Simplified Market Mechanisms for Non-Convex Markets: Evidence from Italian Electricity Market

Christoph Graf[*] Federico Quaglia[†] Frank A. Wolak[‡]

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Abstract

We study the incentives for inefficient behavior by suppliers created by a simplified day-ahead electricity market design currently in place throughout Europe that ignores non-convexities in generation unit and transmission network operation. We show that suppliers systematically alter their offers into the day-ahead market to increase the profits they earn from the energy they ultimately produce in real-time based on the likelihood they are called to operate in a pay-as bid re-dispatch process. The cost of these re-dispatch actions averaged approximately 15% of the total cost of energy consumption valued at the day-ahead price and are likely to increase as the amount of intermittent renewable capacity grows. A counterfactual market design that accounts for many of these non-convexities where suppliers submit offer prices that are 140% of their marginal costs during peak hours of day yields similar average wholesale energy costs to consumers to the existing simplified market design.

Keywords: Zonal electricity markets, Strategic offer behavior, Re-dispatch market power

JEL Codes: L1, L9, Q4

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

[†]Terna S.p.A., Viale Egidio Galbani, 70, 00156 Rome, Italy, federico.quaglia@terna.it.

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

1 Introduction

Many markets such as telecommunications, airlines, railroads, postal delivery, and electricity are fundamentally non-convex because of indivisibilities in levels of production, fixed costs of operating, and increasing returns in production. How to organize these markets to achieve efficient outcomes is a generally unsolved problem in economics.[1] For the case of electricity, these non-convexities are becoming increasingly relevant in markets where the share of energy from intermittent renewable resources is growing.[2]

A classic result from convex markets is that there exists a set of linear prices such that the efficient solution to meeting market demand can be decentralized. Specifically, facing suppliers with these prices makes it unilaterally profit-maximizing for each supplier to produce the same level of output that the supplier would produce under the least cost solution to meeting to system demand. The presence of non-convexities create circumstances where the efficient solution to meeting market demand cannot be decentralized using linear prices.

The following example from an electricity supply industry with two generation units illustrates these results. Assume G1 has capacity equal to 100 MW and a variable cost of \$20/MWh and G2 has a capacity equal to 80 MW and a variable cost of \$100/MWh. Suppose that the market demand is equal to 120 MWh. The efficient dispatch (in the sense minimizing the total cost of meeting the market demand) is 100 MWh from G1 and 20 MWh from G2 and the efficient price is \$100/MWh. Setting a price of \$100/MWh decentralizes the efficient solution. If G1 is offered a price of \$100/MWh it will find it unilaterally profit-maximizing to produce 100 MWh and if G2 is offered a price of \$100/MWh it has no unilateral incentive to deviate from producing 20 MWh.

Now introduce the following realistic non-convexities into the market. Suppose that

[1] Starr (1969) studies equilibria in markets with non-convex preferences. Guesnerie (1975) considers the question of efficient outcomes in markets with non-convexities in production.

[2] More intermittent renewable resources typically increases the number of start-ups of thermal generation units and frequency that they must operate at their minimum operating level. Investments in resources that provide flexibility, such as storage, demand response, and transmission network upgrades can mitigate these events.

G1 has a minimum safe operating level (Pmin) of 10 MW and its maximum output level (Pmax) is still 100 MW. Let G2 have a start-up cost of \$800 and Pmin = 10 MW and Pmax remains at 80 MW. In this case, there are two sources of non-convexities in production for the generation units. First, both units have a limited range of output. Second, there is a start-up cost to operate G2. Suppose that real-time security constraints on transmission network operation require at least 50 MWh of output from G2. The efficient (least cost) dispatch is now 70 MWh from G1 and 50 MWh from G2. This result occurs because G2 must at least run 50 MW if it is turned on so that G1 must be backed off to make room for this block of energy from G2. In this case, the marginal price, which is the increase in the minimized value of the total cost of meeting demand associated with a 1 MWh increase in demand, is \$20/MWh, because G1 is only running at 70 MWh and it is the least cost way to meet the 1 MWh increase in demand. Note that this price does not decentralize the efficient solution, because if G2 was offered a price of \$20/MWh, it would find it unilaterally profit-maximizing not to produce.[3] G1 would still be willing to produce up to 100 MWh at a price of \$20/MWh. Setting the market price equal to \$100/MWh does not decentralize the efficient solution either.[4]

Regulators have taken two basic approaches to designing electricity markets to address this challenge.[5] The first approach, employed early on in the US and currently throughout Europe, assumes away virtually all sources of non-convexities in operating the market. Start-up costs, ramp rates, minimum and maximum output levels for generation units, and most transmission network constraints are ignored in the process of determining the output levels

[3]Producing the efficient output level of 50 MWh would cause G2 to lose \$800 + (\$100/MWh – \$20/MWh) × 50 MWh = \$4800. It would also lose money producing at any positive level of output because of its start-up costs.

[4]G2 would prefer not to operate at this price because it does not cover its start-up cost of \$800. G1 would prefer to produce 100 MWh at a price of \$100/MWh, because it would earn higher profits than producing at 70 MWh.

[5]Non-convexities in the operation of power plants will affect the competitiveness of the markets that follow the day-ahead market because non-operating or non-committed units are unlikely to be able to compete with committed plants especially if their start-up costs are large or they expect to be operating only for a short period of time. Furthermore, transmission network operating constraints, such as voltage regulation, which takes into account the spatial commitment of generation units, can require changes in the operating levels of generation units relative to their day-ahead schedules.

and prices that emerge from the day-ahead market-clearing process.

Suppliers are then responsible for providing operationally feasible schedules at the generation unit level to the system operator that meet these hourly output levels. Then before real-time operation the system operator runs a paid-as-offered and pay-as-bid re-dispatch process to adjust these generation schedules up or down to ensure that they are compatible with secure operation of the grid in real time. In the above example, 100 MWh from G1 and 20 MWh from G2 are both operationally feasible, but a real-time transmission network constraint requires 50 MWh to be produced by G2 and 70 MWh to be produced by G1. This process involves accepting offers for incremental energy (INCs) and bids for decremental energy (DECs) from generation units to achieve physically feasible final generation schedules given the configuration of the transmission grid.

The second approach, and current US approach, recognizes non-convexities at all stages of the market mechanism. Specifically, suppliers submit generation unit-level offers that include the unit's start-up cost, minimum load cost, and a non-decreasing energy offer curve as well as the ramp rate, minimum and maximum output levels of the generation unit. The day-ahead market-clearing mechanism then minimizes the as-offered cost (start-up, minimum load and energy costs) of meeting demands at all locations in the transmission network accounting for all relevant transmission network and other operating constraints in setting output schedules for all generation units. This process results in potentially different linear prices at all locations or nodes in the transmission network. The problem of these linear prices failing to decentralize the market-clearing output levels is addressed through what are typically called "make-whole payments" which ensure that individual generation unit owners have no unilateral incentive to deviate from the market operator's dispatch solution for their units. In our above example, at the efficient price of \$20/MWh, G2 would receive a "make-whole payment" of \$4,800, which is minimum payment required to give G2 no financial incentive to deviate from the efficient dispatch level of 50 MWh.[6]

[6] G2 earns \$1,000 from selling 50 MWh of energy at \$20/MWh, but has a variable cost of \$5,000 and a start-up cost of \$800.

A growing share of intermittent renewable resources, primarily in the form of wind and solar generation units, significantly changes the relative economic efficiency properties of these two approaches to dealing with non-convexities. Thermal generation units must start-up more frequently and operate at minimum load levels for longer number of hours of the year to meet system demand when wind and solar generation units are unable to produce energy. In addition, these controllable thermal generation units operate at significantly lower annual capacity factors because wind and solar resources produce at close to zero marginal cost and will therefore always be accepted to produce energy if the market operator has a choice between these intermittent resources and a positive marginal cost thermal resource. Finally, the frequency and magnitude of congestion in the transmission network are both likely to increase as a result of an increase in energy production from non-controllable wind and solar generation units. All of these factors are likely to increase the costs of achieving physically feasible final generation schedules from the dispatch levels that emerge from a simplified market that ignores virtually all sources of non-convexities in the operation of the electricity supply industry.

In this paper, we study the incentives created by the *simplified* market design currently in place throughout in Europe in a market with significant intermittent renewables, the Italian wholesale electricity market. We find that suppliers take advantage of their knowledge that re-dispatch is likely occur for specific units they own and change their offers into the simplified day-ahead market as a result. Thermal generation unit owners increase or decrease their day-ahead offer prices depending on the probability that their final output will be increased or decreased relative to their day-ahead schedules because of INCs or DECs purchased or sold by the system operator to respect real-time operating constraints. Our most conservative estimate of the impact of a 0.1 change in the probability a unit owner will have its day-ahead schedule INCed in the real-time re-dispatch market implies a day-ahead offer price increase of 5 EUR/MWh. If the probability of a day-ahead schedule being DECed rises by 0.1 the unit owner's offer price is predicted to be 6 EUR/MWh less.

We find a U-shaped relationship between the hourly re-dispatch cost and hourly demand net of intermittent renewables production. The right side of the "U" can be explained by market power in the conventional sense. Specifically, higher net demand implies that there is less competition for a marginal increase of supply because most available generation capacity is required to meet this demand. The left part of the "U" implies a higher re-dispatch cost for lower levels of net demand. This illustrates a different form of market power that can happen when only a few units are required to be on-line. These units may prefer to submit offer curves into the simplified day-ahead market that are incompatible with a secure grid operation and subsequently have their day-ahead schedules increased in the re-dispatch market and receive a large incremental energy payment while other units have their schedules decreased in the re-dispatch market and net a large decremental energy payment.[7] On a system-wide basis, we quantify the relative cost of the re-dispatch process as 15% of real-time energy demand valued at the day-ahead price for the years 2017 and 2018.

We compute counterfactual market outcomes for a US-style market design that accounts for many of the non-convexities in generation unit and transmission network operating constraints using the modeling framework described in Graf et al. (2020). We find that if all generation units set their energy price offers equal to 140 percent of their variable cost of producing energy during the peak demand hours of day of 16:00 to 22:00 the resulting market outcomes yield average wholesale energy costs comparable to average wholesale energy costs under the existing simplified market design. This result demonstrates that there is ample scope for a US-style market design to reduce wholesale energy costs to European electricity consumers. The incentive to pursue the INC/DEC strategies we document for current simplified market design is largely eliminated by current US market designs.[8] We argue that meeting substantially more volatile hourly net demands throughout the day but also very low

[7]A decremental energy payment occurs because the supplier buys back the energy it is unable to produce because of a transmission network or other operating constraint at a price that is below the price at which it sold this energy at in an earlier market.

[8]The DEC part is eliminated because because all relevant operating constraints are respected in the day-ahead market. The INC part is addressed through the automatic local market power mitigation mechanisms that exist in US markets. See Graf et al. (2021a) for a detailed discussion of these mechanisms.

levels of net demands[9] favors the current US market design, i.e., one that accounts for the significantly larger number of operating constraints on generation units and the transmission network necessitated by the large share of intermittent renewable generation capacity.

The remainder of the paper is organized as follows. We start with a review of different electricity market designs in Section 2. The review also revisits economic arguments for different design choices in the light of large shares of intermittent renewables. We provide a description of the Italian electricity market in Section 3 followed by an in-depth description of INC/DEC strategies in Section 4. In Section 5, we describe the data used in our empirical analysis and how we predict the probability that a generation unit will have its day-ahead schedule increased or decreased in the re-dispatch market. In Section 6, we present our empirical results showing that higher offer-price markups over marginal cost are submitted to the day-ahead market when the probability that the unit has its output increased in the re-dispatch market increases. These empirical results also demonstrate that lower offer-price markups are submitted to the day-ahead market when the probability that the unit has its output reduced in the re-dispatch market increases. We complement our results with an extensive set of robustness checks in Section 7. In Section 8, we document the U-shaped relationship between hourly re-dispatch costs and hourly net demand and compute the aggregate re-dispatch costs as a percentage of the annual cost of wholesale electricity over our two-year sample period. In Section 9, we compare actual market outcomes to counterfactual market outcomes that account for non-convexities generation unit and transmission network operation for energy offer prices set at different markups of the marginal costs of the thermal generation units. Finally, in Section 10, we conclude and discuss the implications of our results for wholesale market design.

[9] We refer to Appendix A for descriptive statistics on the change of hourly net demand levels between 2007 and 2018 in Germany and Italy.

2 Electricity Market Design Review

In this Section, we discuss the literature on non-convex markets and how it relates to the design of electricity markets. In general, non-convexities in production can arise from indivisibilities, fixed costs, or increasing returns to scale (Brown, 1991), and all three aspects are present in electricity markets that rely on conventional power plants to serve demand (see, e.g., Borenstein et al., 2002; O'Neill et al., 2005; Chao, 2019; Graf et al., 2020). We revisit our two-generation-unit example to illustrate the potential savings to electricity consumers from transitioning to a US-style market design from a simplified market design. Finally, we discuss the additional challenges facing a simplified market design with large shares of renewables.

2.1 Existing Electricity Market Designs

Electricity markets are a prime example of markets with non-convexities, and as thoroughly discussed in Wilson (2002), there are two extreme market design options on the table. First, a *simplified* design that gives market participants maximal freedom in how to schedule their supply sources. This is operationalized by a sequence of separate forward markets for energy, transmission, and ancillary services,[10] that typically do not account for all non-convexities in operating generation units or the transmission network. Second, an integrated approach where these non-convexities are accounted for in market operation and the market-operator co-optimizes the procurement of energy, transmission, and ancillary services.

It is important to note that in real-time all electricity markets are centralized because a central authority—the system operator—must coordinate controllable sources of energy to ensure that supply equals demand at all locations in the transmission network at all times. Even slight differences between real-time supply and demand at a location in the transmission network can result in brownouts or blackouts. However, the difference between the

[10] Ancillary services typically include primary, secondary, and tertiary operating reserves, as well as other system operating constraints, such as maintaining stable voltage levels, and solving congestions.

two market design philosophies described above is that in the first one, the system operator takes control only after the market participants have chosen their supply schedules. If the un-coordinated schedules are not compatible with a secure operation of the grid in real-time, the system operator will accept INC offers and DEC bids to achieve final generation schedules consistent with the non-convexities in real-time generation and transmission network operation.

The advantage of the integrated approach is that the transmission system operator takes generation unit-level offers of all suppliers and minimizes the as-offered cost of meeting the demand for energy and ancillary services at all locations in the grid in the day-ahead market taking into account all of these non-convexities in generation unit and transmission network operation.[11] In that sense, the schedules are least-cost (for the offers submitted by generation unit owners) and compatible with a secure system operation at all times between the day-ahead market and real-time. Furthermore, there can be severe economies of coordination between energy and ancillary services which can be exploited in the integrated market framework. In practice, there exists hybrid designs between the two extremes, but generally, the first approach was the early US market design and is still the status-quo in Europe and many other countries around the world. The second approach is currently deployed throughout the United States.[12]

A form of the simplified market design described above is currently place in Europe. The day-ahead market sets prices and output levels that are firm financial commitments.[13] The day-ahead market design is simple in a sense that it leaves the scheduling decision to the market participants. Furthermore, the market design is agnostic towards Ohm's law and

[11]Ancillary services are the products purchased from generation units and flexible loads that are required to maintain grid stability and security. These services generally include, frequency control, spinning reserves and operating reserves.

[12]Imran and Kockar (2014) provide a technical comparison on wholesale markets design in North America and Europe. See also Pollitt and Anaya (2016); De Vries and Verzijlbergh (2018); Newbery et al. (2018); Newbery (2018); Ahlqvist et al. (2019); Joskow (2019); Wolak (2021); Eicke and Schittekatte (2022) for different perspectives on the question of how to organize wholesale electricity markets.

