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Felix Muesgens

The New Merit Order

The Viability of Energy-Only Electricity Markets with Only Intermittent Renewable Energy Sources and Grid-Scale Storage

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Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Prof. Dr. Thomas K. Bauer
RUB, Department of Economics, Empirical Economics
Phone: +49 (0) 234/3 22 83 41, e-mail: thomas.bauer@rub.de

Prof. Dr. Wolfgang Leininger
Technische Universität Dortmund, Department of Economic and Social Sciences
Economics – Microeconomics
Phone: +49 (0) 231/7 55 - 3297, e-mail: W.Leininger@tu-dortmund.de

Prof. Dr. Volker Clausen
University of Duisburg-Essen, Department of Economics
International Economics
Phone: +49 (0) 201/1 83 - 3655, e-mail: vclausen@vwl.uni-due.de

Prof. Dr. Ronald Bachmann, Prof. Dr. Almut Balleer, Prof. Dr. Manuel Frondel, Prof. Dr. Ansgar Wübker
RWI, Phone: +49 (0) 201/81 49 - 213, e-mail: presse@rwi-essen.de

Editorial Office

Sabine Weiler
RWI, Phone: +49 (0) 201/81 49-213, e-mail: sabine.weiler@rwi-essen.de

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Werner Antweiler and Felix Muesgens*

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Abstract

What happens to the merit order of electricity markets when all electricity is supplied by intermittent renewable energy sources coupled with large-scale electricity storage? With near-zero marginal cost of production, will there still be a role for an energy-only electricity market? We answer these questions both analytically and empirically for electricity markets in Texas and Germany. What emerges in market equilibrium is the 'new merit order'. Our work demonstrates that as long as free entry and competition ensure effective price setting, an efficient new merit order emerges in electricity markets even when the grid is completely powered by intermittent sources with near-zero marginal costs. We find that energy only markets remain viable and functional.

JEL-Codes: D47, Q41, Q42, L11

Keywords: Renewable energy; energy storage; electricity markets

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* *Werner Antweiler, Sauder School of Business, University of British Columbia; Felix Muesgens, Brandenburgische Technische Universität, Senftenberg – All correspondence to: Werner Antweiler, Sauder School of Business, University of British Columbia, 2053 Main Mall, Vancouver, BC, Canada V6T 1Z2, Email: werner.antweiler@ubc.ca*

1. Introduction

As electricity systems around the world replace the generation of CO_2-intensive power generation from coal, oil and gas with generation from renewable energy sources (RES), the exit of conventional generators running on fossil fuels will also upend the traditional merit order in electricity markets. Whereas conventional peak-load and base-load have set the merit order based on their relative marginal costs, RES (in particular solar and wind) have zero or near-zero marginal costs. Furthermore, they are intermittent and depend on solar irradiation and wind speed to generate electricity. Hence, electricity storage—more formally known as energy storage resources (ESR)—will have a pivotal role in electricity markets of the future. Interesting questions emerge: What will wholesale electricity prices look like? Can energy-only electricity markets continue to function when there are only generators with intermittent renewable energy sources and grid-scale electricity storage present?

Our paper analyses how market clearing will function in an energy system 100% based on RES and storage—purposefully without any other types of generators. We are interested in the viability of energy-only markets under these futuristic but entirely plausible conditions. In short, we find that energy-only markets remain viable and functional, and a 'new merit order' emerges in which grid-scale storage becomes a pivotal technology. Whereas today's grid-connected storage operates at a small scale—thus acting as price takers—storage participation in the 'new merit order' becomes such an essential part of the system that they significantly influence the price structure. In the 'new merit order', storage can recover its fixed cost. Furthermore, the resulting positive prices even at negative residual demand levels provide revenue that finances RES investment. Electricity systems of the future will require large shares of dispatchable storage to complement intermittent RES: intermittent RES produce all net electricity in the system—including both final consumption and storage losses—and dispatchable storage shifts RES production to when it is needed.

The high degree of intermittent RES adds significant new stochastic elements on the supply side to the existing stochastic elements on the demand side. Weather conditions influence conditions for wind and solar power, thus spanning a multi-dimensional empirical distribution in which capacities of various RES and ESR technologies need to be optimised. We are carefully investigating how characteristics of this probability space influence outcomes. At the same time, we are abstracting from many features that characterise dispatch models. We are not investigating the *incremental* addition of RES and ESR into existing grids, but we are envisioning a new grid unconstrained by existing generation and transmission capacities. The purpose of our study is more to envision the outer limits of feasibility and economic viability and less to provide an accurate forecast.

Our contribution to the literate is both theoretical and empirical. We develop a theoretical framework to analyse an energy system consisting of renewable generation and storage technologies only. In this setting, the system is carbon-neutral and all technologies have zero production costs. We develop a general framework with two types of RES (wind and solar power) and two types of ESR (battery and hydrogen storage), with the two storage types differentiated by their losses. There is free entry into RES and ESR, with an equilibrium price emerging. We also develop a simplified linear model for analytic tractability to obtain closed-form algebraic solutions for capacities and prices. The results from both approaches complement each other and identify key elements of the 'new merit order'. Our results show that fears of a horizontally-flat merit order in a 100%-RES system are unfounded. Instead, we show that prices will be positive during most of the year. At the same time, they will provide efficient investment signals for RES and ESR technologies.

Empirically, we use data from the Electric Reliability Council of Texas (ERCOT) and from Germany to estimate the probability distributions for demand and renewable energy supply, and in turn simulate the bulk composition of the four types of capacities under different scenarios for cost parameters, which we vary between 2020 levels and 2050 forecasts. Our empirical model maximises welfare and allows for a price-responsive demand response. There is significant benefit to our empirical modelling approach. It is purposefully 'green-field' (i.e. unconstrained by existing generation or transmission infrastructure) because our time horizon is long-term. As a consequence, the model can be solved relatively fast, which enables us to employ Monte-Carlo simulations of future states of the demand and supply state space. By contrasting two highly different demand and supply state spaces—Texas and Germany—we are able to explore specific local characteristics that emerge from a pure RES+ESR electricity system. We find that the bulk composition is influenced strongly by the correlation structure of the state space of demand and supply.

Furthermore, it can be expected that—assuming identical investment cost—the cost for a carbon neutral system is significantly lower in ERCOT as both solar and wind have higher full-load hours compared to Germany. We not only quantify the cost difference for various parameter assumptions but also decompose the differences into separate components: resource utilisation (more annual generation per MW for both wind and solar power) and state-space correlation effects (e.g. ERCOT as a summer-peaking grid profits more from solar power).

Our paper's theory and empirical results are highly policy-relevant for discussions about the future of electric grids. In some discussions on energy-only markets, advocates of capacity mechanisms argue that while energy-only markets work well at the moment, additional capacity mechanisms are needed when the system transitions to more and more RES. Our work contradicts this reasoning and provides evidence to the contrary: energy-only markets can continue to function just fine. While there remains a need for pricing ancillary electric services separately, the need for capacity mechanisms only arises when energy-only markets are constrained in their operational efficiency, for example through peak price caps. As our model shows, peak prices remain an essential element for fixed-cost recovery, in particular for ESR.

The remainder of our paper proceeds as follows. Section 2 reviews the literature pertinent to our topic. In section 3 we first introduce a general model of a pure RES with ESR system. As the non-linear nature of the model is not conducive to closed-form algebraic treatment, we also introduce a simplified linear model with just one type of RES and one type of ESR. This simplified model can be solved analytically and reveals important properties of our 'new merit order'. In section 4 we introduce our empirical data from Texas and Germany, and we simulate the bulk composition of an RES+ESR system based on cost parameters that we vary between 2020 levels and 2050 forecasts. We discuss ERCOT first, followed by Germany, and compare results. We acknowledge the limitations of our modelling approach in section 5, but also point to suitable extensions and future uses of our model. This discussion is followed in section 6 by putting our results into the context of current policy debates about market design and energy security. Section 7 concludes with a summary of our results and key implications.

2. Literature

Carbon-neutral energy systems receive a lot of attention in the scientific community. Numerous papers analyse their optimal composition, including both renewable and energy storage technologies, and the influence of public policies (Ambec and Crampes, 2019). A recent survey article by Breyer et al. (2022) on 100% renewable energy systems research identifies a total of 739 relevant articles, including articles discussing generic questions and reviews. They also provide an impressive reference list with biographical details for a total of 474 sources. Zerrahn and Schill (2017) reviewed the role of storage in energy systems with high shares of renewable energy.

Research on 100% renewable energy systems models include Luderer et al. (2022); Teske et al. (2021); Bogdanov et al. (2021); Gulagi et al. (2017); Ghorbani et al. (2017); Bussar et al. (2016); Pfenninger and Keirstead (2015); Budischak et al. (2013); Haller et al. (2012). These papers analyse various regions, target years, sectors and technologies. Green (2021) discusses the economics of electricity markets with high shares of renewable energy in a system.

The consensus from that literature is that energy systems that are 100% based on renewable energy generation and complemented by storage are technically feasible. Furthermore, most studies find higher system costs compared to past years. However, first it should be noted that several negative environmental externalities were not properly reflected in the past. Second, the cost in a 100% renewable system mostly depends on the underlying investment cost assumptions, which have declined considerably over the past decades, especially for solar energy. Most of these papers are using energy systems models which minimise total system costs or maximise social welfare. Hence, they are not focusing on the regulatory framework, market design, and the resulting hourly price structure.

A second literature branch relevant to our work analyses the design of wholesale electricity markets and cost coverage of investments. At the core of this debate is the question whether and which instruments are needed to ensure long-term resource adequacy in addition to energy-only markets (Wolak, 2021; Cramton et al., 2013; Muesgens and Peek, 2011). Modern energy-only markets are designed as multi-settlement nodal pricing markets, which are widely used in the United States and Europe. Multi-settlement markets are divided into day-ahead and real-time markets, where the real-time markets clear imbalances relative to the day-ahead market. Nodal pricing is accomplished through *locational marginal prices* (LMPs), which account for the spatial dimension of transmission and other operational constraints. Regulators often impose price caps; in the US, FERC Order 831 puts an effective $2,000/MWh cap on prices. ERCOT (which is outside FERC jurisdiction) has a $9,000/MWh cap. The existence of such price caps introduces a reliability externality, what is commonly referred to as the "missing money problem". Different capacity mechanisms have been proposed to fix this, and one jurisdiction (Alberta in Canada) even considered replacing its energy-only market completely with a capacity market (AESO, 2016).[1]

Capacity mechanisms and markets have been designed in different ways (Aagaard and Kleit, 2022; Cretì and Fontini, 2019; Wolak, 2021); they are sometimes referred to as 'first generation' and 'second generation' designs. First-generation designs involve capacity payments (as \$/kW/year) to generators based on some metric of "firm capacity" that a generator could commit to. Second-generation designs involve fixed-price forward contracts such as those used in PJM's *Reliability Pricing Model*, where generators must deliver on demand during system peaks or owe large payments for non-performance. Capacity is procured in a 3-year-ahead market, along with location pricing for transmissions constraints, based on the system operator's resource requirement curve, also known as the *variable reserve requirement* (VRR). Even these improvements have received criticism; Gramlich and Goggin (2019) suggest that these mechanisms incentivise overcapacity by using VRRs that do not align with the efficiency frontier.

The central question in our paper about the future viability of energy-only markets is linked to this resource adequacy debate in multiple ways. First is the worry that near-zero marginal costs in generation would accelerate the merit order effect and lead to long periods of zero prices. Second is the worry that short periods of extremely high peak prices would be insufficient to pay for capacity in the presence of regulatory price caps. And third is the worry that energy-only markets would insufficiently incentivise the presence of grid-scale electricity storage. For example, Roques and Finon (2017) argue that RES installations tend to lower the average wholesale price and thus needs revenue sources beyond wholesale revenues.

Our analysis suggests that these worried are unfounded. Antweiler and Muesgens (2021) have shown that market equilibria exist with increasing shares of renewable energy and equilibrium investment adapts to additional renewable capacity. While our past analysis was focused on a system in transition which also included conventional technologies, this paper shows that energy-only markets remain viable even when RES and storage operate exclusively. Storage will be able to provide "firm capacity" by holding sufficient energy reserves. Furthermore, while there is a debate whether large scale energy storage increases or reduces emissions during the transition towards a carbon neutral energy system (Linn and Shih, 2019), this question loses relevance in a 100% renewable system as there are no remaining emissions by definition.

Another direction in the literature is the specific role of energy storage. There are at least two sub-streams. The first sub-stream is concerned with the regulation of energy storage. Hoogland et al. (2023) discuss the regulatory framework for energy storage in great detail. Their analysis is performed for the member states of the European Union. The authors argue that several entry barriers for storage have already been removed in the wake of the "Clean Energy Package" regulation introduced in 2019. However, issues such as double taxation (taxing both consumption and production of energy storage) still need to be addressed for energy storage to compete on a level playing field. In a more theoretical con-

[1] In 2016, the Alberta Electricity Systems Operator (AESO) considered replacing its existing energy-only market with a capacity market by 2021 after a new provincial government took office. A subsequent election brought another government into power, which abandoned these plans.

tribution, Helm and Mier (2021) show how storage subsidies can help incorporate climate externalities as a second-best policy, in particular when Pigouvian carbon taxes cannot be set sufficiently high to reach the social cost of carbon (SCC).

The second sub-stream in the storage literature focuses on the optimal charge-discharge path, mostly solving mixed-integer linear programming problems. Electricity prices in these set-ups are typically exogenous. While this is a useful approach to evaluate the competitiveness of storage technologies, it does not take into account the impact that storage investment, especially on a large scale, will have on electricity prices. Antweiler (2021) shows how increased storage deployment reduces the profitability of price arbitrage opportunities. Our work extends this second sub-stream because we analyse market equilibria with endogenous investment in ESR. In equilibrium, ESR investment and dispatch are incentivised by the resulting price level - but they are also–together with RES investment and generation–determining the shape of the price structure.

To sum up, our paper narrows the literature gap about quantitative insights on the equilibrium price structure in an energy system composed exclusively of renewable energy and storage. Such an analysis is lacking in the literature. We are aware of only two notable exceptions, which are both relevant but providing different insight. The first is a case study on market clearing prices performed by Böttger and Härtel (2022). In contrast to our work, they analyse a 95% greenhouse gas reduction target and thus centre the analysis around open cycle gas turbines as a provider of firm capacity. The authors add several technologies and confirm that the price duration curve becomes more and more diverse and less volatile. The second is a study by Korpås and Botterud (2020) in which the authors derive a market equilibrium in a stylised system. An important contribution of their paper is the proof that all technologies cover their costs in equilibrium, even for high RES scenarios where RES are sometimes curtailed. In contrast to our work, they keep the model framework linear (assuming inelastic demand) and deterministic.

3. Theoretical Framework

In what follows we first develop a general model that we later employ for our empirical work. This general model employs two types of renewable energy (wind and solar) and two types of ESR (batteries and hydrogen) in order to identify the bulk composition of an electricity grid that is shaped exclusively by renewable energy and storage. We derive the corresponding 'new merit order' of prices in such an energy-only market. We also develop a second model which is a simplified linear model we can solve analytically for capacities and prices, with only one type of RES and one type of storage for simplicity. This second model allows us to tease out the underlying economic effects more clearly. Lastly, we extend the second model to allow two types of storage.

3.1. General Model

Our general model starts with defining demand and supply. Latent electricity demand, which we define as the demand at a price level of zero, is assumed to follow an empirical distribution $q \sim \mathcal{Q}$. Electricity prices are given by the linear demand function

$$p = \theta(q - x + z) \geq 0 \tag{1}$$

where q is the latent demand at any given time, x is available supply, and z is any curtailed output. When there is excess supply $x > q$, prices fall to zero. The amount of curtailment is

$$z = \max(0, x - q) \tag{2}$$

The prices that emerge are driven by capacity, available supply, and demand conditions. Our theoretical model captures the endogenous determination of capacities and prices in an electricity system composed exclusively of intermittent RES and ESR. We consider two types of RES, photo**V**oltaics and **W**ind, and two types of ESR, **B**atteries and **H**ydrogen, signified by corresponding subscripts. In some discussions we will also refer to RES and ESR jointly, and then we will use subscripts R ('renewables') and S ('storage'). Total uncurtailed output at any given time is

$$x \equiv x_V + x_W + x_B + x_H \equiv v\bar{x}_V + w\bar{x}_W + b\bar{x}_B + h\bar{x}_H \tag{3}$$

where subscripts V and W denote the two types of renewable electricity producers, and B and H denote storage technologies. Renewable energy sources (solar, wind) provide maximum capacities $\bar{x}_V$ and $\bar{x}_W$, with uncurtailed output $x_V(t) \in [0, \bar{x}_V]$ and $x_W(t) \in [0, \bar{x}_W]$. The utilisation rates $v \equiv x_V/\bar{x}_V \in [0, 1]$ and $w \equiv x_W/\bar{x}_W \in [0, 1]$ follow empirical distributions $v \sim \mathcal{V}$ and $w \sim \mathcal{W}$.[2] They are mostly driven by weather conditions, i.e. taking into account that solar irradiation and wind conditions limit effective production of installed capacity. These utilisation rates are often referred to as availability factors in the literature. The unit capacity cost of installed renewable energy capacity and storage are f_i, expressed in the same physical units.[3]

The correlation pattern between $\mathcal{Q}$, $\mathcal{V}$, and $\mathcal{W}$ can be arbitrarily complex. It is useful to describe this empirical relationship through a probability function $\phi(q, v, w)$ so that

$$\iiint \phi(q, v, w)\, \mathrm{d}q\, \mathrm{d}v\, \mathrm{d}w = 1 \tag{4}$$

We will be making extensive use of the triple integral shown in (4), and thus it is useful to introduce short-hand notation for this process. We define

$$\Phi(y) \equiv \iiint \phi(q, v, w)\, y\, \mathrm{d}q\, \mathrm{d}v\, \mathrm{d}w \tag{5}$$

for an arbitrary expression y. Thus with (5) we can write (4) as $\Phi(1) = 1$.

