Market Performance Assessment in Locational Markets with Non-Convexities

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Abstract

We extend the competitive benchmark pricing model of Borenstein et al. (2002) to locational-pricing markets. We further extend this model to account for transmission network security constraints as well as technical constraints on thermal power plants such as e.g., start-up costs and minimum stable production levels that introduce non-convexities in their operating cost functions. We apply both models to assess the performance of the Italian wholesale electricity market for the year 2018. Hourly competitive benchmark locational prices that ignore the impact of non-convexities in generation unit operation fail to provide credible estimates for the intra-day benchmark price profile. Augmenting the model to account for transmission network security constraints and non-convexities resolves this issue. We find that the average day-ahead market-clearing prices throughout the day are close to average competitive benchmark prices throughout the day during 2018. However, accounting for the cost of the re-dispatch market that makes final schedules from the day-ahead financial market physically feasible, raises the average hourly cost of serving demand. Our preferred competitive benchmark pricing model implies annual market inefficiencies in the range of 1 to 1.8 billion Euros in the actual annual cost of serving load in 2018 in Italy.

Keywords: Nodal electricity markets, Security constrained unit commitment, Redispatch market market power

JEL Codes: C61, D47, L13, L22, L94

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1 Introduction

Ambitious targets to increase the supply from renewable energy sources (RES) to comply with emission reduction goals are impacting the operation of electricity markets around the world. The nature of most of the currently available RES is that they have variable cost close to zero and they are intermittent. As a direct consequence of that, fossil-fuel generating units will be displaced *if* RES are available. This leads to lower capacity factors of fossil-fuel generating units but also to a higher ramping demand as well as more start-ups.[1] At the system-level the intermittency of RES but also the seasonal and hourly production profile of e.g., solar power, may increases the demand for reserves to ensure that a sufficient number of fossil-fuel generating units stays online to flexibly balance any change in the real-time net-demand, i.e., the demand net of RES supply. An increase in the reserve requirement also means that more fossil-fuel generating units must be operated in part-load in order to have some slack to react to changes in real time net-demand. On top of that transmission (security) constraints may become binding as the spatial and temporal net-demand profiles require a certain amount of output from controllable fossil-fuel generating units at specific locations.

The standard competitive benchmark model to assess the performance of an electricity market as described in Borenstein et al. (2002) does not account for transmission network constraints or operational constraints of fossil-fuel generating units. In a low RES world these constraints may be of second order and neglecting them to get a simpler representation of the model is reasonable. However, more recently Wolak (2007); Mansur (2008); Reguant (2014); Jha and Leslie (2020a) have shown the importance of accounting for start-up and ramping costs of thermal power plants when estimating market power. Jha and Leslie (2020a) argue that especially in a high RES world, dynamic cost may be important to consider when estimating market power. Sioshansi et al. (2010) provide a non-convex competitive benchmark

[1]Schill et al. (2017) estimate that the overall number of start-ups would grow by 81% (costs by 119%) for Germany between 2013 and 2030 as the share of variable renewables is expected to grow from 14% to 34% if no investment in more flexible technologies including storage was made.

for the New England market with the limitation that transmission network constraints are ignored and so is the demand for reserves and other system services. More recently, Jha and Leslie (2020b) derive a competitive benchmark focusing on start-up cost recovery for Western Australia. Their work does not account for transmission network constraints nor other relevant system constraints such as e.g., a demand for reserves or other system security constraints[2] that may become more relevant as the capacity of RES increases.

In this paper, we include transmission network constraints and operational constraints of fossil-fuel generating units such as start-up costs or minimum output levels to provide market performance measurement tools for markets with non-convexitites. In a first step, we add only zonal transmission constraints to the model. This model can be used also in more general settings for any kind of locational market.[3] In a second step, we tailor the locational benchmark model to a specific power system by adding system security constraints as well as a set of constraints that describe the technically feasible output profile of fossil-fuel generating units. This yields a security constrained unit commitment model, dispatch and pricing model.

We apply the benchmark models to assess the performance of the Italian Electricity market for the year 2018. Unlike in the United States, the electricity markets in Europe and many other regions around the globe rely on sequential markets where the day-ahead market and the real-time re-dispatch market are operated based on different market-clearing engines. While in the day-ahead market, system constraints as well as technical constraints of generating units are mainly ignored, they will only be accounted for in the real-time re-dispatch market. However, given that market participants are able to predict to a certain extend whether there will be a demand for their units in real-time these markets cannot be assessed independently from each other. In a companion paper (see Graf et al., 2021b), we show that these strategies known as "INC/DEC" game are persistent in the Italian electricity

[2]We refer to e.g., Buchsbaum et al. (2021) on the importance of these constraints.

[3]We focus on bid-based markets in this paper, however, as shown in Graf and Wolak (2020) these are conceptually equal to markets with quantity competition and elastic demand.

market. Consequently, the competitive benchmark should be compared to the total cost to serve load that also includes the cost of the real-time re-dispatch because consumers must also pay these costs. Accounting for these, our preferred competitive benchmark pricing model finds annual savings relative to the actual cost to serve load of 1.8 billion Euros.

Our market performance assessment reveals important distributional aspects of the current market design. The real-time re-dispatch market is open only to a subset of eligible units that meet specific technical qualification requirements. Furthermore, different from the uniform-pricing day-ahead market, the re-dispatch market pays as bid or offered. Eligible units that provide incremental energy are paid their offer price and those that provide decremental energy are paid as bid. Market participants with non-controllable supply capacity are excluded from the real-time re-dispatch club. This effectively excludes all (intermittent) renewable resources from the re-dispatch market.

As shown in Graf et al. (2021b), this market design provides strong incentive for suppliers with units that are eligible to participate in the re-dispatch market to schedule their capacity in the day-ahead market to maximize the profits earned from the real-time re-dispatch process. Moreover, it may even be optimal for some suppliers to depress the day-ahead price to achieve this, which reduces the revenues earned by non-controllable resources. From the perspective of electricity consumers, we find that the re-dispatch cost outweighs the savings from the lower day-ahead market cost. This means that the energy part of a customer's bill may be even slightly lower than in the competitive benchmark outcome, but the large transmission operation fee that includes re-dispatch costs will outweigh the lower energy part. [4]

Besides the increased opportunities for certain dispatchable resources to earn additional profits from the re-dispatch market, this market design has both short-term and long-term market efficiency consequences. In the short-term, the spatial and temporal price signals will be watered down as the transmission operation fee is usually averaged over time and

[4]These costs can even become higher as we scale the amount of renewables as shown in Graf et al. (2021a).

space and distributed across final consumer depending on the quantity of electricity they have consumed. In the long-term these watered-down price signals will lead to inefficient location decisions for both intermittent and dispatchable generation units. These issues are discussed in Section 7.

The remainder of the paper proceeds as follows. Section 2 reviews implications of non-convexities on efficient pricing that will be used to construct competitive benchmark prices in such an environment. Section 3 describes the important details of the Italian electricity market necessary to construct our competitive benchmark outcomes. Section 4 how to measure market performance in wholesale electricity markets. Section 5 describes our competitive benchmark models. Section 6 presents the results of our convex competitive benchmark with transmission constraints as well as the non-convex competitive benchmark with transmission and other generation unit operating constraints. Section 7 compares the actual cost to serve load with the competitive benchmark cost to serve load. Furthermore, rent division and distributional effects are discussed. In Section 8, we provide several checks of the robustness of our competitive benchmark results to several of our modeling assumptions. Finally, in Section 9, we conclude the paper and discuss the implications of our results for the design of wholesale electricity markets.

2 Implications of Non-convexities

In this Section, we link the existing literature on efficient pricing in convex and non-convex markets to how to derive competitive benchmarks in both settings.

In a convex market environment, the system operator would dispatch generation according to the merit-order, that is, to start with the unit that has offered the cheapest as-offered cost and to gradually include units with higher as-offered cost until net demand is met. If transmission constraints were binding, the locational net demand may be lower or higher depending on whether the node is exporting or importing. Importantly, the problem is static, i.e., it can be sliced in time as subsequent time periods are not connected to each other. Constructing a competitive benchmark for such an environment as in Borenstein et al. (2002) requires to construct a merit-order stack, sorting units from the cheapest to the most expensive one. The intersection of the merit order with the net-demand determines the marginal production unit that will define the competitive benchmark price. In practice, the merit order is weakly increasing piece-wise constant function with each segment describing a unit's variable cost and capacity. One way to find the intersection of such a function with net demand is to solve a constrained linear program that minimizes the cost of serving demand or, equivalently, maximizes the net welfare assuming that the inelastic net demand is valued at the price-cap or the value of lost-load. The dual variable on the energy balance equation, i.e., the equation that requires supply to be equal net-demand, will then be the competitive benchmark price. The advantage of this more complicated way of formulating the problem to find the marginal production unit and therefore also the competitive benchmark price is that network constraints can easily be included in the optimization problem as described in Appendix B.1. Solving the optimization problem including a network model would return convex locational competitive benchmark prices in line with the the locational marginal pricing model derived in Bohn et al. (1984). In case transmission capacity between locations were infinity, the resulting benchmark prices would be equivalent to the prices derived from the competitive benchmark model laid out in Borenstein et al. (2002).

Some dynamic operational constraints that are important in electricity markets, as for example, a constraint on the change in output between two consecutive periods of a particular unit can easily be included in the convex benchmark model. However, other operational constraints such as fixed start-up or no-load costs, economics of scale and inflexibilities such as minimum generation or block loading requirements will create non-convexities (Chao, 2019). These constraints require an additional set of variables that define whether a unit is on-line (committed) or not. Accounting also for system constraints such an optimization problem is called security-constrained unit commitment (SCUC) model that solves for the optimal commitment and dispatch. Unfortunately, this optimization problem is non-convex because of the binary variables introduced to model the commitment decisions. This has implication on pricing because the primal problem and the dual problem is not necessarily equal if the problem is non-convex. This fact complicates pricing in such markets and as pointed out in Wilson (1993), non-linear pricing will be an integral part of efficient pricing mechanism in non-convex markets (Chao, 2019). In electricity markets across the United States, these non-linear prices typically consists of a market-clearing price that is complemented with side-payments[5], that are paid to some generating units to ensure them to recover their as-offered cost at the given market-clearing price. One attempt to attack this problem is to convexify the optimization problem and use the dual variables to derive prices of the convexified market-clearing. Most prominent example is convex hull pricing (see, e.g., Gribik et al., 2007; Hua and Baldick, 2017; Chao, 2019; Azizan et al., 2020, for more details on that approach) that determines electricity prices that minimizes the total side-payments. A different approach to address the problem of pricing in non-convex markets relies on the notion of "quasi-equilibria" based on the works by Starr (1969) and Arrow and Hahn (1971). Chao (2019) demonstrates how this approach can be applied to non-convex electricity markets. The approach involves to relax the integer constraints on commitment variables in a sense that they stay within the continuous interval between zero and one. Under certain conditions this approach yields good approximations to the more computationally expensive convex-hull pricing.

The most prominent method to derive clearing-prices in non-convex markets is to first solve the commitment problem and then resolve the problem fixing the integer variables to their optimal levels. O'Neill et al. (2005) shows that the resulting prices, i.e., the dual variables of the energy balance constraint together with side-payments retrieved from the dual variables on the constraints that fix the integer variables to their optimal level form an equilibrium. Unfortunately, these side-payments can also be negative, that means units

[5] In the California market these side-payments are called "make-whole" payments, another expression is uplift payments.

would have to pay to the system operator for starting up their unit. In practice, power markets ignore these payments and derive side-payments on whether a unit is able to break even under the clearing-prices. In case a unit does not, the difference is paid as side-payments to the unit. We calculate clearing-prices and side-payments using this approach.

Relating the market-clearing in non-convex markets to the competitive benchmark requires the following information at the unit level: (i) variable cost of production estimates and (ii) estimates on operational data, such as minimum stable production minimum, ramp-rates, minimum up- and down-time.[6] Given these estimates and an exogenously defined optimization horizon, running the non-convex market-clearing described in Appendix C for an exogenous set of consecutive spatial net-demands will result in efficient clearing-prices as well as side-payments. These prices and side-payments would be the outcome of an US-style advanced market-clearing if generators were to truthfully offer their offer parameters.

Our locational non-convex benchmark prices may be a useful metric for central dispatch markets that are in place throughout the United States but also for decentralized markets followed by a re-dispatch market necessary to ensure a secure grid operation. This market design is currently in place throughout Europe and in most other regions across the world except the United States.

3 The Italian Electricity Market

The two primary institutions responsible for operating the electricity supply industry in Italy are Terna—the transmission system operator (TSO) and Gestore Mercati Energetici (GME)—the Italian Power Exchange (PX). The PX—part of the joint European day-ahead market—manages the day-ahead market and a series of intra-day markets that allow market participants to adjust their financial positions after the close of the day-ahead market. Firms submit demand and supply bids, then the European day-ahead market is cleared by solving

[6]In bid-based markets that allows complex bids, all of these parameters may be subject to strategic misreporting (see, e.g., Oren and Ross, 2005, for an example of how a bidders can increase its profits by submitting overly restrictive ramping constraints to increase their profits).

a welfare maximization problem that explicitly accounts for zonal transmission constraints. Given the resulting European day-ahead energy schedules, the PX communicates clearing-quantities as well as zonal clearing prices that are relevant for the domestic supply side of the Italian market and a single uniform purchase price that is relevant for the domestic demand side of the market. The uniform purchase price is effectively the demand-weighted average zonal price.[7] Firms bid into the day-ahead market offers to supply or consume energy the following day for any or all 24 hours. Depending on the intra-day market session, the bidding horizon shortens. For example, in the last intra-day market session, only the positions in the last 4 hours of the same day can be changed. Bilateral deals between buyers and sellers are allowed and firms have the option to self-schedule their bilateral transactions in the day-ahead market (see, e.g., Graf and Wolak, 2020, for more details).

In parallel with the intra-day markets, firms that have eligible units in their portfolio must bid to increase or decrease their output in the TSO's real-time re-dispatch market.[8]

3.1 Market Structure

The Italian electricity generation market appears relatively unconcentrated. We focus on the ten largest market participants that own fossil-fuel generation capacity. "Fossil-fuel" includes generation units that burn natural gas, coal, or diesel fuel. We subdivide natural gas-fired plants into two categories, combined cycle gas turbines (CCGT) and open cycle gas turbines (OCGT). The former is the largest fossil-fuel generation technology in terms of installed capacity in the Italian market. The latter is a more flexible technology with higher variable operating cost but lower start-up cost that is designed to serve peak-demand or to

[7]To be precise, the uniform purchase price is endogenously determined. Calculating it ex-post using the cleared-demand, however, yields almost identical results as shown in Graf and Wolak (2020).

[8]More precisely, the TSO operates several real-time re-dispatch market-sessions aimed at procuring operating reserves, managing transmission congestion, and ensuring secure operation of the transmission network. As pointed out in Graf et al. (2021b), this market is fundamentally different because many more transmission network and generation unit operating constraints are respected. Although, all the constraints can effectively solved with capacity it is more complex as several attributes of the capacity are taken into account. Features such as the location of the generation capacity, the technical characteristics of the capacity—ramp rate, minimum up-time and down-time—the as-offered cost to increase and decrease output and the as-offered cost of changing the configuration or starting up a unit.

balance the system. Table 1 shows the capacity in gigawatts (GW) by fuel type in 2018 owned by each of the ten firms and the competitive "fringe" of the remaining smaller firms in the market. We also report the storage capacity of large pumped-storage hydroelectric units, as well as all the capacity of other generation technologies, labeled as "Rest." The latter includes capacity from small hydro units, intermittent renewable energy sources (RES) such as wind and solar, geothermal units as well as some very small fossil-fuel generating units. We refer to this capacity category therefore also as uncontrollable supply.