[13]There are also multiple intra-day markets after the day-ahead market has cleared that allow market participants to update their positions (see e.g., Ito and Reguant, 2016).

Kirchhoff's laws but also contingencies and other reliability parameters that are relevant for the real-time operation of the power grid.[14] An important feature of this particular market design is that the resulting schedules after the day-ahead market clearing may be individually feasible, but all of them together nevertheless violate system constraints that are not explicitly accounted for in the day-ahead market design. In order to account for this problem, the system operator runs a so-called real-time re-dispatch process to transform day-ahead market schedules to comply with these system constraints. The problematic aspect of this design choice is that any supplier that has eligible capacity to participate in the re-dispatch market has strong incentives to supply a day-ahead market schedule that will get re-dispatched because, the re-dispatch market is less competitive. A fundamental challenge of a simplified day-ahead market is that it has to be complemented by a re-dispatch process or some kind of "congestion management" mechanism to ensure reliable operation of the system in real time (see e.g., Neuhoff et al., 2011; Holmberg and Lazarczyk, 2015, for an overview of different congestion management approaches in Europe). The divergence between the two market-clearing philosophies and the fact that the latter is typically less competitive because it is only open to fully controllable supply units is what facilitates the so-called "INC/DEC-game" that we study.

The "INC/DEC-game" can lead to escalating re-dispatch costs within a short period of time. This outcome caused the PJM market to transition from zonal to nodal rapidly (Newbery, 2011). All other zonal electricity markets in the United States[15] eventually followed suit and the integrated market design is now what is called the "standard" market design in the United States. Recently the topic also has gained momentum in Europe and other places around the world. Hirth and Schlecht (2019) provide some descriptive statistics on the situation in Germany. Recently, Sarfati et al. (2019); Sarfati and Holmberg (2020) developed mathematical models aiming to simulate and evaluate zonal electricity market designs and

[14]The EU market design accounts for congestion between bidding zones but not within bidding zones. Furthermore, the shape of each bidding zone is exogenously determined and its size can be very large. With a few exceptions, most notably for our analysis, Italy, each country is a single price bidding zone.

[15]For the case of California see Alaywan et al. (2004) or Chao et al. (2008).

their performance.

In many of the European zonal markets, the costs of making final generation schedules physically feasible are substantial, particularly in the regions with significant intermittent renewable generation capacity. ENTSO-E (2018) documents the magnitude of the physical firmness costs for solving congestions in European electricity markets from 2015 to 2018. During that time period, annual physical firmness costs averaged slightly less than to 1 billion Euros in the German, Austria and Luxemborg bidding zone, slightly less than 400 million Euros in Great Britain, roughly 80 million Euros in Spain, and 30 million roughly Euros in Italy.[16] In Great Britain, Spain, and Italy the vast majority of these costs were for the INC and DEC re-dispatch actions described above, whereas the majority of these costs in Germany were due to renewables curtailment.[17]

2.2 Simplified versus Integrated Market Design

Our two-generation-unit example with non-convexities can be used to illustrate economic benefits to consumers from an integrated market design. Suppose that a simplified market design with a re-dispatch process is employed. In this case, G2 knows that it must ultimately produce 50 MWh in real time for the reasons discussed earlier. However, because of the simplified market design, G2 must offer to supply energy in the day-ahead market at \$116/MWh because this is the value of the market-clearing price that allows G2 to recover both its start-up cost of \$800 and its total variable cost of producing 50 MWh of energy: \$116/MWh $\times$ 50 MWh = \$ 100/MWh $\times$ 50 MWh + \$800. G1 offers to supply energy at its marginal cost of \$20/MWh, so the market-clearing price is \$116/MWh, but G1 sells 100 MWh and G2 sells 20 MWh in this simplified market. As noted earlier, in the re-dispatch process, the system operator needs to INC G2 to 50 MWh and DEC G1 to 70 MWh for physically feasible operation of the transmission network. Assuming G2 is INCed at its offer price of \$116/MWh and G1 is DECed at its offer price of \$20/MWh yields a total cost to

[16]See Figure 90 in ENTSO-E (2018).
[17]See Figure 91 in ENTSO-E (2018).

load of \$116/MWh $\times$ 120 MWh + (\$116/MWh - \$20/MWh) $\times$ 30 MWh $=$ \$16,800 In this case, G2 earns zero variable profit and G1 earns a \$9,660 variable profit.

Under the integrated market solution with make-whole payments, the market-clearing price is \$20/MWh and the make-whole payment to G2 is \$4,800 so the total cost to consumers is \$20/MWh $\times$ 120 MWh + \$4,800 = \$7,200. Under this solution, both G1 and G2 earn a zero variable profit. In this case, wholesale energy costs to consumers is less than half of what it is under the simplified model where the market-clearing price allows all suppliers to earn at least zero variable profits. This example illustrates the potential for significant wholesale energy cost savings for consumers from an integrated market design when there are non-convexities in generation unit and transmission network operation.

2.3 Challenges with Large Shares of Renewables

The flaws in the simplified market design described above, i.e., the lack of coordination between energy, transmission, and ancillary services that may allow suppliers to sell electricity in the day-ahead market that effectively cannot be used by the system in real-time creates a demand for re-dispatch. However, several conditions limit the need for re-dispatch actions. These are: (i) an extensive transmission grid that is able to move a wide range of quantities of energy from all production locations to final consumers, (ii) a sizeable amount of controllable generators that are on-line operating in a way such there is enough flexible capacity to increase or decrease their output levels, and (iii) demand response or storage able to flexibly and reliably respond to stressed system conditions in real-time incentivized by proper locational price signals. In such a case there is likely to be sufficient competition in the re-dispatch market to render the INC/DEC game unprofitable. Unfortunately, large shares of renewables *can* put additional stress on the transmission network because the locations that are optimal to harvest wind or sun may not be compatible with the existing configuration of the transmission network.

An inevitable consequence of renewables is that they displace conventional controllable units due to their operational cost advantage. Hence, in some hours less thermal capacity will be on-line which will reduce the available options for potential re-dispatch which will increase the ability of suppliers to exercise market power in the re-dispatch market and increase the profitability of the INC/DEC game. In some cases, it even will require to curtail renewables in some locations and to start-up thermal units in a different location. In the integrated market this would be accounted for in the market mechanism and have severe consequences on pricing because renewables that cannot be absorbed by the system could not be sold at the first place.

In line with this logic, Graf et al. (2021b) show that the negative demand shock due to the Covid-19 lockdown—a situation the authors argue is conceptually equal to a higher infeed from renewabless—has led to a substantial increase in real-time re-dispatch costs in Italy.[18] This increase partially offset the consumers' savings due to lower day-ahead market prices during the lockdown period.

3 The Operation of the Italian Wholesale Market

The Italian wholesale market of electricity consists of the European day-ahead market followed by a series of domestic intra-day market sessions, and finally the re-dispatch market. The day-ahead market does not procure ancillary services, only energy. The demand side of the day-ahead market in Italy pays a uniform purchase price, that is a demand-share weighted average of the day-ahead zonal prices in Italy. In the intra-day market sessions, market participants have the option to update their positions resulting from the day-ahead market-clearing or the previous intra-day market session.[19] The day-ahead market as well as the intra-day markets are locational (zonal) marginal pricing markets.

The day-ahead market-clearing, gives a schedule for each unit as well as the zonal price

[18]Badesa et al. (2021) derive a similar conclusion for the case of Great Britain.

[19]Unlike in the day-ahead market the intra-day market clears using zonal prices. However, a non-arbitrage fee due only for demand side transactions aims to eliminate incentives to arbitrage between these markets because of the different pricing rules. The fee is calculated based on the realized uniform purchase price in the day-ahead market and the cleared zonal prices in the intra-day markets.

for every hour of the next day. Shortly after clearing the day-ahead market, two out of the seven intra-day market sessions are run, still a day ahead of actual system operation. After the clearing of the second intra-day market, the first session of the re-dispatch market takes place. In the re-dispatch market, the objective is to transform the schedules resulting from the energy market-clearing into schedules that allow a 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.

From a technical perspective the most important differences between the day-ahead (intra-day) market-clearing engine and the re-dispatch market-clearing engine are the following: (i) the zonal representation of the network is replaced by a nodal transmission grid model reflecting the physical capacity of the 220 kilovolt (kV) and 380 kV network elements, (ii) upward and downward reserve requirements for eligible thermal and hydro (storage) units are respected, (iii) thermal units' operational constraints are respected, (iv) voltage constraints are respected,[20] and (v) contingencies, i.e., the failure or loss of grid elements are considered. To summarize, the optimization model that ensures a secure operation of the grid is very different from the simplified energy-only market-clearing algorithm. Finally, unlike the day-ahead and intra-day markets, the re-dispatch markets pay as offered for energy and start-ups.

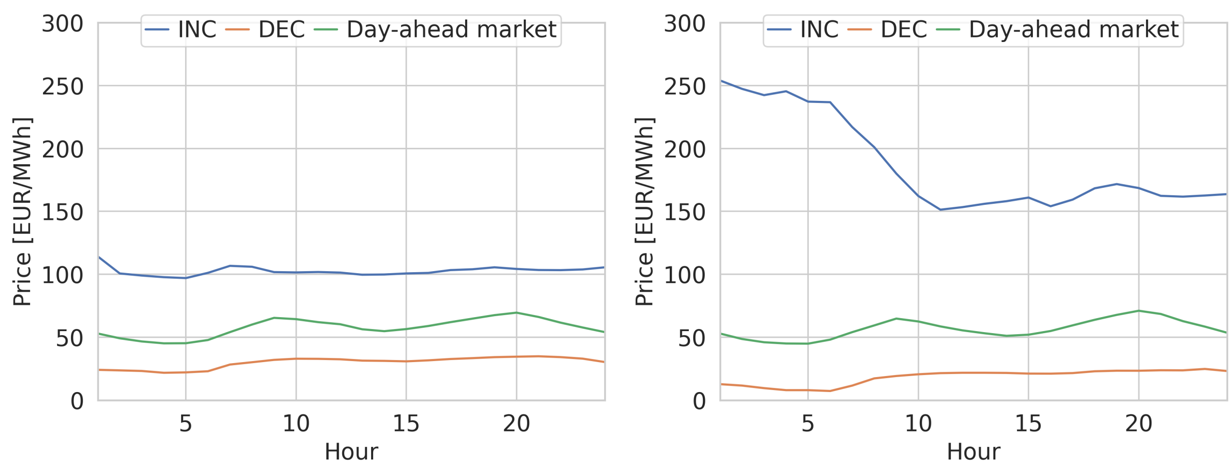
These facts emphasize that the secure operation of an electric grid is more complex than just equating aggregate supply and demand. The supply of energy must be equal to the demand for energy minus net imports at every point of injection and withdrawal from the network during every instance in time. This implies that if a generation resource at a particular location is required to operate to achieve this outcome, output from resources at other locations must be decreased in order to make room for the required resource. The configura-

[20]Operating a power system securely also requires maintaining voltage as well as power flows within operational security limits even after the occurrence of a contingency such as a transmission line or generation unit forced outage. Voltage regulation is a key element for ensuring the security of a power system. Too high voltage levels can damage system devices and machinery, while too low voltage levels can lead to voltage collapse causing local or system-wide blackouts.

tion of the transmission network or other system security constraints can significantly limit the set of units able to have their output reduced.

The real-time operation of all generation units must respect all of these operating constraints, whether or not these constraints are respected in the day-ahead or the intra-day markets. Differences between the constraints on generation unit behavior that must be respected in the day-ahead and intra-day markets and constraints respected in the real-time operation of the transmission network are what create the opportunities for suppliers to play the "INC/DEC Game."

Figure 1: Day-ahead Market versus Real-Time Re-dispatch Market Prices



(a) Northern bidding zone

(b) Center-South bidding zone

Notes: The day-ahead market price is the average hourly marginal price in EUR/MWh. The INC [DEC] price is the average hourly accepted median price in EUR/MWh for INCing [DECing] output in the re-dispatch or real-time balancing market. Observations in which INC or DEC prices were missing because no zonal re-dispatch took place are not included (28/17,424 observations in Panel a and 4,207/17,424 in Panel b). Averages are taken over hours in 2017 and 2018.

4 The INC/DEC Game

We start with a simple characterization of the INC/DEC strategy. Assume, there are two sequential markets, called the day-ahead market and the re-dispatch market. Let us further assume that the re-dispatch market-clearing engine is a richer model compared to the day-ahead market-clearing engine as the former accounts for the constraints described in the previous section. The purpose of the re-dispatch market is not only to match supply and demand, but also to ensure secure real-time operation of the power grid. Assume further that market participants are able to predict with some degree of confidence what reliability constraints must be satisfied in real-time. For example, a thermal unit at a particular location may be able to use the past history of system conditions to predict those conditions that make it likely to be indispensable to reliable operation of the grid. The reason that it must operate at a specific level of output or must not operate could be because of transmission congestion, a grid stability issue, or some other system security constraint. From the market participant's perspective, the reason does not matter, only that the unit owner can predict that more or less energy is needed from this generation unit or if a system security constraint is violated.

If the unit owner knows that this unit is necessary in real-time and it can earn a higher price in the re-dispatch market, then the supplier will opt to withhold the unit's capacity from the day-ahead market by submitting a high offer price in the day-ahead market. Under a market-based re-dispatch process, the unit owner will receive their offer price in the re-dispatch market for the incremental (INC) energy sold.

A system security constraint can also make the real-time demand for energy from a particular generation unit zero. Under certain system conditions, even if a unit is offered into the day-ahead market at its marginal cost and receives a positive energy schedule there are system security reasons why this unit cannot operate in real-time above a certain level. If such events are predictable, a generation unit will find it profitable to offer such a unit to the day-ahead market and benefit from the fact that its day-ahead schedules will be decreased in the re-dispatch market. The owner may even offer into the day-ahead market below the unit's marginal cost because the unit owner knows that the unit will not actually operate in real-time at that level. Under a market-based re-dispatch market, the unit owner can sell back (DEC)the energy at its offer price and earn the difference between the day-ahead market clearing price and its offer price times the amount of energy purchased in the re-dispatch market. The energy balance constraint that equates supply and demand at every instance of time for all locations in the grid is the reason why INC/DEC activity has to be examined jointly. If a generation unit at a particular location is required to operate in real-time, but did not sell any output in the day-ahead market, output from some other eligible supply resources has to be DECed in order to make room for the required energy from that unit.

For bid-based day-ahead and re-dispatch markets, the realized variable profit of generation unit i for a particular hour is:

$$\begin{aligned}
&\pi_i\left((b_i^{\mathrm{DA}}, g_i^{\mathrm{DA}}), (b_i^{\mathrm{RD}}, g_i^{\mathrm{RD}})\right) \\
&\quad = p^{\mathrm{DA}} q_i^{\mathrm{DA}} + b_i^{\mathrm{INC}} \max\left\{0, (q_i - q_i^{\mathrm{DA}})\right\} - b_i^{\mathrm{DEC}} \max\left\{0, (q_i^{\mathrm{DA}} - q_i)\right\} - C_i(q_i).
\end{aligned} \tag{1}$$

The unit's realized profit π_i is a function of the supplier's day-ahead (DA) market offer curve $(b_i^{\mathrm{DA}}, g_i^{\mathrm{DA}})$ as well as the supplier's re-dispatch (RD) market offer curve $(b_i^{\mathrm{RD}}, g_i^{\mathrm{RD}})$, where b_i^J is the vector of offer prices and g_i^J the corresponding vector of increment offer quantities for market $J = \{\mathrm{DA}, \mathrm{RD}\}$. Note that the unit's offer curves for the re-dispatch market consist of an INC and a DEC part. The unit's day-ahead schedule, i.e., the accepted day-ahead market quantities, is equal to q_i^{DA} and day-ahead market-clearing price is p^{DA}. The unit's real-time output is q_i and $C_i(q_i)$ the variable cost of producing this output.