Electricity can be stored in a storage system with power capacity $\bar{x}_S \equiv \bar{x}_B + \bar{x}_H$. Our model focuses on power capacity, not the energy capacity, of the ESR. Our storage technologies are thus assumed to be able to store unlimited amounts of energy. How much power can be called upon when needed? The storage system can charge and discharge individually, so that $x_B \in [-\bar{x}_B, +\bar{x}_B]$ and $x_H \in [-\bar{x}_H, +\bar{x}_H]$. Analogous to $\bar{x}_S$, we define $x_S \equiv x_B + x_H$. Consequently, $x_S \in [-\bar{x}_S, +\bar{x}_S]$. We also introduce the ESR capacity utilisation $s \equiv x_S/\bar{x}_S \in [-1, +1]$

[2]In contrast, b and h, i.e. storage utilisation factors, are determined endogenously in the optimisation.

[3]We express the capacity cost in \$/MW units amortised to the hourly level, which we denote as \$/MW.h, in order to keep physical units compatible to our energy prices, expressed as \$/MWh. The extra dot in \$/MW.h indicates the reference to CapEx.

so that s is the discharge (positive) or charge (negative) share of the ESR, and equivalently $b \in [-1, +1]$ and $h \in [-1, +1]$ for the two types of ESR. Further let $\bar{\boldsymbol{x}}$ denote the vector of all capacities.

The storage system must also obey the energy balance constraint that charging equals discharging over the full time horizon. We capture this by the storage system balance

$$\eta_S \, \Phi \left(\max\{0, -s\} \right) \bar{x}_S = \Phi \left(\max\{0, s\} \right) \bar{x}_S \tag{6}$$

for each type of ESR, as well as the system overall, where $\eta \in]0, 1]$ is the turnaround efficiency and $1 - \eta$ is the storage loss. On the left-hand side of equation (6) is the energy volume charged (bought), attenuated by storage losses, and on the right hand side is the energy volume discharged (sold).

It is also useful to define averages for demand, RES utilisation, and prices:

$$\bar{q} \equiv \Phi(q) \quad \bar{v} \equiv \Phi(v) \quad \bar{w} \equiv \Phi(w) \quad \bar{p} \equiv \Phi(p) \tag{7}$$

Average demand $\bar{q}$, multiplied by 8760 hours per year, gives the annual MWh of energy required by the electricity system. Average utilisation $\bar{v}$ and $\bar{w}$ tells us how nominal RES capacities translate into energy output. Lastly, $\bar{p}$ is the average price. We also introduce

$$Y_V \equiv 8.76 \cdot \Phi(x_V) \quad Y_W \equiv 8.76 \cdot \Phi(x_W) \quad Y_S \equiv 8.76 \cdot \Phi(\max\{0, x_S\}) \tag{8}$$

as total annual system output in Terawatthours [TWh] (which based on our assumptions is purely generated by RES) and as total ESR output.

The market equilibrium captures the cost-minimal solution that entails both private and public costs. The public cost are welfare losses induced by high prices. At any given time, the total available consumer surplus is $\theta q^2/2$ when prices are zero. Any positive prices will reduce this surplus, shifting some to the power produces, and some into a dead-weight loss (DWL). The latter is the triangle $p \cdot (q - x)/2$, and because of the demand system (1), it is also $p^2/(2\theta)$. Therefore, the total private-plus-public cost of the electricity system is given by

$$\mathcal{C} \equiv \sum_{i \in \{S,V,W\}} f_i \bar{x}_i + \frac{\Phi(p(\bar{\boldsymbol{x}})^2)}{2\theta} \tag{9}$$

where the integral term $\Phi(\cdot)$ captures the DWL from any non-zero prices. The private cost is the sum of the capital costs for RES and ESR.

A social planner would choose capacities that minimise $\mathcal{C}$. We show that the free-entry market equilibrium achieves the cost-minimal solution. Using the price equation (1) and the supply equation (3), the first-order conditions for a cost minimum entails

$$\frac{\mathrm{d}\mathcal{C}}{\mathrm{d}\bar{x}_i} = f_i - \Phi \left(p \, \frac{\mathrm{d}x}{\mathrm{d}\bar{x}_i} \right) \stackrel{!}{=} 0 \tag{10}$$

It is immediately apparent that the first-order conditions are identical to the zero-profit conditions that characterise free entry into the competitive market for generation and ESR. Cost are covered by the revenue. We find:

$$
\begin{aligned}
f_V &= \Phi\left(v \cdot p(\bar{\boldsymbol{x}})\right) && (11)\\
f_W &= \Phi\left(w \cdot p(\bar{\boldsymbol{x}})\right) && (12)\\
f_B &= \Phi\left(b(\bar{\boldsymbol{x}}) \cdot p(\bar{\boldsymbol{x}})\right) && (13)\\
f_H &= \Phi\left(h(\bar{\boldsymbol{x}}) \cdot p(\bar{\boldsymbol{x}})\right) && (14)
\end{aligned}
$$

In (11) and (12) the revenue that the RES operator receive depends on the utilisation rates $v, w \geq 0$ and corresponding prices. The ESR operators in (13) and (14) buy ($s < 0$) and sell ($s > 0$) at different times and thus receive revenues and incur costs. The implicit optimisation problem, fully solved by market participation, is therefore choosing capacities $\bar{\boldsymbol{x}}$ that minimise (9) subject to the storage balance constraint (6).

We can also integrate over the price equation (1), make use of the storage constraints (6) for netting out, in order to obtain

$$
\begin{aligned}
\Phi(p) &= \theta\left[\Phi(q) - \Phi(v)\bar{x}_V - \Phi(w)\bar{x}_W + \Phi(z)\right]\\
\bar{p} &= \theta(\bar{q} - \bar{v}\bar{x}_V - \bar{w}\bar{x}_W - \bar{z}) && (15)
\end{aligned}
$$

Therefore, total delivered supply (net of curtailment) on the left equals total realised demand on the right, which is latent demand less the price-induced demand response:

$$
\bar{v}\bar{x}_V + \bar{w}\bar{x}_W - \bar{z} = \bar{q} - \bar{p}/\theta \qquad (16)
$$

The welfare optimisation problem introduced in (9) is non-linear in nature not only because prices enter as a quadratic, but primarily because capacities influence both price and quantities in our 'new merit order', making the combined effect non-linear. The new merit order of electricity prices is hidden in the price schedule. We next turn to how it emerges from the storage constraint. In our general model, we cannot identify the price schedule algebraically, but it follows empirically from solving the optimisation problem.

We will be using mathematical notation for a constraint function that keeps x in the interval $[x_0, x_1]$. Let $\mathrm{con}(x; x_0, x_1) \equiv \min(\max(x, x_0), x_1)$. Further, let $x_R \equiv v\bar{x}_V + w\bar{x}_W$ be the supply of RES. As significant volume of energy output is curtailed without ESR, entering ESR capacity into the system allows for arbitrage. Entry continues until arbitrage profits are zero. ESR operators can buy RES output when net demand is negative ($q < x_R$) and sell it when net demand is positive ($q > x_R$). When arbitrage sets in, ESR operators are eventually bidding up prices to buy up supply. When the ESR system exhausts its capacity, there are either zero prices when RES is curtailed (excess supply), or there are peak prices when a strong demand response is needed to balance supply. What happens in between zero and peak prices defines the bulk of the 'new merit order'. ESR operators buy electricity output from RES which allows RES to earn revenue during the non-peak periods.

If there is only a single type of ESR and no storage losses, we can rewrite the price equation and integrate to obtain

$$
\Phi(s)\bar{x}_S = \Phi\left(\mathrm{con}\left(\frac{q - x_R - p^*/\theta}{\bar{x}_S}; -1, +1\right)\right)\bar{x}_S = 0 \qquad (17)
$$

where the left-hand side is zero because of the storage constraint. There exists a single market equilibrium price p^* that makes the integral on the right hand side zero. We already know that at $p^* = 0$, $\Phi(s)$ is still positive. Thus raising the price lowers the expression in the $\text{con}(\cdot)$ function, which in turn lowers $\Phi(s)$ until it reaches zero. There is a unique equilibrium price p^* that solves this equation.

There is a narrow transition zone as prices rise from zero to p^*. This transition zone is characterised by maximum charging ($s = -1$), but no curtailment yet because prices remain positive. This transition zone is bounded by $0 < x_R - q - \bar{x}_S < p^*/\theta$, with prices $p = \theta(q + \bar{x}_S - x_R)$.

We now expand our discussion to include two types of ESR, which are characterised by two different levels of ESR efficiency, $0 < \nu_H < \nu_B < 1$. Buying one unit of energy allows selling of η_i units of energy for type i. The defining element in our storage system is power capacity, not energy capacity. Storing energy imposes a physical loss that is larger for some types of ESR than for others. If the cost structure is such that more than one type of ESR participates successfully in the electricity system, the ESR type with the higher storage losses must have a lower cost structure. This is very much like the traditional cost scenario in electricity economics: base load plants have high fixed costs and low variable costs, and peak load plants have low fixed costs and high variable costs. The economic logic for ESR is exactly the same. Both types can participate, but in equilibrium both types must break even (with free entry). The 'new merit order', it turns out swiftly, is now defined by the merit order of ESR.

With storage losses, the amount of energy purchased is reduced so that the amount sold is the fraction η_i (the turnaround efficiency). Thus the storage constraint (6) changes to

$$\eta_B \Phi\left(\max(0, -b)\right) \bar{x}_B = \Phi\left(\max(0, b)\right) \bar{x}_B \quad (18)$$
$$\eta_H \Phi\left(\max(0, -h)\right) \bar{x}_H = \Phi\left(\max(0, h)\right) \bar{x}_H \quad (19)$$

Storage losses incur a cost $\tau(\eta_i) > 0$ that drive a wedge between buying and selling so that the buying prices becomes p^* and the selling price $p^* + \tau_i$. Buying one unit of energy and then selling only η_i later would incur losses. So buying one unit at price p^* and then selling it at $p^* + \tau_i$ after incurring the $1 - \eta_i$ loss in energy needs to balance out so that in equilibrium $p = \eta_i(p + \tau_i)$, or equivalently, $p^* + \tau_i = p^*/\eta_i$. This no-arbitrage condition holds for all types of ESR.

How many market prices will emerge as a result of storage losses? With n storage systems, there will be $n + 1$ prices. To see this, consider the buying side first. All storage operators compete for selling energy equally, even when they are fully at their maximum discharging capacity. Storage operators will take advantage of zero-price periods equally, but will also bid up the price for store energy equally. While there is no merit order on the selling side, the most efficient type of ESR can continue buying electricity at a higher price than the less efficient storage type. They will continue buying while the less efficient type has ceased bidding.

Armed with the set of no-arbitrage conditions, we can sum the storage constraints so that we arrive at a pooling equilibrium for selling, and a price-differentiated equilibrium on the buying side. In a market with two types of ESR there is thus one pooled selling price, and two differentiated buying prices that reflect the storage losses of the market participants. We define the fully-committed capacity from lower-loss storage operators defined as

$$\underline{x}_i \equiv \sum_{j:\nu_j<\nu_i} \bar{x}_j \tag{20}$$

and then sum the two storage constraints, matching prices on the selling side.

$$\begin{aligned} &\Phi\left(\operatorname{con}\left(\frac{q - x_R - p^*/\theta}{\bar{x}_S}; 0, 1\right)\right)\bar{x}_S \\ = &\sum_{i\in\{B,H\}} \eta_i\,\Phi\left(\operatorname{con}\left(\frac{q - x_R + \underline{x}_i - \eta_i p^*/\theta)}{\bar{x}_i}; -1, 0\right)\right)\bar{x}_i \end{aligned} \tag{21}$$

The second line of the equation sums all the demand from ESR, with diffuse buying arrangements at prices $\eta_i p^*$. The merit order on the buying side is defined by the storage losses incurred by the ESR operators. Low-loss ESR operates exclusively when excess RES supply is low, while both ESR types operate when RES supply is ample (or RES supply exceeds ESR power capacity). On the selling side, both types offer their stored supply at a uniform market price p^*. It is theoretically conceivable that the pooling equilibrium could also take place on the buying side, with price differentiation on the selling side. However, in our empirical parameterisations this turns out to be less advantageous; the welfare losses are computationally higher in this alternative equilibrium.

To summarise, the new merit order with two types of ESR is characterised by five major zones plus several transition zones where prices rise. From highest to lowest price, there is a peak price period when demand outstrips the maximum capacity, an equilibrium selling price period, an exclusive buying price region for the more efficient ESR type, a pooled buying period where both ESR types are active, and a zero-price period when there is excess RES that ends up curtailed.

Our model shows unique characteristics because there are no marginal costs for energy, and only for capacity. These are defining moments of the future state of the electricity system that deviate significantly from the prevailing paradigm of arbitrage that drives today's ESR profitability. In our model arbitrage drives down arbitrage profits significantly, with revenue earned only because there are phases when charging is free (due to curtailment) and when discharging happens at peak prices. ESR profits are only earned due to these two (important!) margins, and free entry drives these profits to zero. An energy-only market still works just fine in a world of zero marginal costs; capacity mechanisms are not needed. What is necessary, however, is a high degree of competition to achieve the socially optimal outcome.

Our empirical model follows the above theoretical model. We minimise the cost function (9) with respect to the set of capacities $\bar{\boldsymbol{x}}$, subject to the compound storage constraint (21) that determines the equilibrium p^*, and subject to the non-negativity constraints for all capacities and market price p^*. This is a non-linear optimisation problem that is highly dependent on the stochastic properties of demand and supply captured by $\Phi(\cdot)$. Before we turn to the empirical analysis, we investigate theoretical properties of the general solution through a highly-simplified linear model.

3.2. Linear Closed-Form Model with One Storage Type

The preceding section has developed a general RES+ESR model based on observable stochastic properties of demand and supply. This general model does not lend itself to closed-form analytic solutions of capacities; it can only be solved numerically in this general form. To obtain tractable analytic solutions that reveal important insights about the economic intuition underlying the optimal capacity choices, we introduce a number of simplifying assumptions.

1. We only use one type of RES (subscripted R, with cost f_R) and one type of ESR (subscripted S, with cost f_S, and with turnaround efficiency η).
2. We assume perfectly inelastic demand, and thus no demand response.
3. When the system capacity is exceeded, missing energy is priced at the value of lost load (VOLL) $\omega \gg 0$.
4. The distribution of demand is linearised so that $q(\phi) = \bar{q} + \tilde{q}(\phi - 1/2)$, for $\phi \in [0, 1]$. Here, $\bar{q}$ is average demand, and $\tilde{q}$ is the demand range (the difference between highest and lowest demand).
5. RES supply is uncorrelated with demand and assumed available with probability $\bar{u}$ at any given time so that expected net demand is $D(\phi) \equiv q(\phi) - \bar{u}x_R$ when RES capacity is $\bar{x}_R$.

These simplifications eliminate the transition regions that are present in a model with demand response, and flatten the welfare loss when the system capacity is exceeded. These assumptions allow us to segment the merit order into four regions: a zero-price region that ends at ϕ_Z during which RES is curtailed and ESR is charged at maximum capacity; a region from $\phi = 0$ through ϕ_M at which ESR is charged at price $p\eta$; a region through which ESR starts discharging at price p through ϕ_X; and the region from ϕ_X to $\phi = 1$ where the system capacity is reached and load shedding is required and leads to the VOLL at level ω. The three segment boundaries are defined as $D(\phi_X) = \bar{x}_S$; $D(\phi_M) = 0$; and $D(\phi_Z) = -\bar{x}_S$. [4]

In the previous section we had shown how the zero-profit free-entry conditions naturally follow from the cost minimisation problem. Here we introduce the zero-profit equations explicitly along with the ESR constraint. RES is paid whenever prices are positive:

$$f_R = \bar{u}\left[(1 - \phi_X)\omega + p(\phi_X - \phi_M) + p\eta(\phi_M - \phi_Z)\right] \tag{22}$$

ESR buys and sells electricity:

$$f_S = (1 - \phi_X)\omega + p(\phi_X - \phi_M)/2 - p\eta(\phi_M - \phi_Z)/2 \tag{23}$$

ESR balances energy bought, lost due to inefficiencies, and energy sold:

$$1 - \phi_X + (\phi_X - \phi_M)/2 = \eta\ \left[\phi_Z + (\phi_M - \phi_Z)/2\right] \tag{24}$$

The ESR system charges at maximum capacity during $[0, \phi_Z]$, on average charges at half capacity during $[\phi_Z, \phi_M]$ (where the energy charged forms a triangular area due to the linear distribution of demand), discharges on average at half capacity during $[\phi_M, \phi_X]$, and discharges at maximum capacity during $[\phi_Z, 1]$. The two

[4] Note that depending on the parameterisation, the system may end up in corner solutions, e.g. $X_s = 0$ or $\phi_X > 1$, i.e. no price spike observed.

triangular areas are by construction equal in size, and therefore $\phi_X - \phi_M = \phi_M - \phi_Z$.

The above three equations are a system in three unknowns (p, $\bar{x}_R$ and $\bar{x}_S$) and can be solved successively. The market clearing price is determined as

$$p = \frac{(f_R/\bar{u} - f_S)\tilde{q}}{\bar{x}_S(1+3\eta)/2} \tag{25}$$

This solution reveals important characteristics of the market price. First, if ESR is too expensive (or RES too cheap), the numerator could turn negative. For an interior solution, prices have to be non-negative, and therefore $f_R/\bar{u} > f_S$ must hold for prices to be positive. Second, as the turnaround efficiency decreases (i.e., ESR losses increase), prices increase. Third, prices are lower when ESR capacity increases.

