Essays in Energy Economics: On the Coordination between the Electricity Markets and the Grid

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1. Introduction

Prices have a signaling function in markets. They serve as incentives that coordinate producers and consumers in the efficient allocation of resources, ensuring that supply meets demand at optimal cost. As such, prices play a fundamental role in shaping the decision-making processes of market participants in any economic system.

Electricity markets are unique due to the physical characteristics of electricity as a good. Electricity supply and demand must be balanced in real time as supply is subject to short-term capacity constraints and electricity is storable only with the help of dedicated flexibility technologies such as batteries, thermal storage, or demand-side management (c.f. Borenstein, 2005). This creates a need for precise temporal coordination between supply and demand, making the analysis of price signals especially important. In addition, electricity markets are dependent on an interconnected grid that links producers and consumers. The grid is also subject to capacity constraints, meaning that the physical location of production and consumption matters (cf. Joskow and Léautier, 2021). Thus, in addition to temporal coordination, spatial coordination is essential to ensure the efficient operation of the electricity system.

These unique characteristics have gained importance with the ongoing transformation of energy systems. The accelerated adoption of renewable energy sources (RES), the increase in decentralization, and the growing participation of consumers in electricity markets fundamentally alter the market dynamics. In Germany, for instance, RES accounted for 52.5% of gross electricity consumption in 2023 (BMWK, 2024a). The national target of 80% generation of RES by 2030 (EEG, 2023) signals a shift toward a decarbonized electricity system characterized by new supply locations and weather-dependent feed-in patterns. At the same time, consumer participation is growing and, as a result, the demand structure is changing, further driven by the coupling of the electricity, heating, and transport sectors. For example, six million heat pumps are expected to be installed in private households by 2030 (BDEW, 2024), which will lead to changes in the demand structure and may not correspond to the intermittent generation of RES. The implementation of flexibility technologies, like batteries and thermal storage, along with grid expansion, are essential developments for the future electricity system to complement the transformation and ensure the coordination between supply and demand.

The transformation of the energy system increasingly challenges existing pricing mechanisms to provide effective signals to coordinate the electricity market and the grid. Adding to this complexity is the unbundled structure of electricity systems in many countries, which separates competitive wholesale electricity markets from regulated grid operation. Key questions are how to design prices that accurately capture the unique temporal and spatial characteristics of electricity, and how to allocate costs between competitive wholesale markets and regulated grid operation to incentivize efficient outcomes.

Currently, many electricity systems fall short in delivering accurate price signals. For example, wholesale electricity prices often lack a local component, disregarding the grid's physical constraints. Retail tariffs are typically composed of different components including network tariffs, taxes, and levies that add on wholesale market price signals. For example, retail tariffs frequently include volumetric network tariffs that inflate electricity prices for consumers, as they embed fixed grid costs into variable charges rather than reflecting the true cost of grid usage at specific times and locations.

Understanding the price formation, possible interactions between its components, and how market participants react to the price signals is therefore a crucial task in economic research. Price signals guide the decisions of market participants, such as when to produce or consume electricity, invest in capacity, or deploy flexibility technologies. For a market to function efficiently, price signals must be coherent and economically sound. This applies in particular in the case of retail tariffs, consisting of different price components. Otherwise, the economic incentives of price signals may be distorted, undermining the system's efficiency.

This thesis contributes to understanding price signals in the electricity system through four chapters, each based on a single paper to which the authors contributed equally. Using numerical, analytical, and empirical methods, the chapters explore the relationship between price signals, system efficiency, and the decision-making of market participants.

1. The Place beyond the Lines - Efficient Storage Allocation in a Spatially Unbalanced Power System with a High Share of Renewables. Joint work with Berit Czock and Jonas Zinke. *EWI Working Paper 23/01* and under review at *Energy Economics* (Czock et al., 2023)
2. Unlocking Thermal Flexibility for the Electricity System by Combining Heat Pumps and Thermal Storage. *EWI Working Paper 25/03* (Sitzmann, 2025)
3. Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework. Joint work with Samir Jeddi. *EWI Working Paper 21/01* (Jeddi and Sitzmann, 2021)
4. How Prices Guide Investment Decisions under Net Purchasing - An Empirical Analysis on the Impact of Network Tariffs on Residential PV. Joint work with Fabian Arnold and Samir Jeddi. *EWI Working Paper 21/07* and published in *Energy Economics*, Vol. 112, 2022 (Arnold et al., 2022)

The remainder of the introduction provides an outline of the following chapters (Section 1.1), discusses the methodological approaches, and hints at opportunities for future research (Section 1.2).

1.1. Outline of the Thesis

Chapter 2 and 3 are based on numerical models of the wholesale electricity market and the transmission grid, with a particular focus on the integration of flexibility technologies. These two chapters utilize numerical models that optimize a social planner's cost-minimization problem to analyze the electricity system. Under ideal conditions, such an optimization corresponds to the decision-making of market participants guided by the price signals of the wholesale market. The analyses investigate how storage investments can be optimally allocated to different locations, and how the flexibility provision through thermal storage combined with heat pumps impacts the electricity system. Chapter 4 broadens the analysis by incorporating the perspective of the grid operator on pricing, analytically deriving the interactions of spot market pricing schemes and network tariffs on consumer decision-making in a dynamic context. Finally, Chapter 5 studies whether the economic incentives provided by price signals work as expected in theory and emphasizes the importance of these incentives by showing empirically how price signals guide household investment decisions in residential PV systems in Germany. Each chapter is described in more detail below.

The Place beyond the Lines - Efficient Storage Allocation in a Spatially Unbalanced Power System with a High Share of Renewables

Chapter 2 deals with the challenges in grid operation posed by the temporal and spatial variability of increasing shares of wind and solar generation. While grid expansion is restricted in the medium term, storage technologies can potentially increase the power system's efficiency by temporally aligning generation and demand and increasing grid utilization. The analysis is based on a theoretical and a numerical model to evaluate the optimal allocation of battery storage. In a case study for Germany, the results show that batteries can reduce system costs when placed behind the north-south grid bottleneck and near solar power. The supply costs in a setting with uniform prices and a random battery distribution are 9.3% higher than in the theoretical first-best benchmark with nodal prices. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. This corresponds to almost a doubling of supply cost savings per euro spent on battery installation. Due to the lack of spatially differentiated investment incentives under the German uniform pricing scheme, batteries must be allocated by additional policies. Simple allocation rules such as tying battery siting to solar capacity or explicitly identifying a limited number of suitable sites and auctioning capacity can approximate an optimal allocation.

Unlocking Thermal Flexibility for the Electricity System by Combining Heat Pumps and Thermal Storage

The expansion of heat pumps drives the electrification of the heating sector which is important to achieve Germany's ambitious climate targets. **Chapter 3**, therefore, examines the impact of heat pumps in combination with thermal storage on the flexibility of the German electricity system in 2030, focusing on its market and grid impacts. A temporally and spatially detailed electricity market and transmission grid model evaluates the impact of thermal storage. The results show that, overall, unlocking the flexibility of thermal storage consistently reduces total supply costs. However, while the flexibility provided by thermal storage supports the integration of renewable energies and reduces supply costs in the dispatch, the use of flexibility increases grid violations and hence, redispatch measures. By further studying a model setup with locational marginal prices (LMPs), the analysis highlights regional differences in the value of flexibility, which is particularly high in northern Germany, where proximity to wind generation enhances the benefits of thermal storage.

Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework

Since adequately designed prices are essential for efficient coordination between the electricity network and market participants, **Chapter 4** addresses the interactions of the different electricity price components from a competitive wholesale market and regulated network operation. An analytical model is set up to examine different regulatory settings, consisting of alternative spot market pricing schemes and network tariff designs in a dynamic context. While a setting with zonal pricing, i.e. spatially differentiated prices, and fixed network tariffs achieves the highest welfare, a deviation of either the pricing scheme or the network tariff design leads to inefficiencies. The results show that two inefficiently designed price components can be better than one, especially if network tariffs correct for the static inefficiency of the pricing scheme. Besides the network tariff design, network operators must pay attention to the allocation of network costs. It affects spatial price signals and, therefore, the dynamic allocation of investment decisions. Considering these decisions in a dynamic framework increases the requirements for the configuration of network tariffs, especially with volume-based network tariffs.

How Prices Guide Investment Decisions under Net Purchasing - An Empirical Analysis on the Impact of Network Tariffs on Residential PV

Chapter 5 emphasizes the importance of economic incentives arising from prices by showing empirically how price signals guide household investment decisions in Germany. Under the current regulation of net purchasing in Germany, investment incentives for residential PV depend on the remuneration for grid feed-in and the consumption costs that households can save by self-consumption. Network tariffs constitute a substantial part of these consumption costs. In an empirical model, postcode-level data for Germany between 2009 and 2017 is used and the regional heterogeneity of network tariffs is exploited to investigate whether they encourage to invest in PV installations and evaluate how the nonlinear tariff structure impacts residential PV adoption. The results show that network tariffs do impact PV adoption. The effect has increased in recent years when self-consumption has become financially more attractive, and the results confirm the expectation that PV investments are driven by the volumetric tariff. Policy reforms that alter the share between the price components are, thus, likely to affect residential PV adoption. Further, with self-consumption becoming a key incentive, price signals can effectively support the coordination of electricity demand and supply in Germany.

1.2. Methodological Approaches and Future Research

Each chapter of this thesis deals with a specific aspect of coordination in electricity systems and uses different methodological approaches to answer the respective research questions.

Chapter 2 and 3 are based on large-scale numerical optimization models of the European electricity sector. The models are applied to analyze investment and dispatch decisions by taking into account a detailed depiction of the transmission grid. The models rely on the fundamental assumptions of competitive, efficient markets, and rational market participants with perfect foresight. In addition, the models assume the electricity demand to be inelastic and disregard any transaction costs. Under these idealized conditions, the results of the optimization can be interpreted as the decision-making of market participants guided by the price signals of the wholesale market. The model configurations in both chapters are designed to be specific to the research questions raised in each chapter. **Chapter 2** analyzes the efficient allocation of new investments into decentralized battery capacities and studies different policy instruments that could coordinate an optimal battery allocation. **Chapter 3** studies the flexibility provision of thermal storage installed in combination with heat pumps. In this chapter, a dispatch model with flow-based market coupling in hourly time resolution is used to analyze dispatch and redispatch effects of the flexibility provision.

In order to examine spatial effects in more detail, both analyses make use of the concept of nodal pricing (locational marginal prices (LMPs)). Within this setup, grid constraints are considered within the price formation, meaning that all available information can be exchanged between the market and the transmission grid. Without any frictions, such a price formation represents the first-best benchmark for efficient coordination of electricity supply, demand, and the grid. However, in reality frictional losses are likely to distort optimality, for example, reduced liquidity, lack of transparency, market power issues, and increased transaction costs. The first-best nodal benchmark must therefore be interpreted as a theoretical benchmark. Further research could focus on relaxing the assumptions of the model and analyze the impact of flexibility options in a further developed model framework. With regard to the concept of nodal pricing, for example, potential market power issues and reduced liquidity could be investigated.

