge 0, \tag{14h}$$

$$0 \le \mathbf{x}_b \perp \underline{\boldsymbol{\mu}}_b \ge 0, \tag{14i}$$

$$0 \le \mathbf{g}_b - \mathbf{x}_b \perp \overline{\boldsymbol{\mu}}_b \ge 0, \tag{14j}$$

$$0 \le f_{kl} - \sum_{z \in \mathcal{V}} A_{kl}^z \left(\mathbf{1}^\top \mathbf{x}_i^z + \mathbf{1}^\top \mathbf{x}_{-i}^z - \mathbf{1}^\top \mathbf{x}_b^z\right) \perp \mu_{kl} \ge 0,\ (k,l) \in \mathcal{E}, \tag{14k}$$

whereas the matrix $W$ maps bids to zones, $\mathbf{P}$ is the vector of zonal prices, and $\overline{\boldsymbol{\mu}}_{(\cdot)}$ and $\underline{\boldsymbol{\mu}}_{(\cdot)}$ are the dual variables of (11d) and (11e) respectively. Note further, that we split $\boldsymbol{\theta}_o = (\mathbf{b}_o, \mathbf{g}_o)$ into $\boldsymbol{\theta}_i = (\mathbf{b}_i, \mathbf{g}_i)$ and $\boldsymbol{\theta}_{-i} = (\mathbf{b}_{-i}, \mathbf{g}_{-i})$. The market operator's program is a strictly concave-maximization problem, so the KKT conditions are also sufficient.[46] Note that problem (14) 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 constraints.

In a second step we rewrite the firm's expected profit maximization problem and include the twenty KKT conditions as constraints, one for residual demand surface realization. Firm $i$'s expected profit function is the sample average of 20 variable profit function values associated with the 20 residual demand surface realizations.

[46]Note that we have implemented all mathematical programs accounting for uniqueness as described in Sections C.2 and C.3. We decided to omit these additional constants in the notation to make it easier to follow.

# E Additional Figures and Tables

Table 8: Simulated Market Outcomes under Quantity Competition (Maximized Expected Consumer Surplus)

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | Baseline | Divestment in the Center | | | Divestment in the North | | |
| | $J(\{\mathbf{0}, \mathbf{Q}_i^*\})$ | $J(\{\mathbf{0}, \mathbf{Q}_i^*\})$ | $\Delta$ | $\Delta(\%)$ | $J(\{\mathbf{0}, \mathbf{Q}_i^*\})$ | $\Delta$ | $\Delta(\%)$ |
| *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% |
| $Q^C$(Strategic Firms) | 4,884 | 3,929 | −955 | −19.5% | 4,832 | −52 | −1.1% |
| $Q^N$(Strategic Firms) | 7,225 | 7,163 | −62 | −0.9% | 6,401 | −823 | −11.4% |
| $Q^{SI}$(Strategic Firms) | 1,192 | 1,161 | −31 | −2.6% | 1,154 | −39 | −3.2% |
| *Total* | 13,301 | 12,253 | −1,048 | −7.9% | 12,388 | −914 | −6.9% |
| Profit(Strategic Firms)[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% |
| $Q^C$(Strategic Firms) | 4,884 | 3,280 | −1,605 | −32.9% | 4,782 | −102 | −2.1% |
| $Q^N$(Strategic Firms) | 7,225 | 7,143 | −82 | −1.1% | 5,723 | −1,502 | −20.8% |
| $Q^{SI}$(Strategic Firms) | 1,192 | 1,136 | −56 | −4.7% | 1,131 | −61 | −5.1% |
| *Total* | 13,301 | 11,559 | −1,742 | −13.1% | 11,636 | −1,665 | −12.5% |
| Profit(Strategic Firms)[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. Prices in EUR/MWh, costs and profits in k EUR, and quantities in MWh.

[1] Profits adjusted by $QC \cdot PC$ with $PC$ set to the average actual uniform purchase price (103 EUR/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 run marginal costs.