Two points are noteworthy. First, Enel, the former state-owned monopoly owns most of the capacity. However, it is effectively a net-buyer of electricity because it has also a large retail consumer base. Second, while the fossil-fuel generation capacity as well as the storage units are generally controllable, this is the case only to a minor extent for the remaining capacity. On top of that, there is considerable variability in the availability of this type of capacity. In Figure 1 Panel (a), we show the hourly real-time demand for 2018, and Panel (b) gives the daily box plots for 2018 for each hour of the day.

We focus on measuring wholesale market performance and therefore we set the demand to be met in each hour in the competitive benchmark model equal to the actual real-time demand. In Figure 2, we show the average hourly demands (Panel a) for 2018. Italy is a net-importer in effectively all hours of the year and the net-imports can make up to a third of the demand in some instances. Panel (a) also shows the average hourly demands for 2018, net of imports, and net of the production from uncontrollable units. Different to other markets with significant amount of intermittent renewables such as California, the *average* residual demand shape shows only mild "duck-curve" properties. There is, however, a considerable ramp-rate to be served in the morning hours and in some days there is also a very steep ramp-rate to be served in the early evening hours when the sun sets. In particular, during the spring and summer weekend days and holidays this property is more evident.

The residual demand is a useful concept because it gives the demand that is left to be served by controllable units that are likely to set the price. Panel (b) of Figure 2 reveals that there is considerable variability in the residual demand across days for each hour of the day, particularly during the daylight hours. These figures imply that the annual capacity factors of fossil-fuel generating units are quite low. The installed capacity of fossil-fuel generation is above 40 GW but the maximum residual demand to be covered by these power plants peaks at a little above 20 GW. Of course not all of the installed thermal capacity is available all the time (the maximum available capacity in 2018 was 40.6 GW and the minimum was 28.4 GW) due to planned and unplanned outages. Furthermore, as pointed out previously, neither the net-imports nor the non-controllable generation capacity are consistently reliable source of energy to serve the demand.[9]

Table 1: Operative Generation Capacity in Italy

Firm	CCGT	Coal	OCGT	Oil	Storage[1]	Rest[2]	Total
A2A	5.2	0.3		0.9		2.6	8.9
Axpo	1.7					0.5	2.2
Edf	4.7					1.8	6.5
Enel	4.3	6.2	0.9		5.3	5.4	22.2
Engie	1.2		0.3			0.3	1.8
Enipower	4.6					0.2	4.7
Ep	3.1	0.5	0.2			0.1	4.0
Set	0.4						0.4
Sorgenia	3.2						3.2
Tirreno	2.3					0.1	2.4
Fringe	4.1		0.1			16.5	20.8
Total	34.8	7.0	1.5	0.9	5.3	27.5	76.9

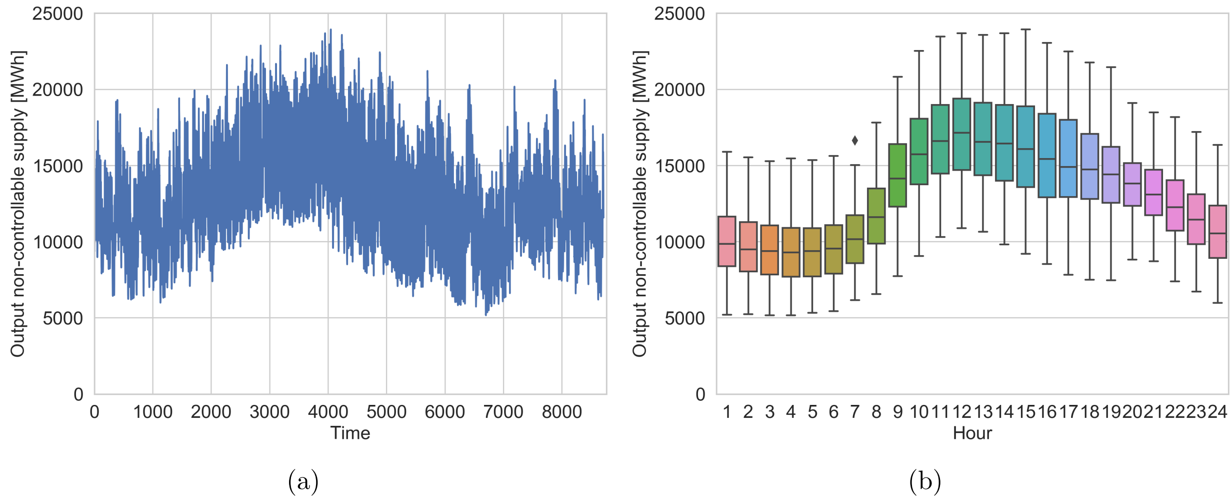
[1] Includes the eight largest pumped-storage hydroelectric units.

[2] Calculated as the yearly maximum of the aggregate hourly real-time production from units not included in any of the other categories listed in this table.

Notes: Capacity values expressed in GW and are valid for the year 2018. We only include capacity that is operative and exclude units that are cold-reserve status or "mothballed" status.

[9]Imports can be unexpected lower because of high demand or generation outages in neigboring countries and renewable energy production can disappear because the underlying resource—wind or sunshine—is unavailable. Furthermore, demand varies with temperature and in that sense 2018 can be seen as an "average" year with no extreme weather events occurred. In addition, the location of generation capacity does not fit with the distribution of demand, hence, transmission network constraints must be accounted for. Yet another reason, why we incorporate these constraints in our competitive benchmark simulations as discussed in Section4.6.

Figure 1: Output of Uncontrollable Supply



Notes: Hourly output of uncontrollable supply (Panel a) and hourly boxplots thereof (Panel b) for all hours in 2018. Boxes represent interquartile range and upper and lower vertical bars equal to the 1 percent and 99 percent.

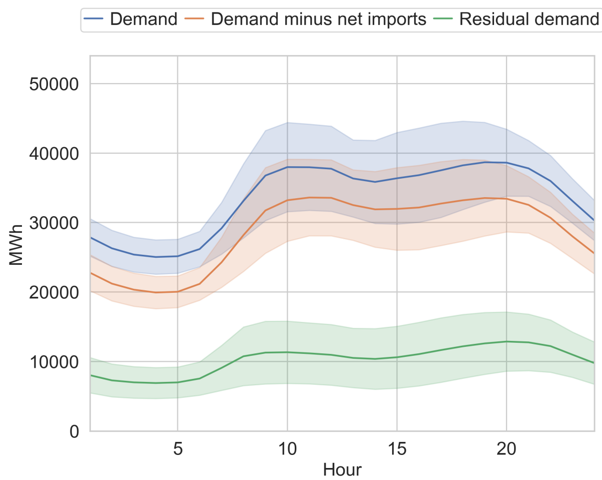
4 Measuring Market Performance in Italy

In a single-price market and assuming non-convexities of fossil-fuel generation unit operations away, the fundamental measure of market power is the margin between price and the marginal cost of the highest cost unit necessary to meet demand. However, because transmission networks have finite transfer capacities, electricity markets are locational. Thermal generation unit with start-up and minimum load costs, finite minimum up-times and down-times, and finite ramp rates give rise to non-convexities in their operating cost functions. In this paper, we provide two competitive benchmarks, one where these operating cost function non-convexities are accounted for and another one where they are not, but both benchmarks account for transmission constraints in the Italian market.

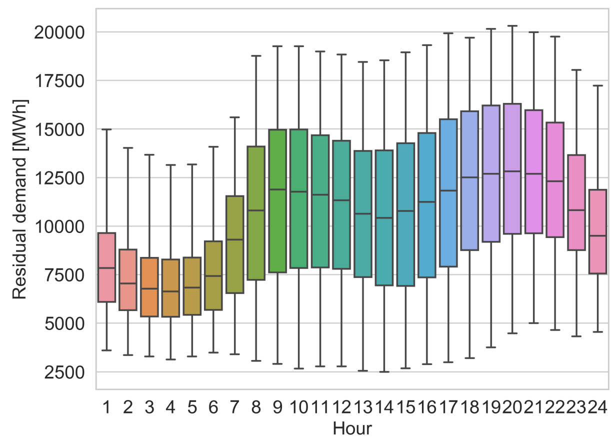
4.1 Market-Clearing Prices and Quantities

The Italian wholesale electricity market consists of several parallel and overlapping markets. The European day-ahead market is followed by a sequence of intra-day markets. The day-

Figure 2: Demand and Residual Demand



(a)



(b)

Notes: Panel (a): Hourly average demand and residual demand, bands around the the average values show the standard deviation; Panel (b): hourly boxplots of the residual demand. Boxes represent interquartile range and upper and lower vertical bars equal to the 1 percent and 99 percent. All hours in 2018.

ahead market as well as all intra-day markets are locational (zonal) marginal pricing markets. In parallel with the intra-day markets, several real-time re-dispatch market sessions are run, with the goal of transforming the schedules that result from the day-ahead market and intra-day markets into final schedules that allow secure grid operation at least cost. The mathematical program that is solved in the re-dispatch market is called a security constrained unit commitment (SCUC) problem.

The problem solved in the real-time re-dispatch market is not simply about matching aggregate supply and demand at every instance of time, but also ensuring that supply matches demand at every location in the transmission network at every instance in time. The TSO must also ensure that there is enough "slack" on the units' schedules to deal with contingencies, i.e., the failure or loss of grid elements, and demand and renewable energy production forecast-errors, what is more formally referred to as operating reserves. Furthermore, the power flows resulting from the final schedules must be compatible with a secure grid operation. That is, all the transmission line capacity limits must be respected and other grid security parameters such as voltage levels must be respected.

Unlike Borenstein et al. (2002), we are unable to rely on argument that suppliers and loads attempts to find the best market to sell or buy energy will produce similar market-clearing day-ahead and real-time prices. In our case, the day-ahead and intra-day markets set uniform prices for each zone, but the re-dispatch prices are pay as-bid or as-offered. Consequently, we add to the cost of purchasing energy from the day-ahead market in given hour the cost of the re-dispatch process to have more accurate estimate on the actual hourly price that is relevant for consumers. Our convex competitive benchmark price accounts for a zonal transmission network as it is currently the case in the Italian day-ahead market model. The non-convex competitive benchmark price accounts for a nodal network model as it is currently the case in the Italian real-time re-dispatch market.

As noted earlier, the day-ahead market price is the load-weighed average price that is paid by the demand side of the market. In the Italian market the prices paid for real-time re-dispatch to increase production are significantly larger than the day-ahead market prices and the prices paid to decrease production are significantly lower than the day-ahead market prices (see e.g., Graf et al., 2021b).

4.2 Marginal Cost of Fossil-Fuel Generation Units

To estimate the marginal cost of production for an efficient market, we divide production into three economic categories: pumped-hydro storage, must-take, and fossil-fuel generation. The optimal operation of storage unit is an intertemporal decision problem, which implies an opportunity cost of production. Must-take generation includes renewable energy supply (RES) such as wind and solar but also the generation from thermal units with an industrial load. Examples include combined heat and power (CHP) plants that are mostly producing steam used for industrial processes or district heating, and electricity is only a side-product. Hence, the electricity generation that occurs at a given level of industrial load can be treated as a must-take generation. We discuss below our treatment of storage units and must-take generation units.

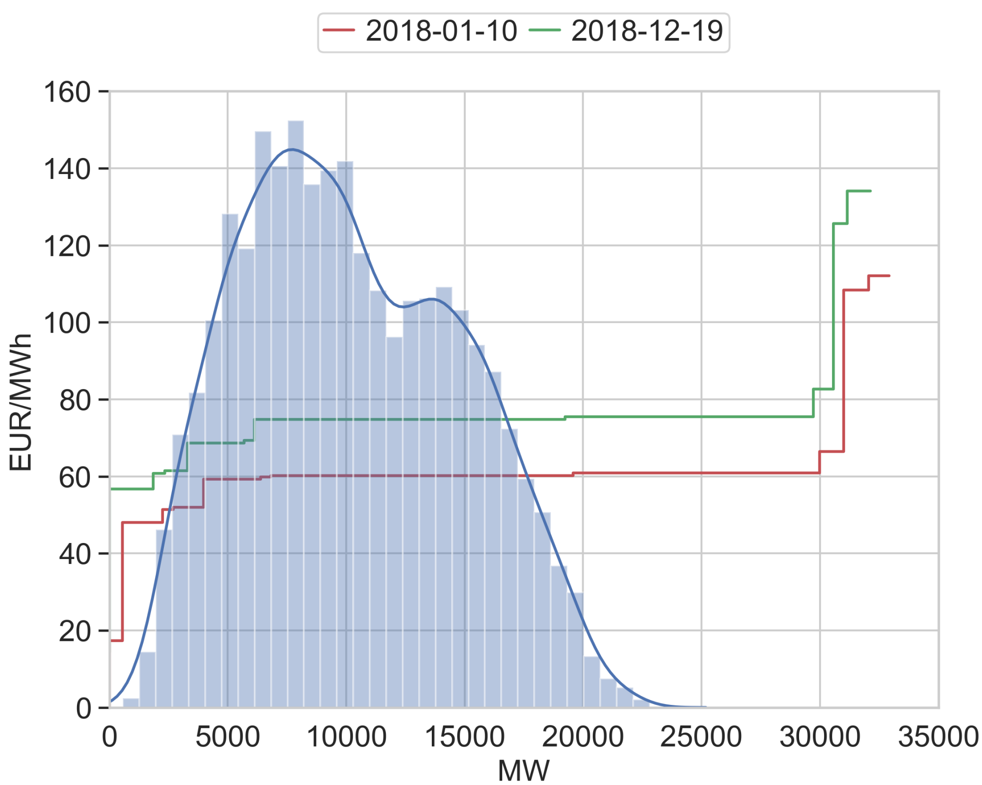
For fossil-fuel generation units, we estimate marginal cost in three components—(1) fuel costs, (2) CO_2 emission costs and (3) variable operating and maintenance (O&M) costs. We also add a variable environmental cost for the residuals from the combustion process—relevant for coal and oil power plants. These cost estimates are detailed in Section A.1. The fuel costs are the Euro per Gigajoule (GJ) cost of the input fossil fuel times the heat rate of the generation in GJ per MWh. The CO_2 emissions costs are the Euro per tonne cost of a CO_2 times the emissions rate of the generation unit in tonnes of CO_2 per MWh. Variable O&M costs are typically available by generation technology on a Euro per MWh basis.

The market rules require generation unit owners to declare the maximum available capacity qualified to participate in the real-time re-dispatch market each hour. These data are used for the real-time optimal power flow runs in the re-dispatch process. In addition, a well-structured and regulated outage planning process is in place in Italy, fulfilling also the relevant European standards in terms of transparency. Planned outages are public information well in advance of their occurrance and forced outages are made public as soon as possible after they are reported. In addition, planned outages must be approved by the transmission system operator (TSO), while average availability levels as well as structural and frequent unplanned outages are investigated by the TSO in the context of the outage planning and adequacy assessment processes, because they could threaten system security and adequacy.

In some electricity markets, it has been observed that generators may have an incentive to strategically schedule their outages (see, e.g., Wolak and Patrick, 2001, for the case of the UK), we consider this phenomenon significantly less relevant for the Italian wholesale electricity market for the following reasons. Participation in the day-ahead market as well as in the intraday markets is voluntary. Although participation in the real-time re-dispatch market is mandatory for eligible units, the absence of a formal market power mitigation process, and pay-as-bid pricing instead of cost-based pricing make any form of strategic outages sub-optimal because the unit owner could earn higher profits by submitting a high offer price to the day-ahead and re-dispatch markets. For these reasons, and different from Borenstein et al. (2002), we believe that the declared available capacity from thermal generation units is a reliable estimate of the actual available capacity from these units for the Italian power system.