Chapter 4 sets up a stylized theoretical model framework of the electricity system which allows for an analytical solution. The analysis is based on a two-node model, including a spot market and the network tariff setting of a transmission system operator (TSO). The theoretical model is able to capture several spot market pricing schemes and network tariff designs. The theoretical approach provides insights into the interaction of the two price components, their potential inefficiencies and the requirements for a dynamically consistent allocation of demand-side investments. The stylized theoretical model relies on several strict assumptions, which include i.a. perfect competition, perfect foresight, constant marginal costs at the supply side, and identical consumers on the demand side. The assumptions made in the model allow the tractability of results, although they are accompanied with a high degree of abstraction and imply a loss of generality. Relaxing critical assumptions, e.g., deviating from the assumption of constant marginal costs or varying the functional form of the demand function, are therefore promising directions for further research. Further empirical or numerical studies could complement the theoretical analysis.

Chapter 5 applies an econometric approach to empirically investigate whether and how price signals impact the adoption of residential PV installations in Germany. A panel data set of PV installations, network tariffs, and socioeconomic covariates on postcode level covering the years of 2009–2017 is used. The regional heterogeneity of network tariffs is exploited to investigate whether they encourage investment in PV installations and to evaluate how the nonlinear tariff structure impacts residential PV adoption. A Poisson quasi-maximum likelihood estimator (PQMLE) with fixed effects is applied, which is a suitable estimator given the structure of the panel data set and allows to control for unobserved heterogeneity across regions and time. However, the use of fixed effects absorbs a substantial part of the within-variance and hence, the analysis is limited in explaining the present heterogeneity of PV installations in Germany. Further research could apply alternative estimation strategies in order to examine the impact of economic and socio-economic factors on the regional heterogeneity across Germany in more detail.

Beyond this discussion, the individual chapters describe in detail the methodological approaches used, discuss their limitations, and point out possibilities for further research.

2. The Place beyond the Lines - Efficient Storage Allocation in a Spatially Unbalanced Power System with a High Share of Renewables

2.1. Introduction

As countries strive for climate neutrality, they aim for high wind and solar power penetration rates. Wind and solar are intermittent, so temporal congruence with demand is not guaranteed. Additionally, resource quality varies across regions, which may lead to a spatial imbalance between supply and demand or extensive transmission requirements that exceed the capacity of existing grid infrastructure. Efficient coordination of investments in wind and solar, as well as in transmission grid expansion and power system flexibility, can mitigate these challenges and decrease system costs. Storage technologies, such as electric batteries, provide such power system flexibility. They can address temporal imbalances by shifting generation and load and reduce spatial imbalances by improving network utilization if allocated accordingly. Whether such an allocation is achieved ultimately depends on the market design. Under nodal pricing, allocation incentives are set by market prices. Such incentives do not exist in uniform pricing systems.

This paper analyzes investment in storage technologies in both a nodal and a uniform setting. We focus on a rapidly changing, spatially unbalanced power system, i.e., where solar and wind capacity expansion is fast, but grid expansion is slow. By applying a stylized, theoretical, and a numerical investment and dispatch model, we answer the following three research questions: Firstly, where in the transmission grid should batteries be allocated? Secondly, how important is storage allocation for the system's efficiency and, thirdly, how could policy instruments be designed to approximate an optimal allocation under uniform pricing?

The importance of storage allocation is first illustrated using a theoretical two-node, two-time-step model that stylizes the characteristics of a spatially unbalanced power system. This model enables us to show fundamentally that storage capacity can increase line utilization depending on its location. We show that both an allocation before or behind a grid bottleneck can be efficient. Which allocation rule dominates crucially depends on the temporal relationship between the volatility pattern of renewable generation, the demand structure, and available transmission capacity. Naturally, the complexity of the allocation question increases as soon as more than two nodes and time steps are considered. Therefore, we provide a comprehensive numerical model to investigate optimal storage allocation in a system with multiple technologies and a detailed grid representation. We use the German electricity system as a case study.

Already today, Germany exhibits characteristics of a spatially unbalanced electricity system. Under the single bidding zone, i.e., uniform pricing, wind generation is dominantly allocated in northern Germany on the shore of the North and Baltic Seas, while electricity demand is historically centered in the south and west of Germany, which is more densely populated and industrialized. As a result of this spatial mismatch, the volume and costs of network congestion measures have risen and are likely to increase further, given Germany's latest renewable capacity targets.

To investigate the optimal allocation of storage and identify policy design options for coordinating investments, we use a linear optimization market and grid model that endogenously determines the allocation of storage and renewable generation technologies. The storage technology is calibrated as short-term battery storage. The model computes a closed-form solution to the investment and dispatch optimization problem while considering a high spatial resolution. We use the results from modeling a nodal setup with consideration of transmission constraints as a theoretical first-best benchmark. This allows benchmarking battery allocation under a uniform setup without consideration of transmission constraints in the investment problem, similar to the current German market design.

The numeric simulation results confirm the significance of local demand, renewable feed-in volatility, and grid infrastructure availability for optimal battery allocation. Especially solar generation, which has a daily generation pattern that matches the batteries' short-term shifting abilities, is a key driver for an efficient allocation. Compared to the nodal first-best benchmark, we see that the uniform setting with randomly distributed batteries increases supply costs by 9.3%. An optimal allocation of batteries can reduce this efficiency gap by 0.7 percentage points to 8.6%. In relation to the cost of battery investments, this corresponds to almost a doubling of the supply cost savings per euro spent. The supply cost savings are realized in redispatch, where the location of batteries is crucial.

In the current system in Germany, such an optimal allocation is not achieved because spatially differentiated investment signals are not available under uniform pricing. However, with the help of an additional policy instrument, location-specific information could be made transparent to provide a reference point for allocating batteries in a system-beneficial way. To get insights on how to design this policy instrument, we model different allocation rules. We find that simple heuristics, such as tying battery allocation to solar generation or explicitly defining a limited number of nodes for capacity auctions, can closely approximate the optimal battery allocation.

2.2. Literature review

Only a limited amount of publications have fundamentally examined the role storage could play in unbalanced power systems. Newbery (2018) argues fundamentally that storage can increase grid utilization, thus decreasing system imbalances. Using theoretical models, Neetzow et al. (2018) analyze whether grid expansion and storage are complements or substitutes, and Weibelzahl and Märtz (2018) examine the effect of storage on the optimal definition of price zones, highlighting the additional complexity storage brings into the system. Predominantly, the current literature is based on more complex, numerical studies considering specific countries or regions. Many of the studies focus on the short-term deployment of storage in uniform price systems (e.g. Abrell et al., 2019, Bertsch et al., 2016, Schill and Zerrahn, 2018, Zerrahn and Schill, 2017). These papers analyze the possibilities of using storage to balance the temporal volatility of renewables but do not include a grid representation. To model spatial allocation and derive market design implications, a representation of grid constraints is crucial. Such an analysis is, for example, carried out by Schmidt and Zinke (2023) for the case of wind generation allocation in Germany in 2030 and similarly, vom Scheidt et al. (2022) investigate differences between a nodal and a uniform pricing system in Germany, focusing on the integration of hydrogen and system-optimal locations of electrolyzers in 2030. Lindner et al. (2023) analyze the impact of batteries used as grid boosters or virtual power lines and place them at two exemplary nodes in the north and south of Germany.

Closest to our analysis is literature on efficient incentives for flexibility assets. Ambrosius et al. (2018) investigate the effects of different market designs on investment incentives for flexible demand in the German industry in various scenarios under nodal and uniform pricing. However, the paper uses a simplified transmission grid representation with just 16 zones. Babrowski et al. (2016) apply a more detailed model but focus on the optimal amount of storage.

Some further publications focus on the longer term and analyze efficient power system configurations with (nearly) 100% renewable power generation in the European power system, e.g., Brancucci Martínez-Anido and de Vries (2013), Bussar et al. (2014), Schlachtberger et al. (2017), and Göke et al. (2021).

Research gap and contribution

Reviewing current literature reveals a lack of systematic analysis of optimal storage allocation and market design implications. Consequently, our paper seeks to bridge the gap between existing publications that address storage, grid issues, or market design as individual issues in power systems with high shares of wind and solar. We contribute a fundamental analysis of storage allocation in a simplified model and verify and expand our findings by employing a numerical electricity market and detailed grid model with endogenous storage allocation in light of the current conditions in Germany. Analyzing storage allocation in a uniform setting and a first-best nodal benchmark allows us to translate the insights from our integrated analysis into policy suggestions.

2.3. The economic rationale for storage allocation

This section introduces a model with two nodes and two time steps to analyze determinants of cost-optimal spatial allocation of storage in a spatially unbalanced transmission network. Generally, electrical storage technologies can shift electricity supply between different points in time.

Depending on their allocation in the grid, storage can use its temporal shifting potential to increase network utilization and thus reduce spatial imbalances. For illustration, consider the following:

Assume a weather-dependent, renewable generation technology in node R, for example, a wind or a solar generator g_{res}, with constant zero marginal costs $c_{res} = 0$. Renewable generation is stochastic and can take two possible states, res_{low} and res_{high}. Demand d is allocated in node D and can also take two possible states d_{low} and d_{high}. For simplicity, demand and renewable availability are assumed not to be correlated, and renewable generation meets demand when both are in the same state, i.e., $res_{low} = d_{low}$ and $res_{high} = d_{high}$. Further, we consider a peak-load technology g_{peak} at node D, with constant marginal costs $c_{peak} > 0$ and enough capacity to serve the demand in each time, i.e., $\overline{g}_{peak} >= d_{high}$.

Both nodes are connected by a transmission line l with line capacity $d_{low} < \bar{l} < d_{high}$. Hence, if both demand and generation in node R are high, node D could still not be fully supplied by the renewable generation technology due to a grid bottleneck. The model is illustrated in Figure 2.1.

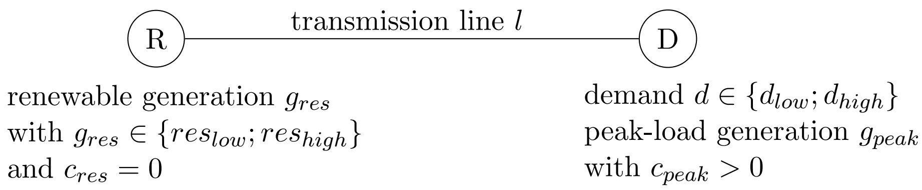


Figure 2.1.: Two-node example

We consider two time steps t_1 and t_2. Combining renewable generation and demand in all its possible states yields eight different cases, shown in table 2.1.[1]

Storage s can either be built in node R or D and comes without any investment costs. We further assume no storage losses or other variable costs in addition

[1] We do not consider combinations in which renewable generation is low in t_1 as storage is per se useless in these cases.

Table 2.1.: Possible combinations of renewable generation and demand in both time steps

	Volatility	t_1	t_2	Allocation rationale
case 1	none	res_{high}, d_{low}	res_{high}, d_{low}	no storage
case 2	none	res_{high}, d_{high}	res_{high}, d_{high}	no storage
case 3	in generation	res_{high}, d_{high}	res_{low}, d_{high}	storage in R
case 4	in both	res_{high}, d_{low}	res_{low}, d_{high}	indifferent (R or D)
case 5	in generation	res_{high}, d_{low}	res_{low}, d_{low}	no storage
case 6	in demand	res_{high}, d_{low}	res_{high}, d_{high}	storage in D
case 7	in demand	res_{high}, d_{high}	res_{high}, d_{low}	no storage
case 8	in both	res_{high}, d_{high}	res_{low}, d_{low}	no storage

to charging costs, such that $c_s < c_{peak}$ when storage is charged with renewable energy. For simplicity, we assume that storage power (charge and discharge) capacity equals supply and demand states res_{high} and d_{high}. Furthermore, storage volume capacity $\overline{s}_{power}$ is sufficient to store at least one period of full charging, i.e., $\overline{s}_{volume} \geq \overline{s}_{power}$.