Table 9: Simulated Market Outcomes under Quantity Competition with Higher Smoothing Parameter Value

| | Baseline $J(\{\mathbf{0}, \mathbf{Q}_i^*\})$ |
|---|---|
| $\overline{P}$ | 94.9 |
| $P^C$ | 102.4 |
| $P^N$ | 84.0 |
| $P^{SI}$ | 151.5 |
| $Q^C$(Strategic Firms) | $4,911$ |
| $Q^N$(Strategic Firms) | $7,282$ |
| $Q^{SI}$(Strategic Firms) | $1,188$ |
| *$Q$(Strategic Firms)* | $13,381$ |
| Profit(Strategic Firms)[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. Prices in EUR/MWh, costs and profits in k EUR, and quantities in MWh.

[1] Profits adjusted by $QC \cdot PC$ with $PC$ set to the average actual uniform purchase price (103 EUR/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 run marginal costs.

Table 10: Average Own- and Cross-Price Inverse Semi-Elasticites 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 11: Average Own- and Cross-Price Inverse Semi-Elasticites 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 12: Paired Sample Test of Mean Own- and Cross-Inverse Semi-Elasticites of Residual Demand Hyper-Surfaces

| | (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 | |

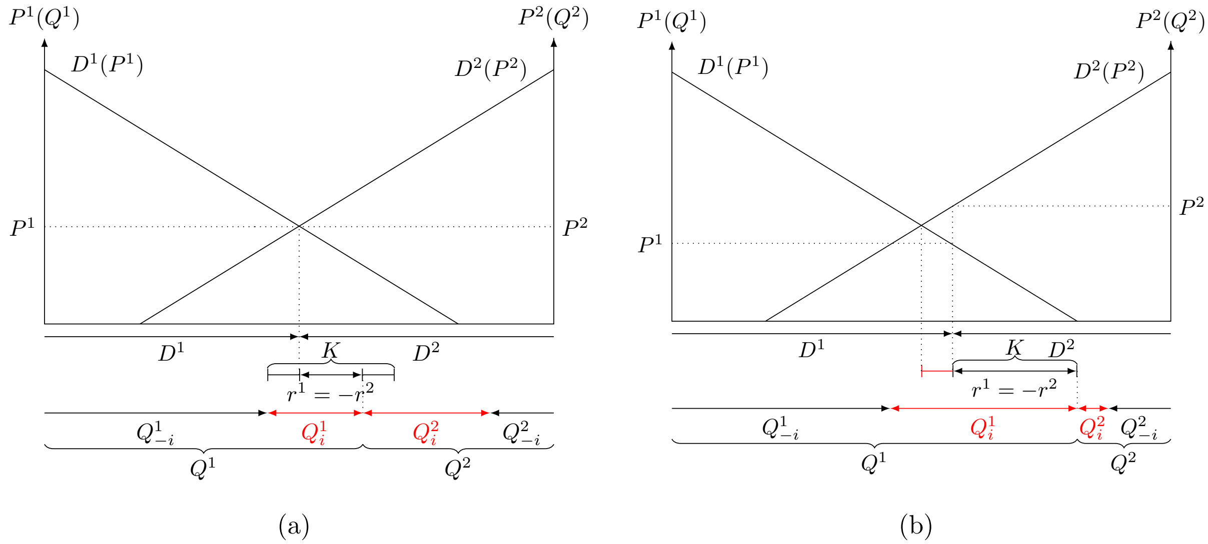
*Notes:* Two-sided Welch $t$-test assuming unequal standard deviations.

