

Redistribution through Efficiency: Theory and Evidence from Three Electricity Markets

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Abstract

Using micro-data on over 160 million bids to buy and sell from three major electricity markets, we study efficiency improvements resulting from technologies such as storage. Consumer benefits arise not from stabilized prices but from changes in general price levels. To unpack the findings, we develop a set of price-theory results, demonstrating that the convexity of market excess demand, derived from the bids, serves as a novel measure that strongly predicts consumer benefits across all markets. This analysis highlights that even small allocative improvements can lead to significant redistributions of surplus, ultimately benefitting consumers.

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1 Introduction

New technologies offer captivating opportunities to enhance efficiency in various markets. In electricity markets, storage technologies represent a specific, concrete example of how new technologies can have transformative impacts not only on efficiency but also on equilibrium prices that consumers face. Given these equilibrium impacts, do consumers end up benefiting from the adoption of storage technologies? This question is natural, especially considering that the adoption of these technologies is accelerated by policies.

To address the question, it is useful to first step back from the technical complexities of storage and note that, ultimately, storage is a trade technology that allows buying when prices are low and selling or reducing consumption when prices are high. How is consumer surplus impacted by the introduction of such trade technologies in an environment where demand and supply can widely vary due to factors such as temperatures, time of day, and fluctuations in renewable energy generation?

To identify the mechanisms behind surplus changes, we conduct the same efficiency-improving counterfactual experiment in three major electricity markets—California, the Nordic countries, and Spain—using micro-data on over 160 million bids from 2015-2020. In the experiment, we use the actual bids for market clearing after adding 1 gigawatt (GW) of capacity for reallocations that improve efficiency, hour by hour. The experiment produces equilibrium impacts of trade technologies broadly, including producers exploiting grid-based storage solutions, retailers controlling customers’ consumption using smart meters and remote controls, and individuals optimizing the charging of EVs. These solutions all conform to the idea of buying market electricity when prices are low and selling (or not using) it when prices are high.

A consistent result arises from all three markets: technologies lead to large surplus redistributions that benefit consumers. Notably, while trade technologies stabilize prices, the surplus benefit is not delivered through reduced price dispersion. Instead, it is the resulting lower average price level that ultimately benefits consumers. We estimate that when trade technologies change the mean price by one euro/dollar, the daily consumer surplus changes by .226 million in California, 1.06 million in the Nordics, and .147 million in Spain. The daily mean price can change in either direction, and therefore the final impact on consumer surpluses accumulates as a function of this variation in days over a year. For 2015–2020, we evaluate that an efficiency improvement of controlled size 1GW, e.g., through a mandate to install grid-based storage capacity, would have benefitted

consumers in all markets. In the Nordics, the surplus gain to consumers from a mandate of size 1GW is ten times larger than the total (gross) social surplus!

To unpack the results from the experiments, we develop a simple price-theory model for settings in which efficiency improvements reduce price dispersion. The model identifies three mechanisms for changes in consumer surplus. First, a market-level improvement in efficiency reduces price dispersion and thus those consumers who can respond to price variations lose gains from the option to do so. Intuitively, a consumer benefits from the option to optimize, e.g., to charge an electric vehicle at occasional bargain prices rather than at a flat mean-equivalent price.¹ The importance of this option can be captured by a pass-through rate measuring the incidence of allocative inefficiency between consumers and producers.²

Second, trade technologies impact the correlation between realized prices and consumers demands. When supplies correlate with demands, consumers benefit from frequent bargains when the correlation is positive and incur losses when it is negative, even without needing to actively respond to prices. A reduction in price dispersion makes such bargains or losses smaller.

Third, trade technologies change the overall price level that consumers face. We develop a novel measure predicting this change: it measures the convexity of market excess demand. Under convexity (concavity), an improved allocative efficiency contributes positively (negatively) to the consumer surplus. The convexity measure links the consumer surplus gains to the market rudiments, the shapes of demand and supply.³

In our empirical analysis, we develop counterparts for the three theoretical mechanisms. Our findings show that the convexity measure of excess demand, derived from bids to buy and sell, is the dominant factor explaining the surplus gains to consumers.

¹This result follows from elementary microeconomics when preferences are quasi-linear – the consumer welfare is convex in prices. The price theory implications of the result were first elaborated by [Vaugh \(1944\)](#).

²This use of the concept can be added to the long list of its applications. The pass-through rate typically measures how firms pass cost shocks to prices (e.g., [Weyl and Fabinger, 2013](#)), with applications in taxation, oligopoly (e.g., [Genakos and Pagliero, 2022](#)), monopolistic competition ([Mrázová and Neary, 2014](#) or [Mrázová and Neary, 2017](#)), international trade ([De Loecker and Goldberg, 2014](#)), and in the energy sector ([Fabra and Reguant, 2014](#)).

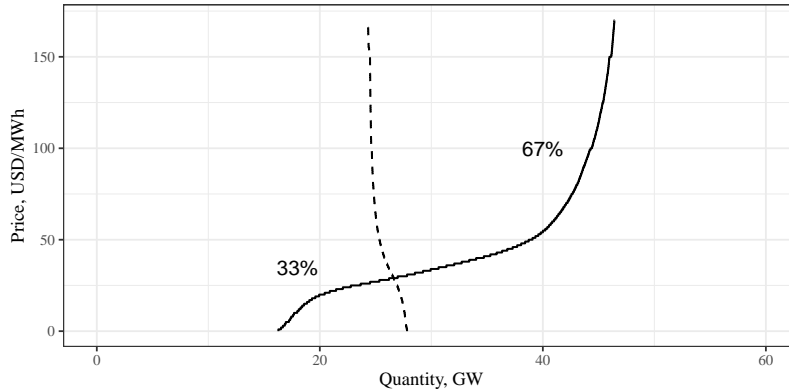
³In contrast to the convexity of profit function or concavity of expenditure function, the convexity of excess demand is not an implication of the theory but rather a primitive linking to the distributions of costs and valuations. Its relevance for price level changes from trade has been acknowledged in the literature on price stabilization ([Just et al., 1978](#)).

This measure explains approximately 90% of the surplus variation in California, 80% in the Nordics, and 40% in Spain during the period 2015–2020.

To understand why the convexity of excess demand plays such a critical role, it is important to examine the economics behind it. The excess demand, the difference between the demand and the supply, inherits its convexity properties mainly from the supply if the demand is relatively inelastic. In Fig. 1, the mean hourly supply curve for electricity in California shows a concave-convex pattern: in our data from 2015-2020, according to Jensen’s inequality, the respective shares of concave and convex parts are 33% and 67% of the hours.⁴

In California, the supply is typically concave in quantities in the spring, when solar PV systems reduce the need for gas-fired generation during the day, but these units must ramp up quickly in the evening; there is a large supply (gas-fired power) coming available when the price exceeds a certain reservation level. In this scenario, efficiency improvements can raise daily price levels, reducing consumer surplus. However, this trend reverses in the summer when higher cooling demand pushes the power system closer to full capacity and supply turns convex in quantities. The efficiency improvement then reduces peak power generation, lowering peak prices more than off-peak prices rise. Our empirical analysis show that consumer benefits primarily arise from the surplus generated by reduced peak prices, which dominate during the study period from 2015 to 2020.

Figure 1: Average supply and demand curves in California, 2015-2020



Notes: The mean of the hourly supply and demand in California, 2015-2020. 33% (67%) is the share of equilibria in which the convexity measure indicates a concave (convex) supply.

The closest paper on the equilibrium impacts of technology mandates is [Butters](#),

⁴It is natural to think that concavity/convexity is w.r.t. the variable on the horizontal axis, and this is what we assume in this discussion. In the formal analysis, we follow the conventions and assume that the demand and supply are functions of the price.

Dorsey and Gowrisankaran (2024). Strikingly, equilibrium battery adoption in California is predicted to remain negligible until 2030, absent subsidies or mandates.⁵ California requires that utilities procure 1.3GW of storage power capacity by 2024; at least seven US states have targets for storage capacity. Our results confirm that the mandates generate low gross surpluses in total in multiple markets; the main impact is distributional. Our approach differs in that it uses granular micro-data on bids to simulate how the equilibria implied by the bids are affected by the mandates. The approach lets the data tell if the excess demand is concave or convex, which allows us to firmly link the empirical and theory results to explain the variation of surpluses in the data. This would not be possible if we assumed given functional forms as in Butters, Dorsey and Gowrisankaran (2024). The results add to the literature that emphasizes nonlinearities in understanding data (Boehm and Pandalai-Nayar, 2022). The nonlinearities of electricity supply seem to be of growing importance because high shares of renewables increase the variation of capacity utilization rates.^{6 7}

In addition to storage,⁸ our results apply to any policy that manages to implement the assumed improvement in the efficiency of allocations. It could, in principle, result from a large-scale program exposing households to real-time pricing such as the one introduced by Spain in 2015 (Fabra et al., 2021).⁹ There is a literature on how to activate consumers to use ever better smart appliances and associated control mechanisms for responding to price variations (e.g., Allcott, 2011; Jessoe and Rapson, 2014; Fabra et al., 2021; Fowlie et al., 2021; Ito, Ida and Tanaka, 2023). The final surplus from the technologies

⁵Karaduman (2021) has a related focus with data from South Australia.

⁶Boehm and Pandalai-Nayar (2022) find that industry-level supply curves are convex (in quantities), with convexity measures linked to the capacity utilization rates. Similar convexity at high utilization is also evident in our data but, in contrast, our micro-data reveals concavity of supply at low utilization rates.

⁷By determining directly from the bids how a given capacity portfolio generates surpluses and what the effect of a marginal investment is, our empirical approach seems relevant for planners who decide on capacity expansions. The capacity portfolio is often determined by capacity mechanisms instead of purely market-based investments (Joskow, 2019; Grubb and Newbery, 2018; Wolak, 2021, 2022).

⁸For robustness, we develop a storage version of our model to map the generic capacity of 1GW into the actual storage needed for the same effect: this analysis shows that the generic 1GW corresponds closely to the storage mandate in California for 2024. In the Nordic market, 1GW translates into a larger storage power capacity, but the main conclusions remain: mandates imply large redistributions of surplus but generate low social values in total.

⁹EU directives 2009/72/EC and 2012/27/EU explicitly target improvements in market efficiency. Wolak (2019) discusses the general motivations for the policies.

will be produced by the market, and therefore a first-order question, not addressed by this literature, is how a large-scale deployment of consumer-side technologies impacts the market equilibrium. Clearly, the demand-side surplus of the wholesale market is not directly the final end-user surplus but it is the root of the gains: how quickly the price impact trickles down depends, e.g., on the organization of retail pricing. There are important differences between the markets in this respect.

Our study contributes to the broader literature on the impact of new technologies on price dispersion and market efficiency (e.g., [Jensen, 2007](#); [Aker, 2010](#); [Allen, 2014](#); [Steinwender, 2018](#)). This body of work has extensively documented the effects on efficiency, but it says little about the incidence of impacts. Our theory is broad enough to shed light on the possible mechanisms in situations considered in the literature. We believe this paper is the first-ever study using a measure of excess demand, a rudimentary concept in economics, in empirical analysis.¹⁰

In contrast to settings where efficiency and uniform prices go hand in hand, classical literature on third-degree price discrimination shows that when prices are dispersed, total welfare may be larger than under uniform pricing. Recent contributions to this literature include [Aguirre, Cowan and Vickers \(2010\)](#); [Chen and Schwartz \(2015\)](#); [Cowan \(2016\)](#); [Dubé and Misra \(2023\)](#). While we rule out market power and total welfare is always lower under dispersed prices in our setting, the literature has noted that the convexity of demand is important for the final impact on output and welfare. [Cowan \(2016\)](#) develops measures of demand convexity that could prove useful in further applications of our results in settings where the shape of demand drives the form of excess demand, especially when demand cannot be directly observed from bids to buy.

Finally, the multi-market approach may prove useful when studying, for example, the impact of data centers and cryptocurrency mining on the “world electricity market”. For such questions, it seems necessary to make apples-to-apples comparisons by transforming bids in different power systems into comparable objects. We offer one approach to making headway in this comparison.¹¹

¹⁰There is a large literature on the welfare impacts of price stabilization; see [Wright \(2001\)](#) for an overview and, e.g., [Newbery and Stiglitz \(1979\)](#). The literature on the energy transition has noted the need to develop measures of the consumer welfare. [Ambec and Crampes \(2021\)](#) study the welfare impact of volatility in a theory model where consumers are risk averse; see also [Helm and Mier \(2021\)](#).

¹¹The literature on electricity concentrates on single market settings, with a few exceptions. [Callaway, Fowle and McCormick \(2018\)](#) look at different US markets in a simulation study focusing on the location-specific impacts of renewable on the electricity systems. Similarly [Abrell, Kosch and Rausch \(2019\)](#) study

2 Consumer surplus and efficiency: Analytics

Abstract first from any particular market interpretation and let i be a “local” market in a set of markets \mathcal{I} . In each $i \in \mathcal{I}$, there is demand $D_i(p)$ and supply $S_i(p)$ depending on price p . The local markets differ because of location-specific demand and supply shocks d_i and s_i ,

$$\underbrace{(D(p) + d_i)}_{\equiv D_i(p)} - \underbrace{(S(p) + s_i)}_{\equiv S_i(p)} \equiv X_i(p).$$

Each market thus shares a common demand primitive $D(p)$, assumed to be decreasing $D'(p) < 0$, and a supply primitive $S(p)$, assumed to be increasing $S'(p) > 0$. The local excess demand $X_i(p)$ is strictly decreasing, $X'_i(p) < 0$, and we assume that there is in each locality a finite price $p_i > 0$ such that $X_i(p_i) = 0$ for all $i \in \mathcal{I}$.

Consider then efficient trade between the local markets: for some price $p > 0$, it holds that $\sum_{i \in \mathcal{I}} X_i(p) = 0$. In the efficient outcome the demand and supply primitives satisfy $D(p) - S(p) = \bar{x}$, with \bar{x} being the mean of the local market conditions $x_i \equiv s_i - d_i$. Intuitively, the efficient trade neutralizes the impacts of shocks across the markets.