The realized profit function of a unit is the sum of four terms. The revenue from the day-ahead market, $p^{\mathrm{DA}} q_i^{\mathrm{DA}}$. The revenue from INCing the day-ahead market schedule, $b_i^{\mathrm{INC}^*} \max\left\{0, (q_i - q_i^{\mathrm{DA}})\right\}$. Because the re-dispatch market is pay-as-offered, the price paid is equal to the offer price associated with the unit's level of production. The third term is the payment for DECing the unit's day-ahead schedule. Again, because the re-dispatch market is pay-as-offered, $b_i^{\mathrm{DEC}^*}$ is the offer price at the unit's final output level. The fourth term is the unit's cost of producing the final output. This equation illustrates the substantial profit opportunities available to generation unit owners that are able to predict when their units will be INCed or DECed in a market-based re-dispatch market.

It is important to emphasize that virtually all fixed-price forward contracts between retailers and generation unit owners in Europe clear against the day-ahead prices using day-ahead energy schedules. Consequently, the fact that generation unit owners have fixed-price forward contract obligations does not eliminate their ability or incentive to play the INC/DEC Game. For example, a generation unit owner could schedule their fixed-price forward contract quantity in the day-ahead market, and then sell either incremental energy or sell decremental energy in the re-dispatch market at their offer price.

We will show that the likelihood of getting INCed or DECed in real-time is predictable at the unit level using only exogenous factors known before suppliers submit their offers to the day-ahead market. These factors include forecasted load levels and forecasted production from intermittent renewable sources. In a second stage, we show that the markup—the difference between a unit's offer price and its marginal cost of producing energy—a generation unit owner submits to the day-ahead market can be explained by the predicted probability of getting INCed or DECed in the re-dispatch market. Specifically, a higher probability of being INCed predicts a higher markup and a higher probability of being DECed predicts a lower markup.

To summarize, withholding capacity from the day-ahead market or overselling capacity in the day-ahead market only makes sense if the likelihood of what will happen in the re-dispatch market is predictable, and that the INC [DEC] price in the real-time market is significantly higher [lower] than the day-ahead market price. In Figure 1, we show the spreads between the average hourly day-ahead market price and the average hourly median paid as-offered prices for INCs and DECs in 2018.[21] Panel (a) of Figure 1 shows the situation in the Northern bidding zone. INC energy sold in the re-dispatch market receives on average about double the price of energy in the day-ahead market. On average market participants

[21]The average hourly median paid as-offered price is computed as follows. For each day and hour during the sample period find the median accepted offer price and then compute the mean of these median accepted offer prices across all days in the sample. The day-ahead market price and the re-dispatching market clears hourly while the real-time market clears quarter-hourly. For the latter product we therefore compute quantity weighted average hourly offer and bid prices.

buy back DEC energy at about half the day-ahead price. The situation is even more extreme in the Center-South bidding zone, especially in the early morning hours, where the average price paid for incremental energy is about five times more than the average day-ahead price and average prices for decremental energy are about a fifth of the average day-ahead price.

The large spreads between the average prices paid for INCs and the day-ahead price and the day-ahead price and the price received for DECs imply a strong incentive to withhold capacity from the day-ahead market and supply to the real-time market or to sell in the day-ahead market and to buy back in real-time. Because of the difference in the operating constraints imposed in the two markets, the day-ahead market is effectively only about matching zonal supply and demand, and the re-dispatch market is about finding the least cost way to operate the grid in real-time given the energy schedules that emerged from the day-ahead market. Competition to supply these incremental and decremental real-time energy needs depends on the capacity and flexibility of the grid, the location and operating level of the generation mix, and the location and temporal net demand pattern. Meeting these transmission network node-level real-time energy needs is subject to significantly less competition than selling energy in the day-ahead market. This fact implies that firms may find it profitable to offer their units in the day-ahead market in such a way that the expected re-dispatch cost is maximized rather than minimized.

Figure 2, shows a stylized INC offer strategy involving the day-ahead market and re-dispatch market. The unit's capacity is offered to the day-ahead market ($b_i^{\mathrm{DA}}(q_i)$) and re-dispatch market ($b_i^{\mathrm{INC}}(\Delta q_i)$) at an offer price that is higher than its short-run marginal cost (c_i). This offer price also exceeds the upper tail of a reasonable day-ahead market price distribution ($\hat{f}_p^{\mathrm{DA}}$). The dispatch graph by market shows that such an offer strategy does *not* accept the unit in the day-ahead market but does accept the unit in the re-dispatch market.

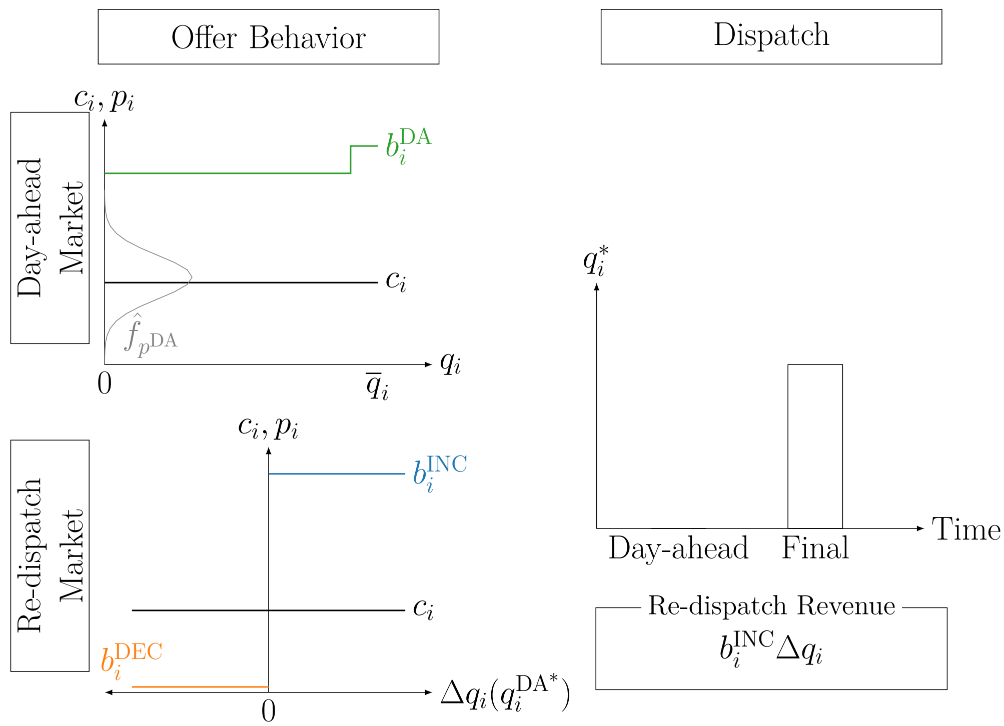
Figure 3, shows a stylized DEC offer strategy involving the day-ahead market and re-dispatch market. In the day-ahead market the unit's capacity is offered ($b_i^{\mathrm{DA}}(q_i)$) below the its short run marginal cost (c_i) and also below the lower tail of a reasonable day-ahead market price distribution ($\hat{f}_p^{\mathrm{DA}}$). Therefore the unit will be infra-marginal in the day-ahead market almost surely but faces the risk that it will not be able to recover its short run marginal cost because the realized day-ahead market price might be below its short run marginal cost. This strategy can still be rational if the unit expects that it will not be needed in real time. Assuming the unit's day-ahead market schedule would be decreased at the unit's DEC offer price ($b_i^{\mathrm{DEC}}(\Delta q_i)$), the unit would receive the difference between the day-ahead market-clearing price and its offer price for this quantity of DEC energy.[22]

Under all market designs there will be a discrepancy between the day-ahead market schedule of dispatchable units and their actual final dispatches, simply because there are uncertainties in e.g., demand or output from renewables that will resolve over time and dispatchable units will be used to *balance* the system on the way to real-time. For instance, the final output of dispatchable units will be above [below] their day-ahead market dispatches if the net demand, i.e., demand net of renewables, is below [above] its day-ahead forecast. That also means that on average the demand for INC or DEC should be zero for the aggregate of dispatchable units if the day-ahead market design would incorporate all relevant real-time constraints. In our setting, where there is a discrepancy between day-ahead market model and real-time re-dispatch market model, we find an *average* demand for re-dispatch that is around 2 GWh as can be seen in Figure 4, Panel (b).

The day-ahead market price effect of INC/DEC strategies depend on whether the units are infra-marginal or extra-marginal. In the example discussed above, the DEC part of the game is likely to affect the day-ahead market price. At first sight this may be beneficial to the final consumer as day-ahead prices may be lower than MC of the marginal unit but the down-side is that the cost of the re-dispatch will still ultimately show up on the electricity bill of consumers. We discuss this point more thoroughly in Section 8.

[22]Note that the zero point for the re-dispatch offer curve is the unit's schedule as of the start of the re-dispatch process. Note further that the units availability for INC and DEC depends on its day-ahead market schedule. For example if a supply unit has not been scheduled in the day-ahead market it can also not be DECed.

Figure 2: Stylized INC Example

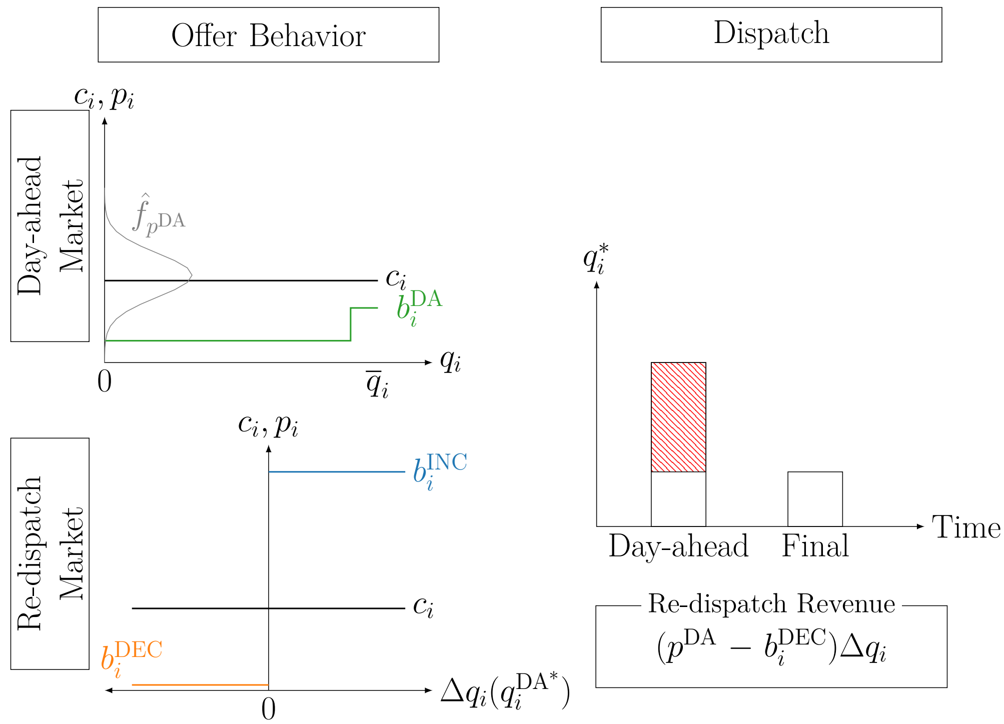


Notes: Unit-level day-ahead market offer curve (b_i^{DA}) above short-run marginal cost curve (c_i) but also more aggressive than expected equilibrium day-ahead market price distribution ($\hat{f}_{p^{\mathrm{DA}}}$). Such an offer behavior can be reasonable if unit expects a demand in the re-dispatch market. In this example, the unit will be dispatched eventually but only in the re-dispatch market even at its aggressive INC offer. Note that the double-sided offer curve in the re-dispatch market is conditional on the day-ahead market schedule. That means the DEC part is only relevant up to the amount the unit has been scheduled in the day-ahead market while the INC part is only relevant up to the maximum output net of the day-ahead market schedule.

4.1 Optimality Conditions

In this Section we present optimality conditions at the unit-level. The following simplifications should enhance tractability and readability: units compete in quantities and a day-ahead market quantity of unit i, $q_i^{\mathrm{DA}} > 0$, means that this quantity is scheduled and settled at the expected day-ahead market price p^{DA}. The day-ahead market is assumed to be perfectly competitive. The demand for unit-level re-dispatch is only a function of the unit's day-ahead market schedule and not of the unit's pay-as-bid offer price in the re-dispatch market. We assume that reasonable re-dispatch prices for INC, b_i^{INC}, and DEC, b_i^{DEC} can be estimated out of expected real-time system conditions X. We assume that a firm cannot update its position after the day-ahead market has cleared and thus the day-ahead market

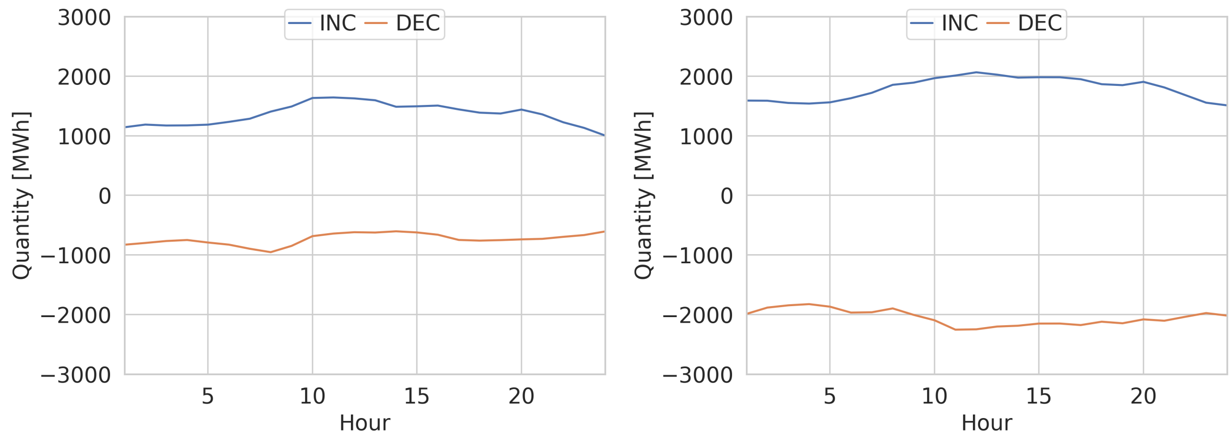
Figure 3: Stylized DEC Example



Notes: Unit-level day-ahead market offer curve (b_i^{DA}) below short-run marginal cost curve (c_i) and also less aggressive than expected equilibrium day-ahead market price distribution ($\hat{f}_{p^{\text{DA}}}$). Such an offer behavior can be reasonable if unit expects to only produce a fraction (including zero) of its day-ahead market schedule. In this example, the unit will be infra-marginal in the day-ahead market and therefore will be scheduled in the day-ahead market but the final output will be reduced in the re-dispatch market. This strategy will make the unit receive the day-ahead price for the hatched red area in the dispatch graph, without incurring any production cost. Note that the double-sided offer curve in the re-dispatch market is conditional on the day-ahead market schedule. That means the DEC part is only relevant up to the amount the unit has been scheduled in the day-ahead market while the INC part is only relevant up to the maximum output net of the day-ahead market schedule.

offer behavior will determine the possibility of revenues streams from the re-dispatch market. Put differently, a necessary condition for the upside of receiving payments in the INC market that exceed day-ahead market payments, the unit must have headroom after the day-ahead market has cleared. If a unit would like to participate in the DEC market it must ensure that the unit has sold $q_i^{\text{DA}} > 0$ in order to being able to get its output reduces. The downside of operating in the DEC market may be that the firm depresses the day-ahead market price if it wants to ensure to be committed as much as possible with the intent to eventually get its output reduced. In the worst case the unit commits to generate at a price that is below

Figure 4: INC and DEC Quantities



(a) (b)

Notes: Panel (a): Accepted quantities in the re-dispatch market, Panel (b): Total INC and DEC quantities including real-time balancing market. Quantities are expressed in MWh and averages are taken over all hours in 2017 and 2018.

its cost. The unit's final cost C is a function of the actual quantity produced in real-time. However, because the unit takes the decision how to allocate its output before the day-ahead market has closed, we assume the cost are a function of the day-ahead market quantity and the expected re-dispatch quantities.

$$\begin{aligned} \mathbb{E}\left[\pi_i(q_i^{\mathrm{DA}}|X)\right] &= \mathbb{E}\left[p^{\mathrm{DA}}(X)\right] q_i^{\mathrm{DA}} + \\ &\quad \mathbb{E}\left[q_i^{\mathrm{INC}}(q_i^{\mathrm{DA}}|X)\right] \mathbb{E}\left[b_i^{\mathrm{INC}}(X)\right] - \\ &\quad \mathbb{E}\left[q_i^{\mathrm{DEC}}(q_i^{\mathrm{DA}}|X)\right] \mathbb{E}\left[b_i^{\mathrm{DEC}}(X)\right] - \\ &\quad C_i(q_i^{\mathrm{DA}} + \mathbb{E}\left[q_i^{\mathrm{INC}}(q_i^{\mathrm{DA}}|X)\right] - \mathbb{E}\left[q_i^{\mathrm{DEC}}(q_i^{\mathrm{DA}}|X)\right]). \end{aligned} \tag{2}$$

Note that $0 \leq q_i^{\mathrm{DA}} \leq \overline{q}_i$, $0 \leq q_i^{\mathrm{DA}} + q_i^{*\mathrm{INC}} \leq \overline{q}_i$, and $0 \leq q_i^{\mathrm{DA}} - q_i^{*\mathrm{DEC}} \leq \overline{q}_i$.