Table 13: Paired Sample Test of Mean Own- and Cross-Price Inverse Semi-Elasticites of Smoothed Residual Demand Hyper-Surfaces

| | (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 | |

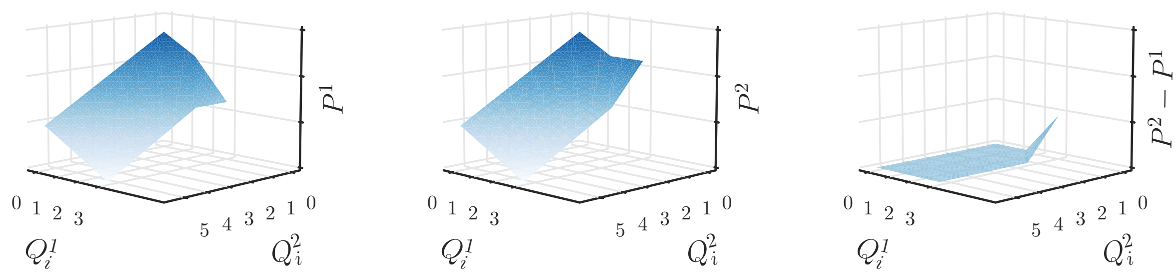
*Notes:* Two-sided Welch $t$-test assuming unequal standard deviations.

Figure 1: Market-Clearing in Transportation Capacity Constrained Symmetric Markets




Panel (a): Uncongested market, Panel (b): Congested markets.

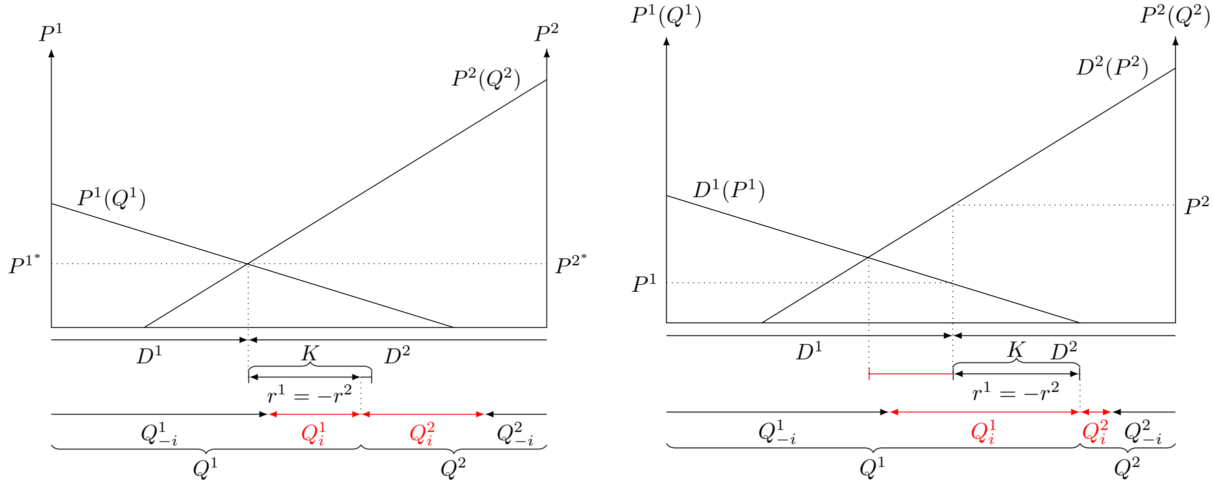
Figure 2: Inverse Residual Demand Surfaces in Symmetric Markets




(a) (b) (c)

Panel (a): Market 1, Panel (b): Market 2, and Panel (c): Price difference between Market 2 and Market 1.

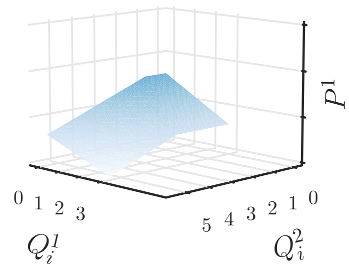
Figure 3: Market Outcomes in Transport-Capacity-Constrained Asymmetric Markets



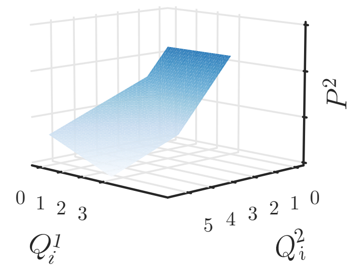

(a) (b)

Panel (a): Uncongested market, Panel (b): Congested markets.