Drop i and take $x = s - d$ as the local market condition, with cumulative distribution function $F(x)$ on domain M . Thus, \bar{x} corresponds to the efficient trade, and the localized outcomes are associated to a mean-preserving spread of \bar{x} given by F . We assume that “technology” determines which outcome holds. For instance, the realizations of x could capture local supply shocks that collapse to \bar{x} once a communication technology allows trading across locations.¹² In electricity markets, the local markets are typically hourly markets in a day, with both components of $x = s - d$ varying across hours, due to, e.g., intermittent supplies and temperatures affecting demands.¹³ The technology captures anything that enables the move from the local to the efficient trade.¹⁴

the differences across locations in Europe.

¹²Jensen (2007) considers fishermen landing in physically separate beach markets. The communication technology allows trading the catch out in the sea before the landings.

¹³In addition, physical locality of supply and demand can be an important characteristic of electricity markets (see, e.g., Graf and Wolak, 2022).

¹⁴The focus on the two extreme cases is inconsequential in this analytical model, and the efficiency impact of a technology will be partial in our empirical model. The empirical model lends itself to the analysis of specific technologies.

We impose a Gaussian structure on F through the following assumptions on s and d ,

$$\begin{pmatrix} s \\ d \end{pmatrix} \sim \mathcal{N} \left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_s^2 & r\sigma_s\sigma_d \\ r\sigma_s\sigma_d & \sigma_d^2 \end{pmatrix} \right)$$

where σ_s and σ_d are standard deviations, and r is the correlation coefficient. Since d and x are jointly normally distributed,

$$\begin{aligned} \mathbb{E}(d|x) &= \mathbb{E}(d) + \frac{\text{Cov}(d, x)}{\text{Var}(x)}(x - \mathbb{E}(x)) \\ &= \frac{\text{Cov}(d, x)}{\text{Var}(x)}x \\ &= ax \quad \text{with} \quad a \equiv \frac{r\sigma_s\sigma_d - \sigma_d^2}{\sigma_s^2 + \sigma_d^2 - 2r\sigma_s\sigma_d}. \end{aligned}$$

A local shock x is a pure supply shock if $\sigma_s > 0$ and $\sigma_d = 0$, and it is a pure demand shock if $\sigma_s = 0$ and $\sigma_d > 0$. More generally, x increases the demand expectation, $a > 0$, if and only if the demand and supply are positively correlated such that $r > \sigma_d/\sigma_s$.

The consumer does not know the price in advance but will know it before the consumption choice is made, giving the expected surplus

$$\mathbb{E}W = \int_{x \in \mathbb{R}} \int_{d \in \mathbb{R}} \int_{v \geq p(x)} \mathcal{D}(v, d) dv dG(d|x) dF(x), \quad (1)$$

where $\mathcal{D}(p, d) \equiv D(p) + d$ for short, G denotes the cumulative distribution function for d , and $p(x)$ is the price as a function of realization x . As usual in models that exploit Gaussian structures (e.g., [Vives, 2010](#); [Bonatti and Hörner, 2017](#)) we ignore non-negativity constraints, and focus on interior outcomes where $p(x)$ follows from $0 = D(p) - S(p) - x$, with $x = s - d$.

Expanding the above surplus gives

$$\begin{aligned} \mathbb{E}W &= \int_{x \in M} \int_{v \geq p(x)} D(v) dv dF(x) + \int_{x \in M} \int_{d \in N} \int_{v \geq p(x)} (d) dv dG(d|x) dF(x) \\ &= \int_{x \in M} \int_{v \geq p(x)} D(v) dv dF(x) + \int_{x \in M} \int_{v \geq p(x)} (ax) dv dF(x) \\ &= \int_{x \in M} \underbrace{\int_{v \geq p(x)} (D(v) + ax) dv}_{\equiv U(x)} dF(x). \end{aligned}$$

Function $U(x)$ is the consumer surplus from the demand-supply realization x . The consumer in one location buys with one price instead of the others but does not know that price in advance. Hence, the surplus $\mathbb{E}W$ measures what the consumer can expect

on average. For electricity, F may capture the share of the daily time when price $p(x)$ prevails, and the correlation structure captures the changes in the consumer's needs. The expected surplus $\mathbb{E}W$ is the relevant surplus measure in such situations.

Lemma 1 *Let $U(x)$ be either strictly concave or strictly convex. Efficient trade increases consumer surplus if and only if $U(x)$ is strictly concave.*

Proof. For efficient trade: the market condition collapses to \bar{x} , distribution F becomes degenerate at \bar{x} , and then the surplus is just $\mathbb{E}W = U(\bar{x})$. Because F is a mean-preserving spread around \bar{x} , we see that the strict concavity of $U(x)$ is equivalent to $\mathbb{E}W < U(\bar{x})$. The strict convexity of $U(x)$ reverses the inequality. ■

We can make strong predictions by building on $U(x)$:

$$U'(x) = -p'(x)[D(p(x)) + ax] + \int_{v \geq p(x)} adv, \quad \text{and}$$

$$U''(x) = -p''(x)[D + ax] - p'(x)^2 D' - 2ap'(x),$$

$$= \underbrace{-p''(x)[D + ax]}_{(i)} \underbrace{-p'(x)[(1 - \rho) + 2a]}_{(ii)},$$

where ρ is the pass-through rate

$$\rho \equiv \frac{S'}{S' - D'} = \frac{1}{1 + \frac{\varepsilon_d}{\varepsilon_s}},$$

with ε_d and ε_s being the elasticities of demand and supply in absolute value, respectively. We assume that the supply elasticity ε_s is finite, and then $\rho < 1$ is equivalent to saying that there is a demand response, $\varepsilon_d > 0$. With these observations, we can isolate the three effects for the consumer's surplus change, starting with pass-through:

Proposition 1 (*Pass-through*) *Assume that $D(p)$ and $S(p)$ are linear and that $\mathbb{E}(d|x) = \mathbb{E}(d) = 0$ (i.e., $r = \frac{\sigma_d}{\sigma_s}$). Then, it holds that the consumer surplus is strictly higher under dispersed prices, $\mathbb{E}W > U(\bar{x})$, if and only if the pass-through rate is less than unity ($\rho < 1$), i.e., there is a demand response.*

Proof. For linear $D(p)$ and $S(p)$, we have $p''(x) = 0$, which implies that term (i) in U'' is zero. For term (ii), it follows that $a = 0$ from $r = \frac{\sigma_d}{\sigma_s}$, and $-p'(x) > 0$ holds as well. Therefore, U is strictly convex if and only if $\rho < 1$. ■

With $\rho < 1$, and the assumptions made, the source of the consumer's welfare gain is that the consumer optimizes: the consumption level is responsive to prices, and therefore

the surplus is a convex function of the price. The effect is conceptually the same as the one that drives concavity of the expenditure function and the convexity of the profit function in elementary microeconomics. The consumer's surplus gain from volatile prices was first documented by [Vaugh \(1944\)](#), and it has been extended beyond quasi-linear settings in [Turnovsky, Shalit and Schmitz \(1980\)](#). Interestingly, in our setting the effect can be expressed with the help of the conventional pass-through rate ρ .¹⁵ Intuitively, ρ measures incidence: the price deviates from the first-best, and the incidence of this depends on who can better respond to the deviation. The consumer surplus becomes more convex, i.e., the gain from the option to respond increases, if we increase ε_d or alternatively decrease ε_s .

The next result isolates the effect from the correlation of demand and supply:

Proposition 2 (Correlation) *In proposition 1 assume no demand response ($\rho = 1$) but add correlation: $\mathbb{E}(d|x) \neq \mathbb{E}(d)$. Then, the price dispersion continues to benefit the consumer, $\mathbb{E}W > U(\bar{x})$, if and only if $\mathbb{E}(d|x) > \mathbb{E}(d) = 0$ (i.e., $r > \frac{\sigma_d}{\sigma_s}$).*

Proof. Term (i) in U'' remains zero. In term (ii), we have $\rho = 1$, so it simplifies to $-p'(x)2a$. Therefore, U is strictly convex if and only if $r > \frac{\sigma_d}{\sigma_s}$. ■

When the consumer has inelastic demand, the pass-through term disappears by $\rho = 1$ and the consumption choices are given. The condition $r > \frac{\sigma_d}{\sigma_s}$ ensures that the occurrences of demand shifters are sufficiently aligned with supply shifters generating surplus gains under dispersed prices. For instance, air conditioning demand can line up with solar power availability.

We isolate next our final effect that depends on the excess demand defined by general $D(p)$ and $S(p)$. The excess demand, which we write with a slight abuse of notation as $X(p)$, is convex ($X''(p) > 0$) or concave ($X''(p) < 0$), depending on the curvatures of $D(p)$ and $S(p)$. This proves useful as the price function $p(x)$ inherits the concavity and convexity properties of $X(p)$. We assume for clarity that either $X''(p) = D''(p) - S''(p) < 0$ or $X''(p) = D''(p) - S''(p) > 0$ holds for all p .

Proposition 3 (Excess demand) *Assume no demand response ($\rho = 1$) and no correlation ($\mathbb{E}(d|x) = \mathbb{E}(d)$). Then, the consumer surplus is strictly higher under dispersed prices, $\mathbb{E}W > U(\bar{x})$, if and only if it holds for general demand and supply that $X''(p) < 0$.*

¹⁵See, e.g., [Weyl and Fabinger \(2013\)](#) for a discussion of the concept.

Proof. The sign of term (i) in the expression for U'' is strictly positive if and only if $X''(p) < 0 \Leftrightarrow p''(x) < 0$. Term (ii) is now zero because $\rho = 1$ and $a = 0$. ■

A concave excess demand implies that the expected price level decreases when a mean-preserving spread is introduced to \bar{x} . Intuitively, the mean of dispersed prices is lower than the price predicted by the law of one price. This effect, captured by excess demand, is distinct from the effect captured by pass-through. Pass-through arises from consumer optimization and can occur without any change in the expected price level, as demonstrated in Proposition 1 with linear demand and supply. Additionally, the effect of correlation operates separately, influencing expenditures, as shown in Proposition 2.

The effects can pull in opposite directions. For instance, Proposition 3 suggests that more efficient trade can increase the price level when $X''(p) < 0$. However, when there is correlation, a higher but stabilized price may protect consumers against the negative correlation between demand and supply ($a < 0$). In such cases, the general expressions yield ambiguous conclusions.

We can offer sharper predictions using an example. Consider an inelastic demand, a situation common in electricity markets. Let the exogenous demand be represented by the mean demand plus a shock: $\bar{D} + d$. Similarly common in electricity markets is the presence of a volatile supply of renewables with low marginal cost and a more predictable supply with high marginal cost. This supply is a step function: any supply $S \leq \bar{S}$ comes with a supply reservation price p_L and any quantity larger, $S > \bar{S}$, has a supply reservation price $p_H > p_L$. The low-price supply is volatile: $\bar{S} + s$. For simplicity, let us assume that $\bar{D} - \bar{S} = 0$. Then, the equilibrium price depends on whether the sum of the two shocks, $x = s - d$, is positive or negative. If $x \geq 0$ holds, then p_L prevails; if $x < 0$ holds, then p_H prevails. The probability of the latter is $F(\bar{x})$, denoted by \bar{F} for short.

With these ingredients, we can evaluate $\mathbb{E}W = \mathbb{E}U(x)$, the expected consumer surplus as

$$\mathbb{E}W = \bar{U} - [p_H \bar{F}(\bar{D} + a\bar{x}_H) + p_L(1 - \bar{F})(\bar{D} + a\bar{x}_L)]$$

where \bar{U} is a fixed expected utility from exogenous consumptions¹⁶ and the expenditures in high- and low-price states depending on $\bar{D} + a\bar{x}_H$ and $\bar{D} + a\bar{x}_L$ in which we used $\bar{x}_H = \mathbb{E}[x|x < 0]$ and $\bar{x}_L = \mathbb{E}[x|x \geq 0]$. Setting $a = 0$ (i.e., $r = \frac{\sigma_d}{\sigma_s}$) gives the benchmark expenditure $[p_H \bar{F} + p_L(1 - \bar{F})]\bar{D}$. When demands correlate sufficiently strongly with

¹⁶We assume this constant is bounded, i.e., the demand becomes elastic for prices high enough.

supplies, $a > 0$, the surplus increases as the expenditures fall below the benchmark, and similarly $a < 0$ reduces the surplus; when $a = -1$, there is demand uncertainty only.

Introducing trade equalizes prices to p_L : the excess demand is zero at this price, $\bar{D} - \bar{S} - \bar{x} = 0$. Setting all prices equal to p_L in $\mathbb{E}W$ gives $\mathbb{E}W = \bar{U} - p_L \bar{D}$, so the surplus comparison reduces to comparing expenditures with and without trade. This case corresponds to what is achieved by a convex excess demand: trade reduces expenditures because, without trade, demand fluctuates around a kink in supply, causing the expectation over p_L and p_H to necessarily exceed p_L . By how much expenditures decrease, depends on the impact of correlation, a , discussed above. In contrast, had we assumed $\bar{D} - \bar{S} > 0$ at the outset, trade would set the uniform price at p_H and the conclusions would reverse. In this scenario, the outcome corresponds to what is achieved by a concave excess demand.

These observations set the stage for the empirical quantification. First, as the same supply typically has concave and convex parts, the empirical assessment depends on which part is relevant for equilibrium price level determination. Second, the expected price-level changes and the correlation structure each contribute separately to the impact of trade technologies on consumer surplus.

3 Empirical implementation

We use micro-data on bids to buy and sell from three electricity wholesale markets for quantifying the equilibrium effects of an efficiency-improvement of controlled size: we add 1GW capacity to each hour for trading allocations within each day. In Section 3.1, we describe the data preprocessing and the replication of actual market outcomes from the bid data. In Section 3.2, we introduce the experiment in which we run the market-clearing task using the bid data with the efficiency improvement. In Section 3.3, we report the descriptives of the data from the experiment, including the consumer, producer, and the total surpluses. In Section 3.4, we develop the covariates for explaining the consumer surpluses, including the convexity measure. The results of the regression with economic interpretations are in Section 3.5.

3.1 Data and the market model

We put together a data set of 162.7 million bids from the operators of three markets, CAISO (California), Nord Pool (Nordic), and OMIE (Spanish/Iberian) in 2015–2020.¹⁷ The unit of observation is a bid for an hour in a day-ahead market, with typically a few thousand observations per hour in each market.

The markets differ in their approaches to technicalities of market clearing, including how: the real-time power system operation is connected to the day-ahead market; some of the actual bids can be submitted in a more complex manner than as simple price-quantity pairs; and the location of bid resource and related transmission constraints in the power system are taken into account. For example, in California there are in principle 3,000 locational markets while in the Nordics there is only a handful of possible price zones.