5 Sample Selection and Data Preparation

This section first describes the set of generation units that can potentially participate in the re-dispatch market. Although the day-ahead market or intra-day markets are open to all generation units, only a subset of the generation units are eligible to provide INC or DEC re-dispatch energy to ensure secure real-time system operation. These units must satisfy certain technical requirements related to how rapidly they can turn on or off and how fast they can increase or decrease their output.[23] From the set of eligible units, we exclude units that have a cost-of-service contract with the transmission system operator in Italy because they have been shown to have a significant ability to exercise unilateral market power. Units with such contracts have regulatory restrictions on how they can offer their capacity in the day-ahead market. Therefore it does not make sense to include these units in a study of the strategic interaction between the day-ahead market and the re-dispatch market. We also exclude open cycle gas turbines (OCGTs) because they are hardly ever scheduled after the day-ahead market-clearing under the current market environment and generation mix. The fact that OCGTs are very flexible thermal units with the highest variable cost but low start-up cost compared to other thermal units, makes them suitable candidates for real-time balancing. In absolute terms, OCGTs capacity amounts only to less than 4% of the total eligible capacity for real-time re-dispatching.

The vast majority of the remaining units are combined cycle gas turbines (CCGTs) and only a handful are coal power plants. The latter are much more "lumpy" compared to the former and most of them are regulated. Therefore we also exclude these units as their lumpiness limits their room for maneuver in real-time and the regulated coal power plants cannot freely specify their offer curves. From the remaining units, we select the units that cumulatively provide about 90% of the total volume of incremental and decremental energy in the scheduling phase of the re-dispatch market.[24] This ensures that only units with a significant share in providing INC or DEC action are analyzed. In total, we selected 40 combined cycle gas turbines (CCGTs) for INC and 32 CCGTs for DEC. These were the main units providing a significant share of INC and DEC energy in the re-dispatch market

[23] European transmission system operators are currently working to relax the requirements for participation in an effort reduce the rate of increase in re-dispatch costs.

[24] The 90% criterion is to a certain extent arbitrary but because our unit-level prediction models uses month-of-sample fixed effects we require at least a few positives (re-dispatch).

in 2017 and 2018. Eleven units are active in both categories and the total number of units in our sample is 61 with a total installed capacity of about 30 GW. Given that the hourly average national demand in Italy was about 35 GWh in the years 2017 and 2018 this is a sizeable amount of capacity.

Recall that the main reason a generation unit may opt to under-schedule or over-schedule in the day-ahead market is that a predictable but relevant real-time constraint is not accounted for in the day-ahead market clearing engine. Such a situation may incentivize market participants that are affected by this constraint to either over-schedule or under-schedule the output of a unit in the day-ahead market to force the system operator to re-dispatch. Consider for a stylized transmission network with two nodes that is frequently congested from the North to the South. If the day-ahead market ignores the transmission constraint, units located in the North would have an incentive to over-schedule and units in the South to under-schedule. In real-time, the transmission operator would have to INC the units in the South and to DEC the units in the North to resolve the congestion. This explains why different units can be either INCed or DECed. However, the relevance of transmission network constraints or any other binding security constraints may depend on the season of the year or the hour of the day which explains the overlap in the categories. To summarize, not all units have the same likelihood of being accepted in the re-dispatch market. Their location as well as other attributes such as their ability to ramp-up or down and the state of the system will determine whether a unit is likely to be INCed or DECed. However, in order to demonstrate that we have not selected the generation units for our analysis to produce the desired outcome, we also provide the results of the analysis using all CCGT units that are eligible to provide energy in the re-dispatch market (see Section B).

We focus on the interaction between the day-ahead market and the scheduling phase of the re-dispatch market. In Figure 4, we see that, on average, more than half of the INC action and about half of the DEC action is already selected in the scheduling phase of the re-dispatch market. The reason why we focus on the scheduling phase is that the sizeable re-dispatch actions typically take place in the scheduling phase and not in the real-time balance market sessions. However, we provide the results where we also include the real-time balancing market outcomes as a robustness check in Section 7.

In order to simplify the analysis, we ignore transactions in the intra-day markets as unlike in Ito and Reguant (2016), we do not observe large price spreads between day-ahead market and intra-day markets on average. Furthermore, trading volume is very low in the intra-day markets.[25] In principle, trading possibilities in the intra-day markets may even aggravate the INC/DEC game as market-participants have several opportunities to schedule their capacity and may use the resulting price and schedules of their own units in the previous market sessions as signal to learn about the state of the system. In that sense our results will be a lower bound on how the expected probability of being re-dispatched will affect the day-ahead market offer markup.

Our final dataset combines hourly unit-level offer data from the day-ahead market as well as the re-dispatch market. The day-ahead offer data is condensed into unit-level day-ahead market offer price markups described in more detail below.[26]

5.1 Predicting the Likelihood of getting INCed or DECed

We now describe the statistical model used to predict the probability that a generation unit is INCed or DECed in the re-dispatch market. We are interested in the interaction between the day-ahead market and the re-dispatch market and how the predicted probability of getting INCed or DECed in this market affects day-ahead market offer-price markups. Our model must predict the likelihood of getting INCed or DECed in the re-dispatch market using information available to generation unit owners before they submit their offers to supply

[25]For the year 2018, the average price in the northern bidding zone—the largest zone in Italy—was 60.7 EUR/MWh in the day-ahead market and 60.3 EUR/MWh in the first intra-day market session. The first intra-day market session is also the most important one in terms of transactions relative to the other intra-day market sessions. Average hourly national purchases amounted to 1.3 GWh in the first session of the intra-day market compared to 34 GWh in the day-ahead market.

[26]We omit observations for hours where a unit's available capacity is below 20% of its installed capacity. For such low levels of available capacity our short-run marginal cost estimate is likely to be off. However, our results are not sensitive to this small modification of the original data.

energy in the day-ahead market.

We use the following exogenous variables that are all known before suppliers submit their offers to the day-ahead market: national zonal day-ahead forecasts for load, wind, and solar energy. Forecasts for the same set of variables for the neighboring countries, i.e., Austria, France, Greece, Slovenia, and Switzerland. We also include these same variables for Germany because Europe has a common zonal day-ahead market of electricity and Germany with its large share of intermittent renewables, plays an important role. We also include the day-ahead market cross-border transmission limits with all adjacent countries and the national zonal transmission limits for Italy.[27] Finally, we use month-of-year, hour-of-day, and workday indicator variables.[28] The values of these exogenous variables are collected to form the regressor matrix X.

We encode the dependent variable y to be equal to one if a unit's schedule is INCed [DECed] and zero otherwise. We separately estimate the parameter vector w for each unit and for each re-dispatch market product, i.e., for INC and DEC energy separately, imposing a model of the form

$$\mathbb{P}[y = 1|X] = F(Xw). \tag{3}$$

The function $F(t)$ in (3) can be replaced by the logistic cumulative distribution function and the model then becomes the standard binary logit model. We apply a logit model to

[27]Data on hourly day-ahead load forecasts as well as hourly day-ahead forecasts for solar and wind at the bidding zone level is publicly available from `https://transparency.entsoe.eu/`. "According to Regulation Article 6.1.b and 6.2.b, a day-ahead forecast of the total load per market time unit; ... shall be published no later than two hours before the gate closure of the day-ahead market in the bidding zone and be updated when significant changes occur;" Day-ahead forecasts for wind and solar shall be published no later than 6 pm Brussels time one day before actual delivery takes place. The day-ahead market session closes at noon and therefore the wind and solar day-ahead forecast is provided a few hours after the closure of the day-ahead market. However, forecast data for wind and solar is a standard product that can easily be procured by market-participants. Furthermore, it can be expected that the solar and wind day-ahead forecast at noon should be highly correlated with the day-ahead forecast published by the transmission operator a few hours later. Nevertheless, we replicate the analysis using a simplified forecast model where we exclude the day-ahead forecasts of wind and solar. The results are presented in Table 12. The qualitative interpretation of the results is unchanged. Data on zonal transmission limits is provided to Italian market-participants by the transmission system operator before the day-ahead market closes.

[28]Workdays are all non-holidays and non-weekend days.

estimate the probability of getting INCed or DECed as well as a machine-learning technique to estimate these probabilities. In particular, we apply a random forest classification model whose hyper-parameter we derive by cross-validation to mitigate the risk of over-fitting.[29] A serious concern in all machine-learning algorithms is over-fitting. For this reason, we apply a cross-validation strategy using 30% of the sample as test data and the remainder as training data. We use five stratified randomized splits that preserve the same percentage for each target class as in the complete set.

We deploy cross-validation to select the hyper-parameter vector $\theta \in \mathcal{S}$ as e.g., described in Murphy (2021). More precisely, we partition the data $\mathcal{D}$ into $K = 5$ folds and train the model on all the folds but the k'th, and test on the k'th fold. Formally,

$$R_{\theta}^{\text{CV}} = K^{-1} \sum_{k=1}^{K} = f(\hat{w}_{\theta}(\mathcal{D}_{-k}), \mathcal{D}_k), \tag{4}$$

where $\mathcal{D}_k$ is the data in the k'th fold, and $\mathcal{D}_{-k}$ denotes the remaining data of all other folds. The function $f()$ is the accuracy score that measures how often the classifier is correct, i.e., summing up the true positives and the true negatives divided by the sample size. Note that we assume the predicted value of y, $\hat{y}$, is equal to one it the predicted $\mathbb{P}[y = 1|X] > 0.5$ and zero otherwise.

The optimal hyper parameter vector will be selected by solving $\theta^* = \arg\max_{\theta \in \mathcal{S}} R_{\theta}^{\text{CV}}$. Finally, we combine training and validation data and re-estimate the model to get final parameter estimates $\hat{w} = \arg\max_w f(w_{\theta^*}, \mathcal{D})$.

We optimize over the maximal number of trees used in the forest as well as over the depth of each tree. Because the parameter values are discrete we deploy a grid search to

[29] Put simply, a random forest model consists of a large number of individual decision trees that operate as an ensemble. Each decision tree model in the forest produces a class prediction and the mode of all the classes, i.e., the most frequent outcome, becomes the model's prediction. We refer to Breiman (2001) for a more technical description of the model. We optimize over two important hyper-parameters; the number of trees in the forest, and the maximum depth of the tree. For the remaining parameters used in the algorithm, we use default values set in the Python package *scikit-learn* (Pedregosa et al., 2011). Because the model's solution procedure includes randomness we use a seed that guarantees reproducability.

solve for the optimal parameter vector.[30] In line with Burlig et al. (2020) we deploy a block-sampling approach when splitting the data into training data and validation data. More precisely, we sample the data at the daily level rather than at the hourly level to account for potential auto-correlation in the data. The selection of this method has been inspired by the bootstrapping literature for dependent processes (see, e.g., Künsch, 1989; Liu and Singh, 1992; White, 2000).

In Table 1, we benchmark the outcome of the two prediction models and summarize their accuracy, precision, and recall values. To compute these model performance magnitudes, we assume the predicted value of y, $\hat{y}$, is equal to one it the predicted $\mathbb{P}[y = 1|X] > 0.5$ and zero otherwise. The "Accuracy" metric measures how often the classifier is correct, i.e., summing up the true positives and the true negatives and dividing by the sample size. The "Precision" metric is how often the positive predicted values are correct, i.e., the number of true positives divided by the sum of the number of true positives and the number of false positives. The "Recall" or "Sensitivity" metric is the true positive rate, that is the number of correctly identified positives divided by the total number of actual positives. We calculate each metric at the unit level, and the table displays the mean and standard deviation across all units. Columns (1)–(2) summarizes the accuracy metrics for the models that predict the probability of getting INCed while Columns (3)–(4) summarizes accuracy of the DEC prediction models. Columns (1) and (3) correspond to the logit model, Columns (2) and (4) correspond to the cross-validated random forest model. The random forest model outperforms the logit model across all measures for INC as well as for DEC, that is why we select it as our preferred model for the probability a generation unit is INCed or DECed.

[30]We use conservative maximum values to further mitigate the risk of over-fitting. More precisely, we search for the maximal number of trees in the following range [10, 20, ..., 100] and for the depth of each tree in [2,3,...,10].

Table 1: Summary of Prediction Models

	INC		DEC	
	(1)	(2)	(3)	(4)
Accuracy	0.89	0.93	0.82	0.89
	(0.06)	(0.04)	(0.07)	(0.03)
Precision	0.67	0.86	0.67	0.94
	(0.09)	(0.33)	(0.06)	(0.07)
Recall	0.29	0.42	0.39	0.53
	(0.18)	(0.26)	(0.23)	(0.27)

Notes: Table displays mean and standard deviation (in parentheses) of unit-level predictions to be INCed or DECed across all units. Results in Columns (1) and (3) correspond to a logit model and Columns (2) and (4) correspond to a cross-validated random forest model.

5.2 Calculating day-ahead offer markups

This section describes how generation unit level markups, defined as the difference between the day-ahead market offer price and the short-run marginal cost for a generation unit, move with probability a generation unit is INCed or DECed. Each unit can be offered into the day-ahead market with a weakly increasing step function offer curve with four price steps. We calculate an offer-quantity-weighed average offer price for each hour and unit.[31] Reducing the offer curve to a single number makes it easy to compare it to the short-run marginal cost. We calculate the short-run marginal cost for each unit and day based on heat-rate estimates, daily market quotations of fuel costs, variable operation and maintenance costs, and monthly average emissions prices (see Graf et al., 2020, for more details). Subtracting the marginal cost from the quantity weighed average offer price results in the markup. We use all day-ahead market price offers (including self-schedules).