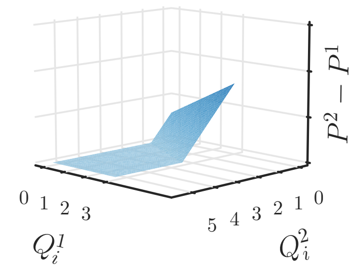
Figure 4: Inverse Residual Demand Surfaces in Asymmetric Markets




(a)



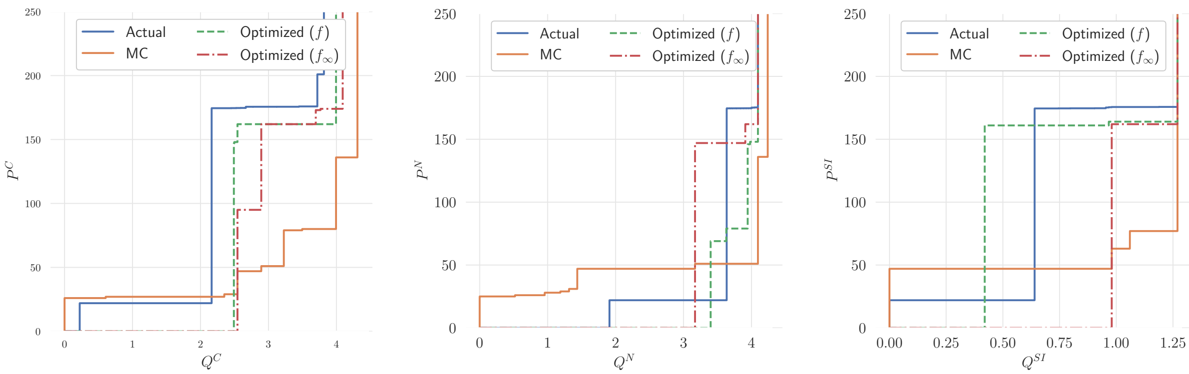

(b)




(c)

Panel (a): Market 1, Panel (b): Market 2, and Panel (c): Price difference between Market 2 and Market 1.