We consolidate the raw data from the operators into one coherent data set in which bids are defined as hourly price-quantity pairs. First, we use ancillary market data to exclude from the bids any resources that are committed to serve the real-time markets. Second, the complex bids, which allow firms to express their ramping up and down costs, are deconstructed to single bids; these are reduced to price-quantity pairs for each hour separately. Third, we construct for each market a “system equilibrium”, i.e., equilibrium price-quantity outcome that would emerge if all transactions within the market area were implemented ignoring the transmission constraints. The system equilibrium is conceptually well defined, i.e., it exists for all markets, although this equilibrium outcome is explicitly reported only by the operator in the Nordic market.¹⁸

We replicate the market-clearing task by a formal model that maps the bid data into market outcomes. The data consists of a set of demand bids, $(p_{i,h}, Q_{i,h})_{i \in \mathcal{D}_h}$, and a set of supply bids, $(p_{j,h}, Q_{j,h})_{j \in \mathcal{S}_h}$, for any given hour h , day, and market (for simplicity, the last two are left out from the notation). Let $Q_{i,h}^d \in [0, Q_{i,h}]$ be the quantity of demand bid $i \in \mathcal{D}_h$ activated in equilibrium, and, similarly, $Q_{j,h}^s \in [0, Q_{j,h}]$ for supply bid $j \in \mathcal{S}_h$. The total demand is then $Q_h^d = \sum_{i \in \mathcal{D}_h} Q_{i,h}^d$, and the total supply is $Q_h^s = \sum_{j \in \mathcal{S}_h} Q_{j,h}^s$. A uniform price auction can be efficiently solved through a linear program for the total surplus maximization, an idea dating back to Samuelson (1952).¹⁹ This program gives us

¹⁷Appendix A is the supporting material for data and quantitative analysis.

¹⁸Appendix A.2 provides the detailed preprocessing steps, and an accompanying data set contains codes for replicating the steps.

¹⁹This is the basic method used by power exchanges (see e.g. Fabra, von der Fehr and Harbord, 2006).

hourly prices such that the excess demand is zero, $X_h = Q_h^d - Q_h^s = 0$. Potential market power and other inefficiencies that may exist in the bid data are not addressed in any way: the formal program (in Appendix A.3) finds the efficient allocation and prices by hour, given the bids.²⁰

The physical locality of demand and supply is an important constraint in all electricity markets, and thus the equilibrium price can vary by physical location within a market. Subject to this caveat, the system equilibrium obtained from our bid data can be tested by constructing system-level equivalents of prices and quantities from the locational data. For the Nordics, the system-level equivalents are reported by the market operator, and we can directly test, e.g., the match between the model output and actual prices (Table A.3). 99% of the modeled Nordic equilibrium prices are within €0.38/MWh of the reported system prices; on average, the gap between the two prices is €0.04/MWh. For Spain, we construct the mean of locational prices for each hour, and find that they differ by €0.03/MWh from our model predictions for hourly prices on average in the data period. For California, the model price on average falls short of the mean of the locational prices by \$2.1/MWh. These findings are expected: the Nordic data is exactly about the system equilibrium that our model seeks to replicate; the Spanish zonal system comes close to the full system equilibrium; and the nodal price data of California implies a greatest deviation from the system outcome.²¹

3.2 Counterfactual experiment: efficiency improvement

Turn next to producing the counterfactuals. Above, we found hourly prices from the bids so that $X_h = 0$ holds separately for each hour of the day, $h \in \mathcal{H}$. Next, introduce trade over the hours of any given day, which, in practice, is often achieved through storage technologies. These technologies imply constraints on the chronological order of trade,

²⁰That is, the bids conceal, e.g., forward contracting which, under market power, impact the bids (e.g., Liski and Montero, 2006; Hortaçsu and Puller, 2008; Lundin and Tangerås, 2020). A question linked to market power, which seems relevant given our focus on variations of demand and supply, is how equilibrium bids aggregate information on private signals. Based on Vives (2010), the implications of information aggregation depend on nonlinearities of demand and supply. This could be an interesting question for future research in settings where there is data on private signals, bids, and market outcomes.

²¹See Appendix A.4 for details. The location distribution of impacts from efficiency improvements is an interesting extension. It calls for a different approach dealing, e.g., with local market power; see Ryan (2021), Gonzales, Ito and Reguant (2023), Graf and Wolak (2022). Kirkpatrick (2020) and Astier, Rajagopal and Wolak (2023) study how storage impacts the grid operations.

losses of stored energy, and capacity constraints. To give a good perspective on the main experiment and the robustness analysis covering storage, consider the set of constraints:

$$\begin{aligned}
X_h &= Q_h^d - Q_h^s, \quad \forall h, \\
-Y &\leq X_h \leq Y \quad \forall h, \\
I_0 &= 0, \\
I_h &= I_{h-1} - (1 + \gamma \mathbb{1}_{X_h > 0})X_h, \quad \forall h \in \mathcal{H} \\
0 &\leq I_h \leq K \quad \forall h \in \mathcal{H}
\end{aligned}$$

The battery storage charges when the supply exceeds the demand in an hour (i.e., excess demand $X_h < 0$) and discharges when the demand exceeds the supply ($X_h > 0$). Charging and discharging are limited by a symmetrical capacity constraint Y . We use I_h to keep track of the battery state, which starts the day empty (i.e., $I_0 = 0$). Round-trip losses are set to burden discharges (i.e., when $X_h > 0$) and are a fixed percentage γ of the amount discharged. The battery capacity is K .

In the main experiment, we set $\gamma = 0$ (no losses), K to infinity, and ignore the chronological order of charging and discharging. We are then left with the first two lines with the requirement that the excess demand over the hours of any given day satisfies $\sum_{h \in \mathcal{H}} X_h = 0$. Our main experiment thus focuses on the special case with Y capturing the size of the experiment, set at 1GW. In Section 3.6, we document the results from the storage model respecting all constraints outlined above.

We assume that the observed bids in the data are unaffected by the experiment.

3.3 Equilibrium impacts of the experiment

Table 1 offers a breakdown of the equilibrium impacts of the experiment as mean changes in quantities, prices, and surpluses.

The surplus measures are the textbook consumer and producer surpluses, obtained from the demand and supply bids. Bearing in mind that the final end-user surplus depends on the structure of the retail market and on costs such as taxes, levies, and grid charges, which are all different across the three markets, we note that the consumer surplus changes in this analysis give one unified measure for the root of consumer benefits. In addition to the consumer and incumbent producer surpluses, there is the surplus to the new technology from efficiently operating $Y = 1GW$. This surplus is the total

Table 1: Impact of 1 GW flexible technology

Area	Obs.	Share	Q		P		Δ Consumer surplus	Δ New tech. surplus	Δ Total surplus
			GW	ΔQ	\$/MWh or €/MWh	ΔP	Change in M\$ or M€ per year		
California	All	1	26.53	-0.004	32.13	-0.23	114.15	55.64	62.17
	Concave	0.33	25.10	-0.026	25.78	0.3	-16.27	16.05	18.04
	Convex	0.67	27.23	0.007	35.27	-0.5	130.68	39.61	44.14
Nordics	All	1	41.24	0.004	28.06	-0.23	156.38	9.91	13.82
	Concave	0.47	39.12	-0.003	28.61	0.26	-26.05	4.08	5.58
	Convex	0.53	43.13	0.01	27.58	-0.67	182.75	5.84	8.24
Spain	All	1	26.74	-0.067	46.96	0.06	27.15	24.87	31.49
	Concave	0.54	27.75	-0.065	49.84	0.33	-14.96	14.08	17.46
	Convex	0.46	25.57	-0.07	43.61	-0.27	41.86	10.8	14.03

Notes: Table reports the mean values of the hourly data for quantities (in GW) and prices (in € or \$ per MWh), change in quantities (in GW), and change in prices (in € or \$ per MWh). Breakdown by observations is based on the convexity/concavity of the daily market (see Section 3.4 below for detail). The welfare measures are mean annual changes, and the Table presents change in consumer surplus, change in the total surplus in the market, and the private gain from trading (millions of U.S. dollars or euro). Data as reported in Table A.1.

equilibrium arbitrage gain from the hourly price differences.²² The surpluses in Table 1 are in millions of euros/dollars per year on average in our data period 2015-2022.²³

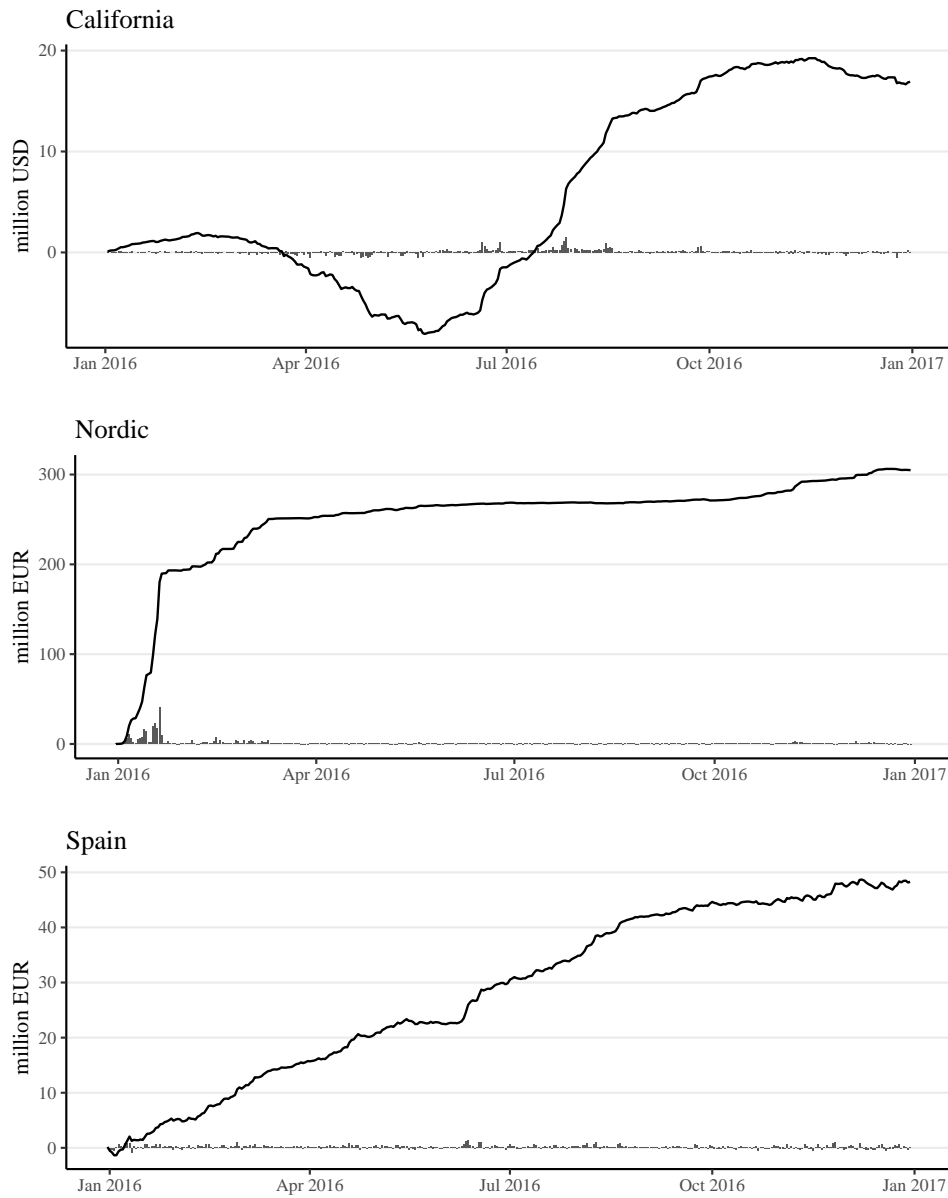
The mean annual total surplus gain is \$62.2 million in California, €13.8 million in the Nordics, and €31.5 million in Spain. For instance, in California the gain *ad infinitum* is ca. \$1.5 billion, with 4% interest rate, giving about \$1,500 per household, if one assumes that the added flexibility of 1GW is equivalent to a demand response from one million households (see Lawrence Berkeley National Laboratory, 2017). The bulk of the total gain is arbitrage surplus, and similarly so in the Nordics and Spain.

The total surplus is the gross social value, equal to what the new technology creates in terms of surpluses. The consumer surplus gain exceeds the gross social value in all markets – by more than ten times in the Nordics! Using the same calculation as just above for California, the consumers’ gain is close to \$4,000 per household in the Nordics. In California and Spain, these gains are ca. two times the social value. What explains the result and the differences in the magnitudes? Table 1 classifies days as “concave” and “convex”, referring to our convexity measure of the excess demand used in the regression analysis of the next Section. The consumer surplus increases (decreases) on average in

²²It is an empirical question if the technologies for arbitrage are used efficiently in actuality. Lamp and Samano (2022) find evidence supporting this conclusion for large-scale storage facilities in California.

²³Appendix B unpacks the seasonal and annual changes in surpluses in the data period.

Figure 2: Change in consumer surplus



Notes: Changes in consumer surpluses in California (top panel), the Nordic market (middle) and Spain (bottom). The comparison is between the counterfactual equilibrium with 1 GW trade and the replicated historical equilibrium. Each bar on the horizontal axis represents the change in surplus over one day (calculated as a sum of the hourly values) and the lines show the cumulative sum of the daily values over 2016. (Data for other years is visualized in a similar manner in Appendix B.1.)

convex (concave) days. To introduce the economic meaning of this convexity, Figure 2 reports the change in consumer surpluses due to the experiment day-by-day (small bars) and its cumulative sum (solid lines) over the course of one illustrative year (2016). The

three markets show notably different surplus developments over the year.²⁴

In California, the hourly price differences within a day start to increase in the spring, with depressed day prices and peaking evening prices. The solar PV systems crowd out a mix of gas-fired generation when the sun rises but the gas-fired units must quickly ramp up when the sun sets.²⁵ In these situations, the supply is typically convex in prices (i.e., concave in quantities), and the demand is relatively inelastic (see [Video, Panel A](#)). Then, the excess demand is concave, and the efficiency improvement works against the consumer surplus, as it increases the daily price level. Consumers lose day-by-day, until the trend is reversed later in the summer. A higher demand for cooling pushes the power system closer to full capacity, and the concave part of the supply curve applies (i.e., convex in quantities, see [Video, Panel B](#)). The efficiency improvement reduces the peak power generation and this lowers the peak prices more than what the prices rise during the off-peak periods. In the end, over the year, the consumer surplus remains positive.