Figure 3 illustrates the aggregate marginal cost curve for fossil-fuel generation plants located in Italy that are not considered to be must-take generation during hour 20 on January 10, 2018 and December 19, 2018. The aggregate marginal cost curve for fossil-fuel units increased between the beginning and the end of the year 2018 due to higher fuel and emission allowances costs.

Figure 3: Aggregate Marginal Cost Curves and Annual Residual Demand Distribution



Notes: The two aggregate marginal cost curves for the Italian fossil-fuel plants are both from hour 20 and outages are accounted for. The residual demand distribution contains all hourly values for the year 2018.

4.3 Non-Convexities of Fossil-Fuel Generating Units

As pointed out in Borenstein et al. (2002), sunk costs, such as capital costs, and periodic fixed capital and maintenance costs should not be included in any estimate of marginal cost. However, the impacts of various unit-commitment (UC) costs and constraints, such as the cost of starting up a plant, the maximum rates at which a plant's output can be ramped up and down, and the minimum time periods for which a plant can be on or off are clearly not sunk for a generating unit that is not operating. These constraints create non-convexities in the production cost functions of firms. Borenstein et al. (2002) ignores all of these constraints—a choice that may has been a reasonable simplification in the early days of electricity markets with no or very little in-feed from intermittent renewable energy sources. However, large amounts of intermittent renewable capacity that has not been complemented with load shifting technologies such as storage or demand side-management, or investments in a more flexible grid, makes these constraints increasingly important determinants of how thermal generation units operate because the residual demand may change quickly from hour to hour. Thermal units have to cope with these rapid changes in the net demand and this may require operating many more of these units a minimum load levels for more hours of the day. The change in operation of thermal units as a response to additional intermittent renewables may even lessen the expected reduction of emissions as shown in Graf and Marcantonini (2017) or Kaffine et al. (2020).

A convex market has the advantage that the dual variable on the demand constraint can be interpreted as the marginal price, that is the change in the objective function given a infinitesimal increase in the demand. If the aggregated offer curve were equal to the aggregate marginal cost curve than the resulting clearing-price can be interpreted as the competitive benchmark price. The reason why convex market-clearing problems are convenient is that the problem effectively can be sliced in time and hence no inter-temporal constraints such as start-ups, minimum load operation, minimum up-times and down-times, and ramping constraints, have to be dealt with. Accounting for non-convexities adds a dynamic component to the model. Consequently, in such problems the choice of the time horizon becomes an important parameter. We will discuss this issue further below.

All electricity markets in the United States solve a non-convex unit-commitment and dispatch problem each day to clear the day-ahead market. Because unit-commitment problems are mixed integer linear or mixed integer quadratic programs and therefore non-convex, duality theory does not hold. However, for any set of integer variables or unit commitment decisions, the problem is convex, and as such, duality theory is applicable and the resulting dual variables on the demand constraint can be interpreted as marginal prices. O'Neill et al. (2005) point out, though, that these prices are only efficient in combination with the duals of the constraints that fix the integer variables to their optimal level. It can happen, though, that these duals are negative for units that are dispatched. This would imply that units would have to pay for being switched on. In the United States, such negative payments are ignored and instead units that are dispatched but not able to cover their as offered cost over the day are compensated with so-called "make-whole" payments or side-payments.

In constructing our non-convex competitive benchmark price we therefore use the efficient prices that are the solution to the convex problem with fixed optimal integer variables in combination with side-payments as it is done in effectively all electricity markets in the United States. In other words, our non-convex competitive benchmark prices are the solution to a market-clearing that explicitly accounts for non-convexities and grid security constraints and where capacity is offered at the marginal cost and no mark-up is put on their start-up cost. The resulting locational marginal prices still represent the change in the objective function for any infinitesimal change in locational demand. We do not account for transmission losses and we also do not price voltage constraints or the fixed unit-commitment constraints. However, as it is handled in the United States, we also account for side-payment that would be necessary to make sure that operating units are able to break even over the day. We ignore payments that would be due for providing reserves.

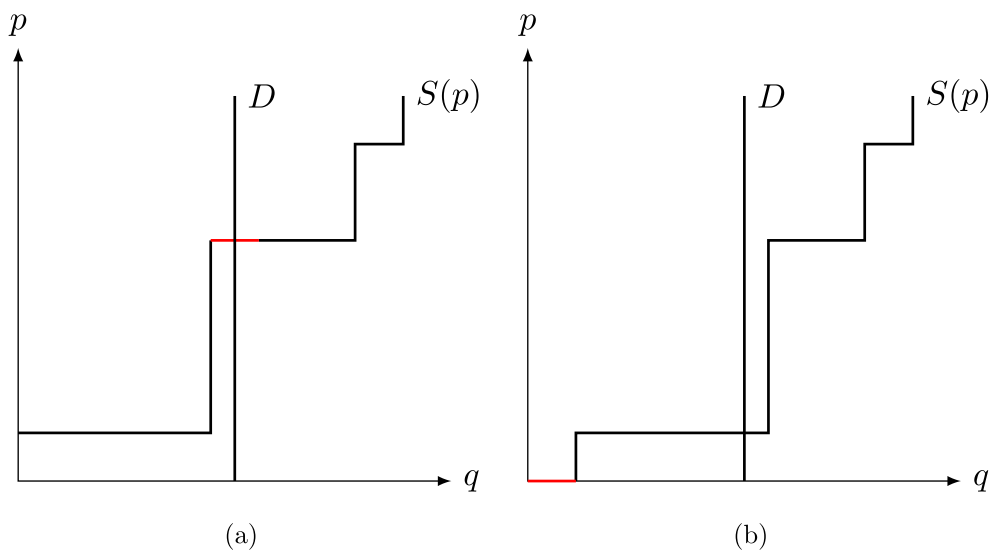
To provide intuition for how our competitive benchmark pricing process differs from that in Borenstein et al. (2002), consider a simple example of market-clearing and pricing in a non-convex market. Assume an optimization horizon of a day, a significant amount of close-to-zero marginal cost supply, such as a must-take hydro resource, an inflexible but controllable fossil-fuel based unit, and a flexible fossil fuel unit. The static merit order of a particular hour is depicted in Figure 4, Panel (a). Assume that the step on this merit order curve where the inelastic demand intersects belongs to the inflexible but controllable fossil-fuel unit, the step to the left is the hydro resource and the step to the right is the flexible controllable unit. In a world without non-convexities and network constraints, the inflexible controllable unit would be marginal and therefore set the price. However, the dispatch level for the inflexible unit is not feasible because the unit is not able to operate below its minimum stable production level that is depicted in the Figure in red.

In a model where non-convexities are included and it is optimal that this unit will be dispatched the unit will be committed at its stable minimum stable production level which effectively shifts the aggregated supply curve to the left as depicted in Panel (b) and sets an significantly lower market-clearing price for the convex sub-problem. There are many reasons why this unit might be committed such as a reserve requirement, voltage constraints, or ramping constraints. This simple stylized example shows that accounting for non-convexities can re-shuffle the merit order and therefore affect the market-clearing price. We provide a more detailed explanation of these dynamic effects as well as how we address the issue that a unit may be dispatched unable to recover its as-offered costs in Section C.2.

4.4 Uncertainty

Power systems require that supply and demand is balanced in every instance of time. While demand, and supply from intermittent renewables can change quickly from one instance of time to another, the TSO requires controllable power plants to be able to react to these changes. Operating reserve requirements ensure that controllable units have some slack left to suddenly increase or decrease their output. Especially, upward reserves are critical as it

Figure 4: Pricing with Non-Convexities



Notes: Panel (a): Convex market-clearing, Panel (b): Non-convex market-clearing ignoring any inter-temporal constraints.

requires inflexible fossil-fuel generating plants to be already running. The reason for this is that they need some lead time to reach their stable minimum production level. We explicitly model these constraints in the non-convex competitive benchmark.

From a conceptual perspective, including the upward reserve gives our non-convex competitive benchmark additional credibility as the resulting schedules are not only feasible for the actual level of demand but are also capable of accommodating a range of system demand and intermittent RES forecast changes.

Consequently, the resulting schedules, but also the resulting benchmark prices are robust with respect to different realizations of the demand and intermittent RES.

In the Italian market, the average hourly upward requirement for tertiary reserve—the most important reserve category in terms of quantity—to be delivered by thermal units was 3.2 GWh (standard deviation 0.6 GWh) in the year 2018.

4.5 Opportunity Cost of Pumped Hydro Storages

One important role of competitively operated storage units is to exploit price differences between peak and off-peak hours.[10] Given, that there are mainly CCGT's in the Italian market all with very similar variable cost there is little opportunity for storing during low-priced hours and selling during high-priced hours (see also Figure 3) based on marginal cost-differences between fossil-fuel generating units. Therefore, a storage model based solely on the profit-making opportunities based on marginal cost-differences between hours of the day laid out in e.g., Graf and Wozabal (2013), will not provide a storage profile that fits the reality of how storage units operate in the Italian market. However, once non-convexities in fossil-fuel generation unit operation are accounted for, specifically their start-up cost, storage may be least cost to utilize in order to save an additional fossil fuel unit start-up cost in a peak-demand hour.

We model the behavior of the eight largest pumped-storage hydroelectric units in the Italian market assuming a round-trip efficiency of 70%, which seems reasonable given the age of these units.[11] In our primary specification, we fix the net output of the storage units to their actual level, but we relax this assumption in Section 8, where we explicitly model the behavior of storage units. The majority of the storage capacity is located in the Italian Alps in the north of Italy but there is some capacity in the south, in Sardina, and in Sicily. The total storage generation and pumping capacity from these units is about 5.5 GW. We use a conservative estimate of the total available reservoir size to be about 52 GWh and we ignore any water inflows because the majority of these storage units are pure pumped storage units without inflows.

[10] Note that arbitraging price differences is only optimal if the storage is operated competitively. See, e.g., Butters et al. (2021) for a dynamic competitive investment model with storage. We refer to Andrés-Cerezo and Fabra (forthcoming); Karaduman (2021); Bushnell (2003) on outcomes with market power in the storage market, the generation market, or both.

[11] This implies storing 1 MWh of energy in order to produce 0.70 MWh of energy later.

4.6 Transmission Network Constraints and Security Constraints

Under the no transmission constraints assumption used in Borenstein et al. (2002) their competitive benchmark price is effectively finding the intersection of the realized aggregate marginal curve and the aggregate demand curve. In locational pricing markets an optimization problem has to be solved to find the locational prices as network flows must be accounted for. In all locational pricing market-clearing algorithms the transmission network is either represented by a simplified zonal network model or by a nodal model that can be described by linear power transfer distribution factors which specify the proportion of flow on a line resulting from an injection of one-unit electricity at a node and a corresponding one-unit withdrawal at some fixed reference node. Hence, market-clearing models that include such network constraints can be convex if other generation unit operating constraints that non-convexities are not taken into account in the market-clearing process.[12] For a detailed description of zonal and nodal market-clearing algorithms see Sections B.1 and C.1.

4.7 Imports and Exports

Italy is a net importer. Imports are especially relevant at the northern border with Switzerland, France, Slovenia, and Austria, ordered from most to least important in terms of available cross-border transmission capacity. However, only a part of the importers/exporters are directly expressing their willingness to import/export in the Italian market as the European day-ahead markets are coupled and cleared jointly. Hence, a substantial part of the net imports are determined implicitly through solving the pan-European day-ahead market-clearing (see Section B.2 for more details). Because we only observe offer curves on the Italian side in the North (N) but not on its neighbors' sides in the European Union, we estimate net imports $q^{N,b}$ at each border b, i.e., France (FRA), Slovenia (SVN), and Austria

[12] Actual alternating current (AC) power-flow models are the solution to a nonlinear system and therefore non-convex. However, in practice a linear approximation is used in market-clearing algorithms. More precisely, power transfer distribution factor matrices are pre-computed and together with the transmission limits included in the algorithm in form of linear constraints.

(AUT) as follows

$$q^{N,b} = \alpha^b + \beta^b P^N + X\delta^b + \epsilon^b, \tag{1}$$

for each border with Italy.

We estimate how the price in northern bidding zone, P^N, affects net imports, $q^{N,b}$. Net imports are affected also by the demand levels in the interconnected countries and also the available transmission capacity. Clearly, the relationship suffers from the simultaneous equation bias as net imports and the equilibrium price in the northern bidding zone are determined jointly. Hence, we apply a two-stage least squares approach and instrument for P^N, using day-ahead forecasts of domestic zonal demand and renewable energy supply (RES) as well as domestic interzonal transmission capacity. Furthermore, we include forecasts of load, RES, and transmission capacity of Greece. We use forecasted system conditions north of the Italian border, cross-border transmission capacities, hour-of-day and week-of-year fixed effects as the included regressors, X. More precisely, we use demand and renewable energy supply forecasts of Italy's neighboring countries in the north (Austria, France, Slovenia, and Switzerland) including also Germany, as well as transmission constraints on the northern border to Italy (see Section A.2 for more details). The results of the second stage regression are displayed in Table 2. The coefficient of interest β is positive and statistically significant for each border b.

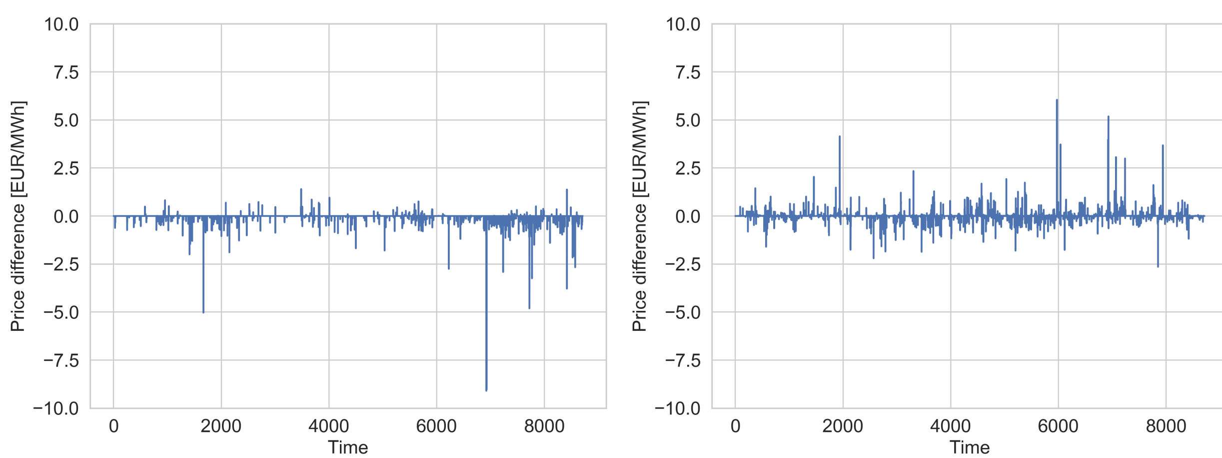
We use the results of these regression to back out an intercept that varies for each border b and every hour h of the sample. More precisely, we solve the following equation for each border and each hour of the year $Q_{h,b} = \tilde{\alpha}_{h,b} + \hat{\beta}_b P_h^N$ using the estimated slopes and actual observations for the net imports and prices in the northern bidding zone.

We extend the objective function of the zonal market clearing algorithm described in Section B.1 by endogenizing the net imports from coupled markets for each border and hour based on our estimates. The market-clearing algorithm maximizes net welfare, i.e, the sum of the the resulting areas when subtracting the zonal offer curves from the zonal demand curves. A positive net import acts as an infra-marginal supply in the Italian market. Net imports can be integrated into the market-clearing algorithm by adding the following terms to the objective function

$$-\sum_b \int_0^Q P(\tau)\mathrm{d}\tau = -\sum_b \frac{Q^2 - 2\tilde{\alpha}Q}{2\hat{\beta}}.$$

We test our approach of endogenizing market-coupled net imports by replicating the market clearing of the day-ahead market at the actual level of net imports compared to the endogenized version of dealing with net imports as described above. Figure 5, Panel (a), compares the uniform purchase price resulting from the replicated market-clearing using actual market-coupled net-imports with the uniform purchase price resulting from the replicated market-clearing using the endogenized net imports. The pattern of the two different replicated clearings match very well and the yearly average uniform purchase price differs only by 0.03 EUR/MWh. In Panel (b), we show the differences between the actual uniform purchase price and price from the replicated market-clearing with endogenous net imports.