For the case that capacity from a generation unit was not offered in the day-ahead market we assign an offer price of 300 EUR/MWh to the available capacity. Participation in the day-ahead market is not compulsory and therefore market participants may opt to withhold (part

[31] In Section B we use different approaches to compute offer price. Our results are robust to these choices.

of) their capacity by either not offering it at all or offering it at a very large offer price. The maximum observed price for the demand side in the day-ahead market was 170 EUR/MWh over the years 2017 and 2018. Hence, setting the offer price as high as 300 EUR/MWh has the same effect as a physical capacity withholding. In Section 7, we provide the results of a robustness check that does not depend on the assumption of employing a fictitious offer price for physically withheld capacity.

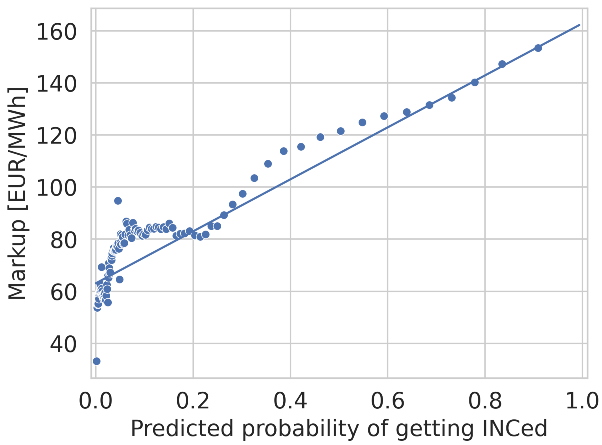
6 Empirical Results

In this section, we show that there is a precisely estimated increasing relationship between the *predicted* probability of getting INCed in the re-dispatch market and the markup set in the day-ahead market and decreasing relationship between the *predicted* probability of getting DECed in the re-dispatch market and the markup set in the day-ahead market.

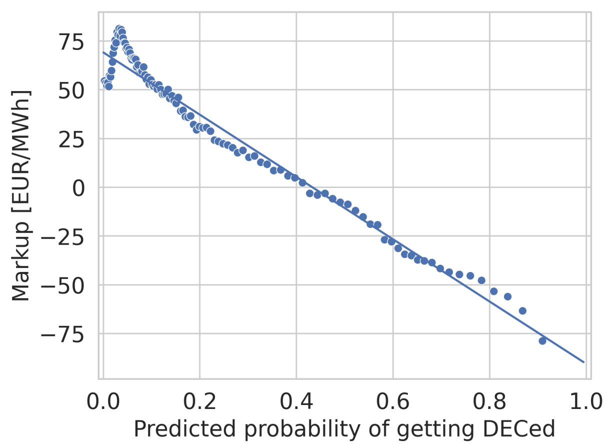
Before we estimate the predicted probability of getting INCed or DECed in the re-dispatch market and the markup set in the day-ahead market using all the units in our sample and different sets of controls, we present a graphical analysis using the binscatter developed in Cattaneo et al. (2019). We control for generation unit-level, hour-of-day, day-of-week, and month-of-year fixed effects and choose the number of selected bins to minimize the (asymptotic) integrated-mean-squared error as recommended in Cattaneo et al. (2019). Figure 5, Panel a, shows an approximate upward sloping linear relationship between the predicted probability of getting INCed and the markup set in the day-ahead market. In Panel b, we find the opposite relationship, i.e., an approximate downward sloping linear relationship between the predicted probability of getting DECed and the markup set in the day-ahead market.

In estimating the relationship between the predicted probability of getting INCed or DECed in the re-dispatch market and the markup set in the day-ahead market we include generation unit level fixed effects that account for the fact that different generation units set

Figure 5: Binscatter of Markups and Predicted Probability of getting INCed/DECed



(a)



(b)

Notes: Panel (a): Day-ahead offer markup and predicted probability of getting INCed, Panel (b): Day-ahead offer markup and predicted probability of getting DECed. Markups in EUR/MWh. Binscatter regression controls for unit, hour-of-day, day-of-week and month-of-year fixed effects using Cattaneo et al. (2019) nonparametric approach. Number of bins minimizes the (asymptotic) integrated mean squared error.

different baseline markups. We summarize these results in Table 2. Columns (1), (2), (3), and (4) show the regression results for the units that supply most of the incremental energy and Columns (5), (6), (7), and (8) for the units providing most of the decremental energy. In Columns (1) and (5), we use a very basic panel data regression specification accounting only for unit fixed effects. In the model specification displayed in Columns (2) and (6), we account also for hour of the day fixed effects as well as month of the sample fixed effects.

The results of a more flexible model formulation accounting also for the interaction effects between unit and month of the sample is presented in Columns (3) and (7). Finally, in Columns (4) and (8), we include cubic polynomials of the forecast net load that is the day-ahead load forecast net of the forecast supply from wind and solar, hour-of-day, day-of-week, and month-of-year fixed effects.

The coefficient of interest in all these regressions is on the predicted probability of getting INCed or DECed. The interpretation of this coefficient is that if the predicted probability of getting INCed [DECed] increases from zero to one the markup increases [decreases] by x EUR/MWh. In Panel A—the specification where we include all observations, the coefficient of the predicted probability of getting INCed [DECed] ranges between 82 and 107 EUR/MWh [-162 and -152 EUR/MWh]. The standard errors are clustered at the unit level to allow for arbitrary forms of autocorrelation and heteroscedasticity in the errors across generation units. Even with these standard errors the parameter estimates are very precisely estimated, confirming that when the predicted probability of getting INCed is high a large markup is set in the day-ahead market. In the DEC case, we observe the opposite effect; when the predicted probability of getting DECed increases the markup on the day-ahead market offer price decreases. As mentioned previously, even a negative markup may be a profitable strategy in case of a high probability of getting DECed in the re-dispatch market and given a spread between the day-ahead market price and the DEC price that is positive.

A potential concern with our analysis may be that we also include market bids that have only a slim chance of being dispatched at all and hence underestimate the effect of the predicted probability of being INCed or DECed on the markup put on the day-ahead market offers. Italy has a substantial amount of CCGT capacity that operates with low capacity factors.[32] Consequently, in some hours there is only very little demand left to be served by these CCGT units. In cases where a unit has a small chance of being dispatched at all or only for a few hours it may be rational to bid a steep offer curve into the day-ahead market. This behavior is enforced by the different market-clearing models. If a unit will be dispatched in the re-dispatch market it will also be compensated for its energy as well as its offered start-up cost. This makes offering capacity in the day-ahead market riskier than selling into the re-dispatch market, because the day-ahead market provides the unit with no guarantee that it will recover its start-up costs. To show that this concern has a tangible impact of our empirical results, we exclude all offers that are not dispatched in the day-ahead market or in the re-dispatch market. The results of this exercise are summarized in Table 2, Panel B. For the INC side we find that of the 612,939 total observations only 331,563 remain, when

[32] Reasons for that are: (i) cheap imports from neighboring countries (nuclear in France and hydro in Switzerland and Austria), (ii) cheap domestic production from hydro (Italian alps) and renewables (wind, solar, and geothermal).

applying our criteria. Comparing the estimates of the intercept for the base-line model using all observations (Panel A, Columns 1 and 5) with the estimates of the reduced sample (Panel B, Columns 1 and 5), we find that the estimated intercept becomes effectively zero.[33] That means, the predicted markup of the average unit is zero when the predicted probability of getting INCed or DECed is zero. Put differently, the average unit is offered competitively to the day-ahead market in case there is no predictable outside option when we restrict the sample to only market-relevant transactions. As a consequence, we find that the coefficient of interest increases by approximately factor two on the INC side. Accounting also for the change in the intercept, the average predicted markup if the predicted probability of getting INCed equals one, is about 230 EUR/MWh compared to 166 EUR/MWh when we do not restrict the sample. This shows that for bids that are market-relevant the average markup moves even more strongly with an increase in the expected probability of getting INCed. On the DEC side, the coefficients on the predicted probability of getting DECed is approximately halved. The qualitative interpretation of our results is unchanged as a result of this sample selection procedure. A high predicted probability of getting INCed predicts an higher markup in the day-ahead market and a higher predicted probability of getting DECed predicts a lower markup.

In order to demonstrate that these results can also be derived by using conventional prediction models such as a logit model or a linear probability model to estimate the probability of getting INCed or DECed at the unit level, we re-run the analysis described above with the only difference that a different prediction model is used. The results are summarized in Table 3 and besides having slightly smaller in absolute value coefficients of interest, our qualitative results are unchanged.

The previous model uses the estimated probability of being INCed or DECed to explain the day-ahead market offer markup. A different modeling approach would be to make the

[33]The intercept is calculated in line with the logic of how it is implemented in Stata and therefore represents the average value of the fixed effects, see `https://www.stata.com/support/faqs/statistics/intercept-in-fixed-effects-model/` for more details.

assumptions that generation unit owners have rational expectations about when their units will be INCed or DECed and these expectations on variables we use to estimate the probability of being INCed or DECed. This assumption replaces the probability of the unit being INCed or DECed with the indicator variable of whether a unit was INCed or DECed and uses the predicted probability as an instrument for this endogenous indicator variable. In Table 4, we present the results separately for all three models to derive the unit-level predictions of getting INCed or DECed. The coefficients are slightly lower for the INC side and slightly larger for the DEC side than in the specifications where we directly use the predicted probability and all of the coefficient estimates are precisely estimated.

6.1 Double/Debiased Machine Learning Estimate

In the previous section we accounted for a fairly limited set of controls in estimating our markup models. We replace the set of controls we used with a rich set variables, including zonal residual demands (national and neighbouring countries and Germany), squared terms and interaction terms thereof; transmission limits; gas prices, gas prices squared; unit, hour-of-day, workday, and month-of-year fixed effects. Given the large number of regressors, OLS estimation of this model may lead to over-fitting. A naïve approach would be to simply estimate the model using a LASSO regression. The advantage of LASSO is that it will pick the most important regressors from the large set of regressors potentially including many irrelevant regressors (sparsity assumption). However, in any case the resulting estimates will be biased due to the regularization term introduced in LASSO. Therefore, we apply the double/debiased machine learning for treatment effects parameters introduced by Chernozhukov et al. (2018).[34] We present the results using this approach in Table 5. The point estimates, are in line with the estimates presented in Table 2, Panel A.

[34] We use Stata's implementation, that is, the cross-fit partialing-out lasso linear regression (*xporegress*). We use the standard parametrization, most importantly, ten folds for cross-fitting.

7 Robustness Analyses

In our main specification for predicting whether a unit will be INCed or DECed in the re-dispatch market, we ignore portfolio effects between generation units owned by the same market participant. Our main argument for this prediction model is that generation units have unique characteristics such as location or technology that makes them an essential resource for balancing the market and ensuring a secure operation of the grid. However, there may still be portfolio effects in the sense that the likelihood of a unit being taken in the re-dispatch market may also depend on how the firm has offered its portfolio of generation unit into the day-ahead market. As emphasized by Graf and Wolak (2020), the spatial distribution of firm level offer curves can impact the prices paid all generation units owned by the firm.

The first modification of our prediction model is therefore to include the zonal quantity the unit owner has offered to the day-ahead market at "competitive offer prices." More precisely, we calculate the aggregate zonal quantity for each firm that has been offered into the day-ahead market at a price lower or equal to its short-run marginal cost. We only account for thermal units that are eligible to be operated in the re-dispatch market. For each of the INC and DEC units under consideration, we then add only the quantity values of the same firm, say firm X owns unit j that is a relevant INC unit; then we add only the capacity offered competitively by firm X as explanatory variable. Adding this feature to the probability of an INC or DEC in the re-dispatch market model improves our forecast metrics (see Table 6, Panel A). Regressing the day-ahead markup using the alternative prediction of an INC or DEC in the re-dispatch market only slightly changes the relevant coefficients though (see Table 7, Columns 1 and 4).

The second robustness check we consider is that instead of using only data from the scheduling phase of the re-dispatch market as our measure of the unit-level re-dispatch INC and DEC demand, we replace it by the total re-dispatch demand for INCs and DECs from the unit. That is the sum of the INC and DEC demand for each unit from the scheduling phase of the re-dispatch market and the real-time balancing market. Only sizeable INCs and DECs, with at least 10% of the unit's available capacity are counted as INCs and DECs for this analysis. The reason for this definition of INCs and DECs is that in practice a unit may be INCed and DECed several times between the day-ahead market-clearing and real-time depending on the several updates of the state of the system. For example a unit may be INCed by 20% of its available capacity in the scheduling phase of the re-dispatch market and the same unit may be DECed by 1% of its capacity to balance the system in real-time. Strictly speaking this unit would not only be INCed in the real-time re-dispatch market but would also be DECed. In order to better filter out the dominant part of the unit-level real-time demand for INC and DEC we apply the 10% criterion. The prediction metrics for this definition of generation unit-level INCs and DECs are presented in Table 6, Panel B, and the regression of the markups on predicted probabilities of an INC and DEC are given in Table 7, Columns (2) and (5). Our qualitative results are not impacted by this modified definition of INCs and DECs.

In Table 6, Panel C, and Table 7, Columns (3) and (6), we present the INC and DEC prediction metrics as well as the markup regression results combining both alternative specifications described above. Specifically, we use the 10% of capacity criteria for INCs and DECs described above and then we account for the portfolio effects described in the second paragraph of this section in the INC and DEC prediction model. Once again, we find that our empirical results for the impact of an increase in the probability of being INCed or DECed on offer price markups in the day-ahead market are qualitatively similar to the results in the previous section.

Another concern may be that we are using the markup set in the day-ahead market. Market participants are allowed to submit non-decreasing step functions with four steps for each unit into the day-ahead market, hence the unit-level markup is a function of the offered quantity. We by-pass this challenge by calculating a capacity-weighted average offer price where we have associated a 300 EUR/MWh offer price to available capacity that is not offered in the day-ahead market. In order to show that our results are independent of both assumptions, we construct an alternative metric, that is the competitively offered capacity share. This share is calculated as the quantity offered to the day-ahead market at an offer price lower or equal than the unit's short-run marginal cost relative to its available capacity. If the firm offers all its capacity at short-run marginal cost or below this metric takes the number one. If all the capacity is withhold from the day-ahead market or offered above the unit's short-run marginal cost this metric takes the number zero. For piece-wise constant offer functions that intersect with the short-run marginal cost of the unit, the metric takes a number between zero and one.

The regression results are presented in Table (8). Note that the signs of the coefficients are reversed now, which is due to the construction of the metric. For example a negative share of competitively offers capacity x for the INC re-dispatch product means that if the probability of getting INCed increases from zero to one, the unit's owner offered x percent less of its available capacity than when the probability of getting INCed is zero. In other words, as the probability of getting INCed increases less capacity will be offered competitively into the day-ahead market. We find the reverse effect for the DEC re-dispatch product. To summarize, the results using the competitive offer share at the unit-level instead of the markup yields effectively the same quantitative results as our markup results.

In Appendix B, we present results replacing the predicted probability of getting a unit's schedule INCed or DECed by the expected quantity of getting INCed or DECed. In other words, we account for the fact that the unit-level day-ahead offer-price markup may be a function of the expected quantity of being re-dispatched. The results turn out as expected that there is a statistically significant positive effect of the predicted INC quantity on the average offer-price markup and there is a statistically significant negative effect of the predicted DEC quantity on the average offer-price markup. We furthermore present a statistical analysis where we include both predicted probabilities for INC and DEC in a single regression and different ways of computing unit-level markups. The qualitative interpretation of our results remain robust to these changes.

8 Total Cost to Serve Load and Re-dispatch Cost

This section explores the market efficiency consequences of the INC/DEC activity documented in the previous section compared to the total cost wholesale electricity to consumers. This section also provides evidence that both high and low levels of net demand, system demand less intermittent renewables production, impacts re-dispatch costs.