In the Nordics, the daily price dispersion is small for a large part of the year, as the hydro resource provides flexibility for counterbalancing the wind power intermittency and demand variation.²⁶ Nearly all of the consumer surplus gain for the full year 2016 comes from a few winter days when a cold spell leads to peaks in electric heating demand and prices. The demand is inelastic, and the supply is concave in prices (i.e., convex in quantities, see [Video, Panel C](#)). 1GW additional capacity for reallocating loads reduces the impact of the market-level supply shortage in production and this brings consumer surplus gains that are significantly larger than for the other markets.

In Spain, the data suggest that the demand is more elastic than in the other markets, bringing stability to the surplus gain development over the course of the year: the demand elasticity reduces price peaks and also prevents prices from falling quickly in a positive supply shock. Intuitively, the demand and supply come close to being linear (see [Video, Panel D](#)), suggesting that the mandate has a moderate impact on the price levels – an alluring consistency with the theory prediction.

We turn next to quantify the contribution of the convexity of excess demand, together with the pass-through rate and correlation, to the consumer surpluses using a regression model including all three determinants.

²⁴Appendix B reports similar figures for all years in the data.

²⁵See, e.g., [Borenstein and Bushnell \(2015\)](#) for a discussion of the phenomenon.

²⁶In a typical year, ca. 50% of power is generated by hydro power in the Nordics. For example, in 2017, the share was 20% in California and 8% in Spain (EIA, Eurostat).

3.4 Reduced form

Motivated by the theory, we consider a linear-regression model for the change in the daily consumer surplus:

$$\Delta CS_t = f(\text{pass-through}_t, \text{correlation}_t, \text{convexity of excess demand}_t, \text{error}_t). \quad (2)$$

The unit of observation on the left is the change of the daily demand-side surplus, ΔCS_t , calculated from the demand bids before and after the technology experiment. The covariates included follow from our Propositions 1-3, constructed from the data as follows:

Pass-through

The pass-through rate measures how the demand and supply respond to the price change induced by the experiment. We obtain a measure of $\rho = \frac{1}{1 + \frac{\varepsilon_d}{\varepsilon_s}}$ from the bid curves for each hour h at date t by taking a $\pm 1\%$ quantity change around the equilibrium quantity and observing the corresponding changes in prices from the bid curves. The unit of observation used in the regression is the mean of ρ over the hours in day t .

Correlation

How the demand shocks line up with supply shocks impacts the consumers' expenditures. The experiment reduces price dispersion, which can benefit or hurt the consumers, depending on the correlation structure. We obtain a measure of the correlation structure from the hourly bid curves. We take a given fixed price and read the quantities demanded and supplied from the original bid curves for each hour of a day, giving 24 observations from each curve. We then vary the price, using the actual equilibrium prices, which gives 24×24 matrix per day both for the demand and supply quantities. From this data we obtain the standard deviations and correlations of demands and supplies at each price level. We take the mean values for the standard deviations and correlations, and use these as the daily observation in the analysis.²⁷

²⁷The correlation structure can be defined in alternative ways with little impact on the main results; for example, we have used only one price level, 100 \$/€ per *MWh*, for generating the quantity data. Panel A of Fig. 3, to be discussed in more detail just below, shows the families of demand and supply curves for two days: the shocks introduce mostly additive shifts of the curves. Scanning through a broad range of prices is intended to give some weight also to the possibility that the shocks alter the shape of the curves.

Convexity of excess demand

We apply Jensen’s inequality to an empirical excess demand to obtain so-called Jensen’s gap, a measure of convexity, for any given day. This is the unit of observation in the analysis. Consider next the construction of the daily excess demand.

In Fig. 3, Panel A depicts all bid data hour-by-hour as the demand and supply graphs for two distinct days in California. On the left, the data is from spring 2020, with the supply curves showing convexity in prices. On the right, the data is from summer 2020, and this time we observe that the supply curves show concavity in prices.

Panel B depicts the excess demands for each hour, derived from the demand and supply schedules shown in Panel A. For clarity, it shows only the side of each excess demand that is relevant for trading across hours. Each hourly excess demand has its own equilibrium price, the dots on the horizontal axis, i.e., at each such price $X_h = 0$. Using these curves for an efficiency experiment, we can look for one price that gives $\sum_{h \in \mathcal{H}} X_h = 0$, i.e., the daily excess demand is zero. This amounts to assuming an unlimited capacity for reallocations, captured by a sufficiently large Y . Visually, all hourly graphs are connected by a vertical line indicating the price at which the daily excess demand is zero.

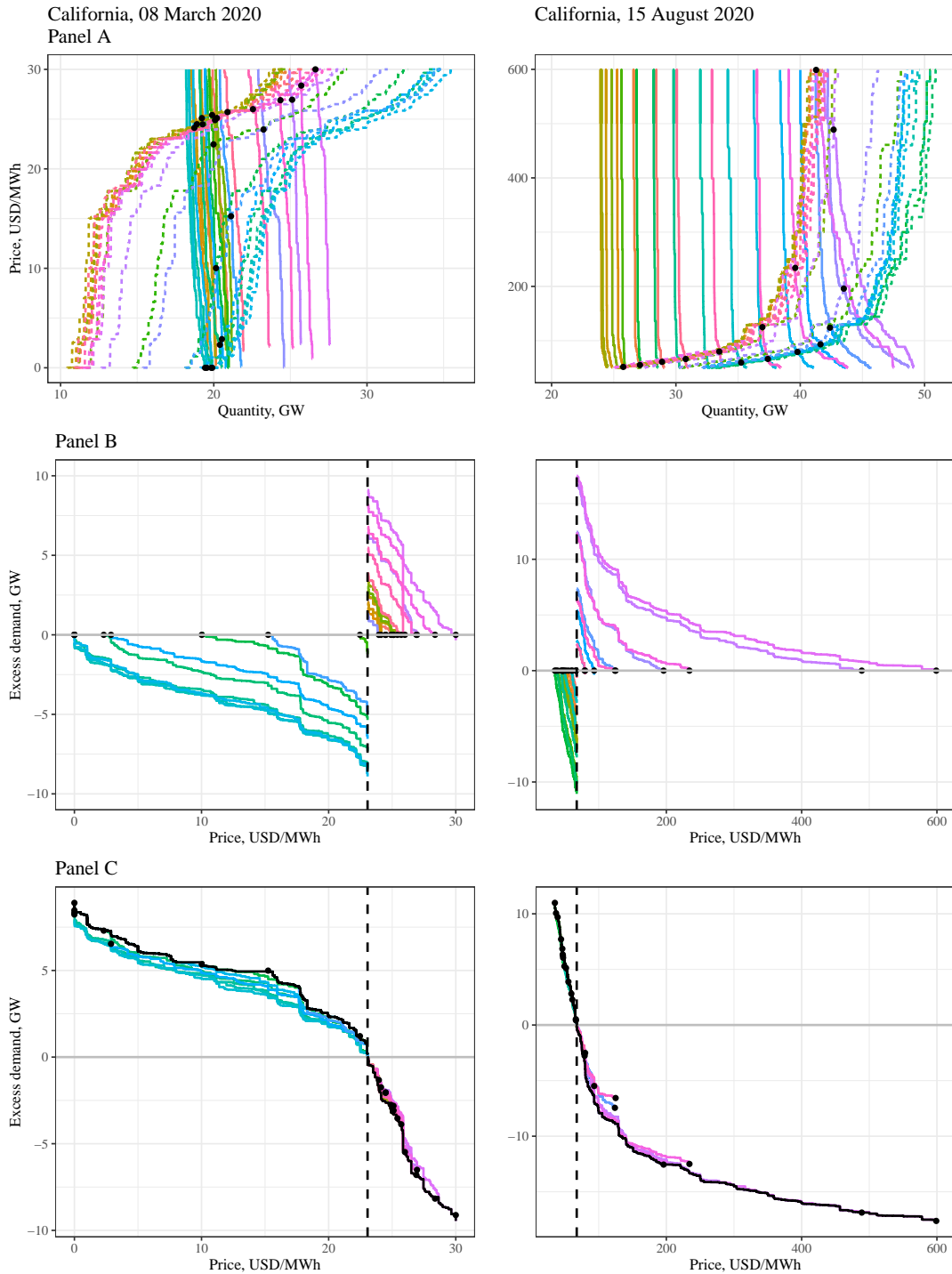
Panel C organizes the data from Panel B to obtain one graph to represent the daily excess demand. At the equilibrium price, the value is zero. At a lower (higher) price, there is positive (negative) excess demand. If all hourly markets had the same primitive demand and supply, as in equation (1) of the theory model, the family of curves in Panel C would collapse to become one representative curve. The variation in the curves calls for an approximation giving a representative curve. We obtain the approximation by an upper envelope of the curves for positive values and by a lower envelope of the negative values. These envelope graphs are depicted in Panel C.²⁸

We construct the envelope curve for each day and obtain a measure of convexity, i.e., Jensen’s gap, from this. Let $\mathcal{X}(p)$ be the step function given by the envelope curve for day t . Then, using $\mathcal{X}(p)$, the price given by this function for any given quantity x is defined by $\mathcal{P}(x) = \mathcal{X}^{-1}(x)$, which defines Jensen’s gap, G , as

$$G \equiv E[\mathcal{P}(x)] - \mathcal{P}(E[x]),$$

²⁸We may, e.g., alternatively construct a mean of the curves in our analysis. We have not found important differences in results caused by the approximation method of the excess demand.

Figure 3: Illustration of bid and excess-demand curves



Notes. Charts illustrate the California day-ahead market in two days. Charts on the left are from 8 March 2020 and charts on the right from 15 August 2020. Panel A (top row) shows demand curves (dotted lines) and supply curves (solid lines) of all hours with the market equilibria denoted by black dots. The excess demand curves of each hourly market, starting from the original market prices, are shown in Panel B (middle row). Panel C (bottom row) shows the same excess demand curves starting from the price at which daily excess demand vanishes, and the upper and lower envelope curves that approximate the aggregate excess demand curve.

where $E[x] = 0$ because the daily excess demand is zero. Price $\mathcal{P}(E[x])$ is thus the efficient price, and $E[\mathcal{P}(x)]$ is the mean of the actual (original) prices. A strictly positive G , associated to a strictly convex excess demand, measures the potential of the prices to decline due to the efficiency. The mean value of G in California is $\$1.43/MWh$, but ca. one-third of the days show negative G values. In the Nordics and Spain, positive and negative G have close to equal frequencies; see Table 1.²⁹

3.5 Regression results

We estimate the linear regression model in (2). In Table 2, the covariates are added successively in columns (1)-(5) to observe the movement in the total variation explained and the stability of the coefficients, in the spirit of the identification by observables approach (e.g., Altonji, Elder and Taber, 2005). We take the price-level effect, i.e., the convexity of excess demand curve as the main effect: it captures the bulk of the variation in all markets, and the coefficient remains precise and stable across specifications. The results are robust to a reordering of the covariates, i.e., to a change in the main effect, suggesting that the covariates are not correlated.³⁰ Possible omitted variables, linearly dependent on the covariates, could be analyzed as in Oster (2019) but the total variation explained suggests that (hypothetical) omitted variables could not eliminate the main effect to a notable degree.

The results for California (Table 2, Panel A) offer a clear message: the convexity measure explains 90 per cent of the total variation, and the remaining coefficients are inconsequential for the total variation of the buyer-side surplus. In the Nordics (Table 2, Panel B), we observe that the convexity, similarly to California, explains almost all of the variation. The results for Spain (Table 2, Panel C) confirm the same pattern, i.e., they show the importance of the convexity measure, but the impact of the other covariates is more nuanced. The correlation structure, including demand and supply variation and

²⁹The descriptives of all covariates are in Appendix B.2.

³⁰See Appendix C.1 for this robustness analysis. For the Nordics, the pass-through term explains a substantial share of the variation. We unpack this result in the Appendix, and show that it follows because the pass-through term is badly defined in situations where both demand and supply are extremely inelastic. These situations are rare but economically significant, and they are correlated with under-supply situations. Therefore, the pass-through term seemingly explains some part of the variation. For this reason, we use the estimation results in column (4), instead of column (5), when discussing the results for the Nordics.

Table 2: Explaining the change in consumer surplus

A. California					
	(1)	(2)	(3)	(4)	(5)
Convexity	0.226 (0.002)	0.226 (0.002)	0.226 (0.002)	0.226 (0.002)	0.229 (0.002)
Variation, Demand		-0.004 (0.008)	-0.007 (0.009)	0.0003 (0.010)	-0.005 (0.011)
Variation, Supply			-0.019 (0.013)	-0.018 (0.013)	-0.032 (0.015)
Correlation				-0.087 (0.056)	-0.017 (0.062)
Pass-through					0.274 (0.326)
R ²	0.90050	0.90051	0.90061	0.90073	0.90798
Observations	2,045	2,045	2,045	2,045	1,844
B. Nordics					
	(1)	(2)	(3)	(4)	(5)
Convexity	1.06 (0.010)	1.07 (0.011)	1.06 (0.011)	1.06 (0.011)	0.740 (0.013)
Variation, Demand		-0.027 (0.013)	-0.052 (0.014)	-0.056 (0.014)	-0.018 (0.012)
Variation, Supply			0.142 (0.033)	0.129 (0.035)	0.112 (0.028)
Correlation				0.102 (0.076)	0.088 (0.062)
Pass-through					-24.1 (0.692)
R ²	0.82786	0.82821	0.82963	0.82977	0.89136
Observations	2,192	2,192	2,192	2,192	2,150
C. Spain					
	(1)	(2)	(3)	(4)	(5)
Convexity	0.138 (0.004)	0.145 (0.004)	0.151 (0.004)	0.152 (0.004)	0.147 (0.004)
Variation, Demand		0.020 (0.005)	0.032 (0.006)	0.029 (0.006)	0.033 (0.006)
Variation, Supply			-0.046 (0.005)	-0.050 (0.006)	-0.047 (0.006)
Correlation				0.041 (0.021)	0.104 (0.022)
Pass-through					-0.398 (0.047)
R ²	0.40631	0.40981	0.42913	0.43013	0.45238
Observations	2,192	2,192	2,192	2,192	2,051

Notes. Panels document reduced-form regression results by market area. The dependent variable is the change in the daily consumer surplus, measured from the demand side bids before and after the technology experiment. *Convexity* is Jensen's gap calculated from the daily excess demand. *Variation, Demand* and *Variation, Supply* are standard deviations obtained, together with *Correlation*, from the daily covariance matrices of quantities read from the bid curves at hourly market equilibriums. *Pass-through* is the pass-through rate using the empirical estimates of local elasticities at equilibrium from the bid curves.

their correlation, contributes by 3% to the explained variation, with all elements having precise estimates. The pass-through covariate explains 2% of the total variation.³¹

The estimate of the convexity term means that when the mandate changes the daily price expectation by one euro/dollar, the daily consumer surplus changes by .226 million in California, 1.06 million in the Nordics, and .147 million in Spain. The mean value of the convexity covariate in California is \$1.43 , €0.29 in the Nordics, and -€0.04 per *MWh* in Spain, calculated over the data period 2015-2020 (see Table B.3). Multiplying with the coefficients for convexity in Table 2 and translating from daily to annual mean values gives predictions of consumer surplus changes: \$118 million U.S. dollar in California, €113 million euro in the Nordics, and -€2.3 million euro in Spain. The experiment shows that, controlled for market size, the consumer benefit of the efficiency improving technology is the largest in California whereas the impact in Spain remains modest (cf. Table 1).