By definition, storage is only useful if there are fluctuations in the system, either in renewable generation or demand. If renewable generation is high in both time steps and demand does not fluctuate either, the transmission line l is already used at capacity and peak generation is minimized. Hence, storage has no benefit to the system as a whole, which holds for cases 1 and 2.

If demand fluctuates and transmission line l is not utilized in t_1 or t_2, temporal shifting becomes useful. Consider the case that renewable supply is high in t_1 and low in t_2 and demand in node D is high in both time steps (case 3). Because there is a transmission bottleneck in t_1, storage could be used to store excess renewable generation $res_{high} - \overline{l}$. In t_2, the stored energy can be released and transmitted to node D, as transmission line l is not utilized because generation is otherwise low. Storage has to be allocated at the generation node R to do so, as l is fully utilized in t_1 when the storage is charged. A similar effect occurs, if demand is low in t_1 and high in t_2 (case 4). In this case, however, the location does not matter. Without storage, line l is not utilized at capacity in either time step. Thus, storage can charge regardless of whether it is allocated at node R or node D. In case 5, where demand is low at both times, no storage is needed because both renewable generation and grid capacity are sufficient to meet demand at both times.

If the renewable generation is high at both times, the benefit of storage depends solely on the demand profile. In case 6, where demand is low in t_1 and high in t_2, storage capacity equal to $\overline{s}_{power} = \overline{l} - d_{low}$ is built in node D to use renewable generation in t_2 instead of the more expensive conventional generation. In cases 7 and 8, where res_{high} and d_{high} coincide, again, temporal shifting has no benefit.

Main findings and generalization

The model demonstrates that storage can decrease supply costs by increasing line utilization and that storage location is crucial to unlock said system benefits. The results suggest that storage can be optimal either before or behind a grid bottleneck. In the simple setup, the optimal location depends on the volatility of the underlying demand and generation profiles. Thus, storage is allocated where volatility is higher. In practice, however, the underlying profiles are stochastic and exhibit more time steps, i.e., a sequence of the individual cases discussed above. When combining the cases into a sequence, the strict dominance of an allocation case ceases to exist, meaning that one of the cases could prevail or storage capacity could be split between the two nodes.[2]

Furthermore, the complexity of the model and the underlying relationships increases as soon as more than two nodes and technologies with different characteristics are considered. Even in the very simple model setup with only two nodes and two time steps, the storage allocation depends on the parametrization of generation and demand volatility. To decide where storage is allocated optimally, it is thus necessary to use a well-parametrized and numerical real-world model.

2.4. Methodology and input data

2.4.1. Model framework

We employ an extended version of the investment and dispatch model SPIDER initially developed in Schmidt and Zinke (2023). SPIDER is a model of the European power sector that considers a detailed depiction of the German transmission grid.[3] The model invests in new power plants and dispatches generation capacities such that the net present value of the variable and fixed costs is minimized.

Demand, which means the structure, spatial distribution, and level, is assumed to be inelastic, i.e., not adjusting to prices. The model relies on the assumption of perfect markets and no transaction costs. Thus, the competition of profit-maximizing symmetric firms corresponds to the model's cost minimization of a central planner.

[2] With a longer sequence of time steps, also the assumption regarding the volume factor of storage $\frac{\bar{s}_{volume}}{\bar{s}_{power}}$ becomes more relevant than it is in the two-time-step example. The volume factor determines the maximum duration of temporal shifting. Different volume factors mean that different parts of a stochastic demand and supply pattern can be exploited, thus also potentially affecting efficient allocation.

[3] For a thorough description of the underlying model and its characteristics, the reader is referred to Schmidt and Zinke (2023).

We set up a linear optimal power flow problem (LOPF) to approximate the inner-German transmission grid infrastructure. To keep the problem linear, DC power flow constraints approximate non-linear AC power flow restrictions. Thereby, the model neglects grid losses and reactive power (c.f. van den Bergh et al., 2014). The implementation of DC power flows is based on the cycle-based Kirchhoff formulation, which has been proven to be an efficient formulation (c.f. Hörsch et al., 2018). Network investments are assumed to be exogenous, which is valid for the 2030 time horizon due to the long approval and construction times. European regulatory authorities usually review and approve grid expansion projects 10 to 15 years in advance (c.f. Bundesnetzagentur, 2019).

In addition to the initial model of Schmidt and Zinke (2023), in this paper, SPIDER is extended to allow for endogenous investments in storage as well as solar power capacities. The model optimizes the allocation of storage, but the ratio of maximal charging power (hereafter referred to as capacity) and stored energy (hereafter referred to as storage volume) is set exogenously. The key formulation of the cost minimization problem and the storage constraints are given in A.2.

Modeling a detailed representation of grid constraints and endogenous investments in generation and storage is a computational challenge. As in Schmidt and Zinke (2023), the model is subject to several limitations: As mentioned above, investments in transmission grid lines are exogenous assumptions. Ramping and minimum load constraints are approximated to avoid a mixed-integer optimization and the model does not include combined heat and power plants. Further, the model abstracts from uncertainty and assumes perfect foresight.

2.4.2. Assumptions and data

The regional focus of the model is Germany, with a spatial resolution at transmission grid node level, i.e., 220 kV to 380 kV voltage levels. The depiction of the transmission grid is based on grid information from multiple sources, including Matke et al. (2016) and 50Hertz et al. (2019). Grid extensions follow the German 2030 grid development plan, which was reviewed and approved by the German grid regulator (c.f. Bundesnetzagentur, 2019).

While the German transmission grid is modeled for 2019 with 380 nodes and 606 lines, Germany's neighboring countries are depicted as singular nodes without intra-country grid restrictions. The model includes interconnectors to as well as between neighboring countries, which are approximated via net transfer capacities (NTC) based on ENTSO-E (2020a).

The regional scope and the depiction of the German transmission grid are visualized in Figure 2.2.

Our analysis covers the years 2019, 2025, and 2030. Each year is represented by 12 representative days at hourly resolution. We derive the representative days by using k-medoids clustering with respect to residual load (c.f. Kotzur et al., 2018).

For our case study, we parameterize the storage technology as large-scale electric batteries. Therefore, these batteries participate in the wholesale market and may be subject to redispatch measures (in the uniform setting).[4] A.3 discloses further assumptions on technology parameters, demand development per country as well as fuel prices.

Existing power plant capacities and their distribution across Germany are derived from data provided by the German regulator Bundesnetzagentur.[5] Power plants are distributed via their postcodes to the nearest transmission grid node. The future distribution of offshore wind farms is based on 50Hertz et al. (2019).

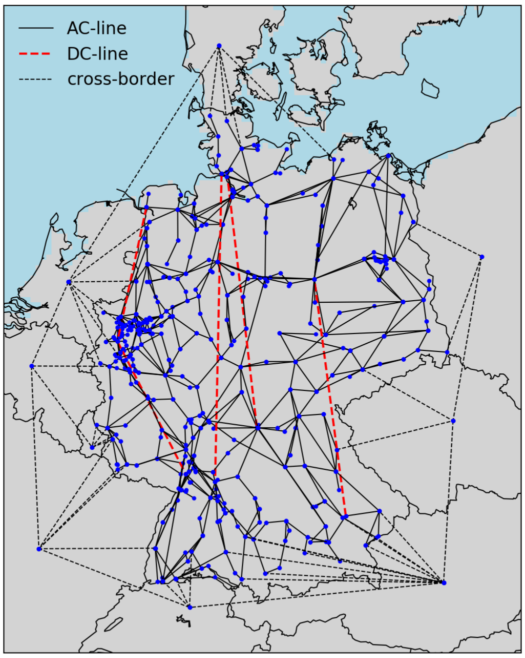


Figure 2.2.: German transmission grid and NTC connections to neighboring countries

Capacity development at the national level is exogenous and follows the *National Trends* scenario in ENTSO-E (2020a) for all countries except Germany. For Germany, the assumed capacity development reflects the legal and political situation. Wind and solar expansion follow the current legal targets (EEG, 2023, WindSeeG, 2023). The legislation does not include a specific capacity target for batteries in 2030. Instead, aggregated battery capacity is an assumption

[4]In practice, this does not apply to small storage systems such as photovoltaic systems or storage for electric vehicles designed to increase self-sufficiency.

[5]Conventional power plants are based on the power plant list (Bundesnetzagentur, 2020a) and renewables on data from the *Marktstammdatenregister* (Bundesnetzagentur, 2020b).

based on *Scenario B* from the 2037/2045 grid development plan (50Hertz et al. (2022)).[6] Table 2.2 shows the assumed expansion of wind, solar, and battery capacities in Germany.

Table 2.2.: Assumed development of installed wind, solar and battery capacities in Germany

[GW]	2019	2025	2030
Wind Onshore	53.4	65.4	115.0
Wind Offshore	7.5	14.3	30.0
Solar	49.2	105.2	215.0
Batteries	0.0	5	15.0

The phase-out of German nuclear, lignite, and coal power plants is implemented according to the path defined in the Act to Reduce and End Coal-Fired Power Generation (KVBG, 2020). In addition, the announced phase-out of lignite-fired power generation by 2030 is considered for the state of North Rhine-Westphalia (BMWK et al., 2022). We assume that the electricity market triggers sufficient investments into backup power plants to meet demand at all times. The location of the required gas capacities is efficiently determined in the nodal setting and fixed for all model runs.

The regional allocation of onshore wind, solar, and battery storage capacity is determined endogenously. Therefore, their regional allocation follows the economic rationale of the considered model setup (see 2.4.3) while considering distributions of determining factors such as demand and resource quality. Since the total installed capacities are the same in all settings examined, the efficiency of regional allocation alone determines the differences in electricity supply costs.

Demand time-series for neighboring countries are based on hourly national demand in 2014, according to ENTSO-E (2020b). The German demand is distributed to the nodes similar to the approach in 50Hertz et al. (2019): Based on sectoral demand shares on the federal state level (c.f. Länderarbeitskreis Energiebilanzen, 2020), household demand is distributed onto nodes proportionally to population shares. The distribution of industry and commercial demand reflects the regional distribution of gross value added for the respective sectors (c.f. Eurostat, 2020)). The demand time series are synthesized in a bottom-up approach using sector and application-specific standard load profiles, which reflect 2014 as a calendar and weather year.

The intermittency of renewable feed-in is modeled via weather-dependent hourly regional feed-in potential. The time series for onshore wind in Germany and solar generation are based on high-resolution reanalysis meteorological data from the COSMO-REA6 model. For onshore wind, the conversion of wind speeds to regional feed-in data is based on Henckes et al. (2017). For solar genera-

[6] In a sensitivity analysis, our results prove robust for deviating total battery capacities of 5, 10, and 20 GW, respectively A.4.

tion, solar radiation was converted to regional feed-in potential as described by Pfenninger and Staffell (2016a). Data for Germany's neighboring countries and German offshore wind power is provided by Pfenninger and Staffell (2016a) and Pfenninger and Staffell (2016b).