We can also characterise the optimal amount of RES, conditional on the amount of ESR:

$$x_R = \frac{\bar{q}}{\bar{u}} + \frac{1-\eta}{1+\eta}\left(\frac{\tilde{q} - \bar{x}_S}{2\bar{u}}\right) \tag{26}$$

Again there are important economic insights. First, when ESR losses are zero, the optimal capacity would simply be determined by average demand and the utilisation rate of RES (i.e., $\bar{q}/\bar{u}$). Second, as η decreases (and storage losses increase), the second term in the above equation grows larger. The higher the storage losses, the more RES capacity is needed. Third, as more ESR capacity enters the system, less additional RES capacity is needed to compensate for the ESR losses.

Lastly, we need to know how much ESR is optimally entered into the system. We find:

$$x_S = \tilde{q}\left[\frac{2\eta}{1+3\eta} - \frac{1}{\omega}\left(f_S\,\frac{4(1+\eta)^2}{(1+3\eta)^2} - \frac{f_R}{\bar{u}}\,\frac{2(1-\eta^2)}{(1+3\eta)^2}\right)\right] \tag{27}$$

ESR is proportional to the demand range $\tilde{q}$. Without storage losses, the optimal ESR capacity would be just $\tilde{q}(1/2 - f_S/\omega)$, which means ESR is driven by ESR costs and VOLL, along with the demand variation $\tilde{q}$. ESR capacity increases with higher VOLL, and decreases with higher cost. When ESR losses are present, the effect of ESR costs f_S increases. At the same time, RES cost has a growing positive impact on ESR capacity as η decreases. Overall, as η decreases and storage becomes less efficient, ESR capacity shrinks. The intuition is that higher ESR losses make ESR more costly.

Returning to the equilibrium price in (25), using the above results without ESR losses yields a closed-form expression that is particularly simple to interpret.

$$p = \frac{f_R/\bar{u} - f_S}{1 - 2f_S/\omega} \tag{28}$$

The equilibrium price is the (normalised) cost difference between RES and ESR, divided by the probability of being in arbitrage mode (i.e., neither in curtailment mode nor in peak-price mode). In the absence of ESR losses our model is symmetric: the probabilities for peak prices and curtailment are the same and can be calculated to be equal to f_S/ω. Thus the denominator is the probability space without these two regions. The denominator in the above equation also has to be positive, which implies that $\omega > 2f_S$ must be sufficiently large compared to the

ESR cost, which we had assumed at the outset. A larger VOLL reduces the equilibrium price, as ESR earns more during peak periods. Higher RES costs increase the market price, while higher ESR costs decrease the market price.

Equation (28) reveals the 'New Merit Order' in its simplest algebraic form, with no ESR losses and perfectly linear residual demand. In this case, the equilibrium price in the arbitrage region for ESR is essentially the scaled-up cost differential between RES and ESR. Recall that ESR does not earn profits when the price equals p because free entry ensures maximum arbitrage. Thus the main role of the equilibrium price p in the 'New Merit Order' is to shuffle revenue opportunities to the renewable energy generators, which now can earn revenue throughout most of the operational phase. The 'New Merit Order' ensures sufficient (and optimal) participation from RES.

To sum up, our linear model has revealed important characteristics of an RES+ESR system. An equilibrium price emerges through the arbitrage operation of ESR, allowing RES to earn income during most periods. ESR capacity is essentially driven by its cost and VOLL along with demand variability, while RES capacity is primarily driven by electricity demand and utilisation rate. ESR losses decrease ESR capacity and increase RES capacity.

3.3. *Linear Model with Two Storage Types*

We can expand on our basic model to comprise two storage types, battery (B) and hydrogen (H), with cost parameters $f_B > f_H$ and efficiency parameters $\eta_B > \eta_H$. We denote type B's share of the total storage capacity $\bar{x}_S$ as α so that $\bar{x}_B = \alpha \bar{x}_S$. First, we find a new equilibrium price

$$p = \frac{\tilde{q}}{\bar{x}_S} \cdot \frac{2[f_R/\bar{u} - \alpha f_B - (1-\alpha) f_H]}{1 + 3\eta_H + \alpha(1+\alpha)(\eta_B - \eta_H)} \tag{29}$$

that looks very much like the previous expressions (25), except that the cost of storage in the numerator is now a weighted average and the expression in the denominator varies between $1 + 3\eta_H$ and $1 + 3\eta_B$ as α increases from zero to one. As the share of hydrogen increases relative to battery (i.e., α decreases), the equilibrium price rises.

Second, we can solve the storage constraint for α. While this expression contains the yet-unknown capacities $\bar{x}_S$ and $\bar{x}_R$, we can tease out the economic intuition without making these solutions explicit. We find that

$$\alpha = \frac{1-\eta_H}{\eta_B + \eta_H} + \frac{1}{\bar{x}_S} \left[\left(1 + \frac{1}{\eta_B + \eta_H} \right) 2(\bar{u}\bar{x}_R - \bar{q}) + \left(1 - \frac{1}{\eta_B + \eta_H} \right) \tilde{q} \right] \tag{30}$$

We know from our previous analysis that the optimal amount of RES is close to $\bar{u}\bar{x}_R \approx \bar{q}$, and thus we can simplify the above expression to approximate it as

$$\alpha \approx \frac{1-\eta_H}{\eta_B + \eta_H} + \frac{\tilde{q}}{\bar{x}_S} \left[1 - \frac{1}{\eta_B + \eta_H} \right] \tag{31}$$

For the efficiencies that we work with numerically in our paper, $\eta_B = 0.85$ and $\eta_H = 0.31$, we find $\alpha \approx 0.595 + 0.134\tilde{q}/\bar{x}_S$. This means that the efficiency ratio constrains the presence of hydrogen tremendously. In an electric grid with more variability (a higher $\tilde{q}$) we will find a higher share of battery storage relative to hydrogen. There is a limiting level of $\tilde{q}$ at which a corner solution is reached, and hydrogen storage disappears entirely. Note that (31) does not depend on storage costs f_B and f_H directly because the storage energy constraint does not depend on the equilibrium price directly; instead the effect of storage costs enters indirectly through their effect on storage capacity $\bar{x}_S$, and to a smaller extent, the RES capacity $\bar{x}_R$.

This brief analysis suffices to show that hydrogen's market share in storage is primarily limited by its technological efficiency. Improving η_H will allow for a greater market share of hydrogen. Our linear model does not shed light on the composition effect that is due to the correlation structure of supply and demand, and the effect of longer-term versus shorter-term storage.

4. Empirical Analysis

Our empirical analysis provides simulation results for energy systems composed entirely of RES and ESR: two types of renewable energies (parameterised as wind onshore and utility scale solar) and two types of ESR (parameterised as Li-Ion Batteries and electrolyser-fuel cell combinations). We analyse two electricity markets: ERCOT, covering most of Texas, and Germany. We chose these two markets because their state spaces of supply and demand vary widely given their geographic distance. Furthermore, they are both markets where RES shares are already high and are based on different regulation. Analysing and comparing results for these two jurisdictions has two main advantages. First, it explores the robustness of our empirical results. Second, it quantifies the effects of variations in wind speed, solar irradiation, demand—as well as their respective correlation—on optimal capacities and prices.

Our empirical analysis identifies properties of an "ideal" RES+ESR system in the absence of conventional fossil-fuel or other generation assets. We assume a "single node" for each market. Furthermore, our study uses a "greenfield" approach. As we are trying to ascertain the bulk composition with respect to RES and ESR, we feel that these assumptions are providing the right balance between tractability and validity. Nonetheless, we acknowledge limitations of our model in a separate section 5, while here we draw on the theoretical foundations developed in section 3.1. Our model includes stochastic distributions of both supply and demand. This allows us to derive novel insights on the correlation structure of demand, wind and solar.

4.1. Data description and modelling

Data assumptions on investment costs and technical parameters for all four technologies will be discussed in the following subsection 4.1.1, utilisation factors as well as demand levels in 4.1.2, and a model to solve the optimisation problem numerically in 4.1.3.

4.1.1. Data Sources for investment costs and technical parameters

Investment costs for wind onshore and (utility scale) photovoltaics are based on data from the International Energy Agency (IEA, 2021), covering capital cost, operation and maintenance costs, technical life time, and financing rates for both technologies for the years 2020 and 2050.[5] While IEA (2021) provides regionally differentiated values (e.g. for China, Europe, India and the US), we chose the US data for both systems to increase comparability. As our model works in a stochastic state space comprising one hour, hourly fixed costs are simply calculated by dividing annualised fixed costs by 8,760 (and multiplying by 1,000 due to the shift from kW to MW). Our resulting cost assumptions for these years are summarised in the following table 1. Investment cost estimates for ESR technologies are based on two main sources: the National Renewable Energy Laboratory (NREL) for battery cost data and Viswanathan et al. (2022) for hydrogen storage.

Table 1: Cost assumptions for RES

	Wind Onshore		Photovoltaics		
	2020	2050	2020	2050	
Operation and Maintenance	37.67	37.67	19.27	19.27	USD/kWa$_{el}$
Investment Cost	1,540	1,320	1,140	420	USD/kW$_{el}$
Depreciation Time	25	25	25	25	Years
Financing Rate	3.7%	3.7%	3.7%	3.7%	Per year
Annualised Fixed Cost	133.15	119.51	89.95	45.31	USD/kWa$_{el}$
Hourly fixed costs for model input	15.20	13.64	10.27	5.17	USD/MWh$_{el}$

Data Source: own, IEA (2021).

For batteries, data are based on two technical reports from NREL: operation and maintenance cost, investment cost, and depreciation time for the year 2020 are taken from Feldman et al. (2021), and the expected cost reduction until 2050 is taken from Cole et al. (2021). For ESR, financing rates are assumed to be identical to the values for wind and solar, provided by IEA (2021). Our ESR data differentiates between capacity based costs for batteries (mostly inverter) and energy based costs (e.g. storage racks) and we assume that batteries have a capacity-to-energy ration of 1:4 (a C-rate of 0.25) when calculating investment cost. For a hydrogen storage system, Viswanathan et al. (2022) provides values for 2021 and 2030. The core of the system consists of an electrolyser, a hydrogen storage cavern and a fuel cell. We used the values published for 2021 as reference for 2020 and calculated values for 2050 on the assumption that the relative cost reduction between 2030 and 2050 is the same as the one estimated for the 2021–2030 period.

Our cost projections for battery storage are focused on the evolution of the currently-predominant lithium-ion technology. We acknowledge that battery chemistry is likely to evolve rapidly. It is conceivable that sodium-ion and iron-air batteries will revolutionise stationary grid-scale storage applications (Stover, 2022; Crownhart, 2023) and lower costs even below the assumptions reflected in table 2. For lithium-based technologies, Mauler et al. (2021) survey 53 studies that provide estimates for competing types. They extrapolate that pack-level costs may drop 70% between 2020 and 20250, from \$224/kWh to \$71/kWh. They acknowledge that in fact there is a widening gap between realised costs and cost forecasts in the examined literature, suggesting that forecasts are biased towards a pessimistic outlook; innovation happened faster in practice.

[5] Variable cost are assumed to be zero for all technology. Note, however, that ESR technologies need electricity to charge, which is provided and priced by (endogenous) investment in RES generators.

Table 2: Cost assumptions for ESR

	Battery		Hydrogen		
	2020	2050	2020	2050	
Operation and Maintenance	17.50	7.53	23.90	9.60	USD/kWa$_{el}$
Investment Cost	2,444	1,051	3,033	455	USD/kW$_{el}$
Depreciation Time	20	20	30	30	Years
Financing Rate	3.7%	3.7%	3.7%	3.7%	Per year
Annualised Fixed Cost	192.59	82.81	192.99	34.94	USD/kWa$_{el}$
Hourly fixed costs for model input	21.99	9.45	22.03	3.99	USD/MWh$_{el}$
Round-Trip Efficiency for ESR	85%	85%	31%	31%	

Data Source: own, Feldman et al. (2021), Cole et al. (2021), Viswanathan et al. (2022).

4.1.2. Data Sources for demand and availability factors

We obtain hourly data for demand (Q), photovoltaic (V) and wind onshore (W) power generation from two sources. Hourly demand[6] and generation[7] data for Texas are directly provided by ERCOT. Data for Germany are provided by the German energy regulator (Bundesnetzagentur) on the SMARD data platform.[8] Wind data combines both onshore and offshore sources. The German load and generation raw data is quarter-hourly.

Generation from photovoltaics and wind is converted to utilisation of installed capacity (in percent). Capacity data are available for both ERCOT and Germany. For ERCOT, we make use of the Form 860 filings with the U.S. Energy Information Administration.[9] Germany's generation capacity data was obtained from Germany's Federal Network Office (Bundesnetzagentur).[10] For ERCOT we augment capacities for solar power with observed maximum generation data as small facilities are not covered by the EIA 860 data.

Tables 3 and 4 show summary statistics for both ERCOT and the electricity market in Germany. Several things are interesting to note. First, both markets are of similar size (ERCOT is around 20% smaller than Germany in terms of overall load levels), and while ERCOT is summer peaking (highest Q in summer due to higher temperatures and installation of air conditioning), Germany is winter peaking (highest Q in winter due to high heating demand). Second, average conditions for both photovoltaics and wind are much better in ERCOT. Especially for photovoltaics, average utilisation is more than twice as high. Mostly following from this, ERCOT has lower coefficients of variations for both renewable technologies. ERCOT will thus have lower decarbonisation costs than Germany as it simply gets more MWh out of each MW of installed capacity. Third, ERCOT exhibits significantly higher correlation between electricity demand and solar feed-in but lower correlation between solar and wind. Both make it easier for ERCOT to decarbonise the electricity system: the sun shines (more) when demand is high and when the sun does not shine wind can take over. Fourth, diurnal correlation between demand and solar power exceeds 0.6 for both markets, which is to be

[6]Hourly Load Data: https://www.ercot.com/gridinfo/load/load_hist
[7]ERCOT Fuel Mix: https://www.ercot.com/gridinfo/generation
[8]https://www.smard.de/en/downloadcenter/download-market-data/
[9]https://www.eia.gov/electricity/data/eia860/
[10]https://www.bundesnetzagentur.de/DE/Fachthemen/ElektrizitaetundGas/Versorgungssicherheit/Erzeugungskapazitaeten/Kraftwerksliste/start.html

expected as both demand and solar output are higher during the day. Noteworthy is the negative diurnal correlation between demand and wind (around –0.6 in both systems), showing that wind produces more during the night.[11] Looking at seasonal correlation last, noteworthy differences between the two systems emerge: ERCOT has positive seasonal correlation between demand and photovoltaics but negative between demand and wind. For Germany, it is the other way around.

4.1.3. Setting up and solving the empirical model

Our empirical model solves the non-linear optimisation problem described in section 3.1 for two types of RES (solar and wind power) and two types of ESR (batteries and hydrogen). Costs and technical parameters for these technologies were presented in sections 4.1.1 and 4.1.2. The basis is hourly data for the four years 2019-22, both for ERCOT and Germany. Hence, we have a total of 35,064 hourly combinations of the stochastic state space in each market.

We make use of latent demand q, and for this purpose we estimate q from observed load and price data as $\hat{q}_t = x_t + \mathrm{con}(p_t/\theta, -\delta, +\delta)$, where we use a cut-off δ of approximately 5% for the implicit demand response (2.8 GW for Germany and 2.2 GW for ERCOT). Armed with estimates of latent demand, we transform latent demand, wind power utilisation and solar power utilisation into a cubic grid of $64 \times 64 \times 64 = 262,144$ cells for simulation purposes, along with corresponding probabilities for each event in this grid. This grid approximates the distribution in our triple-integral $\Phi(\cdot)$. Some cells contain zero probabilities. The state space is sparse for ERCOT and more complex in the German case. We visualise the data in section 4.2 below.

The literature provides a wide range of estimates of price responsiveness of demand; see for example Green and Vasilakos (2011), Knaut and Paulus (2016), Malehmirchegini and Farzaneh (2022), Csereklyei (2020), Puller and West (2013), Joskow and Wolfram (2012), and Guo (2023). Besides being inherently difficult to estimate, price responsiveness also depends on several other factors—in particular the time horizon. In our simulation, we assume a θ of 0.2 USD/MWh for both ERCOT and Germany, and also use it when converting observed realised demand (actual values for 2019 until 2022) to latent demand. However, as demand flexibility in electricity will likely increase over time in parallel to higher penetration of renewable energies, we restrict associated load changes between latent and actual demand to five percent.

As described above, the non-linear optimisation problem presented above needs to be solved numerically. For this purpose we have written simulation code in the C++ language, for speed and efficiency, which is documented in a separate Technical Appendix that is available together with this paper. The simulation code takes a set of parameters and parameter ranges as inputs, and generates output spreadsheets with optimal capacities, output, prices, and state probabilities; 23 output variables in total. We run our model with 2,520 param-

Cost Parameter		Min.	Max.	Inc.
Solar Power	f_V	5.0	10.0	0.5
Wind Power	f_W	13.5	15.5	0.5
Battery	f_B	10.0	22.0	2.0
Hydrogen	f_H	4.0	20.0	2.0

[11] Wind speed in higher latitudes is higher during the night. Hence, modern wind turbines with high hub heights produce more electricity during the night.