3.6 Robustness

The definitions of covariates introduce some measurement errors. The hourly supply and demand curves may experience other than additive shifts, and the daily covariates are obtained from the hourly observations. In addition, Jensen’s gap is calculated from an approximation. We observe that the convexity measure captures the total surplus variation to an extent that the errors in the other covariates should not have substantial implications for the results; in particular, there is no general evidence of correlation between the sets of covariates. Thus, we find that the price-level effect, captured by the convexity of excess demand, is robust in our assessment.

A more basic concern relates to the design of the experiment. Is the 1*GW* experiment “small” to justify the assumption that the bids in the market can be taken as given, i.e., unaffected by the experiment? The concern links to the market structure and how

³¹In Appendix C.2, we consider a scenario in which prices are completely equalized by a large trade capacity of $Y = 50GW$. While this scenario is unrealistic, it allows us to assess whether the convexity measure explains all of the variation when the dependent variable (consumer surplus) is computed under equalized prices. The covariates used are the same as in the main experiment. In California, R^2 increases to 0.98. In the Nordics, R^2 rises to 0.93. In both markets, this increase is almost exclusively due to the convexity measure, which is unsurprising given that the other factors played a limited role in the main experiment. Spain is different in that the correlation structure and pass-through measure continue to contribute significantly to the explained variation, now approximately 12%. In Spain, R^2 rises to 0.87.

potential strategic bidding may be affected. However, even under perfect competition the bids could change in response to a new capacity: for instance, firms may withdraw sets of bids if the new prices after the experiment do not cover ramp-up cost of plants (see, e.g. [Reguant, 2014](#)). This concern is bigger, the larger is the experiment. In the next Section, we consider experiments of varied sizes and find that the impact on consumer welfare remains qualitatively the same for experiments in which Y is reduced to $.1GW$. We also analyze a considerably larger experiment to offer a comparison to [Butters, Dorsey and Gowrisankaran \(2024\)](#).

One limitation of the market-level approach of this paper is that it cannot answer where the new technology should be installed. For instance, a storage technology may have a large impact on prices in certain physical locations, leading to a larger market-level impact than indicated by our system-level approach. The physical location distribution of technologies is an important part of hands-on planning, and addressing the issues related to locality calls for a different approach (e.g., [Graf and Wolak, 2022](#); [Kirkpatrick, 2020](#); [Astier, Rajagopal and Wolak, 2023](#)).

Finally, our new technology is a reduced-form, generic arbitrage capacity. In [Appendix C.3](#), we introduce more structure to model one technology explicitly: a battery storage with a limited capacity and round-trip efficiency losses from the conversion of energy to and from the battery. This richer model tracks the chronological order of trades and the related losses. It confirms the results obtained for the generic $1GW$ mandate for California and the Nordics: the same consumer surplus impact is achieved under $1.3GW$ storage in California (i.e., the size of the actual mandate for 2024), and closer to $2.5GW$ storage in the Nordics. Thus, the mandate translates into different storage sizes in the locations, but the conclusions for the equilibrium impacts remain largely intact. The technology constraints do not lead to large deviations because the daily battery recharging and usage patterns are in congruence with the supply and demand conditions in these locations. The situation is different for Spain where the chronological order imposed on trade and the technology constraints lead to a significant reduction in the consumer surpluses. This finding further supports the conclusion the impacts of technology mandates are more limited in Spain.

4 Policy context

Table 3 reports marginal impacts on the annual mean surpluses from increasing Y in small steps of $100MW$ (i.e., one tenth of the original experiment size). Surplus impacts discussed do not incorporate the costs of storage investments. The market gross return for the first addition of Y differs between the markets, from 63.2 million dollars in California to 37.5 million in Spain and 17.6 million euros the Nordics. The numbers are expressed in euros or dollars per $1kW$ of capacity for a comparison with the main experiment in which, for example, the return to a one-step $1GW$ was 62 million in California, almost the same as for the first $100MW$. In contrast, the decline in equilibrium returns is faster in the other locations. In fact, the marginal return becomes negative after $1GW$ in the Nordics, after $2GW$ in Spain, and after $3GW$ in California.

Table 3: Technology impact: marginal values

Capacity GW	Δ technology surplus			Δ consumer surplus		
	California	Nordic	Spain	California	Nordic	Spain
0.1	63.2	17.6	37.5	122.2	268.4	13.3
1	41.7	4.3	14.3	98.3	84.4	24.1
2	22.8	-1.1	0.7	88.4	44.5	13.2
3	8.5	-2.8	-6.1	78.5	24.5	15.7
4	-2.0	-2.8	-8.1	65.4	14.3	12.1
5	-10.2	-2.2	-7.4	56.0	8.2	10.5

Notes. The marginal value of the new technology and the marginal change in consumer surplus for an additional unit of capacity at the specified capacity level. All changes in annual mean values in the data period, measured in units of million U.S. dollar or euro per GW (equal to dollar or euro per kW). The surplus impacts presented in this table do not incorporate the costs of storage investments.

Quantitatively, the strongly declining technology returns are in agreement with the findings in [Butters, Dorsey and Gowrisankaran \(2024\)](#) who consider only California in a framework that is designed for an equilibrium analysis of a large-scale storage investments. Appendix C.3, which maps our generic mandate into storage technology, confirms that the market surplus for the technology is not sufficient to cover the technology cost. The result is even stronger for the Nordics and Spain. However, consumer surpluses can largely cover the costs of the mandates in California.³²

³²Storage technologies can earn surplus also from other sources than the energy arbitrage, e.g., markets for reserves and frequency regulation. However, for instance, the California storage development pipeline is already larger than the size of the regulation market (Levelized cost of storage analysis, Lazard 2021).

In contrast to the technology surplus, the demand-side surplus gain continues to increase at all levels of Y considered (Table 3), at the expense of the incumbent producer surplus. The result is notable in [Butters, Dorsey and Gowrisankaran \(2024\)](#), and our analysis confirms the same result for the Nordics and Spain.

Policy makers often decide on the portfolio of capacities, and procure the capacities by various capacity mechanisms ([Fabra, 2018](#); [Joskow, 2019](#); [Grubb and Newbery, 2018](#); [Wolak, 2021, 2022](#)). For concerns about the security of supply, price level, and carbon emissions, it is critical to evaluate the equilibrium impacts of new capacity, including investments in renewable energy and storage capacities. The European energy crisis illustrates how technologies that enhance flexibility provide greater societal value than is reflected in their market returns. Policy intervention can then be efficient ([Gerlagh, Liski and Vehviläinen, 2022](#)). During a crisis, technology mandates lower prices, acting as a form of price control. At other times, such mandates may raise consumer prices. However, this issue is minor if the mandates keep prices within acceptable limits, especially since storage provides positive externalities, such as supply security, that our estimates do not capture.

5 Concluding remarks

Do consumers gain when new technologies improve the efficiency of trade? The answer is less obvious than what one may read from the evidence on the benefits of technologies reducing information and other trade frictions. Understanding equilibrium impacts, including how short-run surpluses depend on technologies, is essential for both private and public policy decisions in markets where technologies are regulated or subsidized. This observation is not new (e.g., [Borenstein and Holland, 2005](#)), but our breakdown of surpluses into their sources is novel. In particular, the convexity of excess demand for capturing the price-level effects has gone unnoticed in the literature.

As new technologies improve responsiveness to prices, they may limit market power ([Joskow and Tirole, 2007](#); [Wolak, 2019](#)) and thus have implications for policies on competition. Our result that increasing trade by better technologies can cause a sizeable shift of surplus from producers to consumers can also be read in the other direction: Strategically avoiding the use of such technologies can shift surplus to incumbent producers. The size of our main experiment was ca. 1/50 of the total installed generation capacity in each

market, showing that relatively small trade capacity can be detrimental to incumbent surpluses. This is suggest an important topic for future research.

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A Data and quantitative analysis

The Data Set containing all the codes to replicate the analysis and a sample of the data is available through [this link](#).

A.1 Data sources

The raw data can be obtained from the following sources:

1. CALIFORNIA: CAISO, <http://oasis.caiso.com>

The data is collected from OASIS server via the API-interface. The bids are collected from `Public Bids` and `Public Convergence Bidding` data categories. In addition we use `Ancillary Services`, and `System Load and Resource Schedules` data.

2. SPAIN: OMIE, <http://www.omie.es>

The data is obtained from OMIE server. We use the `datosftp/public cbc` -files.

3. NORDIC: Nord Pool, <http://www.nordpoolgroup.com>

The data is from the ftp-server of Nord Pool (access requires a licence). We use the data from the `System price bid curves` -folder.

The raw data consist of bid data and supporting data required in the preprocessing of data. Table A.1 gives summary statistics of the final bid data set after cleaning and preprocessing.

Table A.1: Bid data statistics

	Data period	Hours with data	Number of bids		
			Demand	Supply	Total
California	03/03/15–12/31/20	49,080	12,632,453	42,622,255	55,254,708
Nordic	01/01/15–12/31/20	52,608	30,875,292	45,709,770	76,585,062
Spain	01/01/15–12/31/20	52,608	7,727,599	23,127,454	30,855,053

Notes: A bid in our data set is an anonymous price–quantity pair for a given hour in a given market. Data for some days or hours is missing or has been removed in the preprocessing e.g. because of incomplete or erroneous data. Data for California not available prior to 3 March 2015.

We follow the steps outlined below to obtain the equilibrium prices and quantities from the supply and demand bids for each hour of the day in the day-ahead markets. All steps are implemented with R and the codes to replicate the steps are included in the Data Set.

A.2 Preprocessing of data

We process the raw data obtained from the market operators to obtain one coherent data set that is an input to the market equilibrium and counterfactual computations. Each bid in our final data set is a price–quantity pair for one hour. We discuss below the detailed assumptions that we have made in the course of data processing by the market area.

California

Ancillary services. The initial allocation of resources in electricity markets is done in the day-ahead energy market where the bulk of the quantities are traded. However, market operators also need to take care, in real-time, of demand and supply shocks that realize after the day-ahead market clears. In California, the operator, CAISO, assesses the quantities of *ancillary service* capacities needed for this and procures the required amounts simultaneously with the clearing of the day-ahead energy market. Each bidder in CAISO can offer the same resource to the day-ahead energy market and potentially to one or many of the ancillary services markets. If the market operator selects a resource to any of the ancillary markets, then the bids from that resource are not included in the energy market calculation. As our interest lies in the energy market, we isolate the effects of the ancillary markets as follows: First, we collect the quantities of procured ancillary services by the hour as reported by CAISO. Second, we use the ancillary service market bid data to identify the least expensive bids and the associated resources to meet the hourly service requirements on each of the ancillary service markets. Third, these identified resources, whose bids we accept in one of the ancillary service markets, are made unavailable in the other markets. To avoid conflicts in deciding which resources are used where, we use CAISO’s cascading hierarchy of the markets: Regulation Up, Spinning Reserve, Non-Spinning Reserve, and finally the day-ahead Energy market³³.

Locational bids. Each bid submitted to CAISO is linked to a node of the power network. There are around 3,000 nodes, and for each of them CAISO calculates a locational marginal price that takes into account the transmission constraints between the nodes. In our quantification, the geographical location of the bids is ignored to obtain

³³CAISO applies a more detailed method where the same resources can be partially allocated to different markets as long as the capacity of the resource in total is not exceeded. Source: CAISO, Business Practice Manual for Market Operations, Version 44, 2015.

the system equilibrium which is comparable to that in the other markets. This approach is similar to the calculation of *system marginal cost of energy* (SMEC) that CAISO reports³⁴. There are also imports and exports from CAISO to the neighbouring market areas. We take reported trade to/from CAISO in the day-ahead market, and add the net trade as one bid per hour to our data set³⁵.

Bid types. CAISO offers a variety of bidding options: *Economic bids*, *multi-stage bids*, and *convergence bids*³⁶. Economic bids consist of price–quantity pairs that feed directly our computations. With multi-stage bids generators can submit alternative schedules: For example, a power plant can be offered for the whole day or the same plant can be offered only for the peak hours but with a higher bid price. Such schedules are accepted only if the market price for all hours of the bid is above the bid price. The data does not identify which of the schedules are accepted; we systematically select the last schedule offered by the bidders and ignore the other schedules³⁷. Convergence bids, often called virtual bids, are financial instruments between day-ahead and real-time markets. They are included in the determination of the day-ahead market prices, and we merge them together with the physical bids. Finally, we also convert all bids to simple hourly bids.

Nordic market

The data on equilibrium outcomes in the Nordic market comes close to the outcomes that our model is designed to produce. The market operator, Nord Pool, runs an energy-only exchange where hourly supply and demand bids in the Nordic area are geographically attached to one of the 12 price areas. Nord Pool carries out two separate rounds of market clearing: one for each price area and another for a system-wide reference price, the *system price*. In the system price calculation bids from all price areas, regardless of their location, form a single supply curve and a single demand curve for each hour. We

³⁴SMEC price is calculated over a *reference bus* that varies across hours in ways that are not disclosed. In price comparisons below, we use the average of SMEC prices across all nodes.

³⁵CAISO provides also bid-level data on imports and exports, but the format does not allow the reconstruction of transmission flows.