Figure 5: Performance of Replicated Market-Clearing



(a) (b)

Notes: Panel (a): Replicated uniform purchase price differences between clearing the market using the actual market-coupled net imports and enogenized market-coupled net imports at the northern border. Panel (b): Differences between actual uniform purchase price and the replicated uniform purchase price using endogenized market-coupled net imports at the northern border. All hours in 2018 except the two days where the clock changes.

Table 2: Net import regressions (second stages)

	$q^{N,AUT}$	$q^{N,FRA}$	$q^{N,SVN}$
P^N	1.33	26.10	4.40
	(0.25)	(2.33)	(0.86)
Confounders[1]	X	X	X
Hour-of-day FEs	X	X	X
Week-of-year FEs	X	X	X
Adj. R^2	0.60	0.65	0.53
N	8,712	8,712	8,712

[1] These include day-ahead forecasts of demand, wind, and solar from Italy's neighboring countries in the north (Austria, France, Slovenia, and Switzerland) and also from Germany. Cross-border transmission capacity between Italy and its neighbors in the north.

Notes: The dependent variables are market-coupled net imports from Austria (AUT), France (FRA), and Slovenia (SVN) into northern Italy (N) for all hours of the year 2018. A handful of missing data points are interpolated due to missing data; the two days were the clock changes are skipped from the sample. Robust standard errors in parentheses.

5 Competitive Benchmark Models

In this section, we present our two competitive benchmarks that account for locational pricing. The first one is a mild improvement of the benchmark presented in Borenstein et al. (2002). Instead of simply finding the intersection of the the aggregate marginal cost curve and the demand curve, we explicitly account for zonal transmission constraints as it is done in the markets run by the PX. The market-clearing algorithm is described in Section B.1. We furthermore, endogenize the net imports into Italy as discussed in Section 4.7. We run the day-ahead market clearing-algorithm after replacing (i) the as-offered day-ahead market demand by the actual demand, (ii) the net imports from coupled markets by our net import model, (iii) the offers of the fossil-fuel generating units by our marginal cost estimates, and (iv) the supply offers from all other physical units by price-taking offers (0 EUR/MWh) at their actual output.[13]

[13] In the non-convex model, it can happen that (locational) output from these units is curtailed which results in a price of 0 EUR/MWh. Given the relatively large amount of storage capacity in the Italian market it seems credible that in such situations electricity can be stored for free and that the resulting market price

The convex competitive benchmark comes with the following downsides. First, the resulting schedules may not be technically feasible, meaning that it could be that the counterfactual pattern of output may not be compatible with the technical operating constraints of these generation units. Second, even if the schedule of each unit was technically feasible, we have not ensured that these generation schedules are consistent the many other constraints required for a secure grid operation. In particular, nodal network constraints could be violated or the distribution of units online across space may not be as such that the network can be operated securely. Third, reserve requirements are missing which means that even if the schedules were technically feasible they may not be robust to a change in the demand forecast, to a change in the forecast of intermittent renewables, or to a contingency.

In order to address these issues, we also provide an advanced competitive benchmark that takes non-convexities into account. A crucial feature of the model is that we also account for the nodal representation of the network covering the actual 220 kV and 380 kV network elements. A detailed description of the model and how prices are derived in such a model can be found in Section C.

As pointed out previously, such a model is very similar to an US-style nodal market-clearing model with co-optimization of energy and reserves. While in the convex competitive benchmark every hour of the day could be looked at separately, this is not the case in the non-convex case were intertemporal constraints are explicitly modeled. In all US day-ahead markets that account for non-convexities, the time horizon is one day. However, for some technologies, such as pumped-storage hydro with a large reservoir, this time horizon may be to short. The typical reservoir size of a pumped-storage unit in Italy is fairly small. Therefore, the unit's optimization horizon should not be over seasons of the year, but a single day may be too conservative. In order not to have our results dependent on the optimal storage operating decision, we fix the hourly storage supply at it actual level as we did in the convex competitive benchmark. However, in Section 8, we present the results of

will reach the price floor that currently is equal to 0 EUR/MWh.

a weekly optimization where we endogenize the storage operating decision. In our preferred specification, we assume that imports are not allowed to set the price. Instead, we fix net imports to the level resulting from the convex benchmark-clearing. The reason for this choice is that in a model with non-convexities it is always a trade-off between dispatching a unit with larger variable cost that has lower start-up cost and dispatching a unit with lower variable cost but larger start-up cost. From the perspective of the importing country, imports are not associated with start-up cost and hence they are treated as a flexible resource. In reality, however, there is also a physical generation unit behind the import with the only difference that it is located in another country. Therefore, in order to prevent an imperfectly competitive import market from setting the benchmark price, we model the imports as price-taker at the level of imports derived from the convex benchmark. We relax this assumption in Section 8.

Our competitive benchmark price metric is the demand-weighted average of the locational prices. However, we will also discuss locational prices associated with congestion in Section 6.3.

6 Results

In this section, we present the results of the convex competitive benchmark and the non-convex competitive benchmark.

6.1 Convex Competitive Benchmark

In a first step, we compare the convex competitive benchmark to the uniform purchase price—the demand weighted average price relevant for the demand side of the market. Surprisingly, we find that the average hourly competitive benchmark price is 64.8 EUR/MWh, while the actual average hourly day-ahead market price was only 61.3 EUR/MWh in 2018.

Zooming in and analyzing the hourly pattern we find that especially during the nighttime hours, the competitive benchmark price is higher than the observed day-ahead market price. For the market-power prone peak-hours—the morning ramp as well as the afternoon/evening ramp—we find that the day-ahead market prices are higher (see Figure 6, green versus red line).

As noted previously, the day-ahead market is the first of several markets that operate before real-time. Hence, we also add the cost of the other market segments and calculate the total cost that it is needed to serve the total hourly load. More precisely, we add the quantities multiplied by the clearing prices paid by the retailers for domestic load in the day-ahead markets and all the intraday markets.[14] On top of that we add the net cost of the energy purchased for real-time re-dispatch needed to ensure a safe operation of the network. Adding these costs and dividing it by the actual domestic demand, we find that the average hourly cost to serve load equals to 68.2 EUR/MWh or 67.6 EUR/MWh if we ignore the cost of the start-up.[15] Hence, both values are larger than our convex competitive benchmark estimate. The hourly comparison of the average total cost with the actual day-ahead market prices, shows that especially during the nighttime hours the gap between the day-ahead market price and the actual total cost is large (see the blue versus the red and the green line in Figure 6).

Our convex competitive benchmark implies a potential savings relative to the actual average hourly cost of serving load of about 3.4 EUR/MWh which amounts to about a billion EUR per year. However, the hourly pattern of the competitive benchmark seems to be unsatisfactory as we find hours of the day where there competitive benchmark price

[14]As discussed in Section 3.1, the consumption side is paying the uniform purchase price in the day-ahead market but not in the sequential intraday markets. However, in order to prevent load-serving entities from collecting systematic profits from exploiting this difference in pricing to loads, the demand side pays or receives a non-arbitrage fee that effectively makes them pay a value similar to the uniform purchase price independent of the market, day-ahead or intra-day, they are buying from. More precisely, if a retailer increases its consumption in the intraday market by one MW, this implies that it has to pay the zonal intraday price for this MW and the fee is the difference between the zonal day-ahead market price and the uniform purchase price multiplied by one MW. Depending on the sign of the difference of the zonal day-ahead market price this fee can be positive or negative. We include the non-arbitrage fee in our cost assessment.

[15]This estimate does not include the cost-of-service contracts with generation units that the TSO currently uses to mitigate local market power. Therefore, the actual cost to serve load is even larger than the value presented here.

appears to be "negative markup" of the actual price. This phenomenon occurred also in the analysis by Borenstein et al. (2002). Ignoring non-convexities of thermal units, including the proper modeling of transmission security constraints were mentioned as a potential reason for it.

We now discuss the results of our second competitive benchmark pricing process that accounts for these fundamental parameters of the electricity market operation in the next section.

6.2 Non-Convex Competitive Benchmark

In this section, we present the results of our primary model specification of the non-convex competitive benchmark. In this specification, we treat net imports as price takers at the level derived from the convex benchmark and also subtract the actual net storage output from the actual demand each hour of the year. A crucial part of the non-convex model is that we explicitly model the operating constraints on the fossil-fuel generation units. In order to that we need to set values for the status of the system at the time before our optimization horizon starts. For an optimization horizon from hour 1 to hour 24 of a day, we need the status of the fossil-fuel generating units of the previous day to determine which units can be ramped, started-up, or shut-down during the optimization period. We solve the non-convex optimization problem for each day d conditional on the the actual output of the fossil-fuel generating units at $d-1$. A potential concern of this approach is that the actual output may not be optimal and therefore we provide a robustness check in Section 8 where we optimize over a weekly time horizon. This longer time horizon ensures that the inter-weekly dispatch is least cost and thus limits the risk of biased benchmark price results due to sub-optimal starting values.

The orange line in Figure 6 shows the average hourly non-convex competitive benchmark results. The results suggest that accounting for the non-convexities helps to get an hourly pattern of prices that seems to be more in line with actual observations. The average hourly non-convex competitive benchmark is 61.5 EUR/MWh.[16] This value is very similar to the actual average hourly day-ahead market price of 61.3 EUR/MWh and it shows the importance of non-convexities. Comparing the non-convex benchmark to the total cost to serve load (ignoring start-up costs and side-payments), we find a difference of about 6 EUR/MWh.

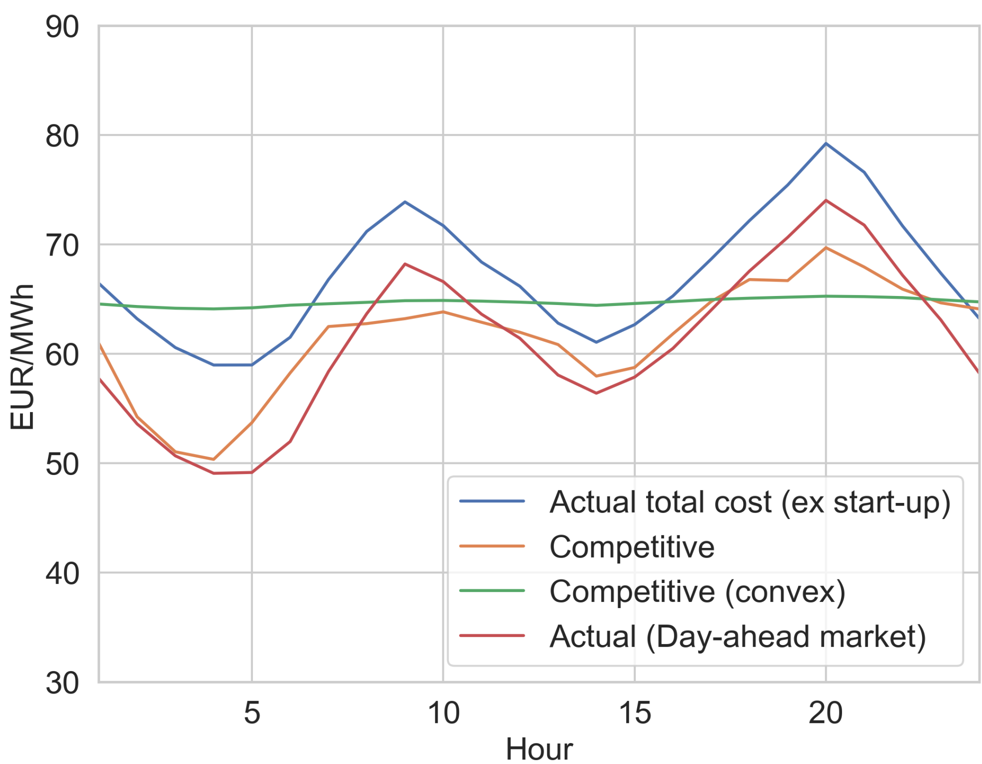
The non-convex competitive benchmark prices reveals that market performance can be poor during nighttime hours. These hours are typically off-peak hours and according to conventional wisdom market power should be less of an issue in these hours. We attribute this poor nighttime performance to "INC/DEC" gaming in the Italian market—an issue addressed in a companion paper (see Graf et al., 2021b). Because important transmission security constraints are ignored in the day-ahead and intra-day-markets, market participants have an incentive to provide schedules to the day-ahead market that have to be undone in order to ensure a secure real-time operation of the grid. Practically, this happens by withholding the capacity in the day-ahead market from some "crucial" units and making sure that less "crucial" units are scheduled after the day-ahead market clearing. A consequence of accounting for reserve constraints and grid security constraints is that a number of fossil-fuel generating units will be required to be online. If the residual demand is low, which can happen during weekends or during the night (see also Figure 3), this means there is effectively excessive supply in the system and insufficient competition among the less crucial units to reduce their output to make room for energy from the crucial units.

[16]The results cover 353 days in 2018. We skipped the two days where the clock changes from day-light saving time in the winter and to day-light savings in the summer. Furthermore, we dropped a handful of solutions where demand would have to be curtailed. Such cases are not representative and hardly ever happen in practice as many of the operational constraints as well as the network constraints can be relaxed to a certain extend. We also fix the output of storage units in this specification and therefore we have less flexible resources available as there are in reality.

We only report solutions with a relative mixed integer program (MIP) gap smaller or equal than 1e-04. The objective function maximizes total welfare but we subtract the constant consumer surplus of the inelastic domestic demand. Hence in the case where we fix the net imports, the objective function is effectively the negative cost of the dispatch for one day. The hourly average hourly demand was about 34 GWh in 2018. Assuming an average cost of 30 EUR/MWh this amounts to daily cost of 24.5 million EUR to operate the system excluding start-up cost. For this case a relative MIP gap of 1e-04 means that the absolute MIP gap is only about 2,500 EUR per day.

Most zonal day-ahead markets around the world have a real-time re-dispatch mechanism that pays as bid or as-offered. If both markets were perfectly competitive, this scheme may even lead to lower costs for the final consumer as less constraints would have to be accounted for in the day-ahead market-clearing. However, in practice this scheme almost never delivers, because market participants typically have considerable local market power in the re-dispatch market. Therefore it is a market of the few with an exclusive set of market participants having the right units at the right place and thereby being able to make sizeable profits. Stoft (2002) examines an example where a transmission constraint is not priced in the day-ahead market but happen to be binding in real-time. We provide an illustrative example in Section C.3 where a ramping constraint is ignored in the day-ahead market design but binding in real-time to create awareness that any constraint that will be ignored in the day-ahead market but is binding in real-time can lead to market distortions.

Figure 6: Competitive Benchmarks



Notes: Average hourly competitive benchmark prices as well as actual day-ahead market prices, and actual total cost for the year 2018.