The *actual* hourly real-time re-dispatch cost, excluding start-up costs, are

$$\sum_j p_j^{\mathrm{INC}} q_j^{\mathrm{INC}} - p_j^{\mathrm{DEC}} q_j^{\mathrm{DEC}}, \tag{5}$$

where p_j^{INC} is the INC price paid to unit j, q_j^{INC} is the INC quantity sold by unit j, p_j^{DEC} is the DEC price paid by unit j and q_j^{DEC} is the DEC quantity purchased by unit j. This is the actual cost of the re-dispatch the transmission system operator passes through to the final consumer in form of the grid fee. We compute total re-dispatch costs and the cost of real-time demand at the hourly day-ahead price for all hours of two-year sample period. Total re-dispatch costs are 9% of this measure of the total cost of real-time demand over our two-year sample period.[35]

However, the re-dispatch cost calculated above does not include the economic value of energy sold in the day-ahead market that is useless in real-time. More precisely, the total DEC quantity that is bought back by the market participants was first sold at the day-ahead market price. The following modification accounts for this aspect

[35]The annual total demand (net of pumping and grid losses) reached 303 TWh in 2018 and 302 TWh in 2017. The average day-ahead market price relevant for the demand side was 61.3 EUR/MWh in 2018 and 54.0 EUR/MWh in 2017. Re-dispatch cost that includes the procurement of reserves as well as real-time balancing was about 1.5 billion Euros per year in 2017 and 2018 (these figures do not include payments for start-up costs and thus represent a lower bound of the actual re-dispatch cost). Thus, re-dispatch cost are $\frac{2\cdot 1.5\cdot 1e9}{(303\cdot 61.3+302\cdot 54)1e6} \approx 9\%$ of the total cost of real-time demand over our two-year sample period.

$$\sum_j (p^{\mathrm{DA}} - p_j^{\mathrm{DEC}}) q_j^{\mathrm{DEC}} + p_j^{\mathrm{INC}} q_j^{\mathrm{INC}}, \tag{6}$$

where p^{DA} is the day-ahead price. Using the metric above, we find the total *economic* cost of the re-dispatch to be 15% relative to real-time demand valued at the day-ahead market price over our two-year sample period.

Figure 6, Panel (a), shows the daily re-dispatch cost defined in (5) as a function of daily net demand. In the re-dispatch market, intertemporal constraints on thermal resources are accounted for and the optimization horizon of the first session of the re-dispatch market is 24 hours. That is why we focus on daily re-dispatch costs as they also include the cost paid to thermal units for start ups. Surprisingly, the figure reveals a U-shaped relationship between the re-dispatch cost and the net demand. The right part of the "U" can be explained by traditional market power logic, i.e., a higher demand means that there is less competition for a marginal increase of supply.

The left part of the "U" requires more explanation. On low-demand days such as weekend days, holidays, or days with typical levels of renewable production, one would expect low re-dispatch costs because of substantial competition between thermal plants that have spare capacity. However, on days with low net demand, the transmission grid may be more vulnerable because little controllable capacity is committed and therefore voltage issues may arise. As a consequence, the transmission system operator usually requires a small number of units to be online at different locations to ensure secure operation of the grid. However, if these unit owners are able to predict when these units are needed, they may decide to schedule different units in the day-ahead market and wait to get paid as-offered to increase the output from these necessary units. As shown in Section 3, the units scheduled in the day-ahead market that cannot meet these locational energy requirements will sell back decremental energy at a lower price than the day-ahead market price. Consequently, a supplier that owns multiple generation units could earn revenues from both INCing and DECing in the re-dispatch market during the same hour of the day.

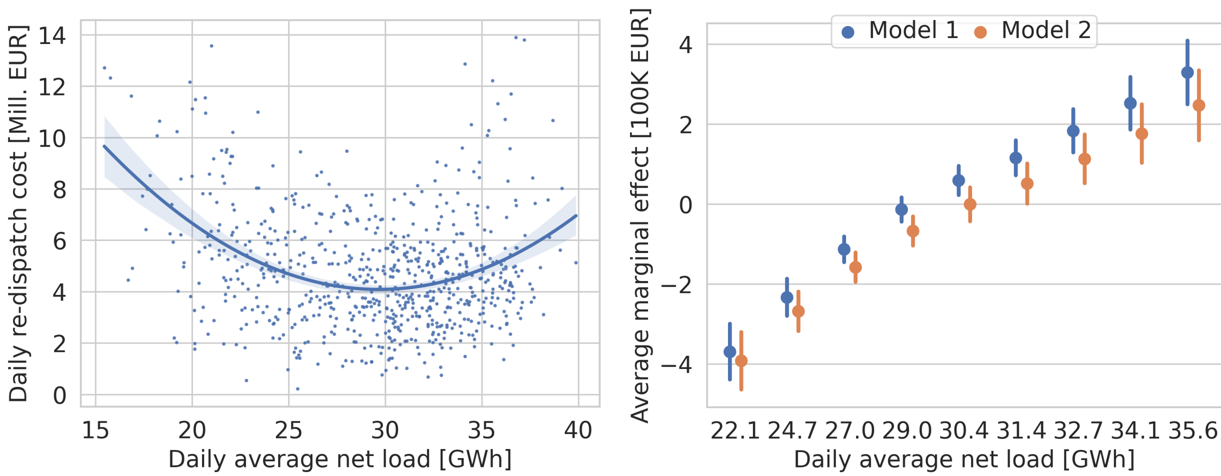
In Table 9, we regress the re-dispatch cost on the net demand (Column 1), use the squared net demand (Column 2), and also include the intradaily standard deviation of the net demand (Column 3). We include month-of-sample fixed effects in all regressions to account for monthly variation in hydro production but also in output from renewable sources (primarily solar photovoltaics). We show the average marginal effects evaluated at different net demand levels for the last two regression specifications in Figure 6, Panel (b). The average marginal effects confirm the fitted U-shaped functional form in Figure 6, Panel (a). Put differently, an increase in net demand in low net demand days predicts a reduction of the re-dispatch cost while an increase in high net demand days predicts an increase of the re-dispatch cost.

There is a vast amount of literature showing that an increase of close-to-zero marginal cost renewables leads to lower day-ahead market prices (see e.g., the literature review in Wozabal et al., 2016). All these papers assume a static merit order stack of conventional power plants and an increase in output of infra-marginal renewables acts as if the demand were decreased and therefore makes a cheaper unit marginal. We find this effect in the Italian day-ahead market (see Figure 7, orange line). The relationship appears to be inverse S-shaped which is in line with what Wozabal et al. (2016) found. We then calculate the total cost to serve load that we define as

$$p^{\mathrm{DA}} Q^{\mathrm{RT}} + \sum_{j} p_j^{\mathrm{INC}} q_j^{\mathrm{INC}} - p_j^{\mathrm{DEC}} q_j^{\mathrm{DEC}},$$

where Q^{RT} is the actual demand in real-time. The second fitted line in this figure represents this total cost per MWh demand and surprisingly we find that the average total cost seem to be diverging from the day-ahead market price on days with low net demand. The U-shaped re-dispatch cost makes the average cost of serving load significantly more expensive on low net demand days. Note that the INC/DEC activity has exactly this effect because capacity is offered to the day-ahead market at offer prices below short-run marginal cost which depresses the day-ahead market price and through INC activity firms earn profits in the re-dispatch market.

Figure 6: Daily Re-dispatch Cost vs. Average Daily Net Load



(a) (b)

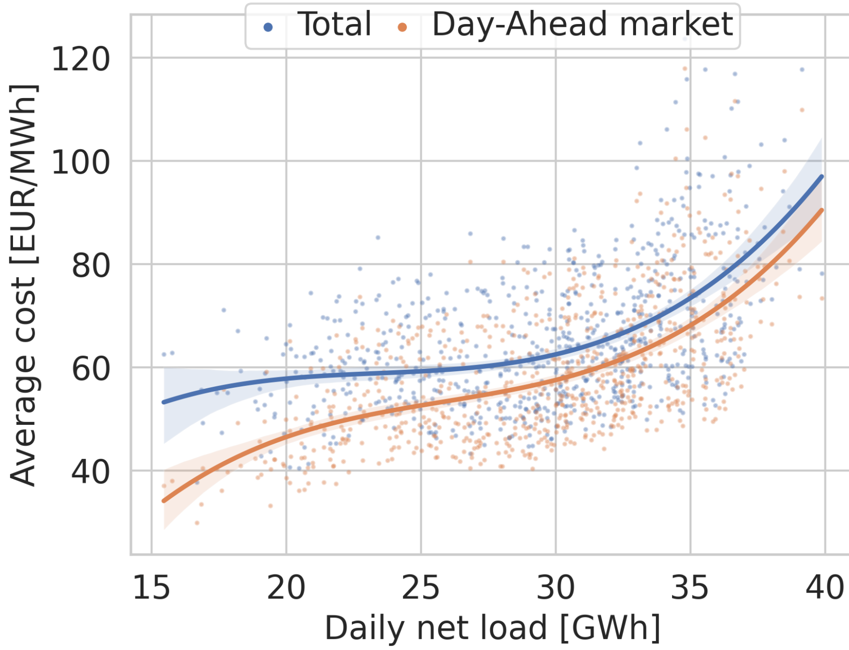
Notes: Panel (a): Average daily re-dispatch cost and average daily net load for the years 2017 and 2018; Panel (b) Corresponding average marginal effects of a change in the daily net load evaluated at the net load deciles. Model 1 refers to a linear regression model aiming to explain the daily re-dispatch cost by the daily average net, the square of it, and month of the sample fixed effects. In Model 2 we also include the intradaily standard deviation of the net load. Both models are summarized in Table 9, Col (2) and Col (3).

9 Counterfactual Analysis

In this Section, we present a counterfactual analysis comparing the actual outcomes in the Italian market to the counterfactual outcomes of an US-style integrated market which explicitly accounts for necessary system constraint already in the day-ahead market-clearing mechanism. Our analysis is based on the market model in Graf et al. (2020)—our companion paper that describes how to derive a competitive benchmark in locational markets with non-convexities. We introduce different distortions from marginal cost offer behavior that yield roughly the same average cost of wholesale electricity to consumers in order to quantify the potential consumer benefits from transitioning the existing market design to a US-style integrated market.

Our earlier two-generator example helps to explain our counterfactuals. In the simpli-

Figure 7: Total Cost to Serve Load vs. Load Weighted Average Day-Ahead Market Price



Notes: Average total cost to serve load (Total) is calculated as the demand valued at the demand-side day-ahead market price plus the re-dispatch cost. This value is then divided by the demand to get an average cost per MWh demand. Demand purchased or sold in the intra-day markets is ignored. Daily averages for the years 2017 and 2018.

fied market design version the market-clearing price of energy in day-ahead market was \$116/MWh to serve a demand of 120 MWh, but because of the need to DEC G1 for 30 MWh and INC G2 for 30 MWh in real-time, the total cost to serve load ended up equaling \$16,880, which implies an average cost to serve load of \$140/MWh. For our counterfactual calculations, we assume a uniform markup of M on the marginal cost of each generation unit and compute the total cost to consumers of wholesale electricity under a US-style integrated market.

In this simplified example we can solve for the exact markup that makes the average cost to serve load equal to \$140/MWh. A value of $M = \frac{6}{13} = 46\%$ yields an integrated market dispatch of 70 MWh by G1 and 50 MWh G2 at market-clearing price of \$29.23 which also equal to G1's offer price. G2 receives \$1461.53 in revenues from selling energy at this market-clearing price plus a make-whole payment of \$6,646.15, the sum of which which recovers G2's start-up cost of $800 and its as offered cost of producing 70 MWh of $7307.69.

This result implies that suppliers could exercise a significant amount of unilateral market power by submitting offer prices that are 146% of the marginal cost of producing energy under the integrated market design and still achieve the same total cost to consumers of wholesale electricity as the simplified market design. Because of the computational complexity of the counterfactuals presented below we are unable to compute the precise markup that yields the same average cost of wholesale electricity to consumers. Instead, we simply present average cost of wholesale electricity for different marginal cost markup scenarios.

9.1 Counterfactual Market Scenarios

The main difference between the integrated market model and the simplified market model is that in the former, the transmission network is modeled at the nodal level, non-convexities of conventional power plants are explicitly considered, and the potential economics of coordination between energy, reserves, and system services are exploited. The simplified market model, in contrast, most system constraints are only considered in the re-dispatch market or put differently, the (locational) demand for system services is only partially reflected in the day-ahead market design. On top of that, market participants can freely schedule their units in the day-ahead market,[36] that includes the decision to schedule units that likely will *not* be needed in real-time.

In order to simplify our analysis and because we found that the congestion within zones is rarely present, we run the counterfactual analysis here using the zonal resolution of the network.[37] Furthermore, we include system constraints such as locational upward reserve requirements as well as voltage constraints. We use actual imports and supply from non-dispatchable units to be convex price taking offers valued at zero EUR/MWh and actual

[36]Unlike in Germany or other European member states, Italy at least enforces cross-zonal transmission capacity limits in the day-ahead market that limits the ability of market participants to submit infeasible generation schedules.

[37]We use a so-called transportation network flow model that is an accurate description in the Italian case because of the radial network structure.

zonal demand and exports by inelastic demand bids valued at the value of lost load that we set to 10,000 EUR/MWh. Dispatchable units are modeled using their actual minimum stable production level, ramp rates, minimum up time, and minimum down time. And the market-clearing is solved conditional on actual supply schedules of these units from the previous day. Units can offer a price for energy as well as a price to start-up the unit. In the competitive benchmark these values are set to the short-run marginal cost and the competitive start-up costs respectively. The analysis comprises all days in 2018 except the two days of the year were the clock changes from wintertime to summer time and vice versa.

Before we model imperfectly competitive behavior, we first compare the actual cost to serve a MWh of demand to the results of the competitive benchmark model. Comparing Columns (1) and (2) of Table 10, we find that the actual per MWh cost to serve demand amounts to 69.2 EUR/MWh in the year compared to 64 EUR/MWh in the competitive benchmark. The benchmark costs consist of two parts the energy costs as well as the so-called "make-whole" payments or side-payments that are necessary because the market-clearing model is non-convex and therefore resulting dual prices may need to be complemented to ensure that each unit is able to earn its as-offered costs conditional on being operating. On an annual level this yields a saving of 1.6 billion Euros given a demand of 300 TWh.

Next, we study the sensitivity of the wholesale energy costs to serve load as a response different energy offer curves for the dispatchable units. It is important to remember that as shown in Section 6, market participants operating under a simplified market design can be incentivized to offer their units below SRMC if they expect to have their output to be decreased in the re-dispatch market. We compute counterfactual market outcomes assuming that the same percentage markup (over short run marginal cost) is deployed by all dispatchable units. We restrict this modification of offer curves to peak hours that we define as business days (i) 6:00–22:00 and (ii) 16:00–22:00. We only alter price offers but not start-up costs. We justify this choice by following the practice of the Californian ISO (CAISO) that currently mitigates a generation unit's minimum load and start-up offers (see e.g., Bushnell et al., 2014). We first alter the price offers of dispatchable units by 10%. In Columns (3) and (4) of Table 10, we find that this would raise the average market outcome from 64.0 EUR/MWh to 67.6 EUR/MWh (6:00–22:00) and 65.4 EUR/MWh (16:00–22:00). Hence, both case are below the actual costs to serve demand. Raising the unit-level offers by 15% (Columns 5, and 6) would still result in an total average cost to serve load that is lower in the evening peak hours and approximately equal using the more tolerant definition of peak hours. Only a drastic increase of unit-level price offers of 40% would lead to approximately the same average total costs to serve demand as in the status-quo.