2.4.3. Nodal and uniform setting, allocation rules, and benchmarking

The model framework is applied to simulate investment and dispatch decisions under two different settings: nodal and uniform. Each transmission grid node constitutes a market in the nodal setting, and grid constraints are considered within the price formation. When grid constraints are binding, prices differ between nodes. In the case of new investments, these spatially differentiated price signals and hence, transmission bottlenecks are considered in siting decisions. Without any friction, the nodal setting represents the first-best configuration for efficient coordination of power generation investments, dispatch, and the grid.

Germany employs a uniform pricing approach. Uniform pricing relies on larger market areas or zones, usually defined by a country's national borders. Under uniform pricing, physical constraints concerning power flows within a market area are not considered in the market clearing. As a result, the scheduled dispatch after market clearing may violate physical grid restrictions and require curative redispatch measures carried out by grid operators. As grid restrictions are not reflected in the market, prices within a market area are the same. We model a uniform setting where transmission bottlenecks are neglected; As a result, coordination between generation investment, dispatch, and the grid is missing. This setup represents the uniform pricing market design currently in place in Germany in a simplified way.[7]

Consequently, the two setups differ regarding the amount of information available or, more specifically, in terms of the consideration of transmission constraints. In the uniform setting, a subsequent dispatch run considering the DC power flow reveals whether the scheduled dispatch with given investment decisions violates grid constraints, i.e., whether a redispatch is required. The difference in supply costs between the initial dispatch and the subsequent redispatch run is considered the resulting redispatch cost.[8] We quantify efficiency losses of the uniform setting by comparing total supply costs with the nodal first-best

[7] We neglect additional factors that might impact siting decisions, such as additional policies or locational factors that relate to the preference of individual investors. Consequently, in the uniform setup, siting decisions for wind and solar are guided by resource quality so that new facilities are primarily built in areas where meteorological conditions allow a maximum yield. Other generators, including batteries, are indifferent to siting in the uniform setup.

[8] We model a perfectly efficient redispatch that includes all generation units in all modeled countries. Thus, the resulting total supply costs, i.e., dispatch plus redispatch costs, would be equal if capacity allocations in the nodal and uniform setting were the same. However, the allocation of new capacity is sub-optimal in the uniform case, resulting in higher total supply costs than in the nodal setup.

benchmark. Capital costs can be neglected since the total installed capacity is the same in each setting.

Assuming that the uniform pricing system is politically desired and will be maintained in Germany, location-specific information could be made transparent with the help of an additional policy instrument that provides a reference point for a system-beneficial allocation of storage capacities. To get insights on how to design this policy instrument, we use the numerical model to analyze different allocation rules for storage investment in an otherwise uniform setting. Thereby, we focus on allocation rules that coordinate the storage allocation isolated from other technologies. Specifically, we test for *heuristic* approaches and *explicit* allocation rules.

Heuristic approaches, on the one hand, allocate storage capacity based on a reference distribution. We select the heuristics based on an analysis of drivers for optimal storage allocation. A similar instrument to such a heuristic is used in the capacity auction for wind power generation. To achieve a broader capacity distribution over Germany, the merit order of capacity bids is altered to compensate for yield losses at sites with lower resource quality. The correction follows a non-linear heuristic based on the deviation from a reference wind generator. Another example of a heuristic allocation approach can be found in Sweden, where generation network tariffs depend on latitude. The differentiation of network tariffs incentivizes generation investment at lower resource quality sites close to demand.

On the other hand, we test *explicit* approaches which allow storage investment at a limited number of candidate nodes identified as suitable in the optimal case. The capacity is then optimized across the candidate nodes. Hence, this approach requires detailed information about load flows. A similar policy is already implemented within the capacity auctions for wind generation, where a certain percentage of capacity is reserved for bids from the so-called south zone, a predefined area below the structural grid bottleneck. A different kind of location-specific capacity mechanism is used to procure the so-called grid reserve. The German grid regulator monitors the capacity demand for redispatchable power plants in the south of Germany. If available capacity is lower than capacity demand, grid operators can procure specific mothballed power plants or power plants scheduled for phaseout for grid reserve.

To rank the different instruments and their efficiency gains, we derive the optimal allocation of batteries for the uniform setup and use it for comparison. To obtain the optimal allocation, we perform a first model run calculating the distribution of wind and solar capacity without considering transmission constraints. Subsequently, in a second model run, we optimize the battery allocation considering transmission constraints and the given distribution of wind and solar. While the optimal allocation represents the upper bound for the efficiency achieved with a storage allocation mechanism, determining a lower bound is somewhat more complicated. In the uniform setting, there is no clear decision rule for storage because resource quality does not vary. Different factors such as demand typology, innovation drive or existing infrastructure could potentially influence storage allocation in the real world without spatially differentiated investment incentives. It is, however, unclear whether and how such factors influence the allocation and we, therefore, cannot include them in our model. Instead of a lower bound, we compute a demand-weighted random distribution of storage across Germany as a benchmark for the lack of coordination incentives. The random distribution is sampled 100 times and averaged to reflect an expected value.

2.5. Numerical model results

2.5.1. Battery allocation

In both settings, placing 15 GW battery capacity reduces supply cost, i.e., dispatch (and redispatch) costs.[9] In the nodal setting, supply costs decrease by 1.1% compared to a case without batteries in the system. In the uniform setting, batteries can reduce supply costs by 1.5%. The drivers for the efficiency gains differ between the two settings. Under the nodal setup, wind, solar, and batteries are allocated in an integrated optimization and under the consideration of grid constraints. This allows wind and solar generation to be shifted to locations with higher full-load hours that were subject to grid constraints without batteries.[10] Thus, renewable power generation increases and higher-cost fossil generation is avoided compared to a case without batteries. In the uniform setting, supply cost reductions are split between cost savings in the initial market clearing and in redispatch. In the market clearing, batteries shift excess renewable energy to peak residual load periods, avoiding high-cost peak generation. The supply cost reductions are realized independent of the location and are equal in both battery allocation cases under the uniform setup. In redispatch, batteries create additional efficiency by avoiding high-cost generation behind grid bottlenecks. To achieve efficiency gains in redispatch, the allocation of batteries is relevant. This is illustrated by comparing a case of optimal battery allocation to a case of random battery allocation. On average, when allocated randomly, batteries can only decrease supply costs by 0.8% in comparison to a case without batteries. An optimal allocation sets the upper bound for supply cost reduction at 1.5%. Figure 2.3 compares the efficiency gains of placing 15 GW of battery capacity in the grid for the three cases.

[9]Note that the amount of battery capacity is imposed exogenously in our setting. Thus, we do not investigate whether the savings in supply cost cover the capital cost of the batteries and hence do not infer conclusions about the economic efficiency of the chosen amount of batteries installed. We discuss some rough estimates at the end of section 2.5.3.

[10]For a more detailed understanding of the different allocations of wind and solar under nodal and uniform setting without batteries, see Appendix A.4.

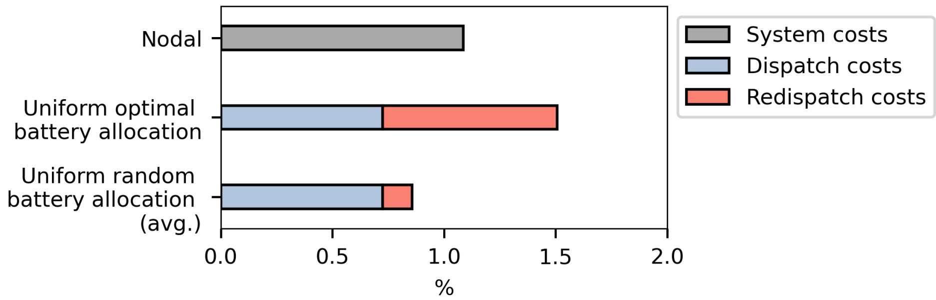


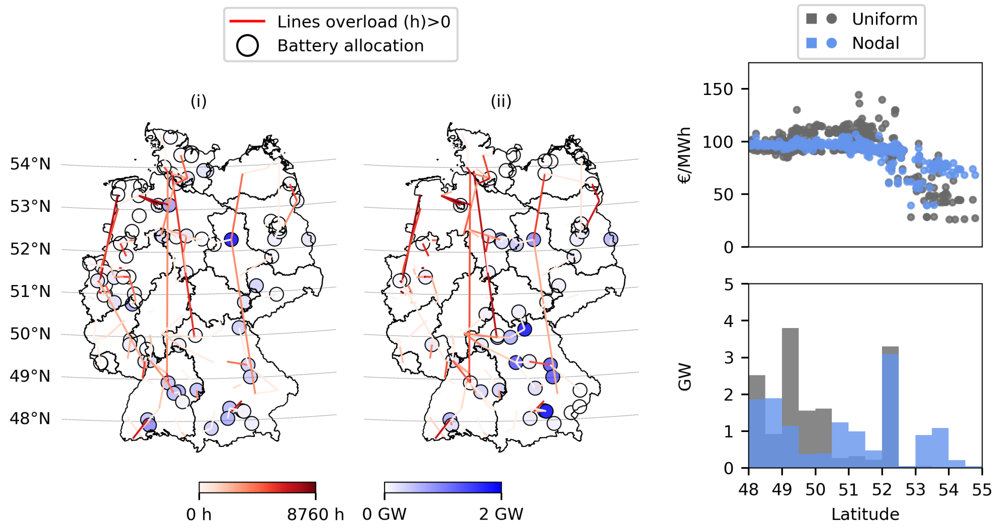
Figure 2.3.: Relative reduction of supply costs due to batteries in the nodal and uniform setting compared to the case without batteries

When comparing the two settings, we find that the total supply costs are 8.6% higher in the uniform than in the nodal setting, even for optimal battery allocation. This cost difference is attributed solely to the sub-optimal distribution of renewable generation capacity.

In both settings, nodal and uniform, the optimal battery allocation follows the allocation of wind and especially solar generation capacity. Thus, in the nodal case, batteries are allocated broadly across Germany, while in the uniform case, batteries concentrate in the south of Germany and especially below the 51st latitude. Moreover, under both settings, batteries are allocated close to congested transmission lines, i.e., lines that are frequently utilized at full capacity (depicted in red).

Grid congestion is illustrated in the upper graph of Figure 2.4b, which shows marginal supply costs at each node over latitudes. In the nodal setting, marginal supply costs equal the nodal prices. In the uniform case, they reflect the supply costs in redispatch. Prices differ between nodes if transmission constraints are binding, i.e., if a bottleneck exists. This is especially the case between the 52nd and 53rd parallel, where price differences of up to 44 EUR/MWh in the nodal case and 70 EUR/MWh in the uniform case occur. The price difference in the uniform setting is higher because the grid bottleneck is more prevalent here. This can be attributed to the sub-optimal renewable allocation in this case. In both settings, placing most of the battery capacity below the grid bottleneck is optimal. It follows the distribution of solar generation capacity. Thus, it is distributed more uniformly across the west and east in the nodal setting, while it is concentrated in the southeast (the federal state of Bavaria) in the uniform setting. Close to solar generation, batteries can flatten the daily solar generation profile, mitigate local grid congestion, and thus reduce local residual demand peaks. Doing so, batteries help to avoid the high-cost (re-)dispatch of conventional power plants in this area.