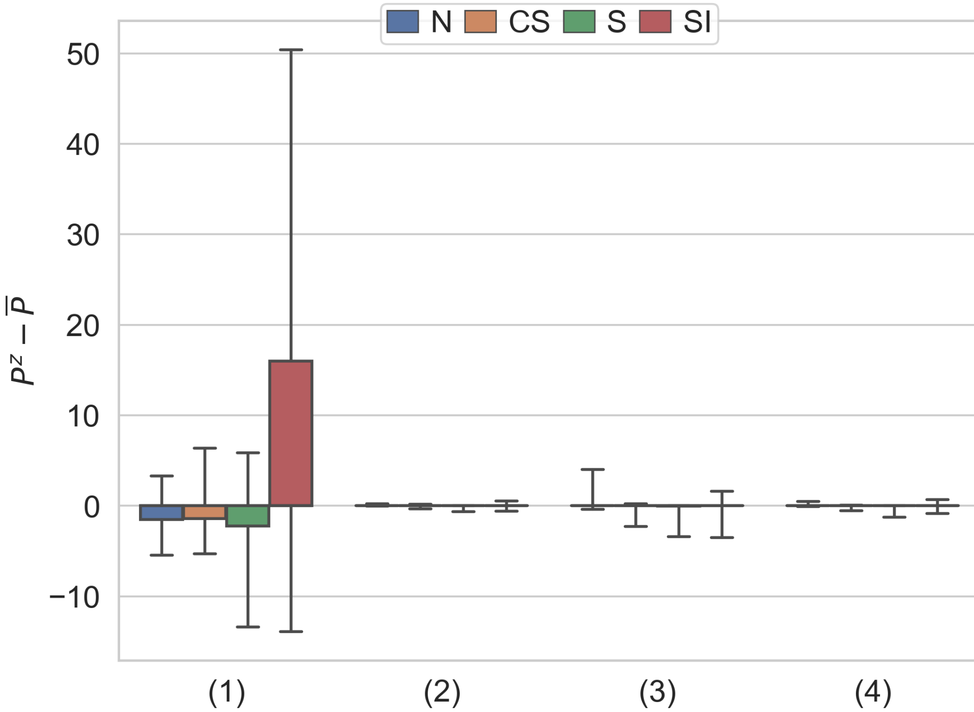
6.3 Network Congestion

Both, the convex as well as the non-convex competitive benchmark prices reveal an important observation about transmission congestion in the system: While we do find frequent congestion patterns in the day-ahead market, we find much less of it in the competitive benchmarks. Several articles, e.g., Borenstein et al. (2000) and Graf and Wolak (2020), have attributed congestion to the exercise of market power by suppliers. In fact, our competitive benchmarks reveal that the spatial distribution of controllable supply capacity together with the existing transmission infrastructure is able to cope with the *current* spatial and temporal demand pattern as well as the current non-controllable supply pattern. Hence, only very little locational "curtailment" of controllable supply is necessary due to insufficient transmission capacity. In Figure 7, we present the hourly distribution of the differences between the demand-weighted zonal price $\overline{p}$ and the zonal price p^z for the bidding zones North (N), Center-South (CS), South (S), and Sicily (SI) for the actual day-ahead market price realizations (1), the convex competitive benchmark prices (2), the non-convex competitive benchmark prices using the nodal network model (3), and the non-convex competitive benchmark prices using only the zonal network model (4). In the last benchmark model, we have replaced the nodal network model by the zonal network model as it is implemented in the current day-ahead market-clearing model. A paired sample z-test on the hourly differences between the benchmark price derived from the nodal non-convex model and the zonal non-convex model was not significantly different from zero. Hence, intra-zonal congestion does not *currently* appear be a major issue for *competitive* benchmark outcomes in the Italian market for 2018.

6.4 Explaining Differences in Benchmark Prices

In this Section, we analyze the difference in convex competitive benchmark prices and non-convex competitive benchmark prices, i.e., $\Delta_t = P(\text{Non-convex Benchmark})_t - P(\text{Convex Benchmark})_t$, where the benchmark prices P are weighted by spatial demand. Because we do not know the

Figure 7: Network Congestion



Notes: The figure shows the hourly distribution of the distances between the zonal price p^z and the demand-weighted average zonal price $\overline{p}$ for the bidding zones North (N), Center-South (CS), South (S), and Sicily (SI) for the actual day-ahead market price realizations (1), the convex competitive benchmark prices (2), the non-convex competitive benchmark prices using the nodal network model (3), and the non-convex competitive benchmark prices using only the zonal network model (4). Boxes represent inter-quartile range and upper and lower vertical bars equal to the 5 percent and 95 percent. Benchmark models are calculated using our the preferred specification. Zonal benchmark prices using the nodal model represent the average of the (supply) nodes in a zone.

precise functional specification of the differences between the benchmark prices, we argue consistent with White (1980) that ordinary least squares estimates always yields a consistent estimate of the parameters of the population best linear predictor function, but rarely yields consistent estimates of the population conditional mean function. In other words, because the functional form for $\mathbb{E}(y|X)$ is likely to be a nonlinear function of the columns of X, we instead focus on estimating the linear combination of the columns of X that yields the best prediction of Δ_t.

We regress Δ_t against the following variables: (i) the number of hourly start-ups that result from the unit commitment model used to derive the non-convex competitive benchmark, (ii) the change of the net demand from one hour to the next, (iii) the number of pricing zones resulting from the pricing model of the non-convex benchmark,[17] (iv) the demand for upward reserves for thermal units, and (v) a proxy to mimic the demand for voltage regulation.[18] The selection of these regressors has been guided by the factors that differentiate the non-convex benchmark model from the convex benchmark models. In Table 3, we present the mean and standard deviation of these variables.

In Table 4, we show the estimates of the coefficients and their robust standard errors. These parameter estimates should be interpreted as consistent estimates of the parameters of a best linear predictor function. Specifically, each regression coefficient quantifies how does our best prediction of Δ_t (in the sense described in White, 1980) given the included regressors changes for a one unit change in that specific regressor. We start by regressing Δ on the number of start-ups and then successively add one variable in the same order as discussed in the paragraph above. In the last specification (Columns 6), we also include 23 lags of the dependent variable to account for the fact that the non-convex benchmark is a dynamic problem. The main findings are that all variables except the voltage demand proxy has a positive coefficient in all the best linear predictor functions of the benchmark price differences. In terms of increment of explained variance (Adj. R-sq), we find that including voltage demand proxy had the biggest impact. This is also reflected in the precise of this coefficient estimate.

7 Rent Division and Distributional Effects

Our non-convex benchmark estimate yields an average hourly price of 61.5 EUR/MWh plus a daily average of 0.7 EUR/MWh Demand for the make-whole payments. Consequently, the benchmark sums up to an annual savings relative to the actual cost of serving load of about

[17]Because congestion is a minor concern in the competitive benchmark solutions as discussed Section 6.3, we compare the non-convex competitive benchmark solution computed with the underlying zonal network rather than the nodal network.

[18]We derive this proxy by summing up number of binding voltage constraints.

Table 3: Descriptive Statistics of Explanatory variables to Explain the Difference between Benchmark Prices

Variable	Unit	Mean	Std. Dev.	Description
Start-ups	Count	0.41	1.02	# of start-ups per hour (Non-convex benchmark)
Net demand Change	GWh	0.00	1.02	$(\text{Net demand})_t - (\text{Net demand})_{t-1}$
Pricing Zones	Count	1.28	0.49	# of pricing zones per hour (Non-convex benchmark)
Demand Upward Reserve	GWh	3.21	0.62	Tertiary upward reserve requirement for thermal units
Voltage Demand Proxy	Count	24.00	4.75	Sum of right-hand sides of all voltage constraints

1.8 billion EUR in the year 2018 on annual system demand in Italy of about 300 TWh. The estimated savings implied by our convex competitive benchmark is considerably lower, approximately 1 billion EUR per year. This is due primarily to the many hours of negative markups, primarily during the nighttime hours.

In Table 5, we report the actual annual variable profits and our competitive benchmark variable profit estimates of the strategic players as well as for the competitive fringe by technology.[19] We estimate that the strategic suppliers make an actual variable profit of 3.5 Billion EUR in 2018 from their fossil-fuel generating units. This is significantly larger than the variable profits earned under our competitive benchmark pricing solution. We estimate non-convex competitive benchmark variable profits to be 2.5 Billion EUR. These profits include side-payments if a unit is not able to break even from operating during a day. However, the side-payments only make up a fraction amount of total revenues—about 2%.[20] These results imply that the actual variable profits earned by the fossil-fuel generating units of the strategic firms are almost 40% larger than they would be under our non-convex

[19]Because we do not know each supplier's capital cost, we can only compute variable profits from sales in the short-term markets, which is the difference between revenues and variable operating costs including start-up costs. Because we do not have access for data on supplier's forward contract obligations, we compute variable profits from the short-term markets.

[20]This is likely to be a very conservative estimate of these costs because we are solving for the competitive benchmark prices conditional on actual real-time demand as well as real-time storage production and net-imports. Consequently, we ignore some of the flexibility in the solution and could reduce the number of starts of fossil fuel units.

Table 4: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
Start-ups	1.30	1.12	1.10	1.20	1.48	1.49
	(0.24)	(0.23)	(0.22)	(0.23)	(0.26)	(0.29)
Net demand Change		0.60	0.63	0.46	0.73	1.23
		(0.09)	(0.09)	(0.10)	(0.11)	(0.11)
Pricing Zones			2.66	2.20	1.45	0.20
			(0.19)	(0.19)	(0.18)	(0.16)
Demand Upward Reserve				2.12	1.37	0.56
				(0.20)	(0.20)	(0.18)
Voltage Demand Proxy					−0.65	−0.25
					(0.03)	(0.03)
Constant	−3.70	−3.63	−7.03	−13.30	5.48	2.32
	(0.15)	(0.15)	(0.31)	(0.67)	(1.13)	(0.91)
Lags $y_{t-1}, \ldots, y_{t-23}$						X
N	8,568	8,567	8,567	8,567	8,567	8,545
Adj. R-sq	0.02	0.02	0.03	0.05	0.12	0.43

Notes: (White, 1980) model misspecification robust standard errors in parentheses.

competitive benchmark estimate.

For the convex competitive benchmark, we calculate the variable profit without start-up costs and the profit including start-up costs. As we have discussed previously, the schedules from the convex competitive benchmark may not be physically feasible. However, to provide an indication of the importance of non-convexities in the Italian market, we subtract start-up costs that are due when a unit switches from zero output to a positive level of output. This is probably an over-estimation of total start-up costs because in many cases the resulting schedules are not feasible. Comparing the total variable profits in columns (4) and (5), we see indeed that the difference is quite substantial. This result should not be surprising because there is a large amount of capacity that has effectively the same or very similar variable cost (see Figure 3). Consequently, the unit-level awarded quantity after the day-ahead market-clearing becomes random to a certain extent when market participants offer to supply energy at their marginal cost of production.

We finally investigate the distributional implications of the current Italian electricity market design. Consider the variable profit distribution presented in Table 5, Column (1).

The strategic firms posses the majority of the fossil-fuel power plants that are eligible to participate in the real-time re-dispatch process. Consequently, these players may have an incentive to offer their capacity so that the expected profits from re-dispatch actions are maximized. Furthermore, the market for energy from fossil-fuel capacity is competitive given the large amount of capacity relative to demand all with roughly the same variable cost (see Figure 3). The pay-as-bid mechanism of is the re-dispatch market pays revenues only to members of the re-dispatch club. Consequently, these players profit disproportionally from the market design.[21] Note also that the average day-ahead market price is similar or even slightly lower than our average competitive benchmark price which highlights the fact that strategic firms may even be willing to forgo some revenues in the day-ahead market. This argument gets even stronger when we account for the fact that fringe firms possess a larger share of the non-controllable supply capacity that is not able to participate in the re-dispatch market. The profits of the fringe firms from their non-controllable supply (Rest) Table 5, Column (1), Panel B, is about 60% of the total profits earned on the non-controllable supply. Hence, a depressed day-ahead market price harms fringe firms disproportionally. Lower day-ahead market prices could even be good news for the final consumers if it were not for the average cost of re-dispatch actions that out-weights the impact of a lower day-ahead market price.

8 Robustness

In the first robustness check of the non-convex benchmark we endogenize net imports for adjacent markets that are part of the pan-European common market-clearing. We use the estimation technique presented in Section 4.7. For all other adjacent markets, we use the observed import and export offer curves. As pointed out previously, from the perspective of the importing country, an import is a flexible supply resource with no start-up cost. As such benchmark prices may rise as overall it might be welfare-maximizing to not start-up an

[21]Profits are also concentrated on a few crucial power plants.

Table 5: Actual and Estimated Competitive Benchmark Profits for the Year 2018

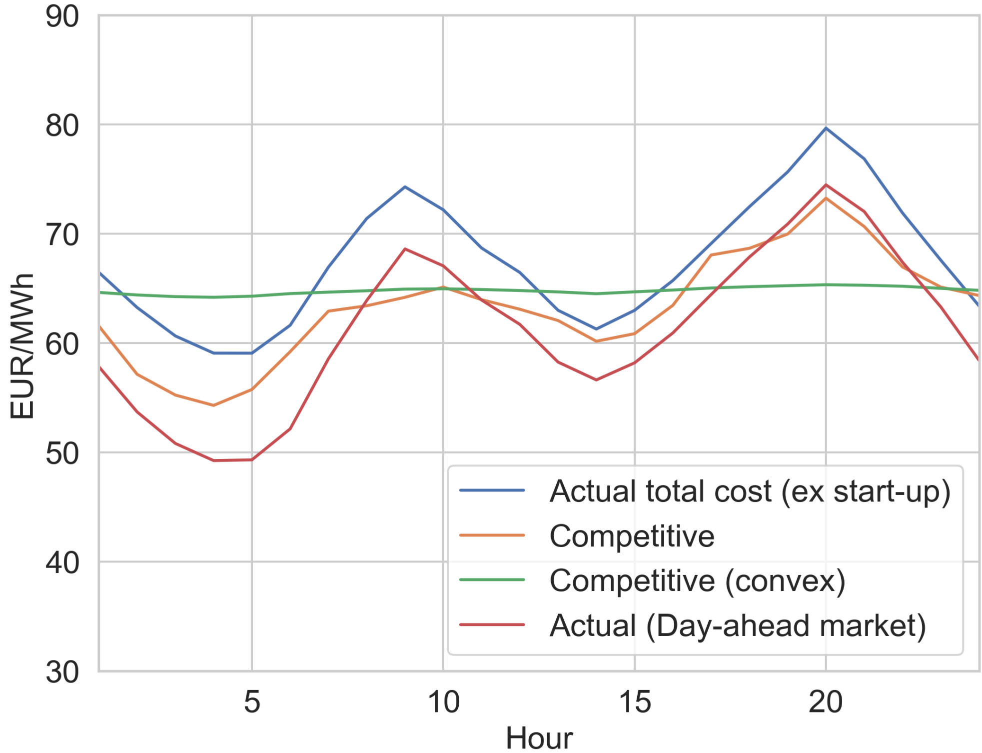
	(1) Actual	(2) Competitive (non-convex)	(3)	(4) Competitive (convex)	(5)
Technology	Profit	Side-payments	Profit	Profit (ex SU)	Profit
		Panel A: Strategic firms			
Fossil-fuel	3.51	0.14	2.54	2.68	2.10
Rest	2.76		2.80	2.92	2.92
Total	6.27	0.14	5.33	5.60	5.01
		Panel B: Fringe firms			
Fossil-fuel	0.87	0.00	0.79	0.83	0.80
Rest	4.16		4.21	4.43	4.43
Total	5.03	0.00	5.00	5.27	5.23

Notes: Yearly profit estimates in billion Euro. Fossil-fuel units include only units that we have explicitly modeled. We assume that the offered quantity associated with our industrial load estimates are valued at zero. Variable cost of uncontrollable units (Rest) as well as units that are under the "CIP-6" subsidy scheme (see Graf and Wolak, 2020, for more details on that) assumed to be zero as well. The Rest-category consists of all the units referred to in Table 1, Column "Rest." Most units in this category are uncontrollable, such as, wind, solar, hydro, or geothermal. The actual profit of these units is derived as the actual output valued at the zonal day-ahead market price. The benchmark profits are derived as the product between the relevant competitive benchmark prices and their actual output. We use the demand weighted benchmark prices because congestion is negligible. We do not consider any contractual obligations the firms may have.

additional supply capacity but clear the market with a flexible import that may be offered at a higher price. In Figure 8, we show how the average benchmark price profile changes when we allow price elastic imports to set the price: The shape of the competitive benchmark (orange line) is very similar to that from our preferred specification depicted in Figure 6. In line with our above argument, we find that benchmark prices increase in the evening hours when demand peaks up to the level of the actual total cost. The reason why we have not selected this specification as our preferred approach, though, is that we are not able to exclude market power in the import markets. The average hourly benchmark price slightly increases to 63.3 EUR/MWh but is still lower than the average convex competitive benchmark value. As an immediate consequence of endogenizing imports and exports leads to a decrease of average daily side-payments to 0.5 EUR/MWh Demand.