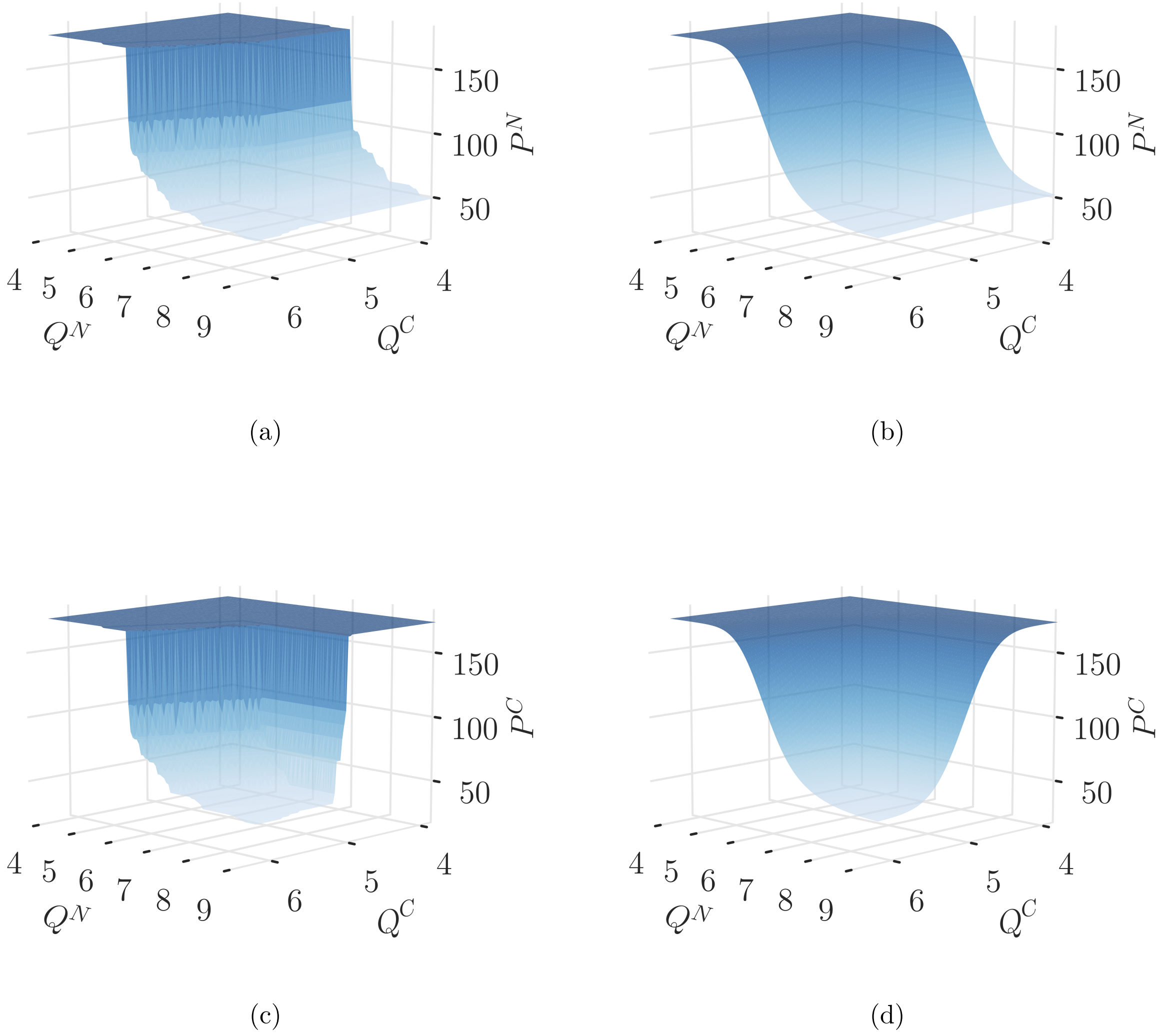
Figure 5: Incumbent's Optimal Zonal Offer Curves




(a) (b) (c)

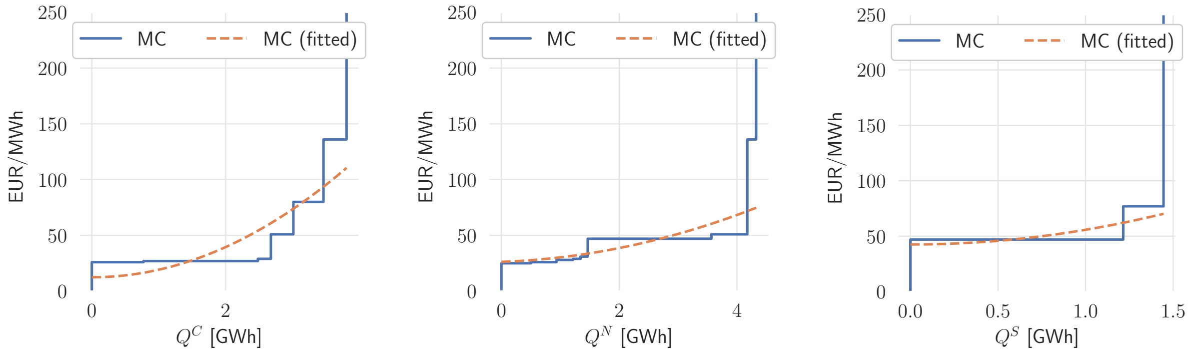
*Notes*: September 5, Hour 12. Panel (a): North; Panel (b): Center, Panel (c): Sicily. Only relevant thermal units. Quantities are in GWh and prices in EUR/MWh.