Furthermore, in both settings, a significant battery capacity of about 3 GW is allocated right above the structural north-south transmission bottleneck. Under the nodal setup, this capacity is shifted closer to western demand centers, where



(a) Spatial distribution of battery capacity expansion and line utilization in the (i) nodal and (ii) uniform setting

(b) Nodal marginal supply costs and battery allocation by latitude

Figure 2.4.: Spatial distribution of 15 GW battery capacity and marginal supply costs in 2030

substantial wind and solar generation capacity is allocated. Through temporal shifting, these batteries increase the utilization of connections to the north and the usage of local wind and solar generation. In the uniform setting, the battery capacity allocated at the structural grid bottleneck is concentrated in the middle and the east of Germany, making use of solar capacity allocated there while at the same time increasing utilization of the easternmost HVDC connection.

The north of Germany, i.e., above the 53rd parallel, attracts a battery capacity of 1.4 GW under the nodal setup. The allocation of this capacity is the result of the simultaneous optimization of battery and renewable capacity allocation. Batteries allocated in the far north increase the north-south transmission utilization at locations where HVDC lines are connected. Thus, they enable wind generation to increase its full load hours by moving further northwards. This rationale does not hold under the uniform setup, where the optimization of renewables and batteries is decoupled. Additionally, the structural north-south bottleneck is too prevalent to achieve a similar transmission. As a result, there are no batteries allocated in the far north.

The numerical model results confirm for the case study of the 2030 scenario of Germany what the two-node model revealed: Storage can reduce supply costs in transmission constraint power systems with high volatility, but allocation matters to unlock the efficiency gains. For the case of batteries, we show that efficiency gains can be made, especially in conjunction with solar generation, as batteries flatten the daily generation pattern. By locating them near solar generation and grid congestion, the batteries avoid high residual demand peaks, i.e., costly generation during dispatch and redispatch.

2.5.2. Policy instruments for battery allocation

The uniform pricing setting sets no spatial coordination incentives for batteries; thus, achieving optimal allocation is unlikely. Therefore, we investigate the supply costs of potential allocations that could be realized by regulatory mechanisms that impose additional price signals under uniform pricing. We test for two types of capacity distribution mechanisms: *heuristic* allocation rules that allocate battery capacities over all nodes according to a predefined distribution and *explicit* mechanisms that allow battery allocation only at specific candidate nodes.

2.5.2.1. Heuristic allocation rules

As shown in the two-node model and the numerical example, optimal storage allocation is driven by the volatility induced by renewable feed-in, demand, and transmission grid constraints. Therefore, the first two heuristics distribute battery capacity proportionally to solar generation capacity and demand, respectively. Even though wind generation allocation is not a driver for optimal battery allocation in the uniform setting, we test whether batteries could exploit the volatility of wind generation and decrease supply costs when distributed according to wind generation capacity in a third heuristic. Heuristic four reflects the allocation of both wind and solar, thus taking a combined approach to renewable volatility. Capturing the dynamic influence of transmission grid constraints in a heuristic approach is more difficult. We investigate whether heuristic five can address grid congestion, which distributes storage capacity proportionally to phased-out power plants. Phased-out plants were historically allocated close to demand and may thus address the north-south bottleneck.

To discuss the suitability of these heuristics, we assess them against the optimal battery allocation given the distribution of wind and solar in the uniform setting discussed in the previous section. The relative increase in total supply costs resulting from the heuristics compared to the hypothetical, optimal allocation of batteries lies between close to 0 and 1.1% (see table 2.3).

Table 2.3.: Summary of relative cost increases and battery capacity factors for *heuristic* battery allocations

	opt. benchmark	random benchmark	solar	wind & solar	demand	phased-out power plants	wind
Supply cost delta [%]	-	0.66	0.27	0.38	0.61	0.90	1.07
Redispatch cost delta [%]	-	3.84	1.58	2.19	3.58	5.25	6.24
Battery capacity factor	0.15	0.15	0.16	0.15	0.16	0.13	0.08

As market efficiency gains are independent of the allocation, the differences in supply costs between the benchmark and the heuristic allocations correspond to the difference in redispatch costs, which are determined by the total redispatch volume and the power plants used in redispatch. The total redispatch volumes are similar in the benchmark case and for all heuristics. Redispatch is mainly caused by high wind power curtailment in the north of Germany. Situations of high wind feed-in and north-south transmission bottlenecks continue for long periods, and therefore the ability of batteries to reduce curtailment volumes is limited.

Hence, redispatch costs differ mainly due to the different types of power plants used for redispatch. Redispatch costs are lowest if batteries frequently shift low-cost electricity in time to avoid costly fossil-fired generation. In our scenario results, this is especially the case in the south and east of Germany, where high solar generation leads to high volatility in local marginal generation costs. Batteries can utilize this volatility by charging when solar power generation is high. They then use this energy to displace lignite power plants and gas turbines, which replace south German nuclear capacities, in redispatch. Conclusively, a heuristic, which distributes capacity according to solar generation capacity, is the most efficient, followed by a heuristic, which considers both wind and solar.

A demand-based heuristic is the third most efficient. Here, more battery capacity is located in the west of Germany, while solar power generation is concentrated in the east and south. Since marginal generation costs are higher in the west, battery charging is more expensive and replacement of fossil power plants in redispatch is less frequent. A similar effect occurs if the batteries are allocated accordingly to phased-out power plants since they are located near demand centers, too.

In contrast, if batteries are deployed close to wind generation, their contribution in redispatch is more limited. Even though batteries prevent more wind curtailment than in the other heuristics, they can only participate in redispatch above the structural grid bottleneck. There, marginal generation costs in redispatch are low, and so is volatility, making this allocation the least efficient. In fact, redispatch costs are even higher than in a case without batteries. This is because batteries increase the share of wind generation in the initial market outcome, which then has to be curtailed in redispatch due to grid constraints. However, market gains outweigh redispatch losses, resulting in lower total supply costs than without batteries. Moreover, the allocations according to wind or phased-out power plants are even less efficient than a random allocation of batteries. The random allocation leads to a broad distribution of batteries across Germany, meaning that at least some batteries are close to solar generation and demand.

The heuristics' supply cost differences are also reflected in battery utilization. In the wind-based heuristic, the battery capacity factor is less than half of the capacity factor of the solar-based heuristic, where a capacity factor of 0.16 is achieved. This corresponds to 345 battery cycles per year or an average of almost one charge cycle per day, i.e., a steady reduction of residual loads. The reason is the assumed capacity-to-volume ratio of 4h, which makes batteries better suited to buffer daily solar generation than wind generation profiles with their coarser volatility.

2.5.2.2. Explicit allocation rules

Secondly, we investigate *explicit* approaches that allow for an optimal battery allocation at predefined candidate nodes. We test the following variations: Starting from the 40 nodes with the highest capacity in the hypothetical benchmark case, we iteratively reduce the number of candidate nodes to 1. The resulting supply costs of these explicit allocation rules are between 0.00 and 0.85% higher than the optimal benchmark. The higher the number of candidate nodes, the lower the supply costs. At 40 or more candidate nodes, supply costs are almost the same as in the optimal benchmark case. Even reducing the allocation to just two nodes leads to a cost increase of 0.37%, which is between the supply costs of the solar heuristic (0.27%) and the heuristic allocation according to solar and wind capacity (0.38%). If the number of candidate nodes is reduced to one, the supply cost delta more than doubles compared to the case with two nodes. With one endogenously chosen candidate node, all capacity is placed at a node in southern Germany. In this case, the battery cannot have its full effect because the installed battery capacity is higher than the sum of renewable and transmission capacity at that node. Consequently, the resulting capacity factor is much lower, and the total supply cost is higher than in the case of random distribution. Nevertheless, it is noteworthy that the single-node allocation is still more efficient than an allocation by wind capacity or phased-out power plants.

The *explicit* approaches that distribute battery capacity to five or more nodes outperform all *heuristic* approaches.[11]

Table 2.4 compares resulting capacity factors and supply costs relative to the hypothetical benchmark for each of the *explicit* options.

Table 2.4.: Summary of relative cost increases and battery capacity factors for *explicit* battery allocations

	opt. benchmark	random benchmark	40	20	10	5	3	2	1
Supply cost delta [%]	-	0.66	0.00	0.02	0.10	0.16	0.29	0.37	0.85
Redispatch cost delta [%]	-	3.84	0.00	0.12	0.57	0.94	1.70	2.14	4.97
Battery capacity factor	0.15	0.15	0.15	0.15	0.15	0.15	0.14	0.13	0.10

[11] When comparing the results, however, it has to be noted that the installed capacity per node is optimized endogenously in the *explicit* cases. In contrast, capacity distribution is determined exogenously in the *heuristic* cases.

2.5.3. Summary

We quantify the efficiency gains of placing 15 GW of batteries in the German transmission grid by comparing supply costs for two settings, nodal and uniform, to equivalent cases without batteries. The results show that batteries reduce supply costs in both cases. In the uniform setting, the efficiency gains are composed of supply costs reduction in the electricity market, which are independent of battery allocation, and in redispatch, which depend on battery location. To compare different allocation rules under the uniform setup, a hypothetical, optimal allocation for a given distribution of renewable capacity is used as an upper benchmark. Furthermore, a random distribution of batteries is used as a benchmark for missing local investment incentives. The analysis shows for our scenario that *explicit* approaches with endogenous battery investment allowed at a limited number of pre-determined nodes can approximate the optimal distribution well, and already from five nodes, it outperforms all *heuristic* approaches with a fixed distribution. Among the fixed *heuristic* approaches, an allocation that mimics the distribution of solar generation capacity performs best. Solar generation is a crucial driver for optimal allocation since batteries can exploit the daily solar generation pattern to reduce gas-fired redispatch. Other *heuristic* approaches prove to be less suitable. An allocation proportional to phased-out power plants or wind generation capacity is less efficient than a random distribution. The wind-based heuristic leads to even higher redispatch costs than the case without any batteries.

The performance of the different allocation rules is compared to the theoretical first-best nodal benchmark. Figure 2.5 shows the relative increase in supply costs compared to this benchmark for the allocation variations ordered by efficiency. It highlights the efficiency gains that can be made by introducing and coordinating batteries. The most efficient allocation rule is the *explicit* allocation to 40 nodes, leading to 8.6% higher supply costs than the nodal benchmark. Least efficient is the *heuristic* allocation by wind capacity (+9.7%). Hence, the range of total supply costs between the best and the worst performing allocation amounts to 1.1% of the nodal supply costs.