³⁶There are also *self-scheduled bids* where the bidder is a price taker; we assign either minimum or maximum price to such bids, and treat them then as other economic bids.

³⁷We have compared the model generated market price realizations with the market outcomes: on average, this simple rule matches better with the data than other fixed orderings or randomization of the order.

take the individual bids underlying the aggregate bid curves as data.

In addition to the simple bids for one hour, Nord Pool has *block bids* that combine a fixed quantity and price over a period of several hours. In contrast to California, the power exchange reports the total quantities of the accepted block bids by the hour, but not the full universe of submitted block bids. This latter property can have an effect on the counterfactuals that we produce, although the effect should not be large based on the small impact of block bids on the baseline allocations. In addition, Nord Pool reports the total net trade flow from the surrounding regions through the transmission interconnections. We incorporate block bids and trade flows by adding corresponding single bids to each hour.

From 3 June 2020 the Nordic market has been served by another exchange, EPEX SPOT, for which we lack the market clearing data. As the trade through EPEX SPOT comprises only less than 4% of Nord Pool’s annual volumes in 2020 the impact on welfare measures can be expected to be minimal.

Spain

Like in the Nordic market, our model produces a close replication of the equilibrium outcomes in the Spanish market, but there are some discrepancies in the way market bids are collected. The operator, OMIE, has special rules to account for e.g. ramping-up and ramping-down restrictions, so the caveat from above applies: the actual bids are divided into accepted and non-accepted sets using rules that are not fully disclosed. Our model replicates precisely the actual equilibrium but the counterfactuals, if they were produced by OMIE, could differ from ours given the additional rules for market clearing.

Finally, we note that the data from OMIE includes also bids from Portugal which we include in the analysis. In 2011–2020 the prices for Spain and Portugal coincided over 90% of the time, i.e. at those hours there was only one price for the whole area.

A.3 From data to market outcomes

We have the data from the three markets for 2015–2020 which we use to replicate historical market prices and compute the counterfactuals. In total, the optimization is solved over 200,000 times. Each individual optimization problem has typically 15,000–35,000 variables (the bid data) and 24 constraints (hourly balance limits), and is easily solvable with any modern LP-solver. We use the Mosek-solver (<http://mosek.com>) for which it

takes less than one second to solve one optimization, i.e., one day allocation.

A.3.1 Replication of market outcomes in the data

We replicate the market-clearing task by a formal model that maps the data to market outcomes. The data consists of a set of demand bids, $(p_{i,h}, Q_{i,h})_{i \in \mathcal{D}_h}$, and a set of supply bids, $(p_{j,h}, Q_{j,h})_{j \in \mathcal{S}_h}$, for any given hour h , day, and market (for simplicity, the last two are left out from the notation). Let $Q_{i,h}^d \in [0, Q_{i,h}]$ be the quantity of demand bid $i \in \mathcal{D}_h$ activated, and, similarly, $Q_{j,h}^s \in [0, Q_{j,h}]$ for supply bid $j \in \mathcal{S}_h$, maximizing the total surplus in a linear program:

$$\begin{aligned} \max_{\{Q_{i,h}^d, Q_{j,h}^s\}} & \sum_{i \in \mathcal{D}_h} p_{i,h} Q_{i,h}^d - \sum_{j \in \mathcal{S}_h} p_{j,h} Q_{j,h}^s & (3) \\ \text{s.t.} & Q_h^d = \sum_{i \in \mathcal{D}_h} Q_{i,h}^d, \quad Q_{i,h}^d \in [0, Q_{i,h}] \\ & Q_h^s = \sum_{j \in \mathcal{S}_h} Q_{j,h}^s, \quad Q_{j,h}^s \in [0, Q_{j,h}], \\ & X_h = Q_h^d - Q_h^s = 0. \end{aligned}$$

The market price is the shadow price of the constraint that supply equals demand, i.e. that the excess demand is zero, $X_h = 0$.

A.3.2 Counterfactual outcomes: effect of trade technologies

The model in (3) finds hourly prices from bids so that $X_h = 0$ separately for each hour of the day, $h \in \mathcal{H}$, whereas the model in (4) does the same by aggregating over the hours of any given day: $\sum_{h \in \mathcal{H}} X_h = 0$. The objective is now

$$\max_{Q_{i,h}^d, Q_{j,h}^s} \sum_{h \in \mathcal{H}} \left[\sum_{i \in \mathcal{D}_h} p_{i,h} Q_{i,h}^d - \sum_{j \in \mathcal{S}_h} p_{j,h} Q_{j,h}^s \right], \quad (4)$$

where we relax the hourly supply–demand balance constraints with a possibility to “trade” a net quantity Y between the hours of one day:

$$\begin{aligned} X_h &= Q_h^d - Q_h^s, \quad \forall h, \\ -Y &\leq X_h \leq Y \quad \forall h, \\ \sum_{h \in \mathcal{H}} X_h &= 0. \end{aligned}$$

Note that now the excess demand, as read from the original bid curves, for any given hour can deviate from $X_h = 0$. After introducing this main counterfactual experiment, we consider storage in Section C.3.

A.4 Replication results

Table A.2 presents summary statistics for the equilibrium outcomes from the model in Section A.3.1. The mean annual value traded through the day-ahead markets is \$8.1 billion in California, €10.5 billion in the Nordics, and €11.2 billion in Spain.

Table A.2: Summary statistics of market outcomes

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
<i>Equilibrium prices</i>							
California (\$/MWh)	49,080	32.37	30.06	0.00	23.29	36.50	1,000.00
Nordic (€/MWh)	52,608	28.30	13.91	0.00	20.30	37.50	200.00
Spain (€/MWh)	52,608	46.90	14.75	0.04	38.12	56.97	102.00
<i>Equilibrium quantities</i>							
California (GW)	49,080	26.53	5.31	17.42	22.54	28.95	49.82
Nordic (GW)	52,608	41.24	8.02	24.03	35.24	46.80	65.26
Spain (GW)	52,608	26.74	4.77	14.72	22.93	30.30	42.98

Notes. Summary of hourly values of equilibrium prices and quantities as calculated by the model. Data from 2015–2020 for those dates where data is available.

To validate the preprocessing steps described above, we compare the equilibrium price outcomes from our model with the historical market prices.

California. The comparison is between the historical hourly averages of the nodal market prices obtained from CAISO and the prices from our model. On average, the model prices are slightly lower than the average of the nodal prices (see Table A.3). This is as expected: we relax both the transmission constraints between the nodes and the ramp-up and ramp-down schedules, which should lead to lower average prices. However, the model does capture within a day price variation, essential for our quantifications; see Figure A.1, Panel A. for an illustration. Here, imperfect modeling of ancillary services may contribute to the differences during the periods with peak prices.

Nordic. The prices from our computations match the day-ahead market prices reported by the operator almost one-to-one, see Table A.3 and Figure A.1, Panel B. The

distribution of the difference between our model price and the reported system price shows a very small upward bias which potentially results from differences in tie-breaking rules for bid curves that coincide in ways that produce multiple equilibria. The differences are inconsequential.

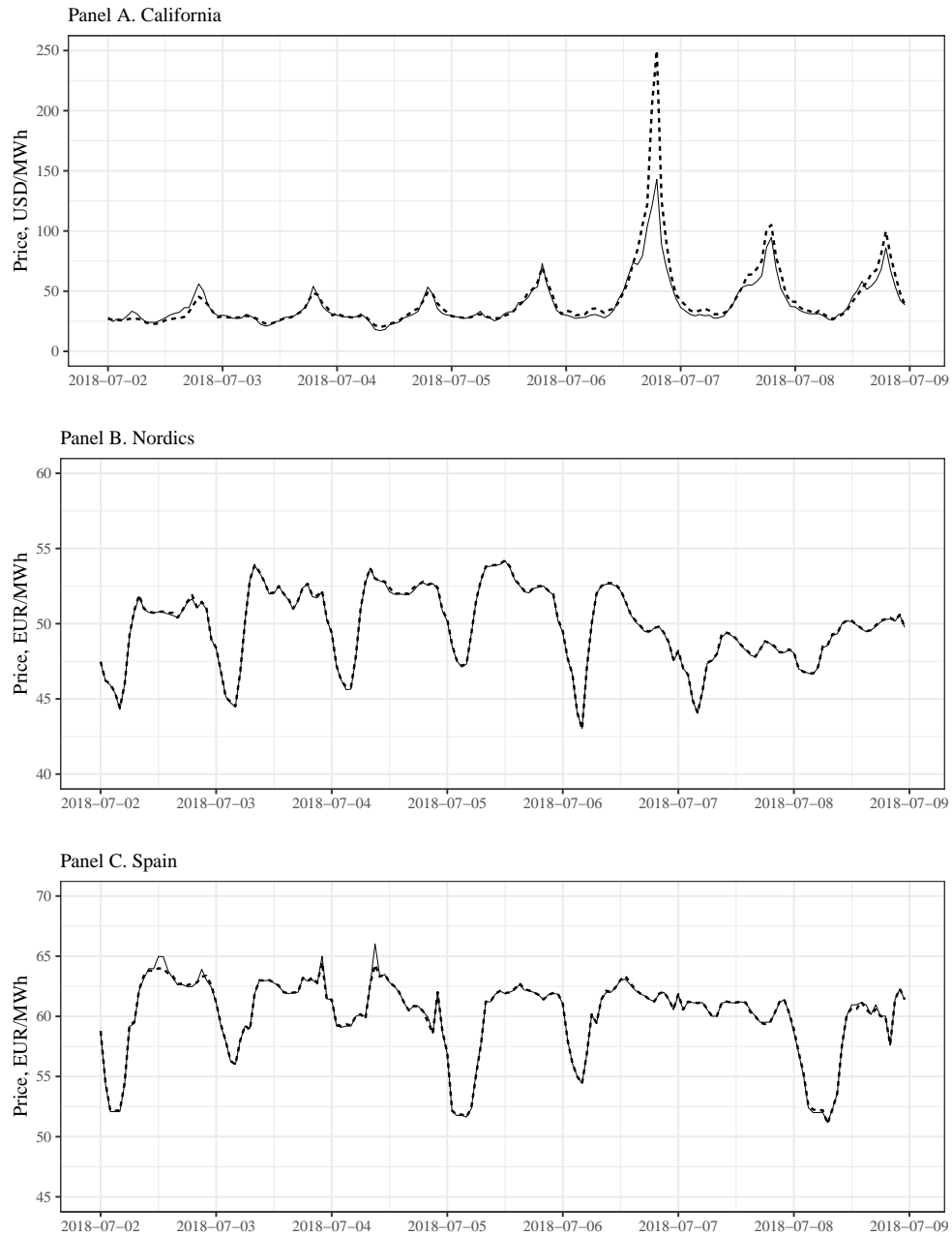
Spain. As in the Nordic case, the discrepancies between the reported and calculated prices are very small in Spain, see Table A.3 and Figure A.1, Panel C. This is not surprising: The European day-ahead electricity clearing is done simultaneous with the same clearing algorithm (EUPHEMIA) for 25 countries that closely resembles our model. The minor deviations likely relate to the additional assumptions made in the data preprocessing stage.

Table A.3: System-level prices from the bids

Area	5 %	50 %	95 %	Mean
California	-12.018	-1.606	4.461	-2.099
Nordic	0	0.031	0.133	0.038
Spain	-0.318	0.025	0.350	0.033

Notes: Reported values are the 5% and 95% quantiles, median and mean from the hourly differences between the model price and the historical price for the whole data period (see Table A.1). The historical price in the Nordics is the system price (up to 3 June 2020, after which comparable prices are not available). The historical price in Spain is the mean price by the hour across the Iberian price zones. For California, the historical price is the mean energy price over the nodes by hour.

Figure A.1: Illustration of the hourly energy prices



Notes: Comparison between the historical hourly day-ahead market prices (solid lines) and model prices (dashed lines). In Panel A. California, historical prices are the mean of the hourly nodal energy prices (SMEC). In Panel B. Nordics the market operator reports direct equivalent to our model price, i.e., the system price. In Panel C. Spain, the historical prices are the mean of the Spanish and Portuguese area prices. Excerpt of data for the week starting on Monday 2 Jul 2018.

B Counterfactual experiment

B.1 Consumer surplus changes

Table B.1 presents the changes in consumer surplus that result from the addition of 1GW capacity of efficiency improvements to the day-ahead market using the model in Section A.3.2. The comparison is between the replicated market outcomes (with no efficiency improvements) and the counterfactual with 1GW capacity added. Table B.2, and Fig. B.1, B.2 and B.3 document the seasonal changes in consumer surplus for the same experiment. In California, the convexity measure and consumer surplus changes are systematically negative in the spring and positive later in the summer. This reflects the seasonal over- and under-supply situations. In the Nordics, over-supply relates to the spring flooding adding to the hydro reservoirs, and the under-supply situations occur in the winter months. The seasonal pattern in Spain is less clear.