Figure 6: Actual versus Smoothed Residual Demand Surfaces (North/Center)




*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 zone. Supply in Sicily fixed to its actual level. Quantities are in GWh and prices in EUR/MWh.

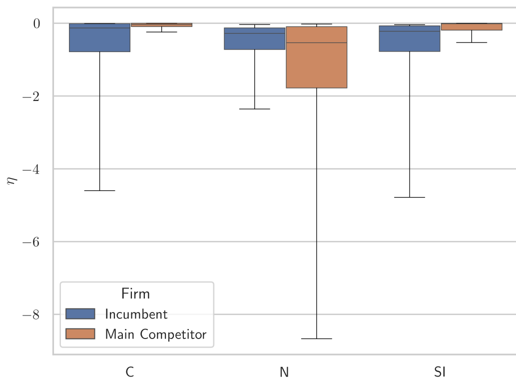
Figure 7: Zonal Marginal Cost Functions



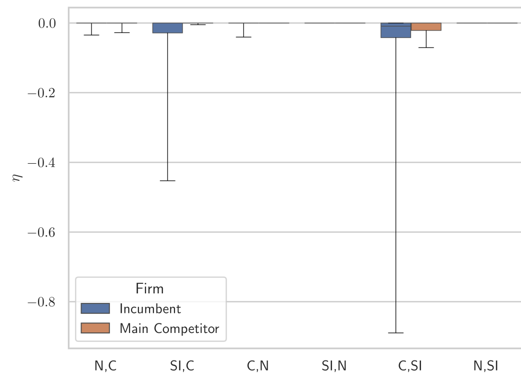

(a) (b) (c)

*Notes*: Incumbent's piece-wise constant 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 EUR/MWh.

Figure 8: Own- and Cross-Price Inverse Semi-Elasticites of Step-Function Residual Demand-Hyper Surfaces



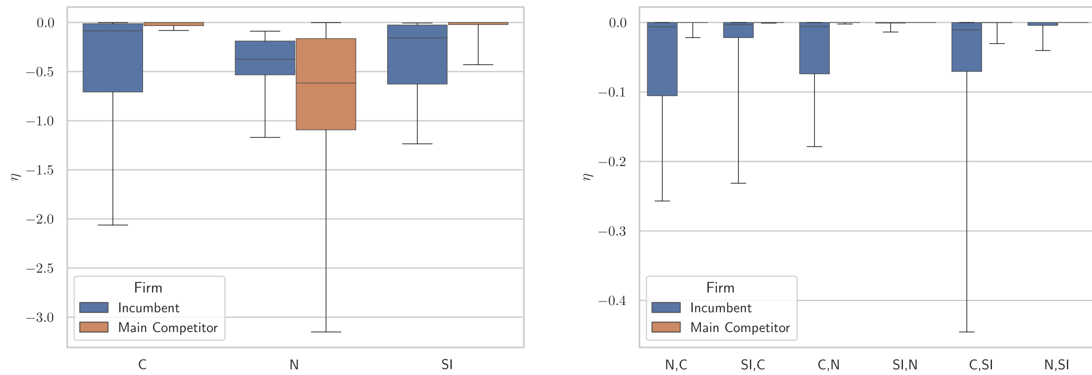

(a)




(b)

Panel (a): Inverse Semi-Elasticites, Panel (b): (Cross)-Inverse Semi-Elasticites. Whiskers represent the 10th percentile and the 90th percentile of the data. Outliers excluded.

Figure 9: Own- and Cross-Price Inverse Semi-Elasticites of Smoothed Residual Demand Hyper-Surfaces




(a) (b)

Panel (a): Inverse Semi-Elasticites, Panel (b): (Cross)-Inverse Semi-Elasticites. Whiskers represent the 10th percentile and the 90th percentile of the data. Outliers excluded.