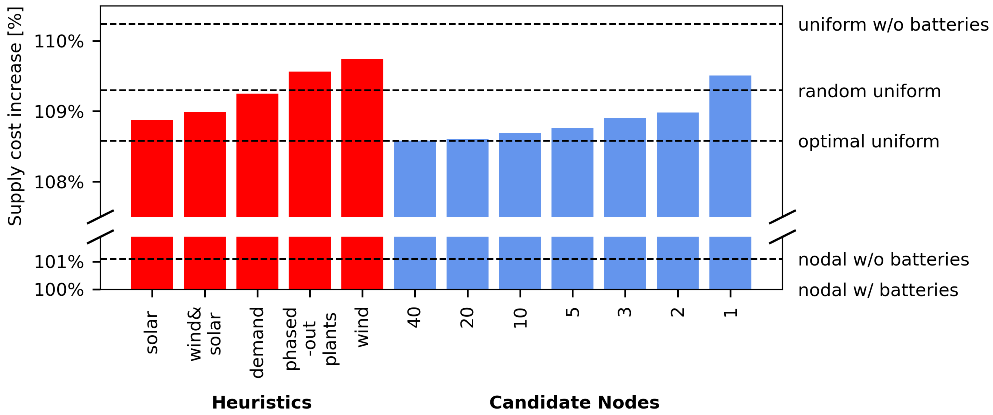


Figure 2.5.: Supply cost differences between allocation rules and the first-best nodal benchmark in 2030

The relevance of appropriate coordination can be further illustrated by relating the supply cost savings achieved by batteries to the capital cost incurred. The supply cost saving of each battery allocation is the difference in total supply costs compared to the uniform setting without any batteries. To calculate the capital costs of batteries, we assume investment costs of 600 EUR/kW, a lifetime of 16 years, and an interest rate of 8% (c.f. EWI, 2021). The ratio of savings to annualized capital cost depends strongly on battery allocation. Batteries can yield 1.08 EUR in savings per euro spent if allocated optimally in the uniform setting. A random allocation reduces the savings by 47 ct per euro spent. With an explicit allocation at five or more candidate nodes, the battery-induced savings come close to the savings under an optimal allocation (0.96 - 1.08 EUR saved per euro spent, depending on the number of nodes). In the best heuristic allocation (solar), the ratio of savings to expenditures is 19 ct lower than with an optimal allocation. In the worst case (wind) examined, the savings drop to just 33 ct per euro spent. Under the assumed capital costs, 15 GW of battery capacity is in the money if allocated optimally. With the help of the allocation rules, savings are higher than the annualized capital costs for explicit approaches at 10 or more nodes. With all other rules, savings are below expenditures. However, batteries can generate additional value not considered in the present analysis through system services, e.g., balancing power provision or avoiding grid expansion in the long run and thus savings can be higher. Further, these results highly depend on the (assumed) capital costs.

2.6. Discussion

2.6.1. Generalization

Although the numerical model results are specific to the chosen setting, they can be generalized for several aspects. First, the finding of the two-node model that optimal storage allocation is driven mainly by volatility is valid and applicable for all time horizons and countries. In our case study, solar power is the dominating renewable capacity driving volatility and, thus, battery allocation. Divergent renewable energy shares may lead to different optimal battery allocations, e.g., previous analyses assuming higher shares of wind power conclude that higher shares of battery capacity should be allocated near wind energy.

Secondly, the numerical analysis at hand focuses on batteries, i.e., a storage technology with a relatively small storage volume compared to installed charging capacity, which complements the daily fluctuations of solar power generation. Therefore, we perform a sensitivity analysis regarding the storage type and show that the optimal allocation depends on the specific technology. In particular, storage with a larger power-volume ratio is favorable at locations with high shares of wind power (see A.4).

Thirdly, we show that storage can generate value in a uniform setting in both the initial market clearing and in redispatch. The latter can only be exploited if the market design allows for the participation of storage in redispatch. If this is not the case, a substantial part of the potential benefits of storage technologies - in our numerical analysis, about 50% - cannot materialize.

Fourthly, the findings for the transmission level can be used to get insights for the distribution grid. Distribution grid operators could use the batteries' flexibility to lower curtailment volumes and required grid expansion if the batteries' allocation matches flexibility demands and technical and regulatory properties allow. However, on the distribution grid level, storage is usually used to increase the self-consumption of solar generation, e.g., home-storage systems. Therefore, these systems are neither dispatched by market signals nor used in redispatch.

2.6.2. Limitations

Several limitations should be noted when considering the results and analysis presented. First, the numeric modeling results are based on several strong assumptions, e.g., perfect foresight, no transaction costs, perfect markets, and the exogenous distribution of inelastic exogenous demand. The mathematical duality between a central planer and a profit-maximization of symmetric firms holds only if these assumptions are all met. In practice, this is rather not to be expected. In particular, the first-best nodal benchmark is a rather theoretical benchmark as in reality frictional losses can distort optimality, e.g., reduced liquidity, lack of transparency, market power issues, and increased transaction costs (c.f. Antonopoulos et al., 2020).

Furthermore, modeling the market setup of uniform pricing, as it is currently in place in Germany, comes along with some simplifying assumptions. We abstract from additional policy instruments for the expansion of wind and solar power. In particular, the reference yield model should affect wind power expansion compared to our modeled distribution. The cost-based redispatch mechanisms applied in practice are less efficient than those modeled in our numerical analyses. In our model, power plants outside Germany and all technologies including storage can be used for redispatch without any restrictions, which is not necessarily the case in practice. In particular, redispatch of hydro-pumped storage in the Alps can be fully exploited in the model which might cannibalize the value of batteries in Southern Germany. Additionally, further efficiency gains of storage deployment are possible, which were not part of the numerical analyses, e.g., avoided grid expansion or increased security of supply.

In addition to these model properties, the results have to be interpreted in light of the specific scenario chosen for the analysis. To demonstrate the robustness of our results, we perform a sensitivity analysis regarding the total installed battery capacity in A.4. Additionally, the scenario-specific renewable energy allocation largely determines the magnitude of the identified efficiency gap between the first best nodal and the uniform setting. Besides resource quality, further aspects, such as land availability and residents' opposition, play into renewable investors' decision process. Hence, the resulting renewable energy distribution for 2030 is likely to be less concentrated in reality, which also impacts the optimal storage allocation and system efficiency.

2.7. Conclusion and policy implications

This paper investigates the allocation of battery storage in spatially unbalanced power systems in the transition to climate neutrality, i.e., with rapidly increasing shares of wind and solar power generation. Specifically, we seek to answer three questions: Firstly, where in the transmission grid should batteries be allocated, secondly, how important is storage allocation for the system's efficiency, and thirdly how could policy instruments be designed to approximate an optimal allocation?

To investigate the drivers of optimal storage allocation, we develop a theoretical two-node, two-time-step model that simplifies the dynamics of spatially unbalanced power systems. We show that an allocation close to volatile renewables or close to demand can be optimal. We find that optimal allocation depends on the volatility and location of demand and generation relative to grid bottlenecks.

These results are verified and expanded in a numerical case study using the example of a spatially unbalanced power system in Germany. The largest efficiency difference occurs between the nodal and uniform setting. Supply costs are at least 8.6% higher in the uniform case than under the nodal setup. This is primarily because in the nodal setting wind and solar generators are allocated optimally and shows that the leverage of a simultaneous allocation and coordination of wind and solar expansion exceeds the leverage of allocating batteries. However, the results in the nodal setting rely on several assumptions that tend not to hold in practice, and switching from uniform to nodal pricing may not be politically feasible.

In practice, there is no allocation coordination under uniform pricing; thus, the optimal battery allocation that minimizes the efficiency gap to the nodal benchmark is not achieved. Our analysis reveals that with a random battery allocation, the efficiency gap relative to the first-best nodal case lies 0.7 percentage points higher than with an optimal allocation. The least efficient allocation that was tested even increases the efficiency gap by 1.1 percentage points. [12] It is, therefore, worth discussing how coordination can be achieved and local incentives can be set even in a system with uniform pricing. In Germany, this question is currently being asked as part of the government initiative *Climate Neutral Electricity System Platform* - a dialogue platform that aims to prepare for an upcoming electricity market reform.

Our model results show that several allocation rules are conceivable to approximate an optimal allocation of batteries in the uniform setting. For example, a heuristic approach that allocates batteries close to solar capacity or explicit approaches that rely on grid analyses to determine a limited number of locations for a capacity auction can reduce supply costs in the uniform setting. In addition, implementing such an allocation rule would ensure that inefficient distributions, like an allocation close to installed wind power capacity, are not realized.

Policymakers designing regulatory instruments based on these findings should weigh the reduction in supply costs resulting from improved allocation against the implementation costs. In the case of the heuristic approaches, the difficulty lies in identifying a mechanism that yields the desired distribution of batteries. Costs could also be incurred if the chosen mechanism leads to a high number of transactions, e.g., if batteries were subsidized via feed-in tariffs. For the explicit approaches that allow the installation of batteries at limited locations in the grid, the allocation could be managed via a limited number of auctions. Here, transaction costs arise from the information asymmetries of the regulator in determining optimal locations and capacities. Further, our results benefit from the assumption of perfect foresight. In practice, it may be more complicated to determine optimal candidate notes ex-ante, in particular, if only a few nodes are chosen and in a dynamic setting the optimality of nodes may change over

[12] However, the benefits of optimal battery allocation in the uniform setup are split roughly half-half between market-based dispatch and subsequent redispatch, underlining the importance of including flexibility assets in redispatch.

time. Choosing a heuristic approach directly connected to the distribution of solar power may be more robust to the deviations from a modeled scenario.

Policies that coordinate wind, solar, and storage capacity in an integrated way could come even closer to the first-best benchmark. The analysis of such an integrated approach could be part of further research. It would likely lead to additional efficiency gains but would be a more complex endeavor with higher implementation costs.

We conclude that it is possible to design a policy instrument suitable to approximate an optimal storage allocation under uniform pricing. Any potential policy should either be simple and low-cost to implement or be part of a comprehensive mechanism that coordinates all types of generation and flexibility with the grid.

3. Unlocking Thermal Flexibility for the Electricity System by Combining Heat Pumps and Thermal Storage

3.1. Introduction

Electrification of the residential heating sector is key to achieve the policy goal of decarbonization, particularly with the increased use of electricity from renewable energy sources (RES). For example, space heating accounted for 63.5% of final energy consumption in the residential sector in the EU in 2022, with 68.6% supplied by fossil fuels (c.f. Eurostat, 2024). Electrical heat pumps are widely recognized as a suitable technology to replace fossil fuels and integrate renewable energies, as they provide heat from a medium such as air or water with low electricity consumption (c.f. Bloess et al., 2018, Maruf et al., 2022).

The expansion of heat pumps in the coming years is a key strategy in the pursuit of Germany's ambitious climate goals, reflected in the government's target to install six million heat pumps by 2030 compared to 1.7 million heat pumps in 2023 (BDEW, 2024). In combination with the government's target to increase electricity generation from RES to generate 80% of gross electricity consumption in 2030 (EEG, 2023), these measures aim to support the transformation of the heating sector. This presents both opportunities and challenges for the electricity market and the electricity grid. On the one hand, heat pumps increase electricity demand, and therefore affect market dynamics and grid load. On the other hand, heat pumps can be combined with thermal storage, which could also bring benefits if the flexibility potential of thermal storage is used for the electricity system, e.g., in order to balance volatile RES generation.

By now, thermal storage is widely recognized for optimizing heat pump efficiency and reducing costs at the household level (see e.g. Frings and Helgeson, 2022), but it is discussed less from the perspective of the electricity system. By decoupling the electricity demand of heat pumps from the heat demand, thermal storage can increase the flexibility of the electricity system, but requires coordination between electricity markets and the grid. As the imbalance between Germany's RES generation concentrated in the north and demand centers predominantly located in the west and south already leads to congestion in the transmission grid, the perspective of the grid should be taken into account when evaluating the flexibility potential of thermal storage.