Before we conclude, we briefly address a potential point of critique concerning the multi-stage planning process prevalent in electricity markets. Virtually all wholesale electricity markets operate a day-ahead market in which the actual locational net demand is uncertain and hence the day-ahead market will be cleared conditional on expected locational net demands. Net demand forecast are likely to change when approaching real-time, hence there will be a demand to change the output from dispatchable units to react to a change in forecast demand or the forecast output of renewables. Assuming that forecast errors are normally distributed and centered around zero and assuming that aggregate real-time willingness to change output curve is linear, these costs will be zero in expectation. Unlike in the simplified market model, the integrated model does typically not require severe re-dispatch actions because all the relevant system constraints are already accounted for in the day-ahead market. This means the day-ahead market outcome will be compatible with the physical reality of the network thus the output from dispatchable units will only be affected by changes in forecast of net demand and not be driven by intentionally scheduling to force the transmission system operator to re-dispatch in order to cope with network and security constraints to securely operate the grid. Needless to say if the real-time offer curves, i.e., the offer curves to change output conditional on the day-ahead market dispatch are highly convex, real-time balancing costs will be non-zero. However, as shown in Jha and Wolak (2021) financial participants that are able to engage in price arbitrage between the day-ahead market and the real-time market are reducing those costs.

To summarize, we find that even when considerably altering offer prices of dispatchable units above short run marginal costs the actual costs to serve demand exceed the counterfactual costs. Focusing on the evening peak hours on business days an offer price increase uniformly over all dispatchable units of 40% leads to approximately the same average total costs to serve demand. We want to point out, that in virtually all US wholesale market an automated locational market power mechanism as reviewed in Graf et al. (2021a) is run before each market session and hence markups of 40% above short-run marginal costs may not even be possible depending on the locational level of competitiveness.

10 Discussion and Conclusion

Because linear prices set by simplified markets are unable to decentralize the efficient dispatch solution based on each supplier's energy offer curve, these markets require a re-dispatch process to produce physically feasible real-time generation unit operating levels. We find that the conditional probability of being INCed or DECed in this re-dispatch market will change the day-ahead offer markup set by market participants for their thermal power plants. In other words, the re-dispatch market provides a lucrative outside option to sell and buy energy because the day-ahead market does not include all the constraints that appear to be relevant for secure real-time operation of the electricity grid.

Our results from the Italian electricity market are a cautionary tale for the European Market design, where a market-based re-dispatch process has been recommended.[38] Unlike in other continental European day-ahead markets, Italy accounts for within-country transmission constraints through bidding zones. Consequently, re-dispatch costs as a fraction of total wholesale energy costs in Italy are likely to be lower than in the single-zone markets that currently exist in other European countries.

The ambitious renewable energy goals in virtually all European countries imply that the

[38] See `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX%3A32019R0943`, Article 13.

cost to electricity consumers of simplified market designs is likely to increase. A number of the US wholesale markets transitioned from simplified market designs to integrated market designs and realized operating cost savings in the range of 2.1 to 3.9 percent.[39] The annual operating cost of wholesale electricity in Europe is easily in excess of 70 billion Euros, which implies that a similar percent savings from transitioning to integrated market designs in Europe could easily exceed 1 billion Euros annually.

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Table 2: Regressing Markups on Predicted Probability of getting INCed or DECed

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All observations								
Predicted $\mathbb{P}_i[y_i = 1 \mid X]$	84.30	91.79	81.80	107.22	-162.26	-160.64	-151.53	-161.52
	(21.13)	(16.91)	(14.50)	(18.03)	(32.09)	(30.60)	(30.32)	(28.83)
Net Load				10.95				-0.59
				(2.24)				(2.29)
(Net Load)^2				-0.44				-0.04
				(0.08)				(0.07)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	81.97	116.07	116.15	69.03	75.73	85.55	86.30	137.34
	(2.89)	(6.66)	(4.89)	(19.25)	(8.05)	(11.59)	(10.73)	(26.87)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148
Panel B: Only observations with market-relevant transactions								
Predicted $\mathbb{P}_i[y_i = 1 \mid X]$	232.40	226.69	215.84	227.24	-62.51	-61.75	-54.57	-63.99
	(30.45)	(31.42)	(30.61)	(31.86)	(17.81)	(17.42)	(16.40)	(17.64)
Net Load				15.08				0.33
				(2.92)				(1.55)
(Net Load)^2				-0.47				-0.01
				(0.09)				(0.05)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	-2.00	19.83	24.10	-123.37	8.00	14.93	9.34	18.49
	(5.62)	(5.88)	(5.37)	(36.13)	(5.06)	(5.79)	(6.02)	(17.12)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	331,563	331,563	331,563	331,563	406,690	406,690	406,690	406,690

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Table 3: Regressing Markups on Predicted Probability of getting INCed or DECed (Alternative Forecast Models)

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Logit model				
Predicted $\mathbb{P}_i[y_i = 1\|X]$	58.73	62.71	49.01	80.40	−127.19	−127.80	−105.13	−130.45
	(20.94)	(15.92)	(14.40)	(16.07)	(27.42)	(25.62)	(27.31)	(23.53)
Net Load				8.64				−1.94
				(2.13)				(2.06)
(Net Load)^2				−0.36				−0.02
				(0.08)				(0.07)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	83.96	115.97	115.05	88.14	68.43	81.86	78.98	156.59
	(3.03)	(6.94)	(4.86)	(18.81)	(7.07)	(10.72)	(10.21)	(23.35)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	578,061	578,061	578,061	578,061	477,666	477,666	477,666	477,666
				Panel B: Linear probability model				
Predicted $\mathbb{P}_i[y_i = 1\|X]$	55.69	61.42	44.80	82.59	−131.34	−131.83	−108.98	−134.92
	(25.69)	(19.13)	(19.09)	(19.44)	(28.04)	(26.21)	(28.67)	(24.11)
Net Load				8.78				−0.87
				(2.09)				(2.14)
(Net Load)^2				−0.38				−0.05
				(0.08)				(0.07)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	85.83	119.88	120.35	95.59	68.08	81.32	78.52	143.65
	(3.54)	(7.49)	(5.74)	(18.67)	(7.06)	(10.53)	(10.23)	(23.28)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Performing logit regressions to predict the probability of getting INCed or DECed at the unit level slightly decreases the number of observations because categories such as e.g., month-of-year, that lead to a perfect prediction are dropped from the sample. Standard errors (clustered at the unit level) in parentheses.

Table 4: Regressing Markups on whether a Unit has been INCed or DECed (Two-Stage Least Squares)

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Instrument is predicted $\mathbb{P}_i[y_i = 1\|X]$ using random forest model							
y_i	55.45	60.18	52.32	70.06	-99.70	-97.69	-85.57	-98.18
	(13.86)	(11.08)	(9.27)	(11.73)	(20.40)	(19.24)	(18.36)	(18.10)
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148
	Panel B: Instrument is predicted $\mathbb{P}_i[y_i = 1\|X]$ using logit model							
y_i	59.10	63.11	49.39	80.85	-126.72	-127.29	-104.54	-130.25
	(20.90)	(15.83)	(14.30)	(16.05)	(27.31)	(25.49)	(27.15)	(23.41)
N	578,061	578,061	578,061	578,061	477,666	477,666	477,666	477,666
	Panel C: Instrument is predicted $\mathbb{P}_i[y_i = 1\|X]$ using linear probability model							
y_i	55.69	61.42	44.80	82.78	-131.34	-131.83	-108.98	-135.30
	(25.69)	(19.13)	(19.09)	(19.51)	(28.04)	(26.21)	(28.67)	(24.13)
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. The four model specifications for INC and DEC correspond to the specifications in terms of fixed effects and covariates presented in Table 2. Performing logit regressions to predict the probability of getting INCed or DECed at the unit level slightly decreases the number of observations because categories such as e.g., month-of-year, that lead to a perfect prediction are dropped from the sample. Standard errors (clustered at the unit level) in parentheses.

Table 5: Markups on Predicted Probability of getting INCed or DECed using Double/Debiased Machine Learning

	INC	DEC
Predicted $\mathbb{P}_i[y_i = 1\|X]$	91.38	-130.58
	(8.69)	(8.47)
N	612,939	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Standard errors (clustered at the unit level) in parentheses.

Table 6: Summary of Prediction Models (Alternative Specifications)

	INC	DEC
Panel A: Portfolio effects		
Accuracy	0.93	0.90
	(0.04)	(0.03)
Precision	090	0.94
	(0.27)	(0.07)
Recall	0.45	0.57
	(0.25)	(0.24)
Panel B: Real-time re-dispatch		
Accuracy	0.93	0.87
	(0.04)	(0.03)
Precision	0.85	0.92
	(0.33)	(0.07)
Recall	0.41	0.59
	(0.26)	(0.23)
Panel C: Real-time re-dispatch and portfolio effects		
Accuracy	0.94	0.88
	(0.04)	(0.04)
Precision	0.90	0.92
	(0.27)	(0.07)
Recall	0.47	0.64
	(0.25)	(0.19)

Notes: Table displays mean and standard deviation (in parentheses) of unit-level predictions to be INCed or DECed across all units. Results correspond to a cross-validated random forest model.

Table 7: Regressing Markups on Predicted Probability of getting INCed or DECed (Alternative Forecast Model Specifications)

	INC			DEC		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Ordinary least squares						
Predicted $\mathbb{P}_i[y_i = 1 \vert X]$	94.99	85.59	95.64	-179.61	-159.35	-181.07
	(21.84)	(21.28)	(21.29)	(30.78)	(30.05)	(30.24)
Unit FEs	X	X	X	X	X	X
N	612,939	612,939	612,939	497,148	497,148	497,148
Panel B: Two-stage least squares						
y_i	63.31	56.30	64.16	-115.64	-93.69	-111.66
	(14.66)	(13.94)	(14.33)	(21.26)	(17.91)	(19.74)
Unit FEs	X	X	X	X	X	X
N	612,939	612,939	612,939	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Standard errors (clustered at the unit level) in parentheses. Predicted $\mathbb{P}_i[y_i = 1|X]$ derived from the random forest model. Columns (1) and (4): Portfolio effects considered in the unit level forecast model. Columns (2) and (5): Real-time balancing quantities considered in the unit level forecast model. Columns (3) and (6): Portfolio effects as well as real-time balancing considered in the unit level forecast model. In Panel (B) we instrument y_i with the predicted $\mathbb{P}_i[y_i = 1|X]$ derived from the random forest model.

Table 8: Regressing Competitive Offer Share on Predicted Probability of getting INCed or DECed

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Ordinary least squares								
Predicted $\mathbb{P}_i[y_i = 1 \vert X]$	-0.37	-0.39	-0.36	-0.44	0.62	0.63	0.61	0.63
	(0.09)	(0.07)	(0.06)	(0.06)	(0.10)	(0.10)	(0.10)	(0.09)
Net Load				-0.05				-0.01
				(0.01)				(0.01)
$(\text{Net Load})^2$				0.00				0.00
				(0.00)				(0.00)
$(\text{Net Load})^3$				0.00				0.00
				(0.00)				(0.00)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148
Panel B: Two-stage least squares, instrument is predicted $\mathbb{P}_i[y_i = 1 \vert X]$ using random forest model								
y_i	-0.25	-0.26	-0.23	-0.29	0.38	0.38	0.34	0.38
	(0.06)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
Net Load				-0.05				-0.02
				(0.01)				(0.01)
$(\text{Net Load})^2$				0.00				0.00
				(0.00)				(0.00)
$(\text{Net Load})^3$				0.00				0.00
				(0.00)				(0.00)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148

Notes: The dependent variable is the competitively offered quantity offered in the day-ahead market relative to the available capacity. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Table 9: Daily Re-dispatch Cost and Net Load

	(1)	(2)	(3)
Net load	$-45,724$	$-1,515,909$	$-1,441,871$
	(17,144)	(147,321)	(153,647)
(Net load)^2		25,948	23,745
		(2,593)	(2,722)
Net load SD			334,233
			(66,874)
Intercept	X	X	X
Month of sample FEs	X	X	X
Adj. R^2	0.38	0.47	0.49
N	726	726	726

Notes: The dependent variable is the daily cost of re-dispatch in EUR. Net load values are daily averages expressed in GWh Net load SD is the intradaily standard deviation. Standard errors in parentheses.

Table 10: Actual and Counterfactual Costs to Serve Demand

	(1) Actual	(2) Competitive	(3) 10% Markup 6:00–22:00	(4) 10% Markup 16:00–22:00	(5) 15% Markup 6:00–22:00	(6) 15% Markup 16:00–22:00	(7) 40% Markup 6:00–22:00	(8) 40% Markup 16:00–22:00
Day-ahead Market Costs [EUR/MWh Demand]	62.6	–	–	–	–	–	–	–
Intraday Market/Re-dispatch Costs [EUR/MWh Demand]	6.7	–	–	–	–	–	–	–
Energy Costs [EUR/MWh Demand]	–	63.6	67.2	65.0	69.0	65.7	78.0	69.2
Make-whole payments [EUR/MWh Demand]	–	0.4	0.4	0.4	0.4	0.4	0.4	0.4
Total Cost [EUR/MWh Demand]	69.2	64.0	67.6	65.4	69.4	66.1	78.4	69.6
Savings [EUR/MWh Demand]		5.2	1.6	3.8	−0.2	3.1	−9.2	−0.4
Annual Savings, 300 TWh demand [Billion EUR]		1.6	0.5	1.2	−0.1	0.9	−2.7	−0.1

Appendix

A Effect of Renewables on Residual Demand

In this Section we show how the capacity expansion of intermittent renewables such as solar and wind have changed the net demand in Germany and Italy over time.

Figure 8 demonstrates the tremendous increase in the range of realized hourly output levels for dispatchable generation each hour of day in Germany between 2007 to 2018, when the annual share of wind and solar energy production went from approximately 7% to 25%. Each colored box in the figure gives the 25^{th}, 50^{th} and 75^{th} percentile of values of the difference between the system demand and renewable energy production for an hour of the day, across all days in the year. The lower end of each arrow is the 1^{th} percentile and the upper end of the arrow is the 99^{th} percentile of the daily distribution of net demand (system demand less renewable energy production) for that hour of the day. In 2007, the difference between the 99^{th} and 1^{th} percentiles was less than 30,000 MWh, whereas by 2018 this range was more than 60,000 MWh for a number of hours of the day. Both the wide range of realized values of the net demand during each hour of the day and the substantially lower 1^{th} percentile in 2018 relative to 2007 imply that there will be many more grid reliability constraints on how dispatchable generation units can operate in 2018 relative to 2007.

The wider range of realized hourly net demand levels is not just a German phenomenon. We also find it for Italy. In Figure 9, Panel (a), we show that the net demand uncertainty has increased especially during the night. Furthermore, the hourly distribution of realized net demand values during each hour of the day has shifted down. The picture gets even more drastic when we focus only on the region south of Tuscany (including the large islands of Sardinia and Sicily). Figure 9, Panel (b), demonstrates that the difference between the 99^{th} and 1^{th} percentiles was about 4,000 MWh, during the night hours in 2007, whereas by 2018 this range was about 8,000 MWh. The major reason for this development is that most of the wind capacity has been installed in this part of the country.

B Additional Econometric Analyses

In this Section, we present additional econometric analyses.

First, we extend the empirical analysis presented in Section 6 by enlarging the sample size. Instead of selecting only combined cycle units that historically did the most INC and DEC action, we now use all combined cycle units that are eligible to participate in the re-dispatch market and do not have cost-of-service contracts with the transmission operator. Excluding the set of units with such contracts is reasonable as these units are obliged to either offer their available capacity at their short-run marginal cost or at zero to the day-ahead market. Hence, even if there were a positive likelihood of getting INCed or DECed in the re-dispatch market, these units are not able to take advantage of it. Our sample comprises now 74 units for the INC product and 73 for the DEC product. The reason why the number of units in the INC category is different from the number of units in the DEC category is that we require at least two days of the sample with an occurrence of an INC or a DEC for each category.