In the second robustness check, we endogenize storage operation. Storage units are

Figure 8: Competitive Benchmarks (Including Price Elastic Imports and Exports)



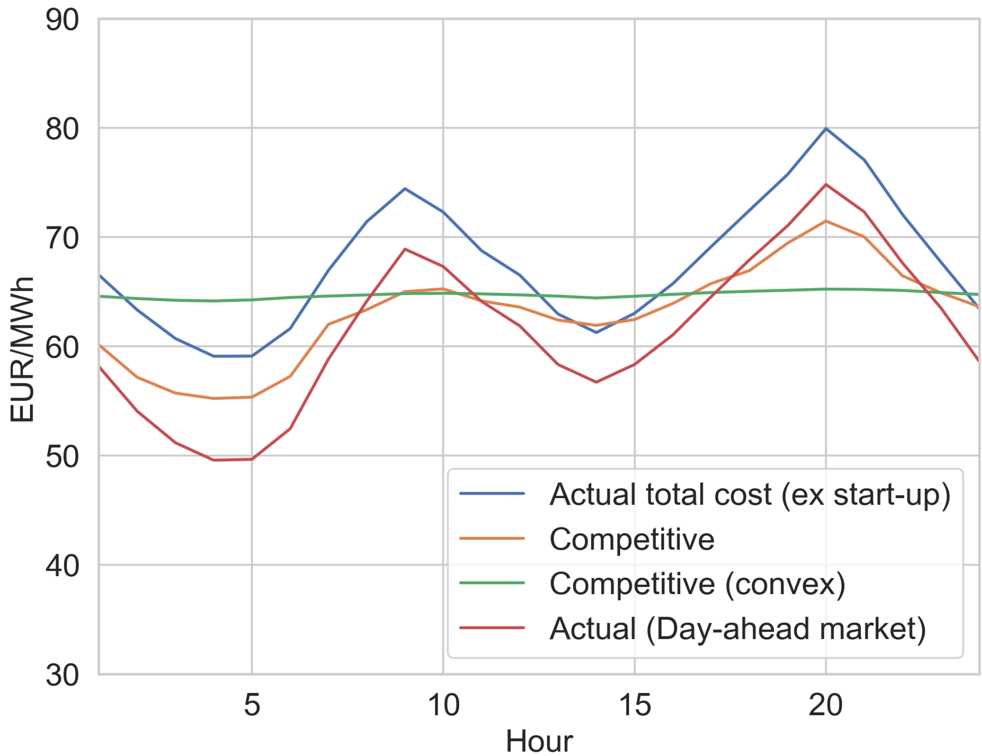
Notes: Average hourly competitive benchmark prices as well as actual day-ahead market prices, and actual total cost for the year 2018.

flexible and can be active on the demand side as well as on the supply side of market. According to the conventional view, storage units operate based on an opportunity cost logic and if operated competitively should inject during high-priced hours and withdraw during low-priced hours. In the convex competitive benchmark, there is little room for storage operation as the thermal units are very similar in terms of short run variable cost leaving little variable profit opportunities for storage units. However, the non-convex competitive benchmark opens up an additional opportunity for storage units to balance the system and the social planner may still operate the storage to avoid the start-up cost of an additional fossil-fuel generating unit. A legitimate concern is that the optimization horizon of a day may not be large enough to use storage units in the most cost effective manner. As described in Section 4.5, the storage units in the Italian market are not seasonal, but an optimization horizon of a day may be too short. Therefore, we have opted for a weekly optimization horizon.[22] This modification comes also with the side benefit that the starting values that determine whether units are online in the period before the start of the optimization horizon become less important. In Figure 9, we show how the benchmark price profile changes when allowing the social planner to shift demand using the available hydro-electric storage capacity within a weekly horizon: The shape of the competitive benchmark (orange line) still matches the shape of the day-ahead market prices and also the actual total cost to serve load. Compared to our preferred specification depicted in Figure 6, we find a smoother average benchmark price profile but also a slight increase of the average hourly benchmark prices especially during night hours but also during noon hours when the solar output peaks. The reason for this is that the excess supply in the night or during noon hours is stored which consequently increases the benchmark price in these hours. Stored electricity is released mostly during the evening hours. In order to comply with the storage balance equation the benchmark price difference will be 1/0.7 because our estimate of the round-trip efficiency of storage units is 0.7. The average hourly benchmark price is now 63.1 EUR/MWh, still lower than the average convex competitive benchmark price value. An immediate consequence of endogenizing storage yields a decrease in average daily side-payments relative to our preferred specification to 0.5 EUR/MWh.

To summarize, the two modifications yield slightly higher average competitive benchmark prices compared to our primary specification of the non-convex benchmark but are able to preserve the same average daily price profile. In addition, the qualitative interpretation of our benchmark pricing results does not change.

[22]Solving over a weekly time horizon leads to a drastic increase in the number of variables compared to solving over a daily time horizon. In order to reduce the number of variables we only include the zonal network model instead of the nodal network model in this benchmark specification. The justification of this choice is that we did not find persistent intra-zonal congestion in our primary specification of the non-convex benchmark as discussed in Section 6.3.

Figure 9: Competitive Benchmarks (Endogenous Storage Operation)



Notes: Average hourly competitive benchmark prices as well as actual day-ahead market prices, and actual total cost for the year 2018.

9 Conclusions

In this paper, we present two improvements of the standard competitive benchmark model when assessing the performance of electricity markets as outlined in Borenstein et al. (2002). The first one is to include also transmission constraints into the convex model. This feature is particularly relevant in large day-ahead market areas where locational sub-markets that use real-time re-dispatch processes exist as it is currently the case in the European Union.

Although this approach is innovative we failed to achieve credible hourly benchmark price profile. To overcome this issue, we implemented a second improvement to the standard competitive benchmark by accounting for non-convexities in fossil-fuel powered power plants as well as security constraints of the operation of the transmission network. This model deals with virtually all of the constraints that are relevant to operating a electricity supply industry. Applying this modification yields much more credible estimates of the benchmark price profile. It also shows us the importance of these constraints that become especially relevant in a world with large amount of intermittent renewables that increase the uncertainty of the residual demand but also the amount of potentially binding operating constraints on generation units and the transmission network.

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A Data sources

A.1 Generation Costs Estimation

The Italian fossil-fuel generation fleet mostly consists of gas fired plants (see e.g., Graf and Marcantonini, 2017). The most important technology is combined cycle gas turbines (CCGTs), followed by coal power plants, open cycle gas turbines (OCGTs), and oil plants.

The Italian Transmission System Operator provided us aggregated estimates on the efficiency level, cost factors for start-up due to increased fuel consumption, variable operation and maintenance (O&M), and variable waste. Power plants are clustered according to their technology and size. In Tables 6 and 7 we display parameters to construct cost functions and cost estimates for the year 2018. Clustering per technology and size is appropriate for the Italian markets as many CCGT's have come online about a decade ago and therefore they have similar heat rates. Coal power plants are less homogeneous, which explain our more granular differentiation of their marginal costs.

To compute variable fuel costs, daily spot market prices for natural gas and coal, monthly spot market prices for fuel oil along with efficiency factors of the generation units are used. For variable emissions costs, CO_2 emission allowance prices together with average emission factors (tons of CO_2 per MWhth) on the technology level that are 0.32 for coal, 0.19 for natural gas, and 0.27 for fuel oil are used. The data was provided to us by the Italian transmission system operator (Terna).

A.2 Demand, Generation, Net imports, and Reserves

National locational demand for every hour is provided by the Terna (and publicly available). The output of must-take and hydro for each hour is also taken from these data. Net imports for each border are calculated as imports minus exports during the hour.

For the net import model described in Section 4.7, we use day-ahead forecasts of national zonal wind generation, solar generation, and load. Furthermore, we use day-ahead forecasts

Table 6: Cost Function Parameters

Type	Size	Efficiency	Start-up Cost Fuel[1]	Start-up Cost O&M[2]	Cost [EUR/MWh] Variable O&M	Cost [EUR/MWh] Variable waste[3]
Fossil Gas (CCGT)	$<$ 300 MW	0.47	210	25	2.4	0.0
Fossil Gas (CCGT)	300–700 MW	0.51	640	25	2.4	0.0
Fossil Gas (CCGT)	$\geq$ 700 MW	0.52	880	25	2.4	0.0
Fossil Gas (OCGT)		0.29	70	20	6.1	0.0
Fossil Oil		0.30	370	36	6.6	2.8
Hard Coal	$<$ 300 MW	0.34	360	50	6.6	2.1
Hard Coal	$\geq$ 300 MW	0.34	2,050	50	6.6	2.1
Hard Coal (waste)[4]	$<$ 300 MW	0.34	360	50	6.6	10.0
Hard Coal (waste)[4]	$\geq$ 300 MW	0.34	2,050	50	6.6	10.0
Hard Coal (new)[5]	$\geq$ 300 MW	0.37	2,050	42	6.6	2.1

[1] Factor that accounts for the increased use of thermal energy consumption per start event. Start-up costs are derived by multiplying this factor with associated costs of burning fuel (including the costs of CO_2 emissions).
[2] Increased O&M costs in EUR/MW warm start. We use per type and size averages of stable production minima to derive per type and size increased O&M costs endured by a startup. The standard values coincide with the values from ENTSO-E (`https://www.entsoe.eu/Documents/SDC documents/MAF/2019/MAF-2019-Dataset.zip`).
[3] This component represent the variable cost of additives, chemicals, catalysts, disposal of waste, combustion waste, as well as eco-taxes but not CO_2 emission cost.
[4] A set of coal units that faces higher cost for combustion residuals (waste).
[5] A set of coal units that is equipped with a more modern technology (super/ultracritical cycle) and therefore more efficient.

of wind generation, solar generation, and load in the neighboring countries (Austria, France, Greece, Slovenia, and Switzerland) including also Germany. These day-ahead forecasts are available for every hour of the next day and are publicly available from the European Network of Transmission System Operators for Electricity (ENTSO-E).[23] We furthermore, use day-ahead market cross-border transmission limits within Italy's zonal bidding zone configuration and also between Italy and its neighboring countries. The data is publicly available from Gestore del Mercato Elettrico (GME).[24] The zonal day-ahead market prices are also publicly available from GME.

[23] See `https://transparency.entsoe.eu/`.
[24] GME is the Nominated Electricity Market Operator (NEMO) in Italy that is in charge for managing the exchange for electricity and natural gas spot trading.

Table 7: Cost Estimates

Type	Size	Variable costs [EUR/MWh]				Start-up costs [EUR/startup]			
		Mean	Std	Min	Max	Mean	Std	Min	Max
Fossil Gas (CCGT)	$<$ 300 MW	72	8	62	83	8,346	766	7,354	9,475
Fossil Gas (CCGT)	300–700 MW	66	7	57	76	24,952	2,334	21,929	28,393
Fossil Gas (CCGT)	$\geq$ 700MW	65	7	56	76	33,689	3,210	29,532	38,420
Fossil Gas (OCGT)		117	13	101	135	3,544	255	3,213	3,920
Fossil Oil		129	15	105	155	16,905	1,700	14,204	19,828
Hard Coal (cheap)[1]	$<$ 300MW	24	4	17	31	7,873	514	7,044	8,628
Hard Coal	$<$ 300MW	58	7	47	69	12,858	828	11,541	14,169
Hard Coal	$\geq$ 300MW	57	7	46	68	53,235	4,720	45,740	60,705
Hard Coal (waste)[2]	$<$ 300MW	66	7	55	76	13,299	828	11,983	14,611
Hard Coal (waste)[2]	$\geq$ 300MW	65	7	54	76	43,985	4,715	36,490	51,455
Hard Coal (new)[3]	$\geq$ 300MW	53	6	43	63	46,735	4,716	39,240	54,205

[1] A set of coal units that faces lower fuel cost because they also burn waste.
[2] A set of coal units that faces higher cost for combustion residuals (waste).
[3] A set of coal units that is equipped with a more modern technology (super/ultracritical cycle) and therefore more efficient.

We explicitly model 128 thermal units which are the most relevant ones in terms of available capacity. The output of all other units is set to their actual level. Estimates of operational constraints of the explicitly modeled thermal plants such as their stable minimum production level, their ramp-up and down rate, and minimum up and down time are based on standard values that have been adjusted further after discussions with Terna.

We use upward reserve requirement data of eligible thermal units for each day and hour. The data is publicly available from Terna.

A.3 Transmission Network and Security Constraints

We use cross-border transmission limits publicly available from Terna and GME. For the detailed nodal representation of the network detailed in Section C.1, we were provided power transfer distribution factor matrices as well as load and import distribution factors by Terna. More details on assembling, purpose, and granularity of these data can be found in Section C.1.

We include relevant grid security constraints such as voltage constraints. A more detailed description of how this data is used in our non-convex competitive benchmark can be found in Section C.

B Market-Clearing Models

B.1 Convex Zonal Market-Clearing Algorithm

The linear market-clearing model in (2) is a mathematical description of the Italian day-ahead market-clearing model. It maximizes net welfare by accounting for a zonal network structure. The demand bid price vector is given by $\mathbf{b}_b$ and the supply offer price vector by $\mathbf{b}_o$. Variables of the model are cleared demand quantities $\mathbf{x}_b$, supply quantities $\mathbf{x}_o$, and the network flow vector $\mathbf{f}$. The network flows are constrained by the limits of what can be transported between zones. The energy balance in (2c) requires that for all zones, the aggregated zonal demand minus aggregated supply must be equal to the net imports into each zone. The matrix A has dimension $L \times Z$ where L is the number of interfaces, i.e., the paths between the zones, and Z the number of zones. The paths between zones are collapsed meaning that there is only one path connecting two adjacent zones. For example, there is a path between C and D but not a separate path between D and C although flows in both directions are possible. The elements a_{lz} in matrix A can have the values 1, -1, or 0. If $a_{lz} = 1$, the path l has its destination at z. If $a_{lz} = -1$, path l has its origin at z. If $a_{lz} = 0$, path l is not connected to zone z. The vector product $A^z\mathbf{f}$ effectively gives the net import into zone z. We account for price and quantity indeterminacy and use a random merit order to prioritize among units with the same price bid (see, e.g., Graf and Wolak, 2020, on how to address these issues).

$$
\begin{aligned}
\underset{\mathbf{x}_b,\mathbf{x}_o,\mathbf{f}}{\text{maximize}} \quad & \mathbf{b}_b^T\,\mathbf{x}_b - \mathbf{b}_o^T\,\mathbf{x}_o && \text{(2a)}\\
\text{subject to} \quad & \left(\sum_{b\in B(z)} x_b - \sum_{o\in O(z)} x_o\right) - A^z\mathbf{f} = 0,\ \forall z && \text{(2b)}\\
& \underline{\mathbf{f}} \le \mathbf{f} \le \overline{\mathbf{f}} && \text{(2c)}\\
& \mathbf{x}_k \le \mathbf{g}_k,\ k \in \{b,o\} && \text{(2d)}\\
& \mathbf{x}_k \in \mathbb{R}_0^+,\ k \in \{b,o\}\,. && \text{(2e)}
\end{aligned}
$$

B.2 Bidding Zone Configuration

Figure 10 shows the bidding zone topology in 2018. The zones can be subdivided into domestic zones, limited production zones, and foreign zones.[25] Domestic 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). The Italian day-ahead market is part of the Price Coupling of Regions (PCR) initiative—a project of European Power Exchanges to develop a single price coupling solution to calculate day-ahead electricity prices across Europe respecting the cross-border capacity of the relevant network elements on a day-ahead basis.[26]

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

[26] In 2018, the project is being operated by seven Power Exchanges: EPEX SPOT, GME, Nord Pool, OMIE, OPCOM, OTE, and TGE; PCR is used to couple the following countries: Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Hungary, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Norway, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the United Kingdom. See, e.g., https://www.epexspot.com/en/marketcoupling#price-coupling-of-regions-pcr. This makes it the largest day-ahead market for electricity in the world with about 2,900 TWh of consumption (based on Eurostat data for 2017). To put things into perspective, the largest integrated US market is the Pennsylvania-New Jersey-Maryland interconnection (PJM) serving all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia with an annual demand of about 800 TWh (https://www.pjm.com/-/media/about-pjm/newsroom/annual-reports/2017-annual-report.ashx).