Against this backdrop, this paper analyzes the impact of the combined expansion of heat pumps and thermal storage on the electricity system, focusing on market and grid dynamics. The paper assesses the system value of the flexibility provided by thermal storage, taking into account the restrictions of the transmission grid.

To do so, the paper presents Germany as a case study and applies a timely and spatially highly resolved model of the Central European electricity markets and transmission grid for the year 2030. The high spatial resolution captures regional variations in electricity demand profiles of heat pumps, which is a relevant aspect due to their dependence on weather conditions.

The analysis evaluates six scenarios, combining two model setups and three heat pump distributions. The first model setup reflects the current German market design with a uniform wholesale price and subsequent redispatch to relieve grid congestion. The second setup represents a theoretical first-best benchmark using locational marginal prices (LMPs). The three heat pump distributions are based on the current geographic locations of heat pumps, the allocation of wind capacity, and the allocation of PV capacity. Each scenario is compared for three storage sizes (2h, 4h, and 8h shifting potential) with a base case of inflexible heat pumps.

Across all scenarios and shifting potentials, flexibility provision through thermal storage reduces total supply costs compared to an inflexible use of heat pumps. The model setup with LMPs confirms its role as the first-best benchmark. Total supply costs are consistently lower than in the uniform model setup and fall continuously with increasing shifting potential for all three distributions. The latter contrasts with the uniform setup, where an increased shifting potential does not generally lead to lower total supply costs. This divergence arises because flexibility provision through thermal storage in the uniform setup affects the market result (dispatch effects) and the grid dynamics (redispatch effects) in opposing directions. While the market results benefit from the flexibility for all heat pump distributions, redispatch measures increase.[13] Specifically, when heat pumps are allocated based on their current locations or PV capacity, the 4h shifting potential results in lower total supply costs than the 8h shifting potential, as redispatch supply costs increase over-proportionally for these distributions.

The comparison of the heat pump distributions further reveals that flexibility provision through thermal storage provides the highest system value when thermal storage is located near wind capacities in northern Germany. The regionalized analysis within the LMP model setup confirms this observation, showing that the system value of flexibility is particularly high in northern Germany.

In summary, within the uniform model setup, thermal storage reduces total supply costs due to the predominantly beneficial market effects, yet at the

[13] By assumption, small scale storage units like thermal storage do not actively participate in redispatch.

same time leading to increasing redispatch costs. Policymakers should therefore promote the installation of thermal storage and its market participation, while simultaneously introducing locational signals to maximize system-wide benefits, taking into account market conditions and grid constraints.

Related literature and research gap

The paper at hand extends the literature by examining the impact of thermal storage on the electricity system in a numerical analysis for Germany, including grid dynamics and spatial differences in heat pump demand profiles.

The paper adds to the literature evaluating the impact of heat pumps and thermal storage on electricity markets. Bloess et al. (2018) and Maruf et al. (2022) present extensive literature reviews on various power-to-heat and thermal storage technologies. Bloess et al. (2018) highlight the role of power-to-heat technologies in integrating RES by reducing curtailment and substituting fossil fuels, with benefits enhanced by thermal storage. Maruf et al. (2022) focus on the European context, emphasizing the technological maturity of thermal storage and highlight its importance in the residential sector in lowering RES curtailment and total system costs.

More recently and similar to the analysis in this paper, Roth et al. (2024) show in a numerical model analysis for Germany in 2030, that coupling heat pumps with thermal storage effectively aligns the electricity demand of heat pumps with the residual demand, and thus reduces overall system costs. Schöniger et al. (2024) find similar results for Austria in 2030, demonstrating that flexible heat pumps cut costs and curtailment of RES in all scenarios examined. However, this literature solely focuses on the impact of heat pumps and thermal storage on the electricity market, without accounting for grid dynamics.

Another strand of literature takes the grid into account when analyzing the flexibility potential of thermal storage in electricity system models. However, these studies focus on sector coupling at a higher level of aggregation in technology modeling, evaluating the combined flexibility of decentralized resources such as heat pumps with thermal storage, electric vehicle charging, and demand-side management. Heitkoetter et al. (2022), for example, assess a large set of demand response options and their endogenous deployment using an energy system model with 100 nodes in Germany. Their findings reveal an equal distribution of demand response options across Germany, with a high expansion in western Germany, where large aggregated demand response potential exists. Büttner et al. (2024) analyze the impact of flexibility options on the German transmission grid in 2035, including the gas, heat and mobility sector. They consider large-scale thermal storage in combination with district heating grids, but do not equip decentralized heat pumps with a thermal storage. Their results show that these technologies, taken together, can reduce total system costs and CO2 emissions. Bauknecht et al. (2024) assess the role of decentralized flexibility options in reducing congestion in the transmission network and the impact on the need for network expansion. The authors show that with increasing shares of RES, decentralized flexibilities are particularly valuable to relieve transmission bottlenecks if they are located close to net feed-in nodes. Further studies analyze the impact of flexibility provision by other technologies than thermal storage, for example, vom Scheidt et al. (2022) for the integration of hydrogen and electrolyzers and Lindner et al. (2023) for batteries as grid boosters. Within a similar model setup, Czock et al. (2023) assess the optimal allocation of battery storage investments in Germany and show that simple allocation rules such as aligning the locations of batteries and PV capacities can approximate an optimal allocation if locational price signals are missing.

This paper combines the two strands of literature: a thorough analysis of decentralized heat pumps combined with thermal storage in a spatially and temporally high-resolution electricity model that incorporates grid constraints. This approach captures regional weather dependencies of heat pumps and assesses the flexibility of thermal storage on electricity markets and the transmission grid.

Adding the spatial component to the analysis improves research on heat pumps and thermal storage in two ways: First, accounting for regional temperature differences is crucial to adequately model electricity demand (c.f. Büttner et al., 2022, Eggimann et al., 2019) and to prevent system over- or undersizing when integrating heat pumps (c.f. Halloran et al., 2024). Second, by representing the grid dynamics, redispatch measures can be included in the analysis, providing a more complete picture of the current electricity system in Germany. For the European electricity system, Frysztacki et al. (2021) show that ignoring congestion can raise system costs by up to 23%. Furthermore, the representation of the grid allows to study alternative pricing mechanisms, such as LMPs. The results provide valuable insights for policymakers to promote the combination of heat pumps with thermal storage and to make the electricity market more accessible for decentralized flexibility options.

The paper is organized as follows. Section 3.2 introduces the model framework and describes the main assumptions, the input data, the scenarios, and the numerical model setup. Section 3.3 presents the results of the analysis for the uniform and the LMP model setup. Section 3.4 discusses the results in relation to model assumptions, data and policy implications. Section 3.5 concludes.

3.2. Methodology

This paper uses the SPIDER (Spatial Investment of Distributed Energy Resources) electricity system model developed by Schmidt and Zinke (2023), Czock et al. (2023) and Zinke (2023) to analyze the impact of heat pumps in combination with the flexibility provided by thermal storage. SPIDER is a model of the European power sector and considers a detailed depiction of the Central

European transmission grid. Dispatch modeling is based on the mechanisms of flow based market coupling (FBMC) and enables dispatch analyses with a high regional and timely resolution (Zinke, 2023). In this paper, commissioning and decommissioning of transmission and generation, as well as total demand and the expansion of heat pump and thermal storage, are exogenous. The methodology is described below, along with the input data, and the numerical model setup. The notation is provided in Table B.1 in the Appendix.

3.2.1. Model framework

SPIDER optimizes the dispatch decisions of the European power plant fleet and the usage of storage by minimizing the variable costs of electricity generation. It minimizes the net present value of the variable costs under several constraints concerning the market equilibrium, technical requirements and the grid. Variable costs are the product of electricity generation, $GEN_{t,m,i}$, in each timestep t, market zone m, and technology i and the technology-specific variable operating costs, $\gamma_{t,i}$:

$$\min! \quad VC = \sum_{t \in T, m \in M, i \in I} \gamma_{t,i} \cdot GEN_{t,m,i} \tag{3.1}$$

The setup of the model in terms of the markets is flexible, i.e. the scope and geographical granularity, down to the representation of individual transmission nodes, can be adjusted according to the research question. The model therefore allows both nodal and zonal modeling, with the latter also enabling a subsequent redispatch analysis (see Zinke (2023) for more details on the methodology).

To ensure computational feasibility, simplifying assumptions are applied, including exogenous investments in transmission, generation, and demand capacities, the exclusion of combined heat and power plants, and approximations for ramping and minimum load constraints.

In this paper, the model is applied to analyze the dispatch of electricity generation and demand, as well as storage technologies. In particular, the impact of the regional expansion of heat pumps and their flexible use through thermal storage is evaluated, taking grid restrictions into account. For this purpose, the model of Zinke (2023) is extended by a detailed representation of the electricity demand of heat pumps and the flexibility of thermal storage.

Heat pumps

The modeling of demand in SPIDER is extended in this paper to include the electricity demand profiles of heat pumps. To account for the relationship between temperatures and the conversion efficiency (COP) of a heat pump, separate weather-dependent heat pump demand profiles, $demand_{t,m}^{heatpump}$, i.e., hourly time series of electricity demand used to operate heat pumps, are constructed for each market zone. The performance of heat pumps, measured by the COP, varies over time and depends on the temperature difference between the source and sink (cop_t). A larger delta between the source temperature and the desired flow temperature results in lower COPs, i.e., colder days result in lower efficiencies, especially for air source heat pumps.

A common approach to incorporate temperature-dependent COP values is to calculate the COP exogenously, assuming a sink temperature and given values for the source temperature, following Verhelst et al. (2012). This approach is used throughout the paper. The heat pump demand profiles are calculated based on information provided by the German DSOs (see Section 3.2.2 for a detailed description) and result in an hourly electricity demand profile for each market zone.

Thermal storage

Thermal storage shifts energy temporally, similar to battery storage, but operates within the constraints of the heat pump's electricity demand profile. Thus, unlike a battery, which charges and discharges freely, thermal storage shifts electricity demand over time without physically supplying electricity. Instead, it reduces the baseline electricity demand that would have occurred during a given hour without the shifting of the thermal storage.

It is important to note, that heat pumps convert electrical energy into thermal energy, which is stored as heat in the thermal storage. For modeling purposes, thermal storage is expressed in electrical terms, requiring consideration of the conversion between thermal energy and electricity. This results in the following storage equations.