Figure 10: Bidding Zone Configuration relevant for Day-Ahead Market Clearing in 2007

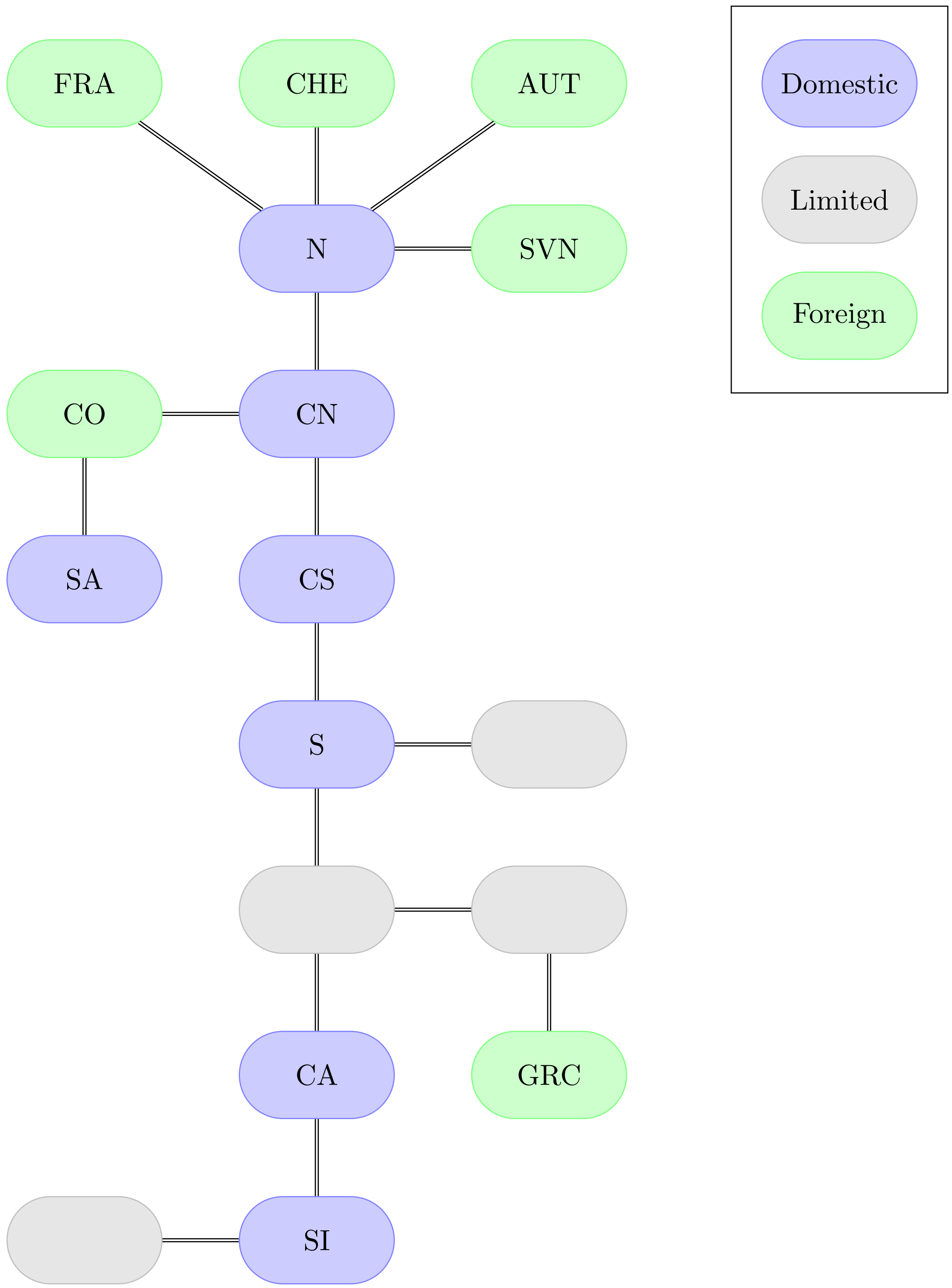


Figure 11: Zonal Day-Ahead Market Price Distributions