Italy's immediate neighbors that are coupled with Italy are France, Austria, and Slovenia. Consequently, the cross-border capacity that is not nominated at these borders will be allocated implicitly through the joint market-clearing. For all other foreign borders, the Italian market players as well as foreign market players can express their willingness to export or import by submitting offer curves in the virtual foreign zones.

C Non-Convex Market-Clearing Algorithm

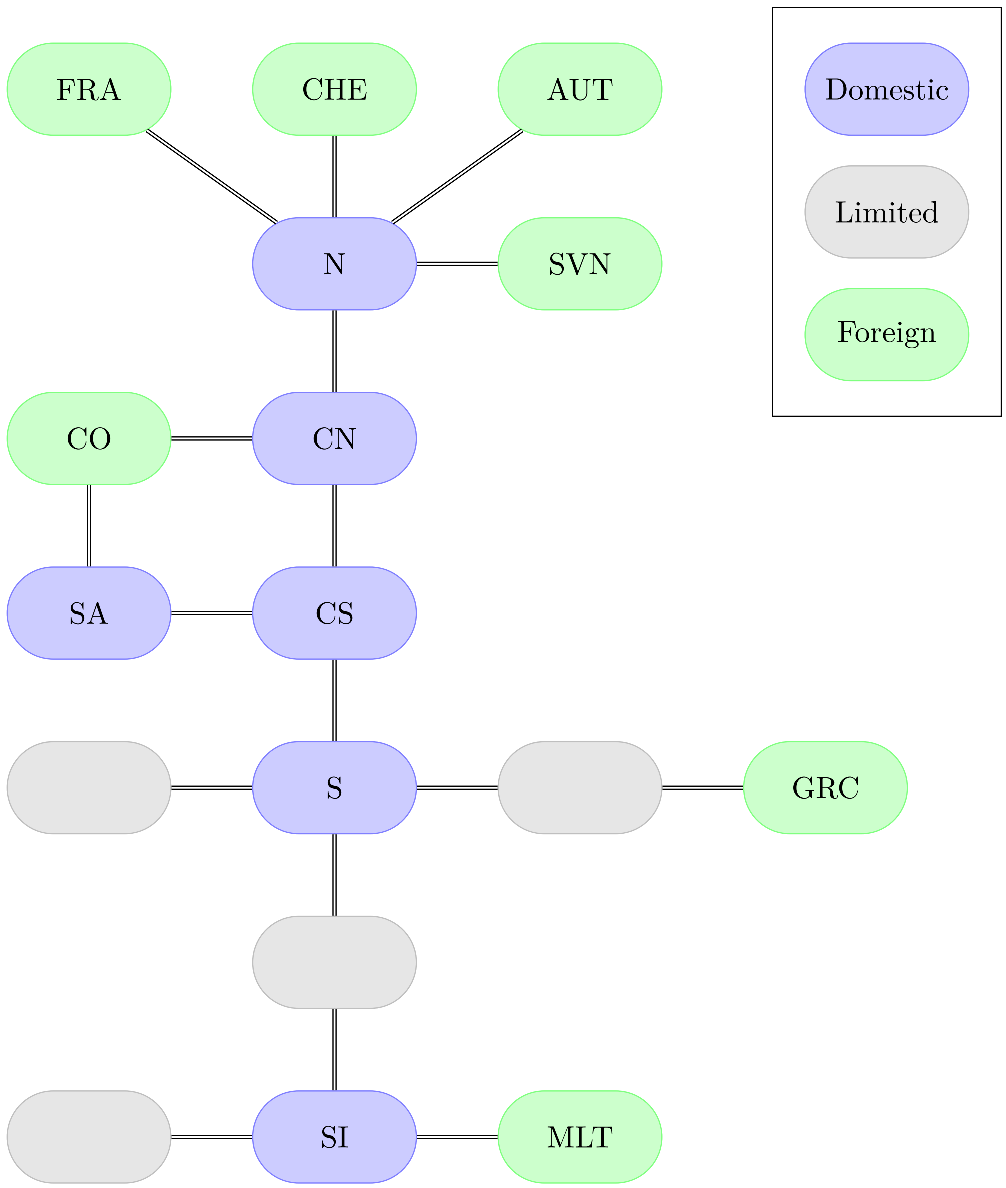
In this section, we describe the security constrained unit commitment (SCUC) model that produces a dispatch compatible with a secure grid operation. In the convex market-clearing model described in Section B.1 it is implicitly assumed that the 24 hours of the day can be sliced and hence all possibly binding inter-temporal operational constraints are neglected. Furthermore, the network is represented in an aggregate way (zones instead of nodes), reserve constraints are missing, and grid security constraints are absent.

The zonal convex market-clearing benchmark prices are computed at the point of intersection of the actual level of zonal demands less zonal net imports and less zonal amount uncontrollable supply and zonal aggregate marginal cost curves for the strategic units. In the non-convex competitive benchmark, we go a step further in a sense that we account for upward reserve constraints for relevant thermal plants. The reason why such constraints are required by the transmission system operator is that between the day-ahead market schedule and real-time there is considerable uncertainty about the exact load level and the exact amount of RES. We evaluate our model at the actual level of load and RES but note that it would also be compatible with any other realization of load and RES if it is within the bounds of the reserve requirement.[27]

The SCUC has additional features compared to the convex market-clearing model described in Section B.1. Most important, it is non-convex a mixed integer program that

[27] An alternative approach would be to solve a stochastic security constrained unit commitment model using a distribution of real-time forecast errors. Such an approach would de facto endogenize the reserve requirement.

Figure 10: Bidding Zone Configuration in 2018



is able to capture the technical constraints of thermal power plants. While in the convex market-clearing supply resources are assumed to only have a marginal cost and can produce anywhere between zero and their maximum capacity each hour of the day, in the non-convex market-clearing ramping constraints, minimum up-time constraints, minimum down-time constraints, and minimum stable production constraints are accounted for. Most conventional units are not perfectly flexible in their operation and if a unit is started-up it is not possible to switch it off immediately after. That is why the problem is also called a unit commitment problem—it is about committing a conventional generation unit for a period of time. This fact makes the problem an inter-temporal decision problem and hence we are optimizing over a time horizon that is typically a day. In the following paragraphs we go through all the modifications in comparison to the convex market-clearing model.

The objective function (3a) also accounts for the cost of starting up a unit (c^{su}). In addition to solving for dispatch quantity of each committed generation unit, we also optimize over the start-up decision for all generation units, $\mathbf{y}$, and the shut-down decisions, $\mathbf{w}$. Other (ancillary) variables are the vector that determines whether a unit is running during a give hour of the day, $\mathbf{v}$, and the reservoir levels of the pumped storage hydroelectric plants, $\mathbf{r}$. The time horizon h are all hours of the exogenously defined optimization horizon. In this paper, we use a daily horizon and a weekly horizon.

The first set of additional constraints accounts for the technical characteristics of relevant thermal units, $i \in I'$, which are the units we are explicitly modeling in the competitive benchmark pricing process. The minimum production constraint requires a unit to either be off or running between its minimum stable production level and its maximum production capacity (3c). Furthermore, in (3d) and (3e), we account for ramping constraints, upward as well as downward. In (3f)–(3i), we model minimum up-time and minimum down-time constraints.

The second set of additional constraints deals with pumped storage hydroelectric facilities ($i \in I''$). We require the storage to be balanced over the optimization horizon, (3j) and (3l).

The reservoir level (3k) increases when water is pumped (x_b) and decreases when electricity is generated (x_o). The round-trip efficiency factor (η) of the pumped storage facility enters the constraint only for pumping.[28] The reservoir level is capacity constrained between zero and ($\overline{r}$) as described in (3m) and so is the maximum amount of electricity that can be stored or generated.

We refer to Section C.1 for a detailed description of the underlying nodal transmission network model. In addition to the nodal transmission network constraints, we also enforce the zonal constraints described in (2). The zonal constraints act as additional grid security constraints. More precisely, limiting the national cross-zonal capacity mitigates low voltage conditions. We calculate the national cross-zonal flows by the sum of flows on the lines connecting two adjacent zones. As before, the model is able to account for imports and exports with neighboring countries including our approach to endogenize net imports from coupled markets.

Besides the detailed network model, we also model another set of transmission grid security constraints that aim to stabilize voltage levels. Voltage regulation is a key element for ensuring the security of a power system: voltages above the limits could damage system devices and machinery, while too low voltages can lead to voltage collapse causing local or system-wide blackouts. In both cases, voltages out of the range lead to a degradation of service quality parameters. Low voltages are experienced during peak hours (when a significant amount of reactive power is absorbed by electrical loads) and/or when flows on the network are high (when the flow on a line is higher than a given threshold it acts as a reactance, requiring reactive power from the system). For this reason, low voltage conditions are mitigated lowering the flows on the critical sections of the network (e.g., by tightening the national cross-zonal capacity limits). High voltages are experienced during low load hours (when less reactive power is absorbed by electrical loads) and/or when flows on the network are low (when the flow on a line is lower than a given threshold it acts as a capacitor,

[28] In order to reduce the load by 1 MWh through pumping increases the reservoir level by η MWh. Put differently, η MWh of electricity can be generated from storing 1 MWh of electricity.

creating an excess of reactive power in the system). In order to cope with these security constraints, a proper reactive power capacity is necessary for supporting voltages. This capacity is typically provided by conventional power plants able to change their voltage set point in order to provide/absorb more or less reactive power according to the transmission system operator's requests.

We explicitly model three types of constraints: A minimum number of units have to be online (3s) in a certain virtual cluster c, the aggregated output of units in a certain virtual cluster must not exceed a certain limit, (3u), and the aggregated output of units in a certain virtual cluster must be larger than a certain limit, (3t). Finally, we model tertiary upward reserve requirement constraints for eligible thermal units. More precisely, eligible units must have some operational reserve to react to changes in real-time demand, changes in real-time ouput from renewalbes, or contingencies. In order to fulfill this requirement they must be online. The reserve requirement is defined and modeled on the national level (3v) and on the zonal level.[29] If there is unused intra-zonal transmission capacity, zonal reserve requirements can also be served by reserve capacity in a different zone, see (3w). We ignore any opportunity costs that may arise from providing reserves.

We solve the security constrained unit commitment model for each day (or week) conditional on the actual dispatch of the previous day. The operational constraints of the explicitly modeled thermal units depend on the state of these units. In particular, the state includes whether each of these units has been online and for how long or for how long it has been offline. Given this information the mixed integer problem in (3) can be solved. Some of the constraints in (3) are formulated as "soft" constraints. These are the ramping and down-time constraints. More precisely, these constraints are relaxed at a large cost (100,000 EUR per MWh violation). We also punish load-curtailment (10,000 EUR per MWh of curtailment) and violation of transmission line capacity limits (100,000 EUR per MWh of violation). This modeling choice ensures feasibility and reflects the existing flexibility in power system better.

[29] We only ensure that provided upward reserves do not violate zonal transmission constraints in case they need to be activated because intra-zonal transmission congestion is currently only a minor issue.

Domestic demand is assumed to be inelastic.[30]

[30] The optimization problems are set solved in *Gurobi 9.0.2*.

$$\underset{\mathbf{x}_b,\mathbf{x}_o,\mathbf{v},\mathbf{y},\mathbf{w},\mathbf{r}}{\text{maximize}} \quad \mathbf{b}_b^T\,\mathbf{x}_b - \mathbf{b}_o^T\,\mathbf{x}_o - (\mathbf{c}^{su})^T\mathbf{y} \tag{3a}$$

subject to

$$\underline{\mathbf{q}}_k \le \mathbf{x}_k \le \overline{\mathbf{q}}_k,\ k \in \{b,o\} \tag{3b}$$

Technical constraints (Relevant thermal units)

$$\underline{\mathbf{q}}_i \cdot \mathbf{v}_i \le \mathbf{x}_i \le \mathbf{v}_i \cdot \overline{\mathbf{q}}_i,\ \forall i \in I' \tag{3c}$$

$$q_{i,h} - q_{i,h-1} \le y_{i,h}\underline{q}_{i,h} + (1 - y_{i,h})ramp_i^{Up},\ \forall i \in I', h = 1,\dots,H \tag{3d}$$

$$q_{i,h-1} - q_{i,h} \le ramp_i^{Down},\ \forall i \in I', h = 1,\dots,H \tag{3e}$$

$$v_i[1, \min(H, 1 + min_i^{Up} - s_i^{Up})] \ge s_i^{On},\ \forall i \in I' \tag{3f}$$

$$v_i[1, \min(H, 1 + min_i^{Down} - s_i^{Down})] \le s_i^{On},\ \forall i \in I' \tag{3g}$$

$$v_i[h, \min(H, h + min_i^{Up})] \ge y_{i,h-1},\ \forall i \in I', h = 2,\dots,H \tag{3h}$$

$$v_i[h, \min(H, h + min_i^{Down})] \le (1 - w_{i,h-1}),\ \forall i \in I', h = 2,\dots,H \tag{3i}$$

Storage constraints

$$r_{i,1} = sInitVol_i - x_{o,i,1} + \eta_i x_{b,i,1},\ \forall i \in I'' \tag{3j}$$

$$r_{i,h} = r_{i,h-1} - x_{o,i,h} + \eta_i x_{b,i,h},\ \forall i \in I'', h = 2,\dots,H \tag{3k}$$

$$r_{i,H} = sFinalVol_i,\ \forall i \in I'' \tag{3l}$$

$$0 \le r_{i,h} \le \overline{r}_i,\ \forall i \in I'', h = 1,\dots,H \tag{3m}$$

Nodal transmission constraints (3n)

$$\sum_{n\in N} netLoad_n = 0 \tag{3o}$$

$$\sum_{n\in N} D_l^n(-netLoad_n) = f_l,\ \forall l \in L \tag{3p}$$

$$\underline{\mathbf{f}} \le \mathbf{f} \le \overline{\mathbf{f}} \tag{3q}$$

$$\sum_{b\in B(n)} x_b - \sum_{o\in O(n)} x_o = netLoad_n,\ \forall n \in N \tag{3r}$$

Voltage constraints

$$\sum_{i\in I(c)} v_{i,h} \ge Req_{c,h},\ \forall c, h = 1,\dots,H \tag{3s}$$

$$\sum_{i\in I(c)} x_{i,h} \ge ReqPMin_{c,h},\ \forall c, h = 1,\dots,H \tag{3t}$$

$$\sum_{i\in I(c)} x_{i,h} \le ReqPMax_{c,h},\ \forall c, h = 1,\dots,H \tag{3u}$$

Reserve requirement constraints

$$\sum_{i\in I'''} \left(v_i\overline{q}_{i,h} - x_{i,h}\right) \ge r,\ \forall h = 1,\dots,H \tag{3v}$$

$$\sum_{i\in I'''} \left(v_i\overline{q}_{i,h} - x_{i,h}\right) \ge r_z - \sum_z \left(A^z\overline{\mathbf{f}}_h - A^z\mathbf{f}_h\right),\ \forall z \in Z, h = 1,\dots,H \tag{3w}$$

Binary constraints

$$y_{i,h} - w_{i,h} = v_{i,h} - v_{i,h-1},\ \forall i, h = 1,\dots,H \tag{3x}$$

$$\mathbf{v}, \mathbf{y}, \mathbf{w} \in \{0,1\} \tag{3y}$$

Ancillary constraints

$$x_{i,0} = s_i^q,\ \forall i$$

$$x_{i,h} = x_{o,i,h} - x_{b,i,h},\ \forall i, h = 1,\dots,H$$

C.1 Nodal Network Model

The nodal network model consists of nodes and grid elements, i.e., lines and transformers, connecting the nodes. Flows on lines can be calculated using the power transfer distribution factor (PTDF) matrices D_l^n, which specify the proportion of flow on a line l resulting from an injection of one-unit electricity at a node n and a corresponding one-unit withdrawal at some fixed reference node (also known as the slack bus). Another approach is to distribute the slack around generation nodes according to their generation capacity at each node. We opted for the latter. The line flows are between the minimum and the maximum thermal capacity of the line. Moreover, load and generation must always be balanced hence the sum of all nodal net loads must add up to zero.