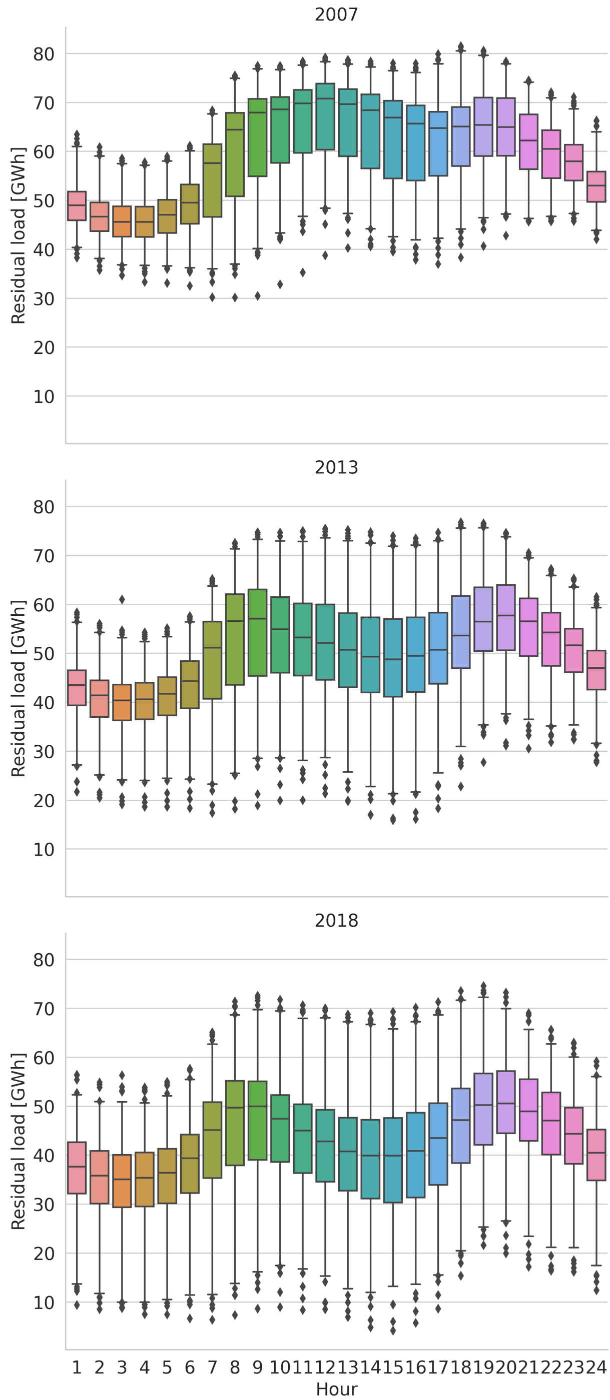
The statistical analysis presented in Table 11, Panel A, is broadly similar to that presented in Table 2, Panel A, with the only difference that we now consider the full set of units. The qualitative interpretation does not change. The only difference is that the coefficients of the INC side are smaller than before but still statistically significant. The results also hold when instrumenting for the indicator variable for whether a unit is INCed or DECed using the predicted probability as instrument (compare Table 11, Panel B, with Table 4, Panel A).

Second, we analyze how the predicted re-dispatch quantity will affect unit-level offer-price markups in the day-ahead market. Again, we rely on a two-step approach where we first forecast the expected re-dispatch quantity separately for each product (INC and DEC) and for each unit. More precisely, we predict the unit-level re-dispatch quantity instead of the binary outcome of being re-dispatched used in our preferred specification. The prediction model is a simple linear regression model using the same explanatory variables as in our preferred specification. Given these unit-level predictions, we perform another linear regression model to explain the day-ahead market markups using the predicted re-dispatch quantities as our main explanatory variable. In Table 13, we present the results of regressing day-ahead markups on the predicted re-dispatch quantities. We find that the average unit's day-ahead market offer-price markup would be 18–37 EUR/MWh larger if a unit expects to get its day-ahead market schedule increased by 100 MWh. The average unit's day-ahead market offer-price markup would be 33–49 EUR/MWh lower if a unit expects to get its day-ahead market schedule decreased by 100 MWh.

Third, instead of running the panel regressions for the INC and DEC product separately we include both predicted probabilities for INC and DEC in a single regression. The statistical analysis presented in Table 14, is broadly similar to that presented in Table 2, Panel A, with the only difference that we now include predicted probabilities of both products in one regression model. Results of the regressions are presented in Table 14 and are qualitatively equal.

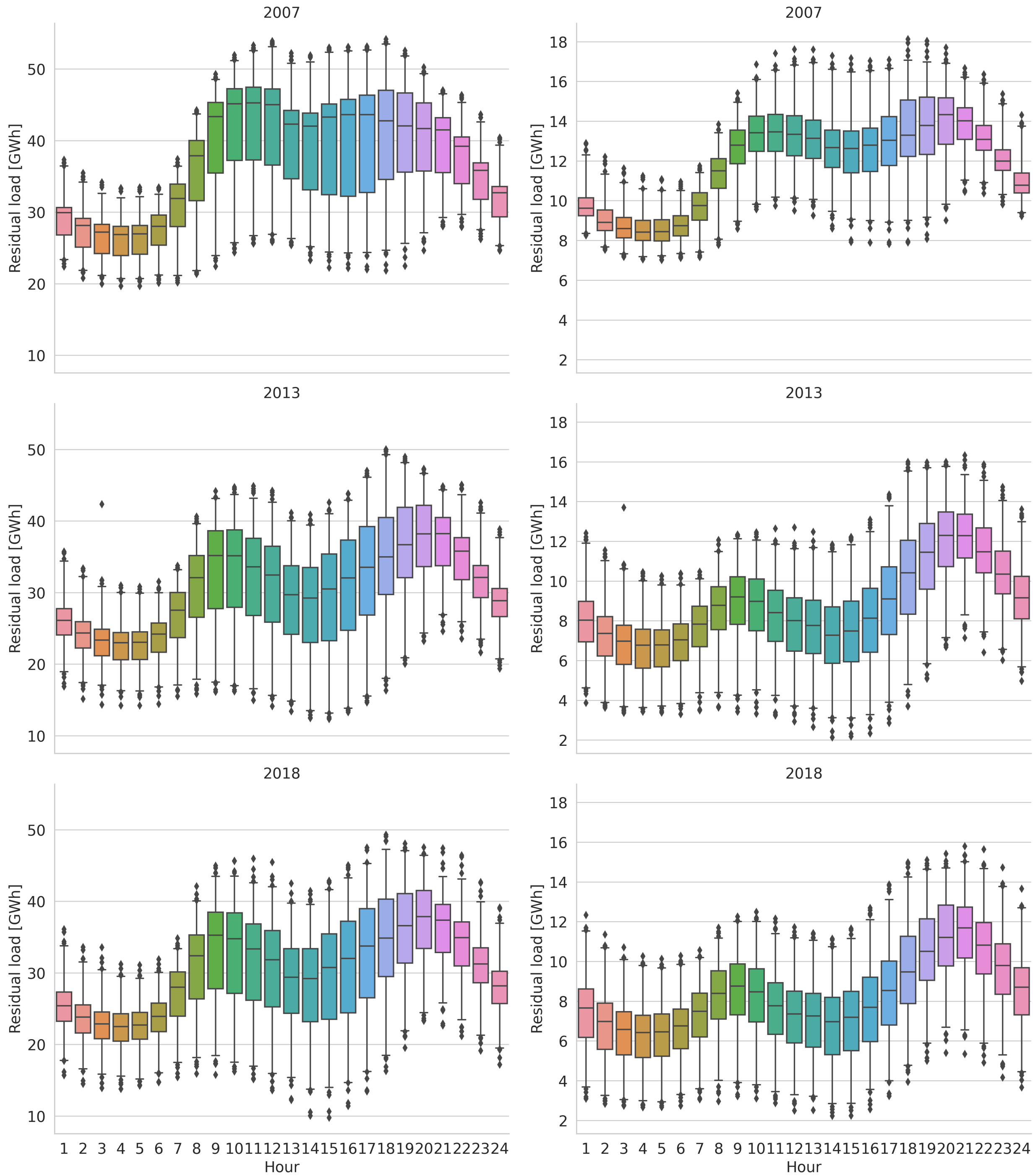
Lastly, we deploy different ways of computing markups. Again the statistical analysis presented in Table 15, is broadly similar to that presented in Table 2, Panel A, with the difference that we compute unit-level markups differently. In the main analysis, we compute markups as the difference between quantity-weighted average offer price and the variable cost estimate for each hour and unit. Here we compute the markup by taking the unit-level offer price at different levels of the offered capacity for each unit and hour of the sample. The results are presented in Table 15. In Panel A, we select the offer price at 90% of offered capacity and in Panel B, we select the offer price at 75% of offered capacity. Both alternatives to compute markups qualitatively confirm our results.

Figure 8: System Demand Less Renewable Energy Production in Germany 2007 to 2018



Notes: Hourly net demand in Germany, i.e., the national load minus the supply from wind and solar. Boxes represent interquartile range (IQR) and upper and lower vertical bars equal to the 1 percent and 99 percent. Diamonds represent outliers not included in the 1–99 percentile. Hourly data for load, wind, and solar for the year 2007 are from Entso-e and the four German transmission system operators (see Wozabal et al., 2016, for a more detailed description on the data sources). Data for the years 2013 and 2018 are from Open Power System Data (2019).

Figure 9: Demand Less Renewable Energy Production in Italy 2007 to 2018



(a) (b)

Notes: Hourly net demand in Italy (Panel a), i.e., national load minus the supply from wind and solar. Panel (b) shows the hourly net demand for the area south of Tuscany. Boxes represent interquartile range (IQR) and upper and lower vertical bars equal to the 1 percent and 99 percent. Diamonds represent outliers not included in the 1–99 percentile. Hourly data for load and wind for the year 2007 was derived from day-ahead market bidding data used in Graf and Wolak (2020). Solar generation was negligible in 2007 and zonal wind generation data was scaled to match the annual output (see `https://download.terna.it/terna/0000/0113/12.pdf`). Data for the years 2013 and 2018 are provided by the Italian transmission operator.

Table 11: Regressing Markups on Predicted Probability of getting INCed or DECed

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Ordinary least squares								
Predicted $\mathbb{P}_i[y_i = 1\|X]$	83.74	86.86	75.24	94.58	−191.72	−183.95	−175.72	−180.44
	(18.04)	(15.56)	(13.47)	(15.21)	(28.47)	(27.47)	(26.67)	(25.94)
Net Load				7.41				4.07
				(1.76)				(1.53)
(Net Load)^2				−0.31				−0.19
				(0.06)				(0.05)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	1,107,013	1,107,013	1,107,013	1,107,013	1,093,849	1,093,849	1,093,849	1,093,849
Panel B: Instrument is predicted $\mathbb{P}_i[y_i = 1\|X]$ using random forest model								
y_i	54.38	56.26	47.59	61.11	−116.48	−110.95	−98.68	−108.75
	(11.75)	(10.16)	(8.57)	(9.95)	(17.86)	(17.10)	(15.93)	(16.11)
Net Load				6.97				4.18
				(1.66)				(1.48)
(Net Load)^2				−0.30				−0.20
				(0.06)				(0.05)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	1,107,013	1,107,013	1,107,013	1,107,013	1,093,849	1,093,849	1,093,849	1,093,849

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Table 12: Regressing Markups on Predicted Probability of getting INCed or DECed (Ignoring Renewable Generation forecast data in Prediction Models)

	INC		DEC	
	(1)	(2)	(3)	(4)
Panel A: Random forest model				
Predicted $\mathbb{P}_i[y_i = 1\|X]$	87.70	92.23	−169.49	−200.16
	(23.52)	(21.13)	(33.06)	(29.76)
Unit FEs	X	X	X	X
N	612,939	1,107,013	497,148	1,093,849
Panel B: Instrument is predicted $\mathbb{P}_i[y_i = 1\|X]$ using random forest model				
y_i	59.77	61.62	−108.97	−127.31
	(16.06)	(14.29)	(22.09)	(19.61)
Unit FEs	X	X	X	X
N	612,939	1,107,013	497,148	1,093,849

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Standard errors (clustered at the unit level) in parentheses. Columns (1) and (3): most important CCGT units; Columns (2) and (4): all eligible CCGT units. In Panel (B) we instrument y_i with the predicted $\mathbb{P}_i[y_i = 1|X]$ derived from the random forest model.

Table 13: Regressing Markups on Predicted Re-dispatch Quantities

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predicted Re-dispatch q_i	0.23	0.27	0.18	0.37	−0.43	−0.44	−0.33	−0.49
	(0.14)	(0.11)	(0.10)	(0.10)	(0.11)	(0.10)	(0.11)	(0.10)
Net Load				8.61				−2.36
				(2.10)				(2.32)
(Net Load)^2				−0.37				−0.04
				(0.08)				(0.08)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Unit-level re-dispatch quantities are predicted using ordinary least squares. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Table 14: Regressing Markups on Predicted Probability of Getting INCed or DECed Jointly

	(1)	(2)	(3)	(4)
Predicted $\mathbb{P}_i[y_i^{\text{INC}} = 1 \mid X]$	66.71	69.09	62.07	76.99
	(16.54)	(14.15)	(13.17)	(13.72)
Predicted $\mathbb{P}_i[y_i^{\text{DEC}} = 1 \mid X]$	−184.43	−175.35	−167.83	−171.09
	(29.87)	(28.52)	(28.09)	(26.48)
Net Load				6.71
				(1.99)
(Net Load)^2				−0.27
				(0.07)
(Net Load)^3				0.00
				(0.00)
Intercept	84.83	99.57	101.98	76.94
	(5.02)	(7.47)	(6.66)	(19.63)
Unit FEs	X	X		X
Hour-of-day FEs		X	X	X
Day-of-week FEs				X
Month-of-year FEs		X	X	X
Unit x Month FEs			X	
N	939,841	939,841	939,841	939,841

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.

Table 15: Regressing Markups on Predicted Probability of getting INCed or DECed with Alternative Markup Definitions

	INC				DEC			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A: Markup at 90% Offer Curve				
Predicted $\mathbb{P}_i[y_i = 1\|X]$	64.43	71.53	64.06	83.99	−190.49	−188.29	−164.81	−189.61
	(18.91)	(15.93)	(13.94)	(17.45)	(29.15)	(26.97)	(29.88)	(25.92)
Net Load				8.23				1.55
				(2.05)				(2.58)
(Net Load)^2				−0.32				−0.08
				(0.08)				(0.08)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	105.75	134.66	135.76	97.46	118.58	134.77	124.65	155.40
	(2.59)	(7.02)	(5.44)	(17.75)	(7.31)	(10.37)	(11.02)	(28.75)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148
				Panel B: Markup at 75% Offer Curve				
Predicted $\mathbb{P}_i[y_i = 1\|X]$	72.53	79.75	70.36	93.86	−154.18	−151.05	−147.60	−152.17
	(19.15)	(15.69)	(13.46)	(17.33)	(34.50)	(32.80)	(31.91)	(30.93)
Net Load				10.19				−0.34
				(2.31)				(2.26)
(Net Load)^2				−0.39				−0.03
				(0.09)				(0.07)
(Net Load)^3				0.00				0.00
				(0.00)				(0.00)
Intercept	99.86	132.39	132.94	79.91	93.59	108.16	107.55	152.12
	(2.62)	(7.18)	(5.48)	(19.63)	(8.66)	(12.52)	(11.50)	(27.01)
Unit FEs	X	X		X	X	X		X
Hour-of-day FEs		X	X	X		X	X	X
Day-of-week FEs				X				X
Month-of-year FEs		X	X	X		X	X	X
Unit × Month FEs			X				X	
N	612,939	612,939	612,939	612,939	497,148	497,148	497,148	497,148

Notes: The dependent variable is the markup in the day-ahead market in EUR/MWh. Net load is equal to the day-ahead forecast of the system load minus the forecast supply from wind and solar measured in GWh. Standard errors (clustered at the unit level) in parentheses.