Table 3: Summary Statistics for ERCOT Market, 2019-22

Time Period	Averages			Coeff. of Variation			Correlation		
	Q [GW]	V [%]	W [%]	Q [–]	V [–]	W [–]	Q/V [–]	Q/W [–]	V/W [–]
Overall	45.48	24.71	32.97	0.223	1.265	0.524	0.438	−0.161	−0.318
Spring	40.91	26.32	38.70	0.185	1.228	0.441	0.433	0.072	−0.296
Summer	54.79	32.87	29.75	0.194	1.062	0.548	0.599	−0.075	−0.361
Autumn	44.24	22.27	29.94	0.200	1.324	0.550	0.455	−0.189	−0.388
Winter	41.84	17.18	33.49	0.152	1.473	0.528	0.053	−0.241	−0.255
Diurnal				0.116	1.129	0.146	0.643	−0.617	−0.931
Seasonal				0.143	0.268	0.142	0.765	−0.634	−0.176

Note: Demand is expressed in Gigawatts [GW], while wind and solar production is expressed as a percentage of capacity. Coefficients of variation for these are the standard deviation of the estimates divided by the mean for the entire time series.

Table 4: Summary Statistics for German Electricity Market, 2019-22

Time Period	Averages			Coeff. of Variation			Correlation		
	Q [GW]	V [%]	W [%]	Q [–]	V [–]	W [–]	Q/V [–]	Q/W [–]	V/W [–]
Overall	56.73	10.17	22.69	0.174	1.532	0.741	0.270	0.162	−0.213
Spring	55.95	13.77	22.51	0.167	1.293	0.733	0.372	0.093	−0.174
Summer	53.26	16.21	13.66	0.168	1.152	0.744	0.612	−0.034	−0.075
Autumn	56.81	7.32	22.63	0.170	1.658	0.661	0.312	0.084	−0.163
Winter	60.99	3.23	32.15	0.163	2.176	0.593	0.260	0.068	−0.059
Diurnal				0.120	1.217	0.051	0.735	−0.585	−0.825
Seasonal				0.067	0.559	0.346	−0.786	0.798	−0.764

Note: Demand is expressed in Gigawatts [GW], while wind and solar production is expressed as a percentage of capacity. Rows 'overall' through 'winter' are based on 15-minute raw data. Rows 'diurnal' and 'seasonal' are based on 24 estimates each of diurnal and seasonal (semi-monthly) indicator variables. Coefficients of variation for these are the standard deviation of the estimates divided by the mean for the entire time series.

eterisations as follows (all in USD/MW.h
equivalent units). The minimum costs represent our year-2050 parameterisation, whereas the maximum costs represent our year-2020 parameterisation. Because hydrogen storage cannot be more expensive than battery storage due to higher storage losses for hydrogen, parameter combinations where $f_H \geq f_B$ are excluded from the simulation.

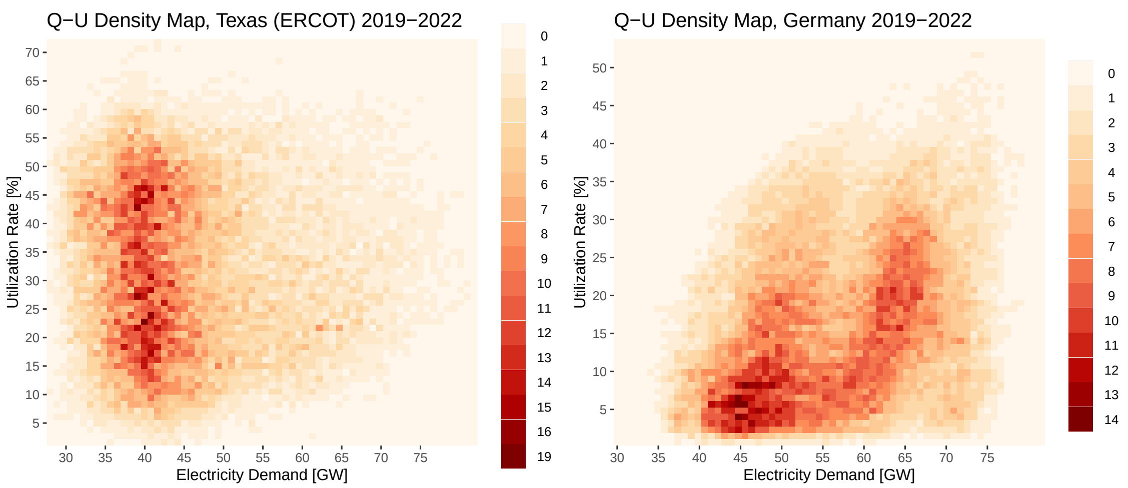
Our simulation code makes use of the NLopt optimisation package (Johnson, 2007). For each parameter quadruplet $\{f_V, f_W, f_B, f_H\}$ we obtain a corresponding optimal capacity quadruplet $\{\bar{x}_V, \bar{x}_W, \bar{x}_B, \bar{x}_H\}$, along with an optimal price p for the pooling equilibrium on the ESR-discharge side of the market; the buying prices are implicitly $\eta_H p < \eta_B p < p$. In order to make the optimisation fast and efficient, we have nested the optimisation procedure so that for each capacity choice we solve the storage constraint for the optimal equilibrium price using a simple bisection algorithm; see equation (21).

The empirical results discussed below are a relatively small sample of the wealth of results calculated. We focus on the 2020 and 2050 end points, holding one pair of costs fixed at 2050 levels, and letting the other cost parameters vary between their 2020 and 2050 levels. In our appendix we repeat this exercise by pivoting around the 2020 cost levels instead of 2050.

4.2. *The Demand-RES State Space*

A critical element in all of our theoretical and empirical analysis is the joint probability distribution of RES output (wind and solar) and latent demand. We visualise this space for the two grids in our study, ERCOT and Germany, in figure 1. We show the distribution for the RES total (wind W plus solar V) and refer to these maps as Q-U maps (with U=V+W summarising RES availability). The two diagrams in the figure show how different the two systems are.

Figure 1: Demand-RES (Q-U) Diagrams for Texas and Germany



Notes: The scale indicates probabilities times 10^{-4}.

Two observations stand out about ERCOT: demand is massed around the 40 GW level but has a long upper tail, while wind appears relatively uniform over the 15-50% range, and is rarely below. North-western Texas has very favourable wind locations, and wind capacity continues to grow rapidly. All of wind generation in Texas is currently onshore, but the first offshore wind farm is planned near

Galveston. ERCOT has relatively low wind output during hot summer days, and more wind output during summer nights.

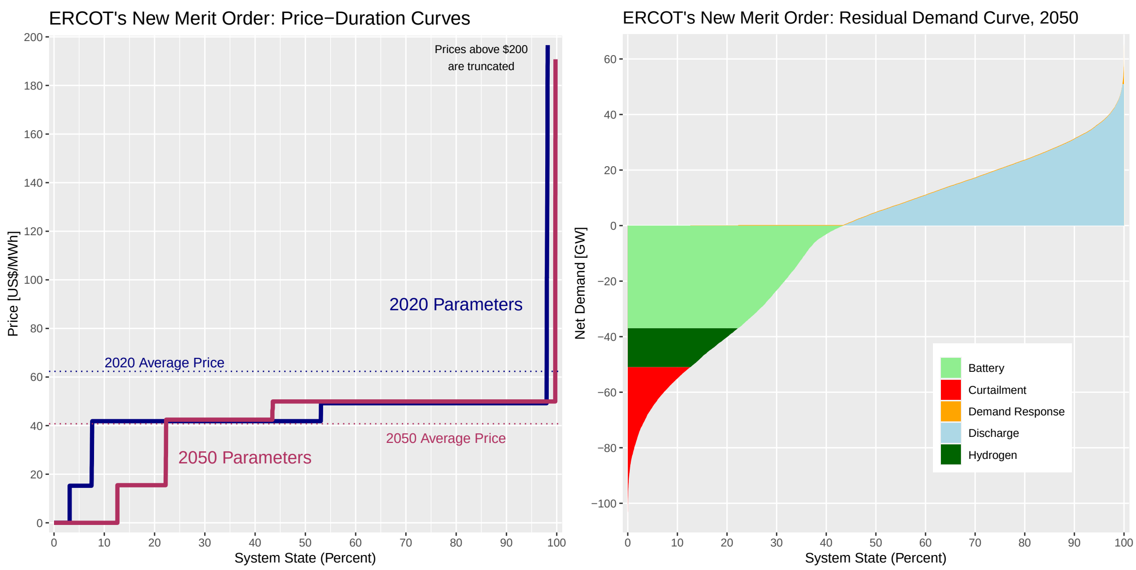
Germany's Q-U map looks rather different with two distinct "branches." A lot of mass is centred at low demand and low RES utilisation. The can be explained with both demand and solar generation being low during the night. The remaining RES fluctuation during low demand levels is caused by wind power, which is slightly higher during the night than during the day. The right-side branch standing out shows high demand and high-RES in the summer when hot days lead to high electricity demand (for cooling) and high solar output. Germany also has lower overall RES utilisation than ERCOT, caused by lower RES availability factors and a higher share of solar than wind in the mix.[12]

4.3. Empirical results ERCOT

4.3.1. Base cases with cost assumptions for 2020 and 2050

Figure 2 shows our empirical key result: the new merit order for the ERCOT system (left part) as well as residual demand and ESR utilisation (right part). Starting with the merit order on the left, it is depicted both based on cost assumptions for the year 2020 (blue line) and the year 2050 (red line). Even at first glance the new merit order looks similar to today's: relatively few hours have zero prices, a vast middle section has positive prices (mostly in the range of 40-50 $/MWh), and few hours have peak prices. This is good news for both consumers and producers. Consumers can expect price variations, providing incentives to provide flexibility, but volatility will not be excessive. Producers of renewable electricity will earn revenues during most hours of the year. Hence, their revenue stream will be relatively stable in equilibrium. This is also good news for regulators, as fears of a flat "zero-cost" merit order, with renewable investment costs financed exclusively during extreme spikes (or not at all due to self-cannibalization), are unfounded.

Figure 2: ERCOT's New Merit Order



[12] Utilisation rates for wind turbines are significantly higher than for photovoltaics in both jurisdictions, compare 3 and 4.

These properties of the merit order already manifest with our purposefully stylised model assumptions. Increasing complexity, e.g. including more technologies (biomass, nuclear, hydro pump storage, compressed air energy storage), or even just allowing for heterogeneous technical parameters within existing storage technologies, or accounting for inter-temporal effects, will add additional price levels to these graphs. Figure 2 also shows the average prices as dotted lines. Average prices for 2020 cost assumptions are around 60 $/MWh. This is broadly competitive even today, especially when negative externalities of conventional technologies (CO_2, respirable dust emissions, etc.) are fully priced.[13]

The right part of the figure shows the residual load duration curve for 2050, i.e. latent demand minus aggregated uncurtailed RES production. It also visualises the optimal dispatch and investment decisions for the two ESR types: when residual demand is extremely negative, all ESR is charging at full capacity and excess generation is curtailed. To the right of that point, ESR is charging in partial load. Hydrogen starts partial load operation first, battery storage follows. At load levels slightly lower than 50%, ESR starts to discharge, first in partial load. At rare peak load events, all ESR discharges at full capacity and prices spike.

We compare these empirical results to the the current system; table 5 provides summary statistics about the ERCOT system today as the average of the four year period 2019-22. During this time, generation from wind was significantly higher than solar. The average annual realised demand (total consumption) amounts to 400 TWh, and the average price was 66.99 $/MWh.

Table 5: ERCOT Summary Statistics, Actual and Projected

	Generation			ESR		Total	Avg.
	Total	Wind	Solar	Batt.	Hydr.	Cons.	Price
	TWh	%	%	TWh	TWh	TWh	$/MWh
Actual (2019-22 Average)		23.0	3.3			403.29	66.99
2020 Parameters	410.95	73.3	26.7	53.77	12.21	395.65	62.34
2050 Parameters	441.94	39.4	60.6	68.88	26.16	396.60	40.76

Comparing the actual numbers with our simulations, several things stand out. First, as we restrict electricity generation to wind and solar, their shares add up to 100%—and thus are both significantly higher than today. Furthermore, as the assumed investment cost for solar power and hydrogen storage decrease more than wind and battery storage from 2020 to 2050, the optimal share of solar and hydrogen storage is much higher in 2050 than in 2020. But even at 2020 investment cost assumptions, the ratio of wind to solar is about 3:1, while today's ratio is around 7:1. Taken together with the fact that even the cost assumptions of 2020 lead to average prices broadly in line with actual price levels, we can deduce that—purely based on economic considerations—ERCOT should have more renewable energies, especially more solar power.

Furthermore, looking at total consumption, our results show a small decrease

[13]On the one hand, our model assumes higher flexibility than real world settings, e.g. due to our simplified storage constraint. On the other hand, the model is restricted to the use of only four technologies, limiting available technologies and increasing costs above real world expectations. Nonetheless, average prices and costs in the real world would probably be higher than our estimates.

of consumption in the two simulations: consumption is around 2% lower than in the actual system. While this result is significantly driven by the assumptions on θ, fears of large shares of insufficient energy supply are unfounded in the market equilibrium.

4.3.2. Transition and Sensitivity Analysis

Our cost parameters in the previous section represent the years 2020 and 2050. In this section, we will explore the values in between: first, to shed light on the transition path from 2020 (high costs) to 2050 (low costs), and second, to allow for the uncertainty of the future development of costs. While we know that costs have fallen in the past due to technological improvements and economies of scale, it is not clear to what extend this trend will continue in the future. Hence, we complement the preceding analysis of 2020 and 2050 with a systematic exploration of the parameter space in between.

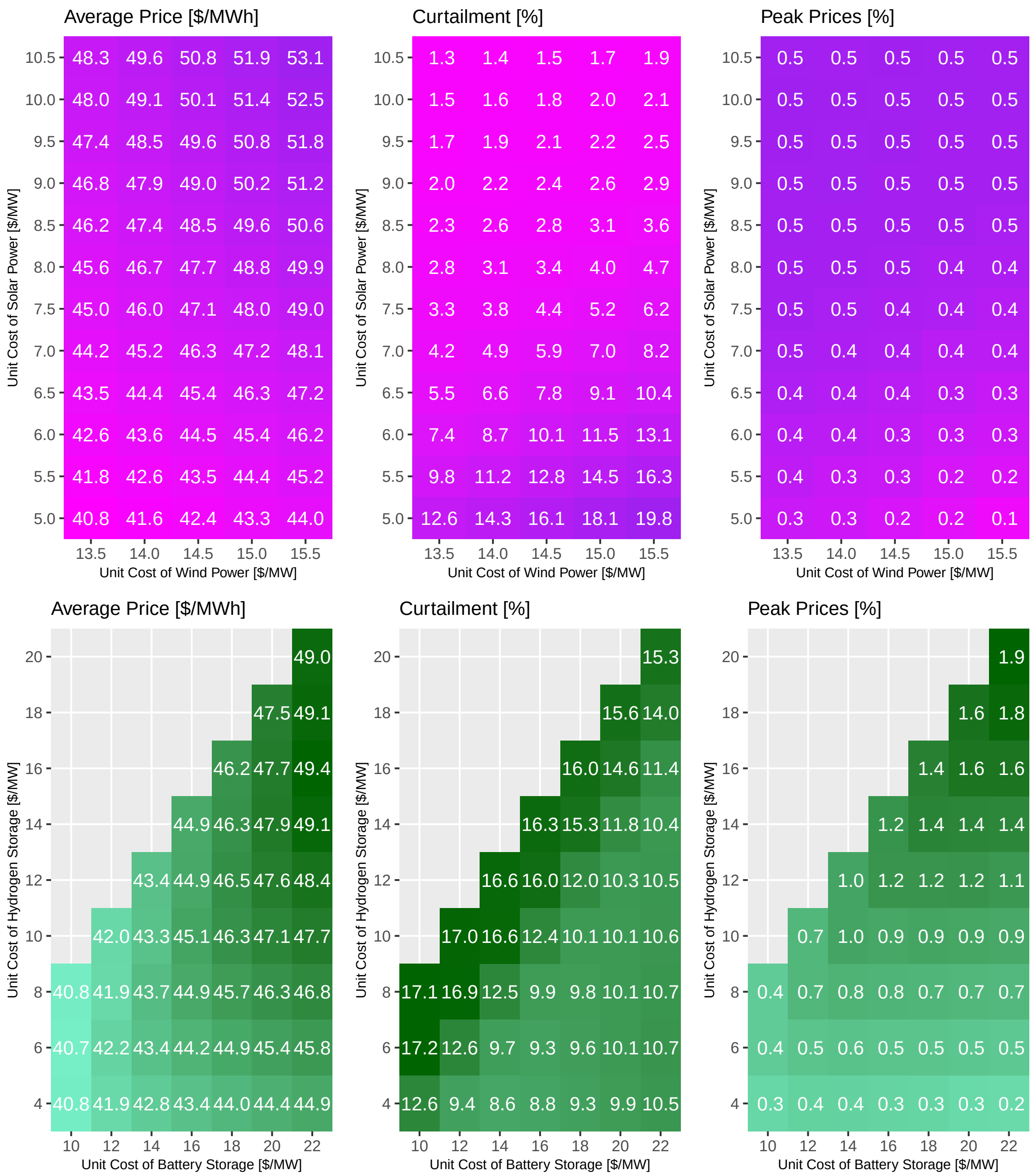
Figure 3 shows how average prices, curtailment and the duration of peak prices are affected by changes in the unit cost of solar and wind power (upper part of figure) as well as the unit cost of hydrogen and battery storage (lower part of figure). The degree of variation depends on the expected difference between 2020 and 2050. Hence, unit costs for solar power differ more in absolute terms than for wind because the latter has a relatively low expected cost change between 2020 and 2050. Note that the two parameters not varied in each table (i.e. the unit costs for ESR in the three upper tables, and the unit costs for RES in the three lower tables) are set equal to 2050 values. For example, the upper right cell in the average price table reflects 2020 values for both wind and solar unit costs (rounded to .5-levels), while the corresponding unit costs for ESR are for 2050. We present analogous figures with 2020 unit costs in the appendix. In the lower row with varying hydrogen and battery unit costs, we only present numbers for cases with both technologies in the mix. This requires hydrogen unit costs being below battery hydrogen costs.