We focus on transmission network congestion in the 220 kV and 380 kV grid elements. We use Plexos—a commercial market simulation software—to derive 679 PTDF matrices for the year 2018. These capture all the different network topologies registered in 2018. In a DC power flow network model the PTDF can be calculated using solely the properties of the grid elements. Note that unlike in the zonal model, the PTDFs account for Kirchhoff's voltage law that may also lead to counter-intuitive power flows (see e.g., Kirschen and Strbac (2004) for a more detailed discussion on electricity flows).

We are explicitly modeling thermal power generators and pumped storage hydroelectric units connected to the 380kV and 220kV transmission network. These are the most important units in the Italian power system in terms of capacity. We net the supply of all other units from the load (demand), and use so-called load distribution factors (LDFs) that distribute the zonal net-load to the relevant nodes in the system.

We use a similar technique to deal with net imports using so-called import distribution factors (IDFs). These describe how net imports are distributed to relevant domestic nodes. Net imports from the coupled markets can be endogenized as described in Section 4.7. We use IDFs for the most important connections, i.e., at the northern Italian border, and treat positive net-imports from Malta and Greece as negative zonal net-load. We furthermore respect the cross-border transmission constraints with connected neighboring countries (see Figure 11 for the schematic model). As discussed in Section C.1, we also enforce the domestic zonal cross-border transmission capacity limits. Corsica is included in the domestic nodal grid model and the domestic zonal cross-border flows are calculated by summing up the flows between the zonal cross-border elements.

Both, LDFs and IDFs, depend on the state of the system and are therefore not constant over time. We computed LDFs and IDFs according to actual real-time system snapshots, derived from real-time system measurements processed by a state estimation algorithm. The state estimation is a computationally expensive task and in order to economize on resources a k-means clustering algorithm is applied to find states that have similar attributes in terms of zonal demand, zonal net imports, zonal hydro supply, and zonal intermittent renewable energy supply (wind and solar). We select 40 clusters covering all hours in 2018.

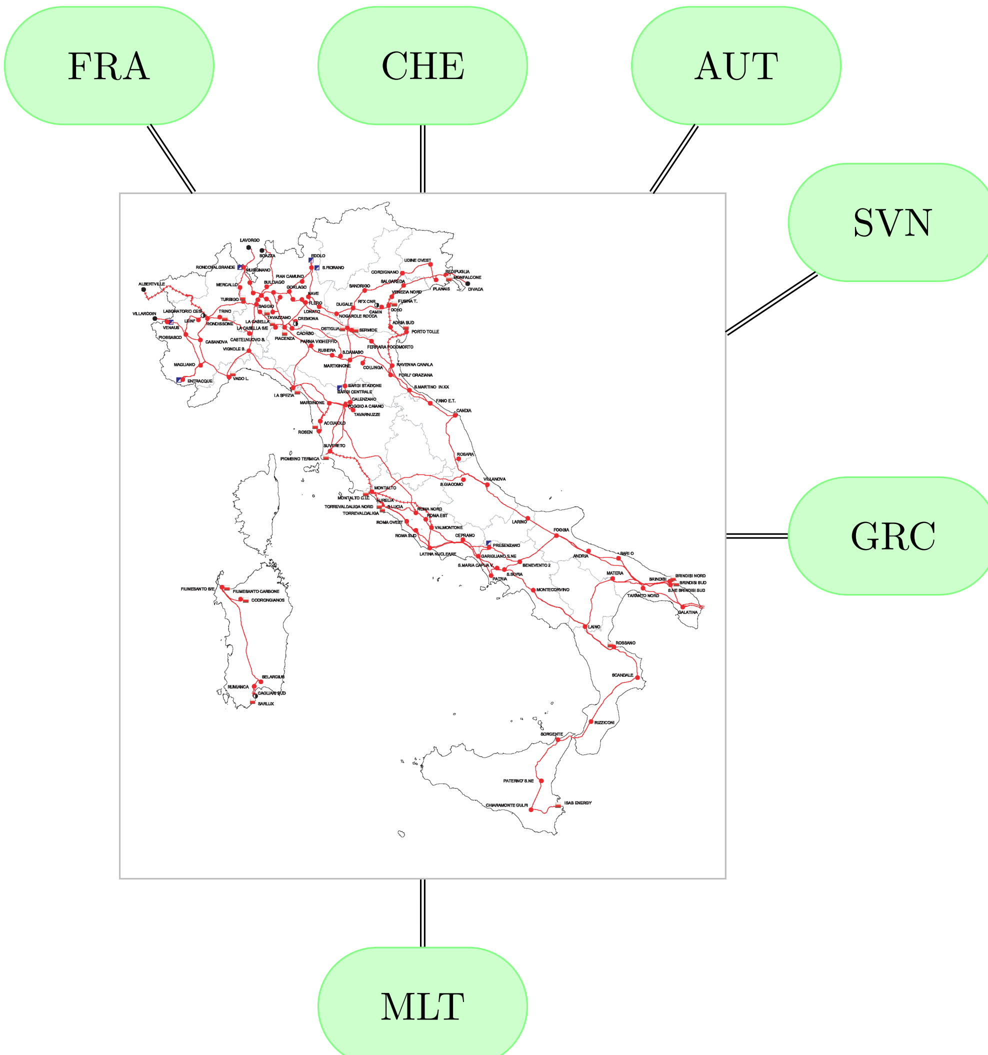
We only monitor congestion on the the 380kV elements as transmission operators typically use other means to deal with congestion on the lower level voltage lines, i.e., by topological remedial actions, and only in extreme cases, with re-dispatching.

In the security constrained unit commitment model also contingencies, i.e., the failure or loss of grid elements are accounted for. In practice, this may be done using contingency shift factors which specify how line flows change in case a grid element trips. Effectively, this kind of security constraints will lead to a less extensive usage of the transmission network. A popular approach used in the engineering literature, (see, e.g., Breuer et al., 2013; Felling and Weber, 2018) mimicking the impact of contingencies is to reduce the line capacity limits. We follow this approach and set the line capacity limit to 70% of the actual limit.

C.2 Pricing in Markets with Non-Convexities

In this section, we provide a simple example to demonstrate how pricing in markets with non-convexities works. A more detailed explanation can be found in e.g., O'Neill et al. (2005). The main challenge is that duality theory is not applicable for non-convex optimization

Figure 11: Nodal National Model Including Foreign Market Zones



Schematic Italian nodal network model. Source: `https://www.geni.org/globalenergy/library/national_energy_grid/italy/italiannationalelectricitygrid.shtml`.

problems. A common approach to still elicit dual variables from non-convex mixed integer programs is to first solve the mixed integer problem as is and then fix the integer variables to their optimal level and re-solve the problem. Note that e.g., a mixed integer linear program is a linear program for any given set of integer variables. The resulting dual variables can then be interpreted as marginal prices for a given set of integer variables. However, the resulting prices may not be incentive compatible, that is, some generators may not be able to recover their as-offered cost. One approach to solve this incentive compatibility problem is outlined in O'Neill et al. (2005), that is, to consider also the duals on the fixed integer variables. The approach has one drawback though: it can happen that money has to be paid out to units for staying out of the market. Although, such prices support the equilibrium outcome, it is hard to explain in practice why someone gets paid for not producing. Therefore, in electricity markets in the US firms only receive side-payments or make-whole payments when they are producing but are unable to recover their as-offered cost.

In order to show some of the differences between the convex market-clearing and the non-convex market clearing, consider a simple stylized electricity market with only two consecutive periods. Assume further that there are only three supply units with increasing marginal cost (SRMC), increasing ramping flexibility (rampUpMax, rampDownMax), decreasing output capacity (pMax), and decreasing start-up cost (Start cost). We furthermore, assume that unit one and two have been online (q_0). In Table 8, we provide an overview of all relevant parameters for the supply side. We assume inelastic demand and that the demand in period one is lower than in period two.

In Table 9, we show the difference in the clearing-prices as well as quantities for two sets of demand realizations. In the first set—that we consider to be a moderate upward change in the demand—we find market clearing prices equal to 50 and 60 when cleared with the convex market-clearing engine and prices equal to 40 and 60 when cleared with the non-convex market-clearing engine (Panel A). When analyzing the clearing quantities we find the convex market-clearing is not technically feasible. In particular the second unit would have to ramp up from 0 to 0.6 which exceeds its maximum upwards ramp rate of 0.5. In the non-convex market-clearing the ramp-rate is explicitly accounted for and hence the resulting dispatch is also technically feasible for each unit. The resulting prices in the convex-clearing are easy to explain, as the convex market-clearing is effectively building the merit order stack and finding the intersection with the inelastic demand curve. In the non-convex clearing, however, we find a price in the first period that is not equal to the marginal cost of any of the units. We also see that for the first unit the maximum upward ramping capacity is binding. If we would increase the demand of the first period infinitesimally, we would lower the production cost in the second period as the first unit could increase its output in the second unit. The second unit is committed for both period as it is needed for the production in the second period and therefore has to be online also in the first period as it cannot be ramped up by more than 0.5. Hence, the prices have to be understood taking the whole sequence into account.[31]

In the second example (Panel B), we decrease the demand in the first period and therefore increase the ramping rate by almost 30% relative to the previous example. The clearing prices of the convex market-clearing do not change but we learn that the static merit order may not hold in the non-convex clearing. More precisely, there is no feasible combination of output for unit one and two that would allow them to manage the ramp-rate of 0.91 jointly. Hence, in the optimal solution the merit order will not be respected and units one and three will be dispatched. An interesting aspect is also the pricing in such a situation. The price in period two is the marginal cost of the third unit. To explain the market-clearing price of the first period we again must look at both periods together. If we would increase the demand in the first period infinitesimally, we would increase the output by the same amount at a cost of 50 (SRMC of unit one). As a consequence, unit one could increase production infinitesimally in the second period and hence save the production of unit three by the same amount at a cost of 120 (SRMC of unit two). Hence, an infinitesimally increase in demand in period one

[31] In this example, make-whole payments would have to be paid out to unit two.

would change welfare by $50 - (120 - 50) = -20$, that is, the marginal price.

C.3 Separate re-dispatch market

The results of the example with the steep ramping rate described in Section C.2 and summarized in Table 9 show that the resulting prices from the non-convex market-clearing can be very different compared to the convex market-clearing prices. The load weighted average price over the two periods was 56.06 in the convex-clearing and 64.85 when applying the non-convex clearing method. The advantage, of the latter, though, is that the resulting schedules are feasible and no re-dispatch is necessary. Assume now there is a market design that relies on a convex market-clearing mechanism that is followed by a re-dispatch market. In a first step, we look at the final results if the re-dispatch market was a perfectly competitive pay-as-bid market, i.e., where market participants buy and sell at their SRMC. In Table 10, Panel A, we show what would happen to the unit's profits if generation from units one and two would be reduced in period two and unit three would sell electricity by the same total amount. As a result, none of the three units would make a profit and the cost to serve load would increase to a level that is slightly below the non-convex clearing benchmark. This example shows that if both markets were perfectly competitive the cost to serve load would be lower than when applying the non-convex clearing that price constraints right away. Notice that the difference in cost to serve load are due to the fact that the non-convex market-clearing pays marginally while the convex market-clearing plus re-dispatch market is a combination of marginal pricing and pay as bid.

In Panel B of Table 9, we show that these results do not hold if players have market power in the re-dispatch market. Let us assume that players put a markup on their short run marginal cost of 50% for increasing their output as well as decreasing their output. For example, player 2 would have to buy back his awarded quantity of 0.6 and she does this by asking 30 instead of 60 (her short run marginal cost). A markup of 50% may sound extremely large, however, in practice, only a few players with eligible capacity are allowed to trade in the re-dispatch market, hence, market power may be an issue in this market segment. Furthermore, strategic under- or over-scheduling in the day-ahead market may even increase the need to re-dispatch. The cost for the consumers increases significantly, if there is market power in the re-dispatch market, and is now also much larger than the cost to serve demand under the non-convex market-clearing. We also see that player two—who does not produce in real-time—makes a positive profit.

In this stylized example, the bottleneck is the upward ramp-rate. A solution to this problem would be a storage technology or any other way of shifting demand from one period into the other. The resulting inter-temporal price variance when using the non-convex clearing algorithm accounts for that and gives price signals that are compatible with the system's need for more flexibility. This is not the case in the convex market-clearing plus re-dispatch design as the cost to serve load variance is way lower.

Table 8: Stylized Supply Side Parameters

Unit	SRMC	pMin	pMax	rampUpMax	rampDownMax	Start cost	q_0
1	50	0.5	2	0.3	0.3	200	1.8
2	60	0.25	1	0.5	0.5	100	0.25
3	120	0	0.7	0.7	0.7	0	0

Table 9: Results of Stylized Market-Clearing

Panel A: Moderate ramp-rate									
		Convex				Non-convex			
Period	Demand	P^*	q_1^*	q_2^*	q_3^*	P^*	q_1^*	q_2^*	q_3^*
1	1.9	50	1.9	0	0	40	1.65	0.25	0
2	2.6	60	2	0.6	0	60	1.95	0.65	0
Δ	0.7	Δ	0.1	0.6	0	Δ	0.3	0.4	0

Panel B: Steep ramp-rate									
		Convex				Non-convex			
Period	Demand	P^*	q_1^*	q_2^*	q_3^*	P^*	q_1^*	q_2^*	q_3^*
1	1.69	50	1.69	0	0	-20	1.69	0	0
2	2.6	60	2	0.6	0	120	1.99	0	0.61
Δ	0.91	Δ	0.31	0.6	0	Δ	0.3	0	0.61

Table 10: Separate Re-Dispatch Market

Panel A: Perfectly competitive re-dispatch market									
		Convex				Non-convex			
Period	Demand	Cost	π_1^*	π_2^*	π_3^*	Cost	π_1^*	π_2^*	π_3^*
1	1.69	50.00	0	0	0	-20.00	-118.30	0	0
2	2.60	74.12	0	0	0	120.00	139.30	0	0
Demand-weighted average/Total		64.62	0	0	0	64.85	21.00	0	0

Panel B: Market power in the re-dispatch market									
		Convex				Non-convex			
Period	Demand	Cost	π_1^*	π_2^*	π_3^*	Cost	π_1^*	π_2^*	π_3^*
1	1.69	50.00	0	0	0	-20.00	-118.30	0	0
2	2.60	102.87	20.25	18.00	73.20	120.00	139.30	0	0
Demand-weighted average/Total		82.04	20.25	18.00	73.20	64.85	21.00	0	0