Table B.1: Summary statistics for the changes in consumer surplus

	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
California	2,045	0.31	1.84	-1.23	-0.06	0.23	33.76
Nordic	2,192	0.43	1.83	-2.45	-0.06	0.27	40.71
Spain	2,192	0.07	0.30	-0.99	-0.13	0.23	1.89

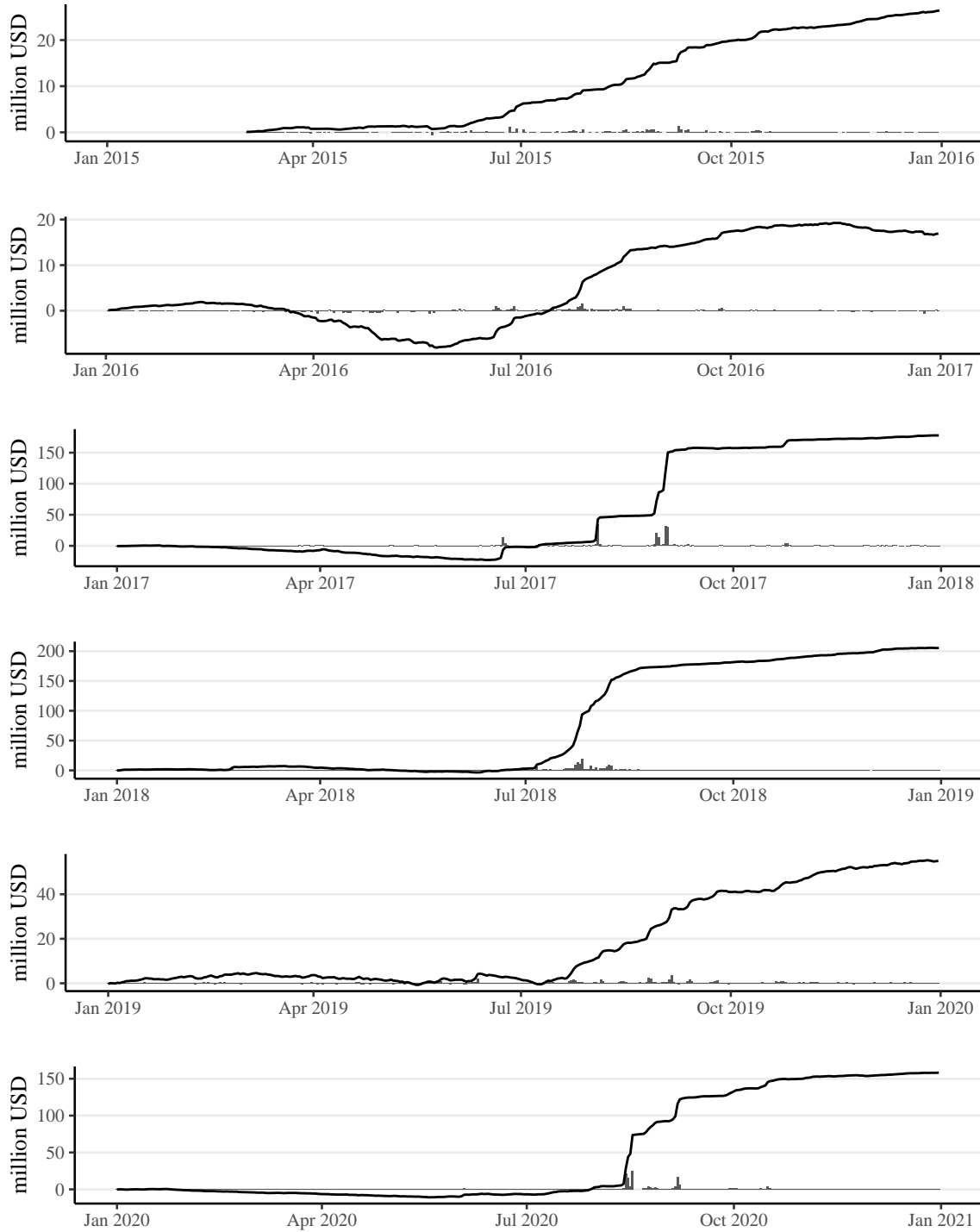
Notes. Daily change in consumer surplus measured in millions of U.S. dollar or euro per day from 1GW of capacity for efficiency improvements in the model in Section A.3.2. Data as reported in Table A.1.

Table B.2: Seasonal pattern in consumer surplus change

	California		Nordic		Spain	
	Convexity measure	Consumer surplus change	Convexity measure	Consumer surplus change	Convexity measure	Consumer surplus change
Jan	0.16	0.02	1.34	1.73	-0.39	0.08
Feb	-0.38	-0.005	0.88	1.08	-0.18	0.09
Mar	-0.40	-0.05	0.56	0.66	-0.10	0.08
Apr	-0.61	-0.13	0.15	0.19	-0.05	0.05
May	-0.22	-0.06	-0.30	-0.06	0.09	0.06
Jun	0.89	0.22	-0.20	-0.03	0.31	0.14
Jul	3.64	0.83	-0.12	-0.01	0.02	0.11
Aug	6.53	1.51	0.02	0.07	0.11	0.09
Sep	3.55	0.79	-0.06	0.04	0.10	0.06
Oct	1.95	0.27	0.05	0.12	0.18	0.07
Nov	0.92	0.12	0.77	0.77	-0.18	0.05
Dec	0.52	0.11	0.46	0.59	-0.47	0.01

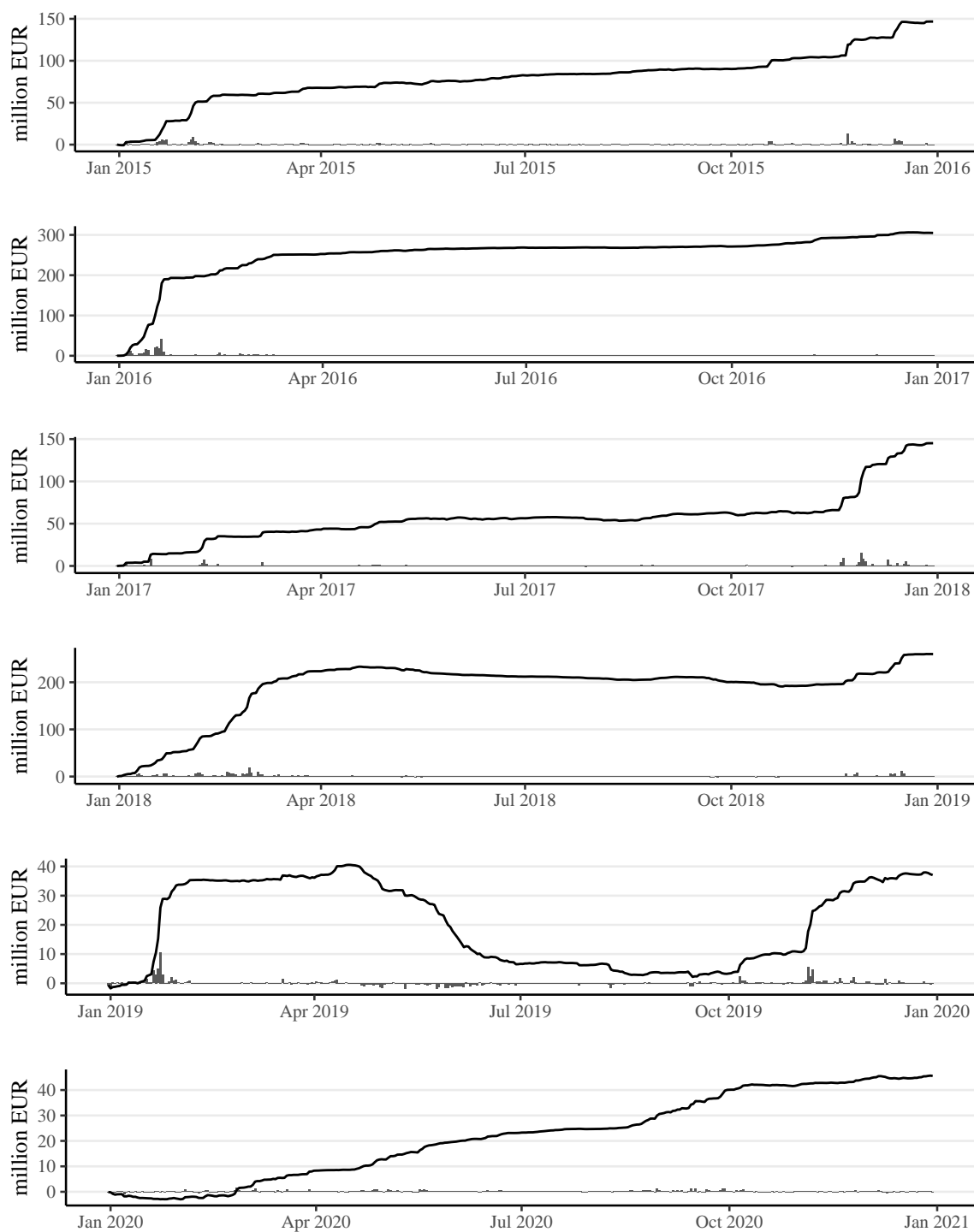
Notes: Monthly means of the daily values of the aggregated excess demand convexity measure and consumer surplus in three different markets. Convexity measure is in U.S. dollar or euro per megawatt hour and consumer surplus change measured in million U.S. dollar or euro. Data as reported in Table A.1.

Figure B.1: Change in consumer surplus in California in 2015–2020



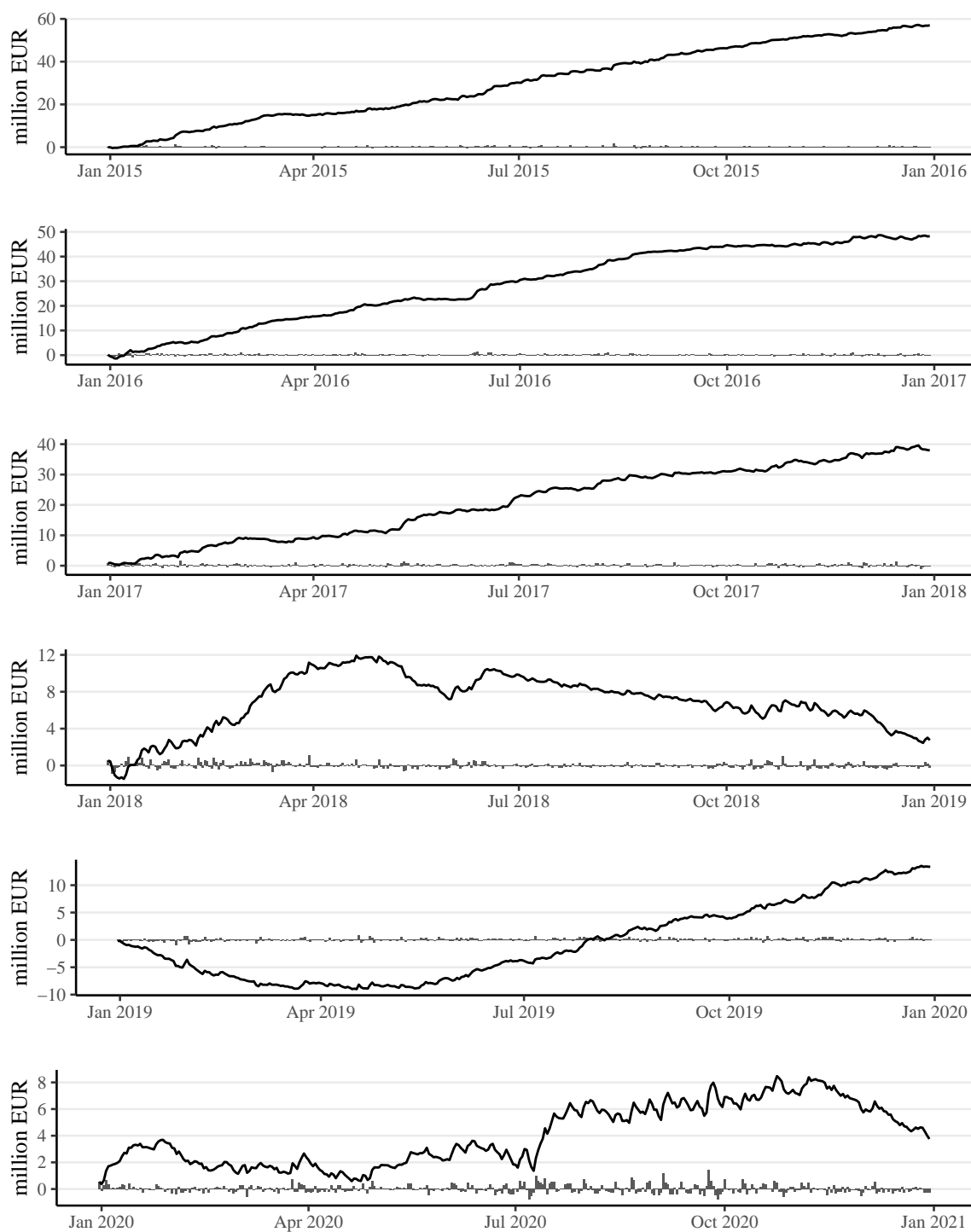
Notes: Changes in consumer surpluses in California. The comparison is between the counterfactual equilibrium with 1 GW trade and the equilibrium without trade. Each bar on the horizontal axis represents the change in surplus over one day (calculated as a sum of the hourly values) and the lines show the cumulative sum of the daily values over one year. Each panel shows the years from 2015 (Top) to 2020 (Bottom).

Figure B.2: Change in consumer surplus in the Nordic market in 2015–2020



Notes: Changes in consumer surpluses in the Nordic market. The comparison is between the counterfactual equilibrium with 1 GW trade and the equilibrium without trade. Each bar on the horizontal axis represents the change in surplus over one day (calculated as a sum of the hourly values) and the lines show the cumulative sum of the daily values over one year. Each panel shows the years from 2015 (Top) to 2020 (Bottom).

Figure B.3: Change in consumer surplus in Spain in 2015–2020



Notes: Changes in consumer surpluses in Spain. The comparison is between the counterfactual equilibrium with 1 GW trade and the equilibrium without trade. Each bar on the horizontal axis represents the change in surplus over one day (calculated as a sum of the hourly values) and the lines show the cumulative sum of the daily values over one year. Each panel shows the years from 2015 (Top) to 2020 (Bottom).

B.2 Descriptives: covariates used in the regressions

Table B.3 reports the summary statistics for the covariates used in the regressions. The convexity measure gives the convexity (+) or concavity (-) of the daily excess demand curves in euro or dollar per *MWh*. All covariates are defined in the main text.

Table B.3: Summary statistics of the covariates

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
<i>Convexity measure</i>							
California (\$/MWh)	2,045	1.43	7.72	-8.95	-0.32	1.21	132.54
Nordic (€/MWh)	2,192	0.29	1.57	-6.44	-0.23	0.41	19.43
Spain (€/MWh)	2,192	-0.04	1.40	-6.04	-0.88	0.78	6.65
<i>Variation of demand</i>							
California (GW)	2,045	4.15	1.70	1.42	2.92	5.14	11.08
Nordic (GW)	2,192	4.04	1.31	0.83	3.05	4.94	7.55
Spain (GW)	2,192	4.04	1.03	1.70	3.24	4.73	7.70
<i>Variation of supply</i>							
California (GW)	2,045	3.66	1.01	1.03	2.94	4.37	6.57
Nordic (GW)	2,192	1.44	0.56	0.19	1.03	1.80	3.39
Spain (GW)	2,192	2.92	0.96	0.81	2.22	3.56	7.07
<i>Correlation between demand and supply</i>							
California	2,045	0.15	0.27	-0.61	-0.02	0.34	0.81
Nordic	2,192	0.80	0.24	-0.76	0.75	0.94	1.00
Spain	2,192	0.71	0.27	-0.69	0.62	0.89	0.99
<i>Pass-through</i>							
California	1,844	0.87	0.05	0.68	0.85	0.91	0.97
Nordic	2,150	0.98	0.03	0.62	0.98	0.99	1.00
Spain	2,051	0.73	0.12	0.28	0.68	0.82	0.96

Notes. Covariates are defined in the main text.