Starting with average prices—and looking at both the upper and the lower left graph—we see that falling unit cost of RES contribute more to price reductions than falling ESR costs. Turning to the two graphs on curtailment of renewable energy, we find curtailment correlates positively with unit costs of renewable energies but negatively with ESR costs. Furthermore, the influence of renewable costs on curtailment is larger. Looking at the duration of peak price periods on the right, we find their changes are mostly driven by ESR costs reductions.

Figure 4 has a similar structure as as figure 3 in regard to unit cost variations, with a base setting of unobserved parameters for 2050, with RES variations on top, ESR variations at the bottom. The difference is that the figure depicts solar/wind ratios (left), hydrogen/battery ratios (middle), and aggregated ESR/RES ratios (right).

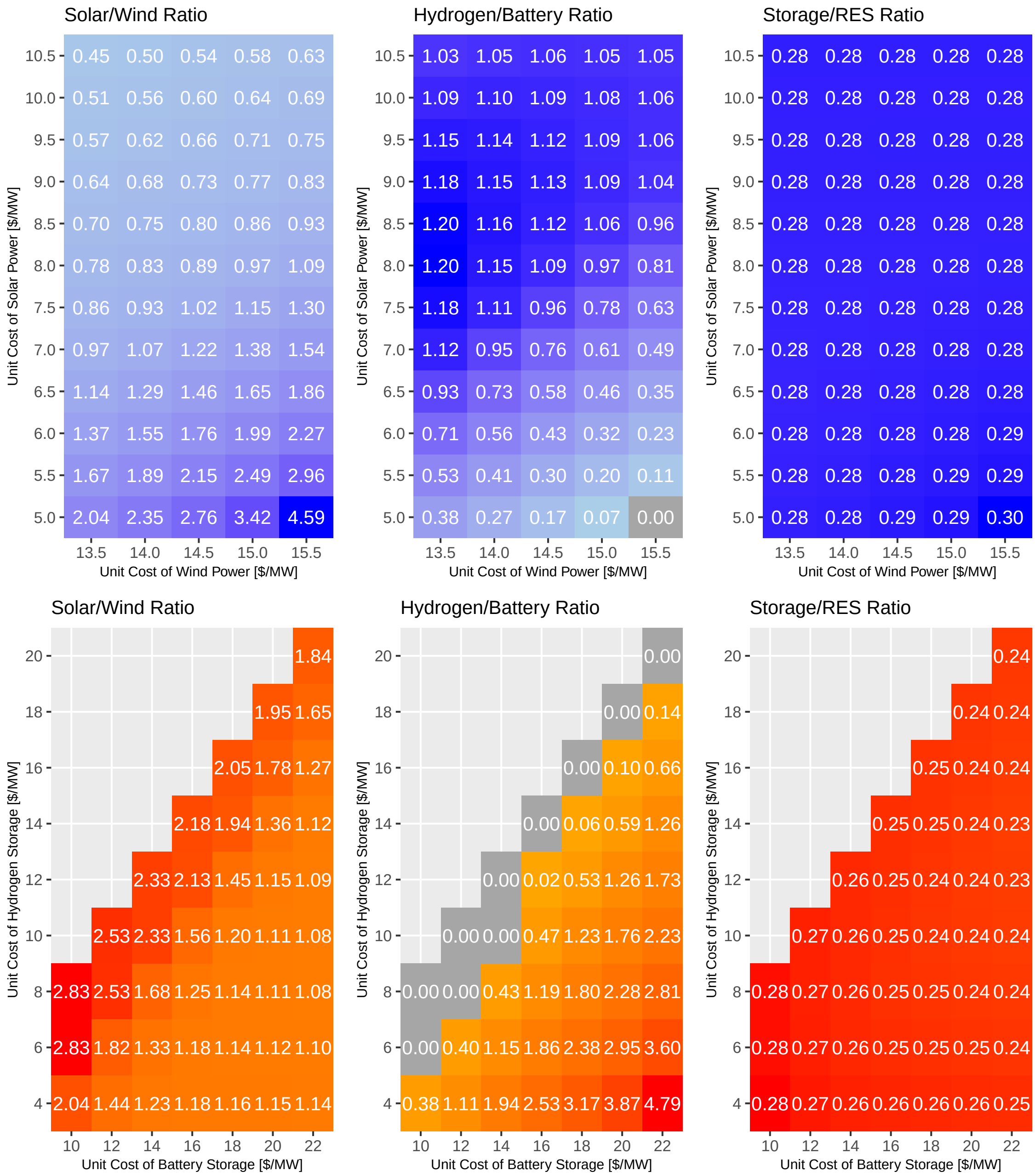
The upper left diagram shows the sensitivity of the solar-to-wind ratio to unit cost changes. When solar cost are highest and wind cost are lowest, the optimal ratio of solar to wind is 0.45, roughly one GW of solar capacity for two GW of wind. At the other end of the spectrum, with solar at its lowest and wind at the highest, this ratio changes to about 4.6. The optimal ratio of solar to wind is also affected by the unit costs of battery and hydrogen. While the differences in optimal ratios is considerably lower, it still varies between 1.14 and 2.83 (again only depicting combinations with hydrogen at lower unit costs than batteries to

Figure 3: ERCOT System - Cost, Curtailment and Peak Prices



Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 10$ and $f_H = 4$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 13.5$ and $f_S = 5$. These cost choices represent 2050 forecasts.

Figure 4: Simulation Results for Texas (ERCOT)



Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 10$ and $f_H = 4$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 13.5$ and $f_S = 5$. These cost choices represent 2050 forecasts.

compensate for their lower efficiency).

The two middle tables show that cost variations in solar and wind also affect the hydrogen-to-battery ratio. This ratio is highest at medium levels of solar unit costs combined with low wind costs. In contrast, low solar costs combined with very high wind costs drive hydrogen completely out of the system. Battery technology is not neutral with respect to the RES mix; they can be both complements and substitutes. Intuitively, more ESR capacity reduces the need for more RES capacity: a substitution effect. However, there can also be complementarity due to the correlation structure of the state space, which can prefer different energy-to-capacity ratios. Cheap hydrogen capacity offers more energy storage despite its greater losses, which goes well with the higher seasonal nature of solar power in ERCOT.

The influence of hydrogen and battery unit costs on their composition (lower table in the middle) is of course more direct and thus also more pronounced. We already pointed out that hydrogen unit costs above battery unit costs drive out hydrogen. However, at the other end of the spectrum (low hydrogen cost combined with high battery costs), the ratio becomes 4.79:1.

The two tables on the right report aggregate ESR-to-RES ratios, which appear to be mostly unaffected by the unit costs of any of the four technologies. This can be explained by the fact that the energy in the system needs to be generated from RES, and ESR is needed to shift it from negative to positive residual demand situations. While technologies' respective investment costs change the composition within the technology types (i.e. wind vs solar as well as hydrogen vs battery storage), the total amount of either ESR or RES is fairly constant.

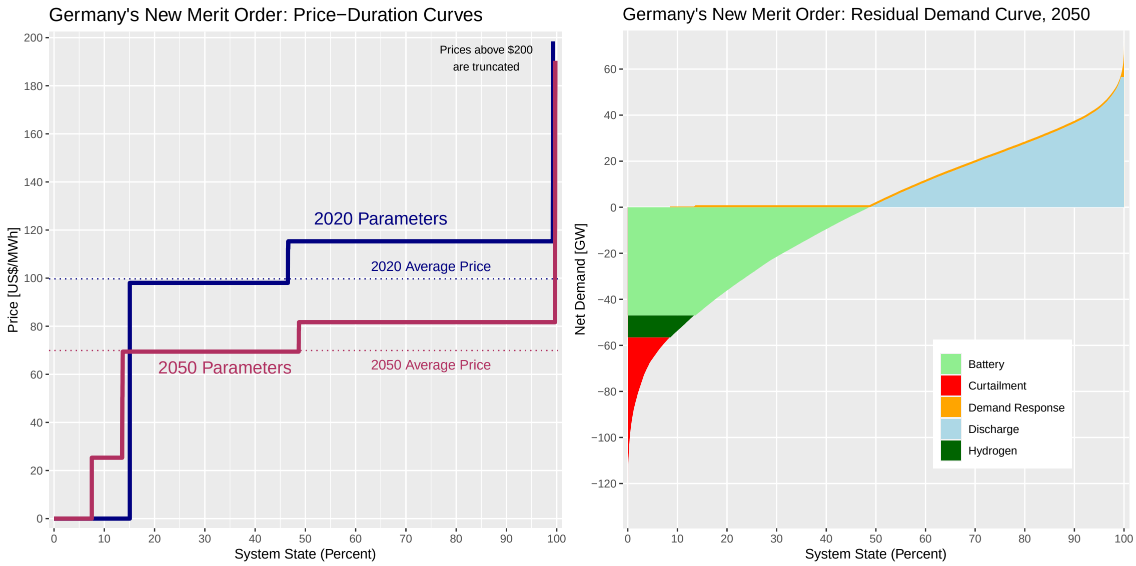
4.4. Germany

4.4.1. Base cases with cost assumptions for 2020 and 2050

Figure 5 shows our paper's empirical key result for Germany: the new merit order for a pure RES+ESR system. In the left diagram, average prices for the 2020 cost parameters are around 100 \$/MWh. For the reduced cost assumptions in 2050, this figure drops to 70 \$/MWh. The merit order for 2020 (blue line) has two price levels in addition to renewable curtailment (price at zero) and price spikes: one price level slightly below 100 \$/MWh and one around 115 \$/MWh, with the difference explained by the battery ESR efficiency of 85%. Based on our theoretical analysis, we can conclude that the optimal solution for 2020 is in fact a corner solution: only battery storage is present but no hydrogen. By comparison, the price duration curve with 2050 parameters (red line) has lower price levels throughout the probability space, with one exception: the additional price level at low residual demand levels. This third price level confirms that in 2050 both batteries and hydrogen storage are part of an optimal system. This is also confirmed in the right part of the figure, which shows how residual demand corresponds with ESR utilization.

An important conclusion from the figure is—as in ERCOT—that the new merit order has many hours with positive price levels between \$30 and \$120/MWh. So the key result that a market equilibrium exclusively based on zero variable cost RES and ESR provides a supply function not fundamentally different from today is robust—even in the extreme case of just battery storage in the system.

Figure 5: Germany's New Merit Order



Our results are summarised and compared to actual values in table 6.[14] The actual numbers show that total generation from wind and solar in the German system exceeds 35%. Average total consumption was close to 500 TWh and the average price was $60.47/MWh.

Table 6: Germany Summary Statistics, Actual and Projected

	Generation			ESR[1]		Total	Avg.
	Total	Wind	Solar	Batt.	Hydr.	Cons.	Price[2]
	TWh	%	%	TWh	TWh	TWh	$/MWh
Actual (2019-21 Average)		24.8	9.5			497.65	60.47
2020 Parameters	552.30	95.0	5.0	118.14	0.00	492.60	99.70
2050 Parameters	531.17	68.1	31.9	86.88	22.60	493.90	69.90

Notes: [1] Discharged (sold) ESR volume reported; the charged (purchased) volume is larger due to ESR losses. [2] A USD/EUR exchange rate of 1.1 was applied to convert German prices to US equivalents.

Based on 2020 cost parameters, a fully renewable system would consist of wind (95%) and solar (5%). As was pointed out when discussing figure 5, the ESR system is 100% focused on battery storage. The price is close to $100/MWh and thus considerably higher than the actual historic average. Total consumption is only 5 TWh (around 1%) lower than the actual level, implying that relatively little demand is not supplied due to price responsiveness. Our 2050 cost assumptions lead to lower prices (around $70/MWh). Furthermore, the significantly higher reduction in investment costs for both solar and hydrogen storage improves their competitiveness compared to wind and battery storage, respectively.

[14]Note that actual German values are the average of the three years 2019-2021. While data for 2022 are available, prices were extremely high due to the Russian invasion of Ukraine. Hence, we omitted that year for not being representative.

4.4.2. Transition and Sensitivity Analysis

This subsection shows the results for a transition period, i.e. values between 2020 and 2050, which the values not depicted on the axis taken from 2050.[15] As for ERCOT, this can also be interpreted as a sensitivity analysis, exploring the cost parameters' inherent uncertainty.

Figure 6 shows how variations in the unit costs of wind (horizontal axis) and solar (vertical axis) affect average prices (top left), curtailment (middle) and peak price probability (right). Variations in average prices lie in the area of \$69.9/MWh (all parameters based on 2050, lower left corner of figure) and \$91.0/MWh. The same figure shows that reducing the costs of one technology has a higher effect on costs when the second technology is expensive. For example, when wind is expensive, reducing solar cost from max to min saves nearly \$15/MWh. However, when wind is cheap the potential cost savings are reduced to \$10/MWh. Curtailment varies between 7.5% of the time in the 2050 cost setting and 13.0% with high solar but low wind costs. Again, peak prices and significant load shedding are a rare event, occurring with a maximal probability of 0.3%.

The three lower graphs in the figure show the same parameters for variations in ESR costs on the two axes. For average prices, it is noteworthy that variations in ESR cost have a moderate impact on the price (between 69.9 and 80.0). The take-away is that the renewable cost parameterisation for 2050 already reduces prices considerably. A similar argument can be made for curtailment based on ESR cost variations. On the contrary, peak price probability increases with ESR cost variations. However, peak episodes remain rare except when ESR costs are very high.

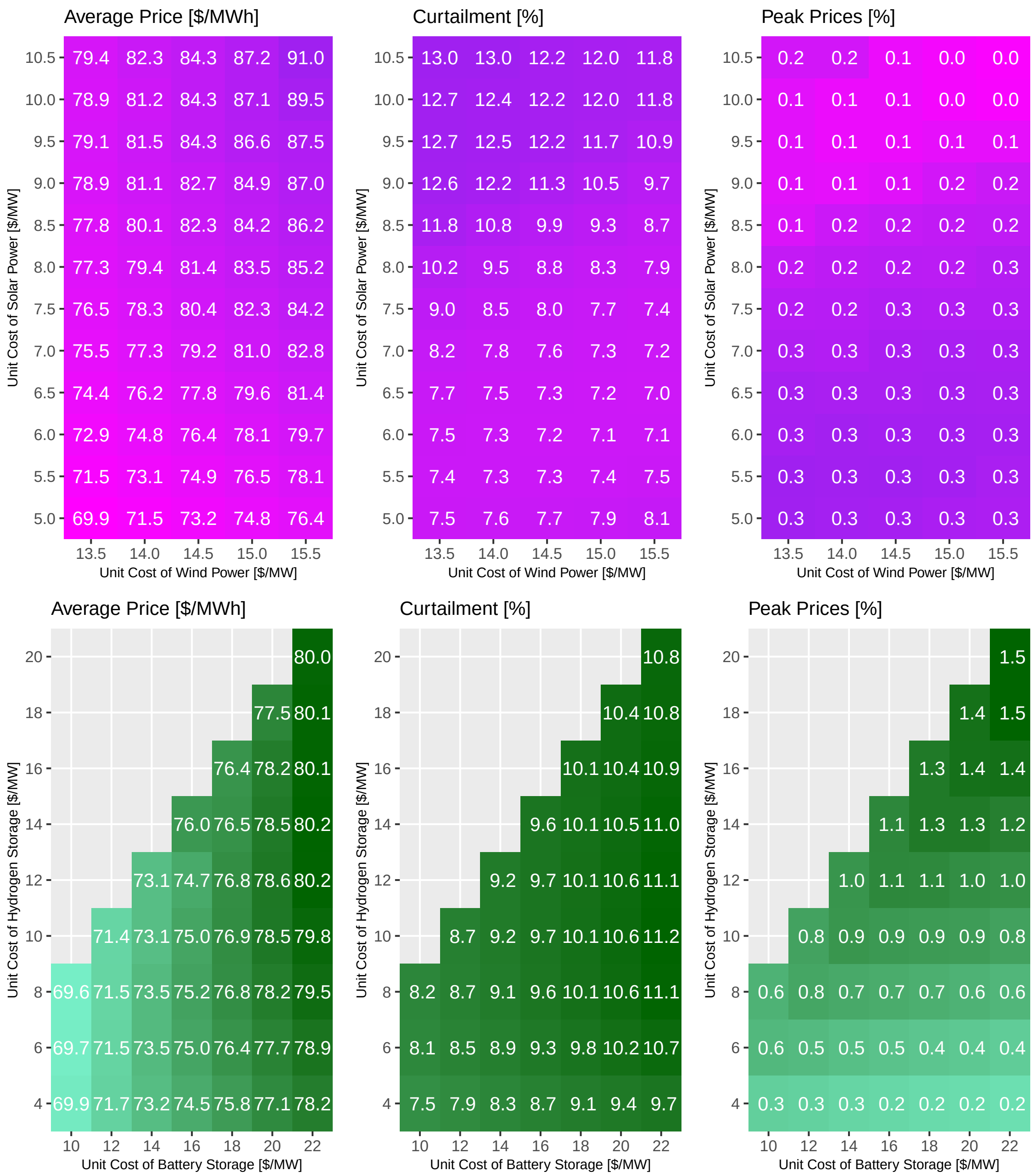
Figure 7 shows the different ratios of technologies, solar generation capacity to wind generation capacity (left), hydrogen to battery (middle) and aggregated ESR to aggregated renewable energy capacity (right). In all cases, we report nameplate capacities (in GW), not generation (in TWh). As wind tends to have higher utilisation rates than solar, more solar capacity is needed to generate the same output than wind capacity.

Starting in the top row, solar power's role depends significantly on its investment cost. While solar's capacity share is virtually zero at high investment costs (independently of the unit costs for wind), it increases to more than one at low investment costs, i.e. the system has more installed solar capacity than wind capacity. The effect for wind is smaller, but that is in part due to the lower variation in unit cost. In the middle, we see that the impact of renewable investment costs on the hydrogen to battery ratio is comparably small. However, the share of hydrogen increases at low costs of solar—which in the German system is the renewable technology with lower generation share. On the right, the ESR-to-RES capacity ratio is more responsive to changes in solar costs than wind costs.

The lower part of the figure shows the same ratios, but dependent on changes in ESR cost. The left figure confirms that the impact of ESR cost changes on renewable ratios is limited. In the middle figure, the hydrogen-to-battery ratio is very sensitive to cost changes. While hydrogen can provide more than half of total ESR capacity when its cost is low and battery cost is high, it can also be driven out of the market completely. The ESR-to-RES ratio on the lower right is

[15]The tables with values not depicted based on 2020 are shown in the appendix.

Figure 6: German System - Cost, Curtailment and Peak Prices



Figures with renewable energy unit cost variation hold battery costs fixed at $f_B = 10$ and $f_H = 4$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 13.5$ and $f_S = 5$. These cost choices represent 2050 forecasts.

not sensitive to changes in ESR investment cost.

To better understand how RES and ESR cost reductions affect capacity of RES and ESR, we have also regressed our simulated capacities on unit costs f_i; the results are shown in appendix tables A.8 and A.9. Dropping unit costs for f_i increase capacity $\bar{x}_i$, and thus the diagonal entries in the table are all negative. Substitute technologies (wind/solar, battery/hydrogen) have the opposite effect on capacities due to the relative price effect. What is interesting to see is how RES costs affect ESR capacities, and ESR costs affect RES capacities. In Germany, lower solar costs decrease battery capacity and increase hydrogen capacity. Lower hydrogen cost is associated with much more solar capacity and some more wind capacity, while lower battery costs reduces the need for solar capacity. Lower battery costs means less solar power is wasted due to curtailment, while lower hydrogen costs means more solar power can be brought into long-term storage.

4.5. Comparison

Our empirical calculations have revealed both differences and commonalities between ERCOT and Germany. Significant differences have been observed for the average prices. The Texan system is cheaper than the German system, even under our assumption of identical technology costs and technical parameters. The explanation lies in differences in the supply and demand patterns and their correlation structure.

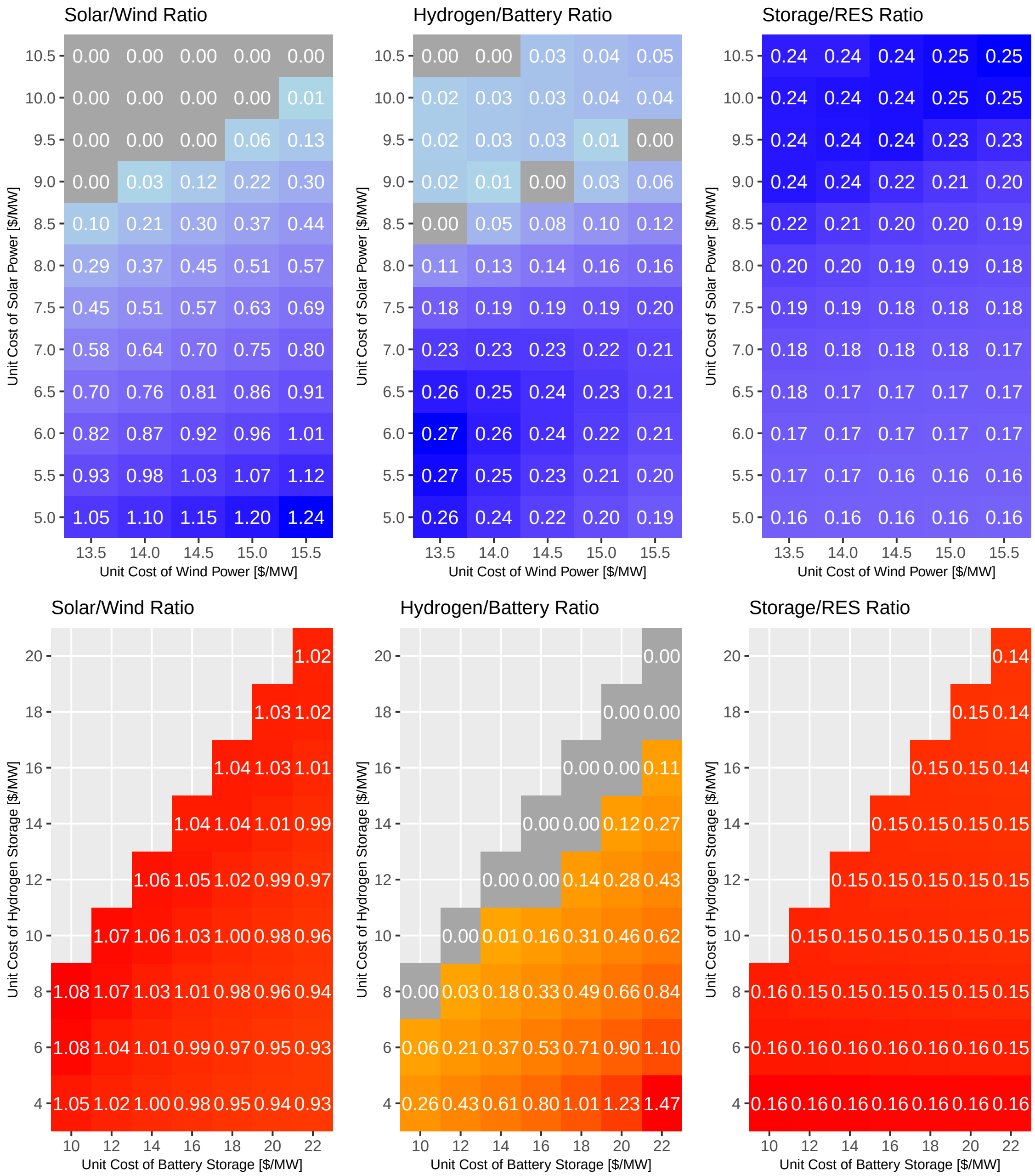
To further disentangle the source of the price difference, we conduct a counterfactual experiment. We take the Texan RES distribution and scale it to German levels. Germany's average utilisation rate for wind farms is 68.82% the level in Texas; the equivalent ratio for solar is 41.16%. These differences alone imply significantly lower cost in the ERCOT system. The remaining effect can be attributed to the correlation between demand and supply: the more RES output is correlated with demand, the cheaper the system can be supplied. Furthermore, a negative correlation between solar and wind output provides more stable electricity generation. We can quantify the first effect directly, running the Texan system with scaled down German levels. This enables us to quantify the second effect indirectly, as the difference between the German average price and the scaled ERCOT average price.

Table 7: Decomposition of Texan and German Average Prices

	Avg. Price [$/MWh]			Difference	
	ERCOT	Scaled	Germany	Utilis.Eff.	Corr.Eff.
2020 Parameters	62.34	87.46	99.70	25.12	12.24
2050 Parameters	40.76	64.42	69.90	23.66	5.48

Table 7 shows the results of these counterfactual calculations. The columns labelled "ERCOT" and "Germany" show the results previously shown for 2020 and 2050. The column "Scaled" in between shows the average price of our counterfactual calculation for ERCOT, imposing on ERCOT the less favourable average German solar and wind utilisation rates. The last two columns show the decomposition into two separate effects. We label the effect of scaling as the "utilisation effect," shown in column "Utilis.Eff.", and we label the effect attributable to the different correlation structure of the state space as the "correlation effect," shown in column "Corr.Eff.". Germany's significantly higher system cost can be

Figure 7: Simulation Results for Germany



Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 10$ and $f_H = 4$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 13.5$ and $f_S = 5$. These cost choices represent 2050 forecasts.

attributed largely to the utilisation effect, and this effect is stronger in 2050 than in 2020. Given current technology, the correlation effect accounts for roughly one-third of the difference in 2020, but the cost advantage for solar power in 2050 magnifies Texas's significantly better utilisation rate for solar power. Germany suffers from a sunshine deficit!

Texas and Germany also differ in notable ways in terms of the complementarity of RES and RES, as is found in our regression results shown in appendix tables A.8 and A.9. For Germany we had found that falling solar unit costs reduced the need for battery capacity: a substitution effect. In Texas, cheaper solar power boosts battery capacity and reduces hydrogen capacity. Cheaper batteries decrease wind capacity and boost solar capacity, while cheaper hydrogen storage increases wind capacity and reduces solar capacity. These noticeable difference are attributable to the different correlation structures of demand with supply in the two locations. RES+ESR complementarities are strongly location-dependent!

4.6. Peak Prices and the Role of Curtailment on Peak Events

Peak prices play an important role in energy-only markets. In conventional electricity systems with fossil-fuel generators, they cover most of the fixed costs, especially for peak-load plants. The arrival of RES has threatened the viability of peak-load generators due to the well-documented merit order effect, which is largely a transitional phenomenon; see Antweiler (2021). In the 'new merit order', peak prices continue to occur with some frequency. In appendix figure A.7 we show scatter plots with the probabilities of peak events and corresponding average peak prices for ERCOT and for Germany. In ERCOT, average peak prices range between about \$700-1,000/MWh and occur with a frequency between 0.2 and 2.2%. In Germany, the range of peak event probabilities is between 0-1.5%, with average peak prices trending somewhat lower than in Texas. In both locations, the 2050 parameterisation is associated with lower peak prices and event probabilities than the 2020 parameterisation.[16]

The existence of peak events is not a precondition for the viability of grid-scale storage. In Germany we find scenarios where there are no peak events at all! Despite eliminating arbitrage profits at the margin (limited by the η-efficiency constraint), grid-scale storage earns profits when electricity can be charged for free (during curtailment events) and sold later at a positive price. If curtailment events are sufficiently frequent, grid-scale storage may not need peak events to cover its fixed cost, just curtailment events. In this sense, occasional curtailment in the 'new merit order' is not an aberration or inconvenience, it is a salient feature!

5. Limitations and Extensions

5.1. Climate Change and Future Demand

Our simulation utilises observed 2019-2022 data. Electricity demand in 2050 could look different due to climate change. Electricity demand for heating in the winter could increasingly shift to electricity demand for cooling in the summer.

[16]We also analyse peak prices and probabilities through a linear regression of the 2,520 simulation results with respect to (combined) storage capacity and RES capacities for wind and solar, shown in the appendix table A.10.

Allen et al. (2016) find that “electricity demand increases caused by temperature rise have the greatest impact over the next 40 years in areas serving small populations, and that large population influx stresses any affected service area, especially during peak demand.” Auffhammer et al. (2017) also note that there will be significant impacts on the frequency and intensity of peak load consumption during hot days, which in turn will necessitate significant new investments in peak generating capacity—or ESR. For Germany, Tanaka et al. (2022) point to local heterogeneity in climate effects as well as increased demand and price spikes.

Our estimate of the empirical supply and demand (Q-V-W) distribution using 2019-2022 does not yet account for the expected changes to the climate system in Texas and Germany. Yet, our model is particularly suited to such an exercise, which we envision for a follow-up paper. Climate change will induce changes to the Q-V-W space, both on the demand *and* supply side, with changes in the correlation structure. This can significantly affect the optimal composition of RES, and to a lesser extent ESR. Increasing electricity demand during the summer months is a strong case for a larger share of solar power.

5.2. Transmission Infrastructure

There is no explicit transmission infrastructure in our model. In practice cross-border or inter-regional interconnectors reduce required RES investments. Furthermore, Abrell and Rausch (2016), p. 107, find that ”[g]ains from trade depend positively on renewable energy penetration.” Hence, allowing for and optimising investment in inter-regional transmission capacity would lower costs and average prices presented above. However, the optimal composition of technologies would change. Furthermore, Yang (2022) rightly points out that transmission capacity may increase emissions during the transition when conventional technologies benefit more from the additional flexibility than renewable technologies. Flexibility from storage capacity may have a similar effect, as shown by Carson and Novan (2013).

Our analysis focuses on wholesale prices, which do not comprise grid fees—neither in ERCOT nor in Germany. Of course, intra-regional grid investment is a technical necessity. Including it in the investment adds complexity about location choice: where ESR should be built (on which voltage level, before or behind the meter, etc.). In the empirical implications, we expect that including grid costs would benefit battery and solar technologies, as they are more decentralised than both wind and hydrogen storage. Conventional modelling that involves combinations of short-term dispatch and long-term investment models is more suitable for incremental changes to existing grids, whereas our aim is to look at the far future and investigate the *viability* of these future grids as costs for competing technologies can span a wide range, and our focus is on the bulk composition of RES and ESR.

5.3. Additional Generation Technologies

The *raison d’être* of our paper is the exclusive presence of RES and ESR in an electricity market. However, there can be other types of electricity generation even in a 100% carbon neutral system, for example nuclear power plants, hydroelectric dams, biomass plants, and geothermal plants. They all tend to have relatively low marginal costs. Their presence is completely compatible with the model we have outlined above and would not change our 'new merit order' significantly because they would set market prices only infrequently if at all.

Similar reasoning applies to the number of ESR technologies. The future energy system will have room for more than two technologies. In addition to batteries and hydrogen, pumped hydro storage, vanadium redox flow batteries, compressed air storage, and numerous other novel technologies will compete for market share (see e.g. Frate et al. (2021) for an overview of these technologies). Battery technology will also span competing types of chemistry with different costs. This will lead to an even more differentiated structure of the merit order, at least on the buying side, as was theoretically shown in section 3. By focusing on two ESR technologies that are quite disparate in performance we hope to capture the breadth of available options.

5.4. Storage Constraint

Our model emphasises the importance of ESR power capacity, with ESR energy capacity implicit. The preeminence of power capacity is included in our model with a fixed capacity-to-energy ratio in the cost assumptions. In reality, investors can vary and optimise the capacity-to-energy ratio. Furthermore, the ESR constraint in our model guarantees that a market-wide ESR balance is maintained. While we explicitly take into account cycling losses (i.e. efficiency), additional constraints exist in reality. First, the amount of energy stored at any given time is bounded: downwards, it cannot become negative, i.e. ESR needs to charge chronologically before discharging. Upwards, it is restricted by ESR energy storage capacity (e.g., the physical volume of hydrogen storage caverns). Second, time-dependent storage losses exist; for example, batteries 'self-discharge' over time. Such storage losses for lithium-ion batteries are described as 1-2% per month in the literature, while the long-term properties of storing hydrogen are still being studied and depend on particular storage technologies (Andersson and Grönkvist, 2019).

5.5. Market Power

All analyses in our paper assume free entry and perfect competition. How would our model work in the presence of market power? The presence of significant market power in electricity markets is highly problematic due to the price-inelastic nature of demand. Besides ownership concentration, economies of scale for some types of generators (e.g., nuclear power) has provided an economic basis for market power. In the context of our analysis, economies of scale are less pronounced for wind and solar farms. Emerging market power and strategic behaviour for ESR systems is harder to predict during early stages of deployment. At least for ESR connected directly to solar power, there is good reason to think that market power effects would be limited due to the distributed and decentralised nature of a significant number of smaller systems. Because local ESR can reduce transmission costs, a more decentralised system is conceivable. Hydrogen will operate differently because of the need for industrial-scale electrolysers, storage, and pipelines. Yet, our empirical model finds limited scope for hydrogen, in particular due to the relatively high cost of ESR.

5.6. Other Markets and Revenues

Our paper analyses market equilibria on the wholesale electricity market. However, ESR in electricity systems can earn additional revenues in other markets. Relevant is in particular the balancing market, where transmission system operators buy and sell energy to keep the system frequency stable. At the other end of the time scale, investors often sign long-term contracts for electricity delivery to "lock-in" a revenue stream which can finance the investment. While the required financial product is rather complicated for ESR and as of today not traded widely, we acknowledge parts of the investment costs required for ESR may be covered by revenue streams beyond the scope of our work. Hence, future work could pursue how the different revenue sources for ESRs interact, how they change the shares in optimal investment and also analyse which changes in the current market design may be advisable in a 100% carbon emission free system discussed in our paper.

6. Policy Discussion

6.1. Market Participation

Our theoretical model suggests that ESRs need to be allowed to participate freely in the market as buyers and sellers in order to find the equilibrium price that achieves the efficient allocation outcome with free entry. How ESR firms are allowed to participate in markets is evolving on a regulatory level.

In most liberalised wholesale electricity markets, generators of electricity submit bids to a market operator, who then arranges all bids to supply electricity in ascending order and intersects the resulting curve with the demand side of the market. The selected lowest bids receive compensation equal to the market clearing price. Market participation on the buying side works similarly, and the process is well established and revenue neutral.

This general market design fits the needs of ESR well. When charging, they are active on the demand side of the system and compete with all other consumers, with the market clearing price deciding who gets electricity. When ESR are discharging, they are active on the supply side of the market and compete with all other generation sources. Nonetheless, there is still scope for developing new rules and regulations for ESR participation—both in the US and in Europe. The problem is that the whole process is not necessarily as nondiscriminatory as theory suggests.