B.3 Annual variation

Table B.4 unpacks the trends underlying the results presented in Table 3 in the main text. Table B.4 shows the results of Table 3 for marginal impacts at 1GW efficiency mandate separately for all years. In California, the technology surplus increases over time: the rapid increase in solar power during the time period has increased the value of technologies that counterbalance the increased intermittency. In Spain, the changes in bid curves suggest an increase in the market-level demand response, reducing the technology surplus due to the mandate. In the Nordics, we see no similar systematic trends.

Table B.4: Technology impact: marginal values

Year	Δ technology surplus			Δ consumer surplus		
	California	Nordic	Spain	California	Nordic	Spain
2015	12.5	4.3	19.1	27.8	105.0	56.3
2016	19.8	5.2	14.1	15.8	153.5	34.4
2017	48.0	3.6	16.6	172.3	78.4	24.6
2018	68.0	5.3	15.0	200.4	121.3	6.3
2019	49.5	5.3	11.5	53.5	22.7	13.2
2020	52.5	1.9	9.8	119.9	25.3	9.6

Notes. The marginal value of the new technology and marginal change in consumer surplus at 1GW efficiency mandate. All changes in annual mean values measured in units of million U.S. dollar or euro per GW (equal to dollar or euro per kW).

C Robustness

C.1 Correlation of covariates

Table C.1 reports the results from regressing each of the covariates in the main analysis (see Table 2) individually. The only covariate in addition to the convexity measure that explains variation in the consumer surplus is the pass-through measure for the Nordics (column 5, Nordics). We show next that the result follows because pass-through as a variable is badly defined in serious under-supply situations.

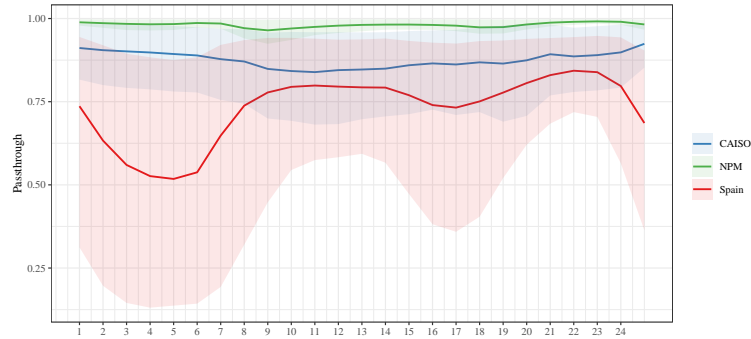
Table C.1: Explaining the change in consumer surplus

A. California						
Model:	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.313 (0.041)	-0.010 (0.013)	-1.45 (0.099)	0.889 (0.153)	0.251 (0.046)	5.53 (0.840)
Convexity		0.226 (0.002)				
Variation, Demand			0.425 (0.022)			
Variation, Supply				-0.157 (0.040)		
Correlation					0.422 (0.153)	
Pass-through						-5.93 (0.959)
R ²		0.90050	0.15395	0.00743	0.00371	0.02035
Observations	2,045	2,045	2,045	2,045	2,045	1,844
B. Nordics						
Model:	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.428 (0.039)	0.120 (0.017)	-0.991 (0.123)	-0.983 (0.104)	-0.295 (0.137)	54.5 (0.768)
Convexity		1.06 (0.010)				
Variation, Demand			0.351 (0.029)			
Variation, Supply				0.980 (0.067)		
Correlation					0.909 (0.165)	
Pass-through						-55.1 (0.782)
R ²		0.82786	0.06274	0.08848	0.01372	0.69804
Observations	2,192	2,192	2,192	2,192	2,192	2,150
C. Spain						
Model:	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.074 (0.006)	0.081 (0.005)	0.360 (0.025)	0.146 (0.021)	0.149 (0.018)	0.598 (0.040)
Convexity		0.138 (0.004)				
Variation, Demand			-0.071 (0.006)			
Variation, Supply				-0.025 (0.007)		
Correlation					-0.106 (0.024)	
Pass-through						-0.719 (0.054)
R ²		0.40631	0.05778	0.00595	0.00879	0.07923
Observations	2,192	2,192	2,192	2,192	2,192	2,051

Notes. Panels replicate reduced form regression in Table 2 by introducing one covariate at a time. The dependent variable is the change in the daily consumer surplus, measured from the demand side bids before and after the technology experiment. *Convexity* is Jensen's gap calculated from the daily excess demand. *Variation, Demand* and *Variation, Supply* are standard deviations obtained, together with *Correlation*, from the daily covariance matrices of quantities read from the bid curves at hourly market equilibriums. *Pass-through* is the pass-through rate using the empirical estimates of local elasticities at equilibrium from the bid curves.

First, Fig. C.1 shows the underlying hourly data that is used to construct the daily pass-through measure. The pattern in California and the Nordic market is stable over all the hours of the day and variations in the 10%–90% band are modest: both markets are characterized by high pass-through, indicating low demand elasticity in normal times. In Spain, the pass-through is lower and more volatile, indicating more elastic response from the demand side.

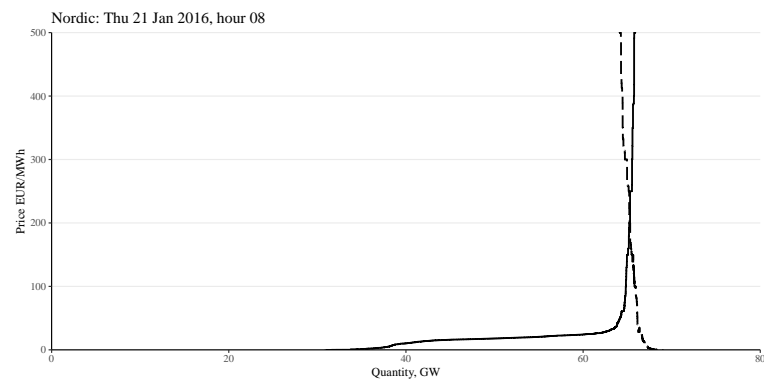
Figure C.1: Pass-through by the hour and area



Notes: Means and 10% and 90% percentiles of the hourly pass-throughs by the market for all the data.

Second, the modest variation of the pass-through shown just above is difficult to reconcile with the variable explaining 70% of the changes in consumer surplus in the Nordic market, as in Table C.1. We have scrutinized the occurrences of low pass-through values: they are correlated with serious under-supply situations such as those described in Fig. C.2. The pass-through takes low values in these situations not only because the demand elasticity is high but because the supply becomes close to vertical. As a result, the pass-through measure captures the convexity of supply in quantities. This way it captures the same phenomenon as the convexity of excess demand in such extreme situations.

Figure C.2: Example of bid curves in the Nordic market when prices are high



Notes: Example of the market primitives during the highest price hour in the Nordic market in our data set. Demand is not more responsive, but high pass-through is explained by the inelastic supply.

C.2 Full price convergence: regression results

Table C.2 reports the consumer surplus regression results, similar to the main analysis, but with the size of the experiment increased from 1 GW to 50 GW, which is sufficient to guarantee full price convergence across all days and price areas. Note that in this experiment only the dependent variable changes; all covariates remain as they are in the main experiment. The experiment can be interpreted to show the upper bound for R^2 achievable with these covariates. The largest changes are observed for Spain, where the convexity measure becomes more salient, but the contribution of demand and supply variation remains significant, accounting for approximately 12% of the total variation.

Table C.2: Consumer surplus changes under full price convergence

A. California					
	(1)	(2)	(3)	(4)	(5)
Convexity	1.24 (0.004)	1.24 (0.005)	1.24 (0.005)	1.24 (0.005)	1.25 (0.004)
Variation, Demand		0.006 (0.021)	0.015 (0.021)	0.082 (0.025)	0.046 (0.026)
Variation, Supply			0.049 (0.034)	0.055 (0.033)	0.041 (0.036)
Correlation				-0.781 (0.139)	-0.630 (0.145)
Pass-through					0.272 (0.769)
R^2	0.97744	0.97744	0.97747	0.97781	0.98161
Observations	2,045	2,045	2,045	2,045	1,844
B. Nordics					
	(1)	(2)	(3)	(4)	(5)
Convexity	1.65 (0.012)	1.64 (0.013)	1.64 (0.013)	1.64 (0.013)	1.27 (0.015)
Variation, Demand		0.031 (0.015)	0.029 (0.017)	0.025 (0.017)	0.070 (0.014)
Variation, Supply			0.014 (0.040)	0.0009 (0.042)	-0.021 (0.034)
Correlation				0.095 (0.090)	0.079 (0.074)
Pass-through					-28.4 (0.826)
R^2	0.89280	0.89300	0.89301	0.89306	0.93110
Observations	2,192	2,192	2,192	2,192	2,150
C. Spain					
	(1)	(2)	(3)	(4)	(5)
Convexity	0.544 (0.007)	0.615 (0.007)	0.646 (0.006)	0.643 (0.006)	0.645 (0.006)
Variation, Demand		0.211 (0.009)	0.281 (0.008)	0.297 (0.008)	0.300 (0.008)
Variation, Supply			-0.231 (0.008)	-0.196 (0.008)	-0.199 (0.008)
Correlation				-0.308 (0.029)	-0.268 (0.031)
Pass-through					-0.189 (0.066)
R^2	0.75115	0.80109	0.85925	0.86600	0.87261
Observations	2,192	2,192	2,192	2,192	2,051

Notes. Panels document reduced-form regression results by market area. The dependent variable is the change in the daily consumer surplus with a capacity of 50 GW, measured from the demand side bids before and after the technology experiment. *Convexity* is Jensen's gap calculated from the daily excess demand. *Variation, Demand* and *Variation, Supply* are standard deviations obtained, together with *Correlation*, from the daily covariance matrices of quantities read from the bid curves at hourly market equilibriums. *Pass-through* is the pass-through rate using the empirical estimates of local elasticities at equilibrium from the bid curves.

C.3 Storage application

Our main model for counterfactuals (see Section A.3) poses no limits on trade across hours, other than the capacity limit Y for the exports and imports, and no losses occur if trade takes place. Here we impose more structure on the problem and explicitly model a battery storage with limited capacity and round-trip efficiency losses from the conversion of energy to and from the battery.

Model with storage: We start with the model (4) and maintain the limit on the aggregate trade over the hours of any given day: $\sum_{h \in \mathcal{H}} X_h = 0$. The objective remains

$$\max_{Q_{i,h}^d, Q_{j,h}^s} \sum_{h \in \mathcal{H}} \left[\sum_{i \in \mathcal{D}_h} p_{i,h} Q_{i,h}^d - \sum_{j \in \mathcal{S}_h} p_{j,h} Q_{j,h}^s \right], \quad (5)$$

but now we need to track the chronological order of trade and losses. Battery is charged, when the supply exceeds the demand of an hour, i.e. excess demand $X_h < 0$, and discharged when demand is less than supply, $X_h > 0$. Like in Appendix A.3, we use Q_h^d and Q_h^s short for the sum of demand and supply of the hour respectively. Charging and discharging are limited by a capacity constraint Y that is here set symmetrically. We use I_h to keep track of the battery state. Battery starts the day empty, i.e., $I_0 = 0$. Round-trip losses are set to burden discharges, i.e., when $X_h > 0$, and are a fixed percentage γ of the amount discharged. The full set of constraints for the battery problem are thus:

$$\begin{aligned} X_h &= Q_h^d - Q_h^s, \quad \forall h, \\ -Y &\leq X_h \leq Y \quad \forall h, \\ I_0 &= 0, \\ I_h &= I_{h-1} - (1 + \gamma \mathbb{1}_{X_h > 0}) X_h, \quad \forall h \in \mathcal{H} \\ 0 &\leq I_h \leq K \quad \forall h \in \mathcal{H} \end{aligned}$$

The computations are for a typical battery specification, similar to those in Butters, Dorsey and Gowrisankaran (2024): the round-trip efficiency of the battery is .85 ($\gamma = .15$ above), and we use 4-hour duration, i.e. $K = 4Y$. The results from running the experiment with varying storage capacities are presented in Table C.3. The results for surpluses for the California mandate level of 1.3GW come close to those from our generic technology experiment with lower capacity (1GW). For the Nordic market, the consumer surplus impact of the generic mandate is reached at the storage capacity closer to 2.5GW.

Qualitatively the storage specification produces the same results as our main model for California and the Nordics: the technology surplus remains low but the consumer

Table C.3: Technology impact: storage

Energy MWh	Power MW	Technology surplus			Consumer surplus			Annual battery cost
		California	Nordic	Spain	California	Nordic	Spain	
4	1	0.04	0.01	0.02	0.04	0.3	0	0
100	25	1.1	0.2	0.5	2.5	5.2	-0.1	2
1000	250	10.1	1.8	4.8	22.1	37.2	0.6	24
5200	1300	42.5	4.7	16.1	105.4	116.1	4.5	123
10000	2500	65.0	4.3	18.6	188.3	163.0	2.5	236
25000	6250	76.4	0.6	7.4	360.9	214.1	7.3	589
50000	12500	26.7	0	0.1	513.3	217.7	15.7	1,178

Notes. Technology surplus and consumer surplus with varying battery energy and power capacities. Round-trip efficiency of 85% is used throughout. Surplus changes reported in annual mean values in the data period, measured in units of million U.S. dollar or euro. Battery costs are in million U.S. dollar and calculated based on an overnight cost of \$1,270/kW that is converted to annuity values using a WACC of 6.2% and a 30-year cost recovery period (as in U.S. DOE, Annual Energy Report, 2023).

surplus increases in the capacity. The results look drastically different for Spain where consumer benefits are wiped out when stricter constraints are put on the technology. A part of the explanation is given by Fig. C.1: the battery is optimally charged during the night when the demand elasticity is consistently higher, which leads to a rise in average prices, and this together with the technology constraints limits the gains from optimally utilizing the storage in the other hours. In the Nordics, the losses in efficiency reduce technology surplus, but the consumer surplus remains high in the data period; the constraints for the storage do not eliminate its ability to cut the peak prices. Finally, in all markets, sufficiently large increases in the battery storage reduce the technology surplus from the technology; in the Nordics and Spain the whole benefit is eliminated with a 50,000MWh battery.