In the U.S., the *Federal Energy Regulatory Commission* (FERC) addressed potential barriers for market entry and operation of ESR in Order 841, issued in 2018. The order directed market operators (RTOs and ISOs) to develop rules governing ESR participation in energy, capacity, and ancillary service markets.[17] Importantly, ESRs are allowed to buy and sell power at the wholesale locational

[17]FERC Order 841 rule states: "The participation model must (1) ensure that a resource using the participation model is eligible to provide all capacity, energy, and ancillary services that the resource is technically capable of providing in the RTO/ISO markets; (2) ensure that a resource using the participation model can be dispatched and can set the wholesale market clearing price as both a wholesale seller and wholesale buyer consistent with existing market rules that govern when a resource can set the wholesale price; (3) account for the physical and operational characteristics of ESR through bidding parameters or other means; and (4) establish a minimum size requirement for participation in the RTO/ISO markets that does not exceed 100 kW. Additionally,

marginal price (LMP), and they can set the wholesale market clearing price as both a wholesale seller and wholesale buyer. FERC Order 841 was held up for some time by court challenges initiated by the National Association of Regulatory Utility Commissioners and the American Public Power Association, but the United States Court of Appeal in the District of Columbia ruled in July 2020 in favour of FERC Order 841. This outcome levels the playing field for ESR to compete with conventional generators (Konidena, 2019; Kagerer, 2021). Dual market participation by ESRs raises some new concerns: dispatch as both load and generation during the same market interval could imperil grid reliability. Order 841 gives Regional Transmission Operators (RTOs) the flexibility to prevent this. Our 'new merit order' suggests that the market mechanism prevents that in a pure ESR+RES world, but price signals can be muddled in a hybrid market with conventional generation assets.

The regulatory landscape in Europe is different. ESRs are market participants on the hourly day-ahead market as well as reserve and balancing markets. For example, batteries fulfil the technical properties—in particular a very fast response time—to provide primary reserve. Hydro pumped storage also earns significant revenues on balancing markets. Nonetheless, the situation varies across EU member states; see Hoogland et al. (2023) for an overview of the regulatory framework.[18] In Germany, ESR may both buy and sell electricity on the wholesale market and provide balancing power. However, there was a debate about the allocation of grid costs. The general rule is that—except for plant-side grid connections—grid costs are paid exclusively by consumers. Hence, ESR would have to pay grid fees, even though for their consumption only. For now, this debate concluded with partially exempting ESR from these grid fees.

6.2. *Public Policy*

Our empirical simulations show that energy-only markets can deliver the first-best efficient outcome for allocating generation and storage capacity, conditional on the specific empirical distribution of supply and demand that differs across locations. There is no *prima facie* case for production or investment subsidies, and their use in practice is often technology-biased. Feed-in-tariffs in power purchasing agreements, as well as contracts-for-difference, often favour one RES type over another, which distorts the market outcome and introduces inefficiencies. What matters overall is lower cost of generation and storage, and this only comes about through more innovation. Subsidies can be helpful if they correct market failures in innovation (e.g., due to imperfect intellectual property rights), but they should be technologically neutral.

There is evidence that public and private incentives for deploying RES capacity can become misaligned when markets provide incomplete spatial price signals: wind farms tend to cluster in favourable wind locations, preventing a

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each RTO/ISO must specify that the sale of electric energy from the RTO/ISO markets to an ESR that the resource then resells back to those markets must be at the wholesale locational marginal price."

[18]There are numerous policy debates in the European Union about electricity markets, and there is an extensive body of laws and regulation including Regulation 2019/943 of 5 June 2019 on the internal market for electricity. Importantly, Article 10 prohibits non-technical price restrictions on wholesale prices. Article 6 mandates non-discrimination between market participants, including ESR.

more beneficial portfolio effect from location diversification (Antweiler, 2017). Correct spatial incentives are perfectly compatible with energy-only markets if markets use locational marginal prices (LMPs), or at least zonal prices. LMPs reflect grid congestion, but also excess supply or demand conditions. Increasing spatial granularity in energy-only markets can help steer investments where they are most beneficial, thus re-aligning private and public benefits (IRENA, 2019).

6.3. Energy Security

Renewed concerns about energy security have emerged in the wake of Europe's 2022 energy crisis. Secure sources of supply are essential for electricity systems that rely on fossil fuels. North America is more self-reliant than Europe, given the continent's vast hydrocarbon resources. Yet, transitioning to renewable energy and electricity storage raises questions not only about seasonal, but also about long-term and *strategic* electricity storage. The cost of new long-duration energy storage (LDES) technologies remains relatively high, and our model shows that the share of hydrogen as LDES remains relatively low. Our model reveals optimal *power capacities* for ESR and is silent about the implicit *energy capacity*. This is by design, as grid-wide system performance is all about power capacity balancing supply and demand in real time. Yet, there is a distinct possibility that *energy capacity* could end up insufficiently incentivised if energy capacity is not physically linked to power capacity, as is the case with pumped-hydro storage, flow batteries, and hydrogen storage. Energy adequacy requires liquid forward markets, and these remain immature especially for far horizons. If strategic energy storage is a public good, it would need to be treated as such.

Pure RES+ESR systems will be less reliant on energy imports, thus improving energy security. However, some of the energy security concerns may shift to concerns about increased reliance on technology imports for RES and ESR equipment—especially if it involves scarce resources such as critical minerals. Hydrogen imports could also become a substitute for (some) fossil fuel imports, turning hydrogen electrolysers from a pure storage asset into net generating asset. Transitioning to an RES+ESR system is no panacea for energy security.

7. Conclusions

Can energy-only markets continue to function when electricity grids are composed entirely of renewable energy supply (RES) and energy storage resources (ESR), all operating at near-zero marginal costs? What will replace the conventional merit order in such an energy-only electricity market?

Our paper provides cogent answers to both questions. Energy-only markets remain perfectly viable even when they are dominated by RES and ESR. The conventional merit order, the electricity supply curve that stacks suppliers in order of their marginal cost, is replaced with a new merit order where ESR becomes a pivotal market participant on both sides of the market and effectively sets the market price for electricity most of the time. We show how the equilibrium price emerges in a general model and a simplified linearised model. While grid-scale ESR recovers part of its fixed cost through peak prices similar to peak-load plants today, it also benefits from acquiring electricity when prices drop to zero due to excess RES supply (and curtailment). Meanwhile, renewable energy plants receive positive revenue throughout their operation except when excess supply requires curtailment (and zero prices). Our simplified theoretical analysis shows that the equilibrium price in this market is, in the simplest form, the difference between the output-normalised unit cost of RES and the unit cost of ESR, scaled up to account for curtailment and peak periods.

Empirically, our paper investigates the feasibility and consequences of a pure RES+ESR market for Texas (ERCOT) and Germany, two markets with significant shares of renewables already. We determine the optimal mix of solar and wind power, and two types of storage, batteries and hydrogen. We set aside the continuing role of base load from nuclear power or hydro. Their continued presence does not fundamentally alter our theoretical results, only the emerging empirical generation mix. We show that with cost scenarios based on actual 2020 data and credible 2050 forecasts, average market prices in ERCOT could actually become cheaper than currently observed, while in Germany average market prices would rise significantly at today's unit costs but only gently with unit costs anticipated for 2050. The prevalence of peak prices does not increase dramatically. A pure-RES+ESR world is not unaffordable.

Our empirical simulations reveal important differences between Texas and Germany in terms of RES and ESR composition. In Texas, shifting RES unit costs from 2020 to 2050 would raise the optimal (nominal) capacity ratio of solar-to-wind capacity from about 0.6 to 2.0, while in Germany it would shift from none to about 1.0. Perhaps unsurprisingly considering geographic latitude and the correlation structure of RES and demand, solar power should play a much larger role in Texas than in Germany. Based on our 2050 cost parameters, solar's share in ERCOT's power output would need to increase from 3% today to 61% in 2050, while wind output would need to increase from 23% today to 39% in 2050. In Germany, wind's share of power output would need to increase from 25% to 68%, and solar's share from 10% to 32%.

We also find that ERCOT will require a higher nominal capacity ratio of ESR-to-RES (about 0.28) compared to Germany (as low as 0.16). ERCOT's overall ESR-to-RES ratio varies little, but as the relative share of solar capacity increases, there is less need for long-term (inefficient) hydrogen storage and more need for short-term (efficient) battery storage. In Germany, the pattern is reversed. As the ratio of solar-to-wind capacity increases, there is less overall need for storage, and the ratio of hydrogen-to-battery storage increases. Our analysis shows that the optimal composition of RES and ESR is strongly location-specific. It is not technological innovation alone (and shifting relative costs) that determines RES/ESR composition, but also very strongly the supply and demand correlations in the stochastic demand and supply space.

A pure RES+ESR system is much more expensive in Germany than in Texas, even assuming identical technology unit costs. We conduct a counterfactual experiment and apply Texan RES supply patterns and scale it to Germany, while using Germany's demand pattern. We find that Germany's significantly higher system cost can be attributed largely to the utilisation effect, which lowers cost due to better utilisation rates of RES, rather than the correlation effect, which lowers cost due to positive correlation of demand with RES supply. Simply put, Germany suffers from a sunshine deficit compared to Texas.

As an additional policy lessons, our paper shows that market rules, such as those adopted in FERC Order 841, need to enable ESR market participants to buy and sell at marginal prices. ESR plays a pivotal role in the 'new merit order' because it sets prices on the buying and selling side most of the time.

Our paper is not meant to forecast future electric grids. We explore the economic feasibility of a pure RES+ESR system theoretically by determining the 'new merit order', and empirically by providing estimates of the bulk composition and market prices in two far-apart locations. We find convincingly that energy-only markets remain perfectly viable and that storage replaces the role of conventional peak-load plants. Expected cost reductions in RES and ESR technologies appear to make a fully-decarbonised electricity system economically attainable. Do not fear the 'new merit order': it doesn't look all that different from the old.

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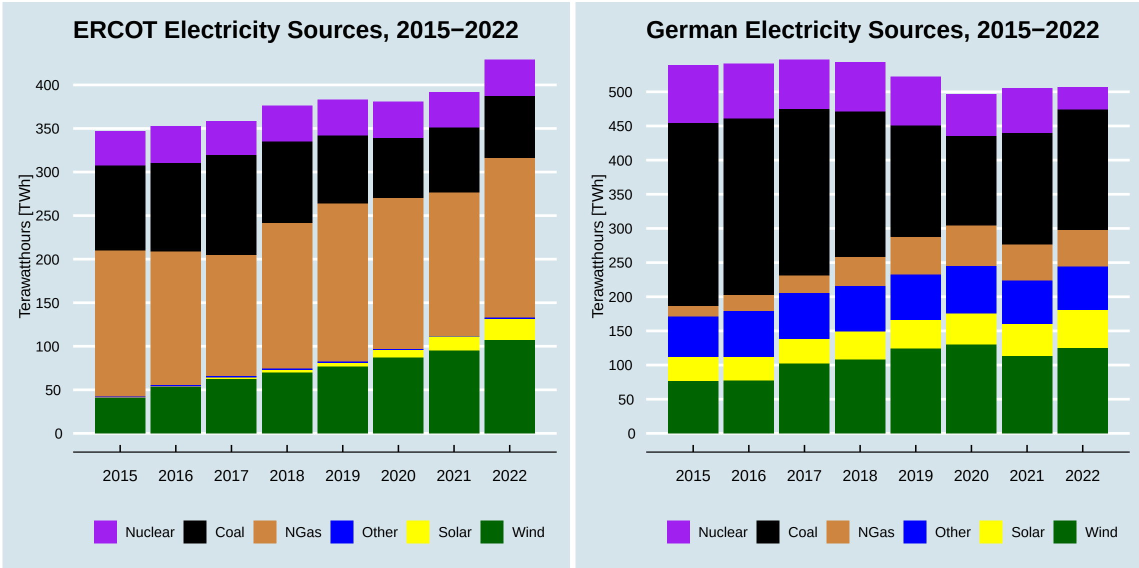
Appendix A. Additional Figures and Tables

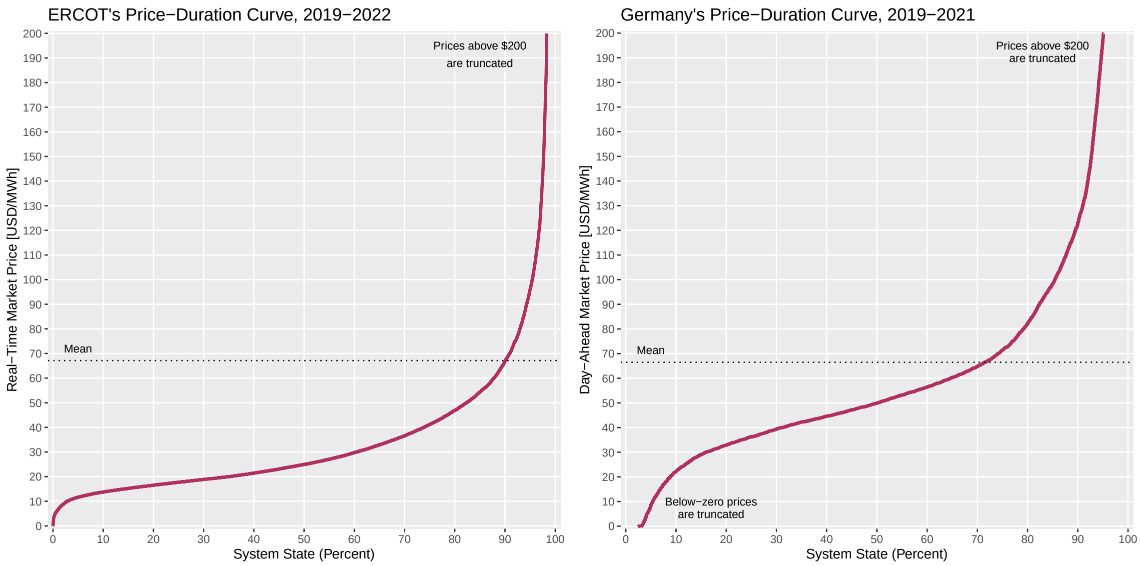
Figure A.1: Electricity Generation Mix



(a) ERCOT (Texas)

(b) Germany

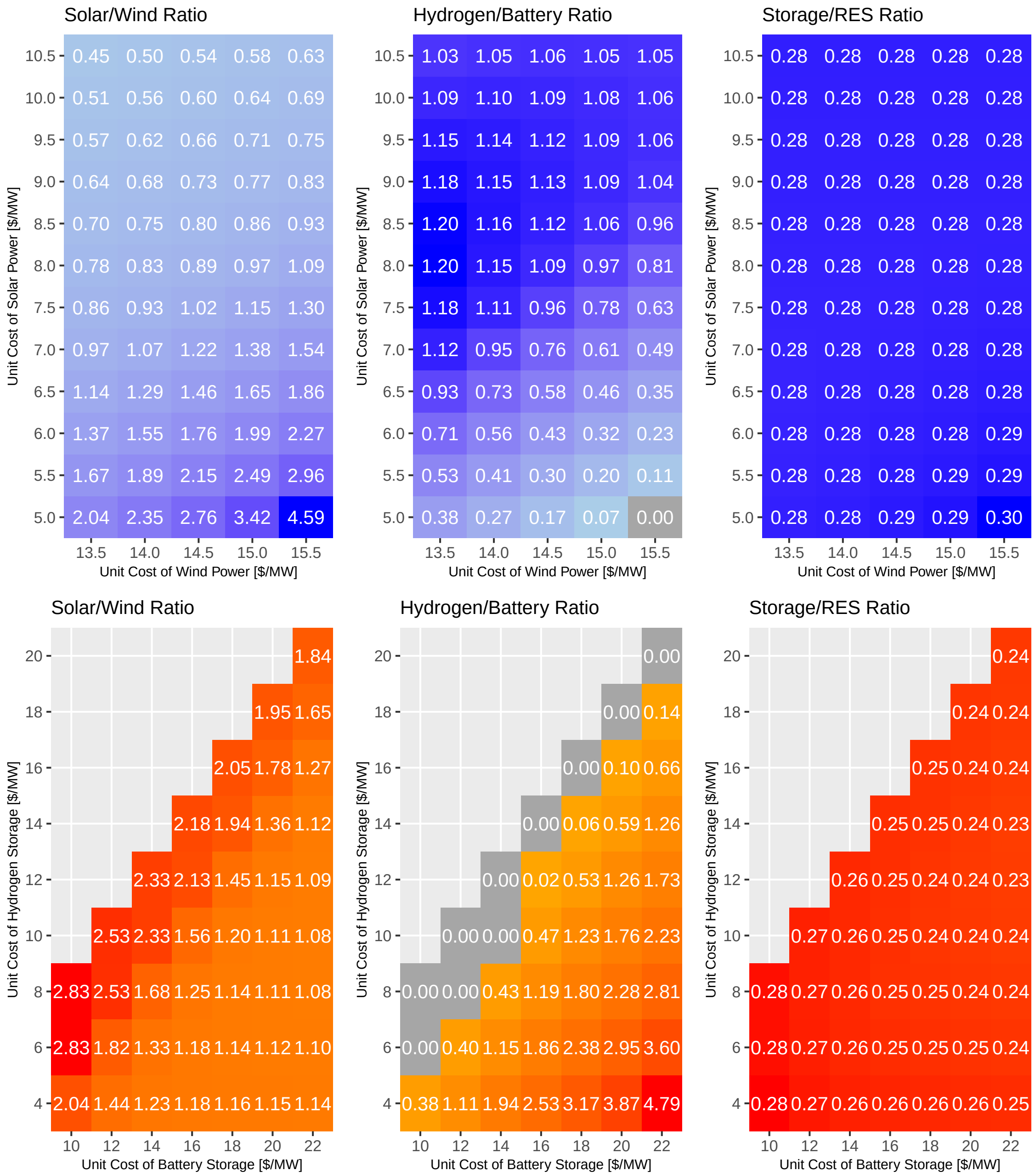
Figure A.2: Price-Duration Curves



(a) ERCOT (Texas)

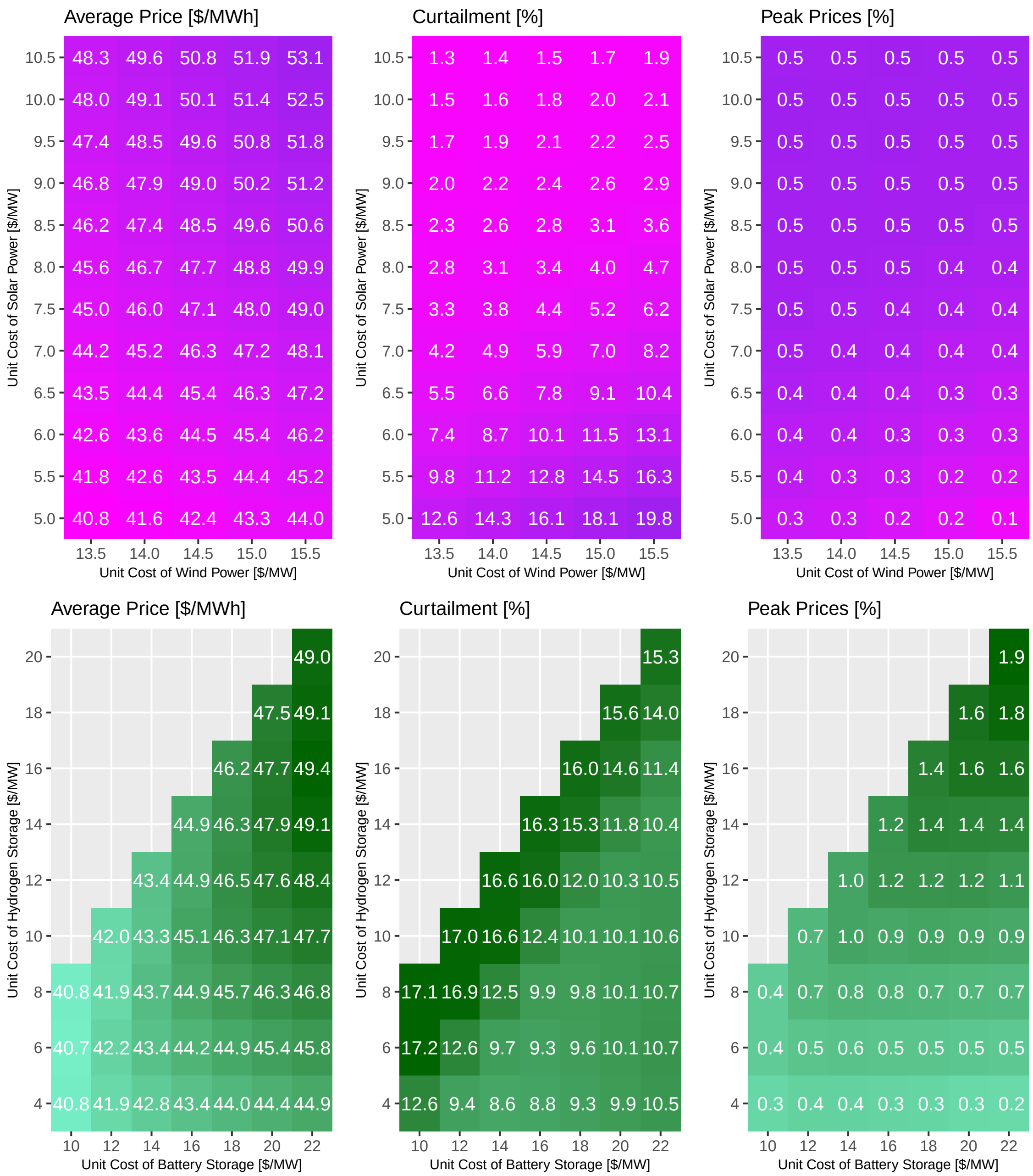
(b) Germany

Figure A.3: Simulation Results for Texas (ERCOT): Pivot at 2020 Costs



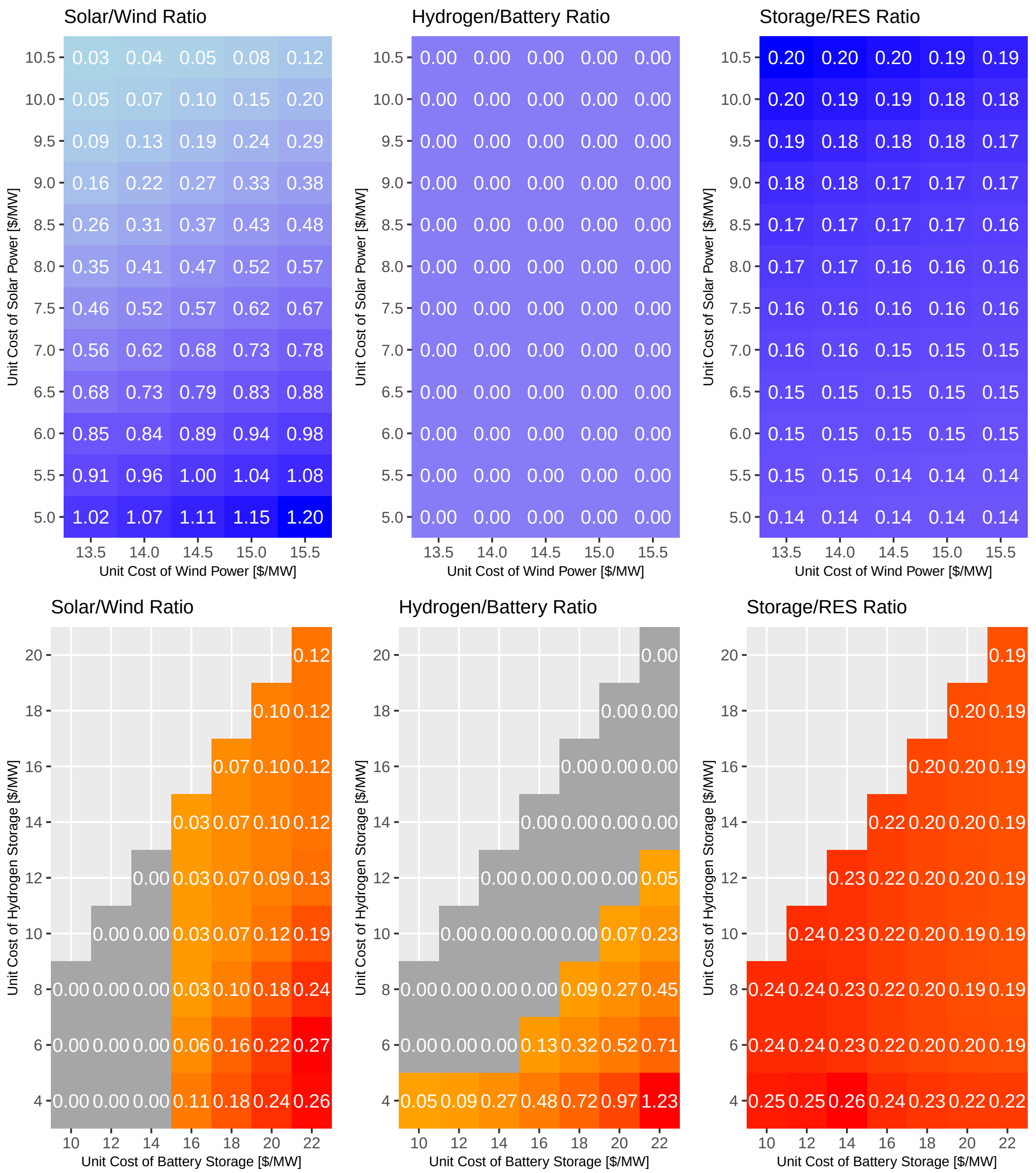
Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 22$ and $f_H = 20$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 15.5$ and $f_S = 10.5$. These cost choices represent 2020 levels.

Figure A.4: Simulation Results for ERCOT (continued): Pivot at 2020 Costs



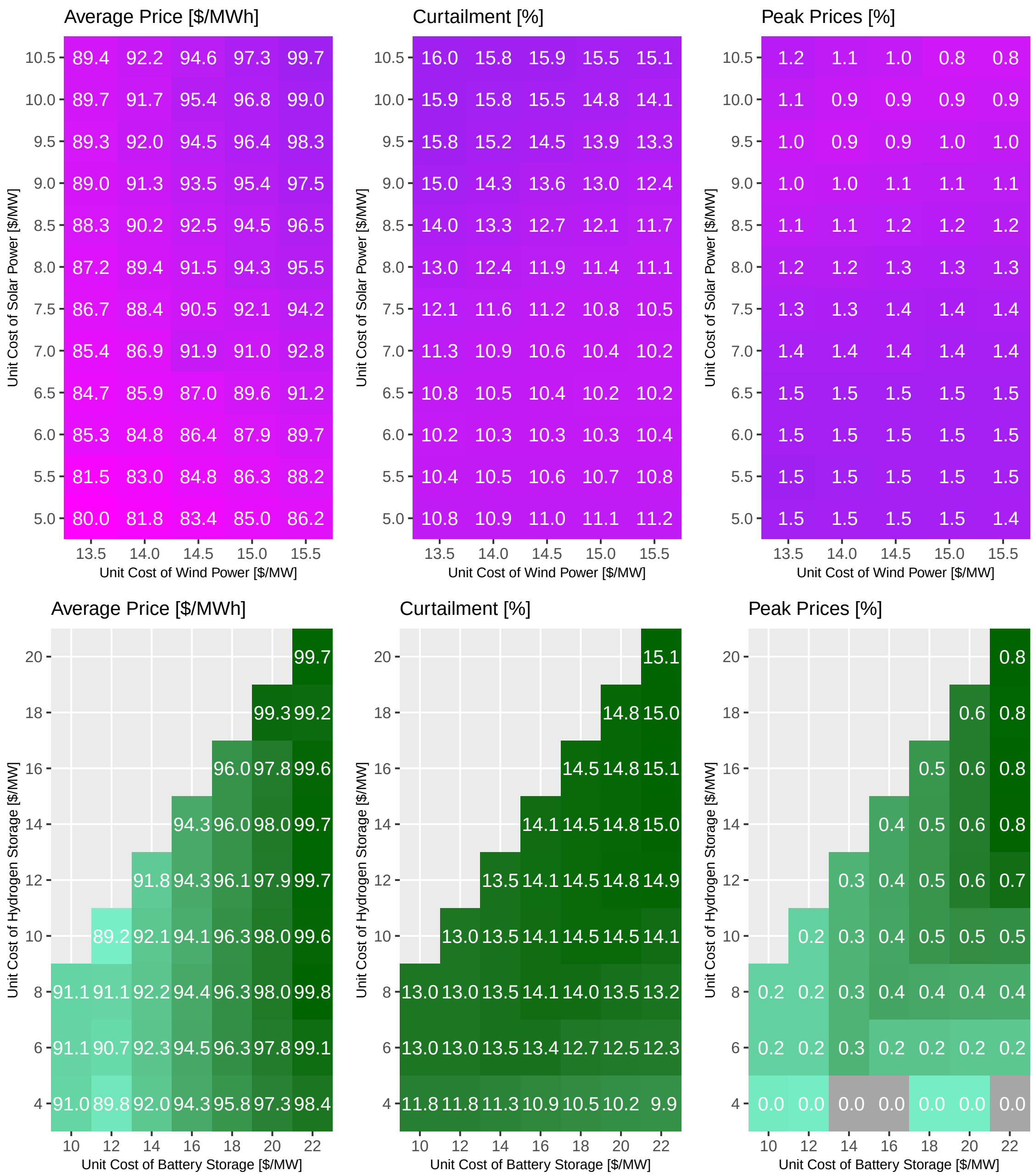
Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 22$ and $f_H = 20$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 15.5$ and $f_S = 10.5$. These cost choices represent 2020 levels.

Figure A.5: Simulation Results for Germany: Pivots at 2020 Costs



Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 22$ and $f_H = 20$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 15.5$ and $f_S = 10.5$. These cost choices represent 2020 levels.

Figure A.6: Simulation Results for Germany (continued): 2020 Costs



Diagrams with renewable energy unit cost variation hold battery costs fixed at $f_B = 22$ and $f_H = 20$. Diagrams with ESR cost variation hold RES unit costs fixed at $f_W = 15.5$ and $f_S = 10.5$. These cost choices represent 2020 levels.

Table A.8: Regression Analysis of Simulation Results for ERCOT

Generation Capacities [GW]	Wind	Solar	Battery	Hydrogen
(Intercept)	83.14***	89.20***	30.05***	18.05***
	(2.31)	(3.31)	(2.13)	(1.72)
Unit Cost: Wind (f_W)	-4.860***	6.969***	1.94***	-1.236***
	(0.152)	(0.218)	(0.14)	(0.113)
Unit Cost: Solar (f_V)	6.9682***	-11.3884***	-1.8852***	0.8827***
	(0.0623)	(0.0892)	(0.0574)	(0.0463)
Unit Cost: Battery (f_B)	1.7863***	-1.4634***	-2.2361***	2.0018***
	(0.0316)	(0.0452)	(0.0291)	(0.0235)
Unit Cost: Hydrogen (f_H)	-1.0893***	0.4517***	1.953***	-2.3237***
	(0.0272)	(0.0389)	(0.025)	(0.0202)
Num.Obs.	2520	2520	2520	2520
R^2	0.871	0.880	0.794	0.859

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A.9: Regression Analysis of Simulation Results for Germany

Generation Capacities [GW]	Wind	Solar	Battery	Hydrogen
(Intercept)	223.08***	114.06***	55.06***	8.44***
	(3.01)	(4.87)	(1.35)	(1.54)
Unit Cost: Wind (f_W)	-9.346***	16.70***	-0.0265	-0.301**
	(0.198)	(0.32)	(0.0886)	(0.101)
Unit Cost: Solar (f_V)	17.7496***	-35.146***	1.9577***	-1.0375***
	(0.0811)	(0.131)	(0.0363)	(0.0415)
Unit Cost: Battery (f_B)	0.0466	2.1584***	-2.2470***	2.178***
	(0.0411)	(0.0665)	(0.0184)	(0.021)
Unit Cost: Hydrogen (f_H)	-0.2895***	-1.2222***	1.8193***	-2.4751***
	(0.0354)	(0.0572)	(0.0158)	(0.0181)
Num.Obs.	2520	2520	2520	2520
R^2	0.952	0.968	0.900	0.897

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A.7: Average Peak Prices and Probabilities

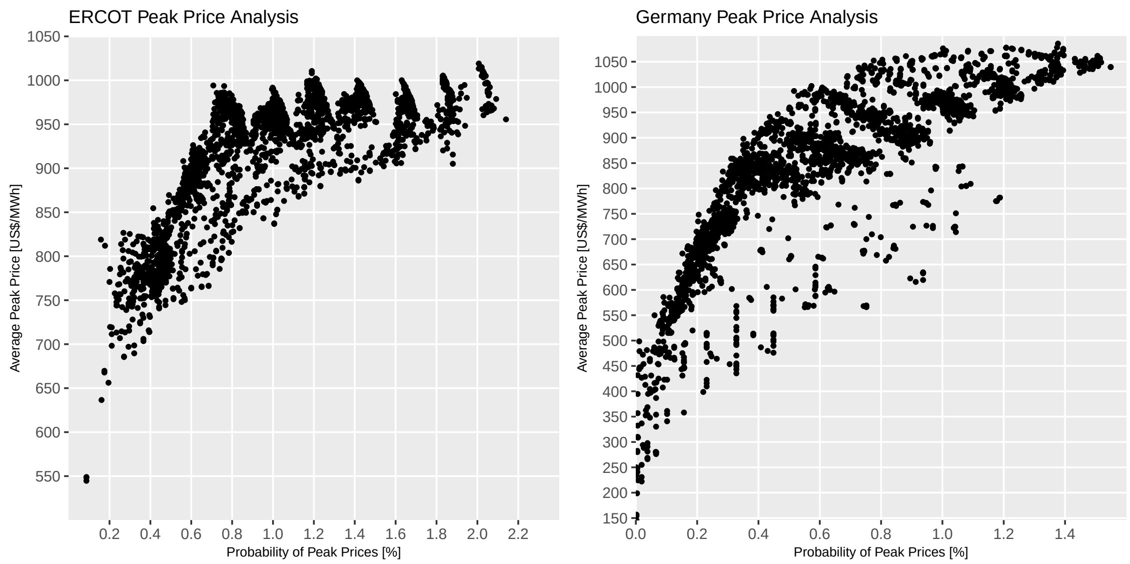


Table A.10: Average Peak Prices and Probabilities

	ERCOT		Germany	
	Log Prob. of Peak Events	Avg. Peak Price [US$/MWh]	Log Prob. of Peak Events	Avg. Peak Price [US$/MWh]
(Intercept)	12.0547***	2039.9***	14.287***	3172.1***
	(0.0404)	(20.5)	(0.381)	(48.2)
Storage	-0.199488***	-28.441***	-0.22653***	-49.335***
	(0.000565)	(0.287)	(0.00224)	(0.283)
Wind	-0.034654***	-0.072	-0.00622***	1.911***
	(0.000316)	(0.160)	(0.00152)	(0.192)
Solar	-0.007826***	1.172***	-0.003932***	0.9403***
	(0.000241)	(0.122)	(0.000747)	(0.0943)
Num.Obs.	2520	2520	2491	2491
R^2 Fit	0.989	0.866	0.857	0.945

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Note: Some simulations for Germany have solutions with no peak price events.