The storage volume, $STOR\_VOL_m$, is defined by the hourly shifting capability, vol_factor, and the installed capacity, cap_m (eq. 3.2). The charging level of storage, $STOR\_LEVEL_{t,m}$, cannot exceed the storage volume, $STOR\_VOL_m$ (eq. 3.3).

$$STOR\_VOL_m = vol\_factor \cdot cap_m \tag{3.2}$$

$$STOR\_LEVEL_{t,m} \leq STOR\_VOL_m \tag{3.3}$$

In eq. 3.4, the storage level is determined by the storage level in the previous time step and the net balance of the current shift with the thermal storage, i.e., the difference of charged (consumed), $CON_{t,m}$, and discharged (supplied), $GEN_{t,m}$, electricity. Static efficiency, ϵ^{static}, determines the losses per hour and dynamic efficiency accounts for the losses during storage charging, $\epsilon^{dynamic}$. The storage level is parameterized in electrical terms, but corresponds to a storage of thermal energy. Thus, one has to account for the time-varying COP of the heat pump by including the ratio of the COP of the previous and current time step, $\frac{cop_{t\text{-}1,m}}{cop_{t,m}}$.[14]

$$
\begin{aligned}
STOR\_LEVEL_{t,m} = \frac{cop_{t\text{-}1,m}}{cop_{t,m}} \cdot (1 - \epsilon^{static}) \cdot STOR\_LEVEL_{t\text{-}1,m} \\
-GEN_{t,m} + (1 - \epsilon^{dynamic}) \cdot CON_{t,m}
\end{aligned}
\tag{3.4}
$$

$$
GEN_{t,m} \leq demand_{t,m}^{heatpump} \tag{3.5}
$$

The electricity supply of thermal storage, $GEN_{t,m}$, is constrained by the demand of heat pumps, $demand_{t,m}^{heatpump}$, in the respective hour (eq. 3.5). This limitation reflects that the thermal storage buffers the electricity demand of the heat pump and shifts it between different times.

3.2.2. Input Data

The configuration of the model corresponds to that in Zinke (2023). At regional level, the model represents Central Europe with a high spatial resolution at transmission grid node level, i.e., 220kV to 380kV voltage levels, covering the 13 European countries participating in the "Core Flow-Based Market Coupling project". The model is based on the published grid information provided by Joint Allocation Office (2022). In order to reduce complexity, the initial grid of 1063 nodes is reduced to 533 nodes and 859 lines in 2021 using a grid reduction algorithm proposed by Biener and Garcia Rosas (2020). Italy, Switzerland, Denmark, Norway, and Sweden, that are outside the FBMC area, are depicted as singular nodes without intra-country grid restrictions and interconnectors to these markets are approximated via net transfer capacities (NTC). Grid extensions are included in accordance to the German grid development plan (c.f. 50Hertz et al., 2023), and ENTSO-E's Ten-Year Network Development Plan (c.f. ENTSO-E and ENTSO-G, 2022). The regional scope and the reduced transmission grid are visualized in Figure 3.1.

The development of installed capacities and expansion of renewable energies are exogenous to the model. For all countries except Germany, the installed capacities are based on the scenario *Global Ambition* in ENTSO-E and ENTSO-G (2022). For Germany, the development of installed capacities follows the current legal and political targets and is shown in B.2. The time series for hourly onshore wind and solar generation are computed based on high-resolution reanalysis of meteorological data from the COSMO-REA6 model based on Henckes et al. (2017) and Pfenninger and Staffell (2016a), respectively. The generation poten-

[14] The formulation is derived from substituting $STOR\_LEVEL_{t,m}^{thermal} = cop_{t,m} \cdot STOR\_LEVEL_{t,m}^{electric}$ for both time steps t and $t-1$ and by taking into account the $cop_{t,m}$ for $GEN_{t,m}$ and $CON_{t,m}$ in the thermal formulation of a typical storage level constraint (see e.g. Ruhnau et al., 2020).

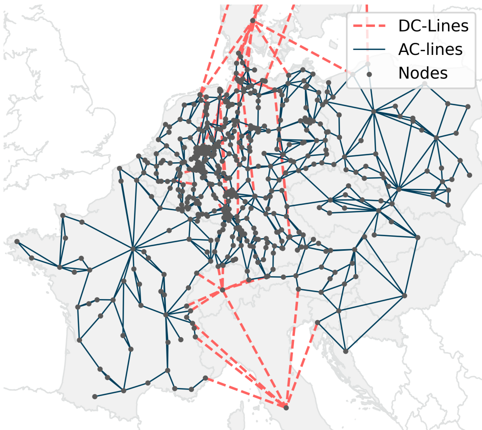


Figure 3.1.: Transmission grid

tial of offshore wind regions (hourly) and hydropower (weekly) is provided by Copernicus Climate Change Service (2020).

The analysis covers the year 2030 with an hourly resolution. Time series of country-specific hourly electricity demand are taken from ENTSO-E and ENTSO-G (2022). German demand is taken from Fraunhofer ISI et al. (2022) (see Table 3.1) and is then distributed by sectoral demand shares on the federal state level (c.f. Länderarbeitskreis Energiebilanzen, 2020). For residential demand, the distribution is assumed to follow population shares, while industrial and commercial electricity demand is distributed in proportion to the regional gross value added (c.f. Eurostat, 2020). This approach is similar to the one used by the transmission grid operators in Germany (50Hertz et al., 2022). For the other countries, the assumed demand distribution follows the population per local administrative unit (Eurostat, 2023).

Heat pumps

For Germany, in addition to the data on total electricity demand, the electricity demand of heat pumps is required. The annual electricity demand of heat pumps as well as the number of installed heat pumps and the installed capacity of heat pumps are from Fraunhofer ISI et al. (2022) (see Table 3.1). The installed capacity of thermal storage listed in table 3.1 is parametrized corresponding to the annual peak demand of heat pumps, following Ruhnau et al. (2019) and Marijanovic et al. (2022). The annual peak demand of heat pumps can be derived from the electricity demand profiles of heat pumps. The procedure for deriving these profiles is described in detail below.

In order to incorporate the temporal dimension of heat pump demand, hourly electricity demand profiles for heat pumps are derived for each transmission node. As the demand profiles of heat pumps are dependent on the weather, re-

Table 3.1.: Demand development and heat pump expansion in Germany

		2021	2030
Total electricity demand	[TWh]	532	624
Electricity demand of heat pumps	[TWh]	8.5	34.7
Number of heat pumps	[Mio]	1.4	5.9
Installed capacity of heat pumps	[GW]	6.5	26.7
Installed capacity of thermal storage	[GW]	3	12.3

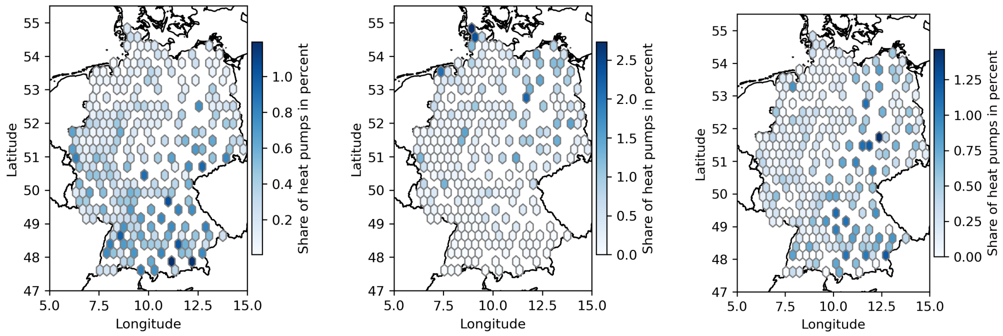
gional temperature differences are taken into account when creating the profiles. Meteorological data on temperature is used for this purpose, provided by Copernicus Climate Change Service (2020). The temperature time series are combined with temperature dependent load profiles for heat pumps published by the DSO SWM Infrastruktur (2024).[15] The DSO's load profiles and thus the resulting heat pump demand profiles ($demand^{heatpump}_{m,t}$) capture the current operation of a heat pump and thus implicitly reflect the technical optimization of the heat pump. This includes, for example, taking into account passive storage from the thermal inertia of the building and the consumption relevant properties of the heat pump. The latter includes in particular that the COP of the heat pump is already taken into account in the load profiles. The resulting demand profiles per node of the transmission grid depend on the temperature and therefore differ regarding their level.

Three alternative distributions are considered for the regional allocation of the installed capacity of heat pumps in Germany. The first distribution, referred to as the *hp-distribution*, is based on the current geographic locations of heat pumps. This distribution is derived from Heitkoetter et al. (2021), who provide regional data for the installed capacity of heat pumps in 2030, using historical data on building types and heating technologies at the district level. The second distribution, the *wind-distribution*, aligns heat pump capacity with the locations of onshore wind capacity. The third distribution, the *pv-distribution*, allocates heat pump capacity based on the locations of PV capacity.

Figure 3.2 illustrates the three distributions of installed heat pump capacity at transmission nodes and shows the percentage of heat pump capacity at each transmission node relative to the total heat pump capacity in Germany in 2030.

With the *hp-distribution*, heat pump capacity increases from north to south, with most capacity concentrated in southern regions below the 50th parallel, while eastern and western regions show a relatively even allocation. In contrast, the *wind-distribution* concentrates heat pump capacity in northern Germany, predominantly above the 53rd parallel, with fewer installations in southern regions. The *pv-distribution* results in a broad allocation across Germany, resem-

[15] The methodology for creating the profiles was initially developed by the formerly German Association of DSOs VDN and the University of Cottbus. For more information see Verband der Netzbetreiber (VDN) (2002).



(a) (b) (c)

Figure 3.2.: Heat pump capacity at transmission nodes as a percentage of total heat pump capacity in Germany in 2030 distributed by (a) currently installed heat pump capacity, (b) installed onshore wind capacity and (c) installed PV capacity

bling the *hp-distribution* in its southern concentration below the 50th parallel. However, due to the greater expansion of PV in eastern Germany, heat pump capacity is more pronounced in that region. The differing heat pump distributions impact electricity demand within the grid. Variations in demand at individual nodes arise from both the reallocation of heat pumps and their associated electricity demand and from location-specific differences in demand profiles due to varying weather conditions (see Figure B.1 in the Appendix).

Thermal storage

This paper incorporates thermal storage capacities to analyze the system-friendly shifting of heat pump demand. It is assumed that each installed heat pump is equipped with a thermal storage and that this is used exclusively for system-friendly use. By assumption, the technical optimization of heat pump operation, i.e., optimizing the operation according to the COP, is done by separate 'technical storage capacity' excluded from the analysis. This is because already today heat pumps are commonly installed together with some thermal storage capacities in order to optimize the technical operation of the heat pump. As the heat pumps' electricity demand profiles are based on DSO data, this technical optimization is likely to be included in the current data. The thermal storage capacities considered in this paper are assumed to be installed in addition, such that system-friendly heat pump operation can be performed in addition to the technical optimization.

The thermal storage is parameterized in terms of an hourly load shifting potential. The shifting potential, i.e., the storage size, is varied throughout the analysis. It is assumed that thermal storage is able to store twice the installed capacity (2h shifting potential). This corresponds to the already allowed interruption interval for DSOs during network peak times (§14a EnWG, 2024). Further, a shifting of four hours (4h shifting potential) and eight hours (8h shifting potential) is considered. At the household level, this corresponds to storage units of 400 l, 800 l, and 1500 l, typical for single- and multi-family homes (Agora Energiewende, 2023).

The efficiency of the thermal storage is set as follows: as an average estimate, the dynamic losses, $\epsilon^{dynamic}$, are set to 5% and static losses, ϵ^{static}, are set equal to 1% (Frings and Helgeson, 2022, Ruhnau et al., 2020). COP values for heat pumps and data on the mix of currently installed systems, used to calculate an average value for Germany, are retrieved from Ruhnau et al. (2019).

The formulation of the thermal storage can be interpreted as a classical hot water-based heat storage, which is the most used thermal storage i.a. due to its low cost, compactness, scalability, and usability (Maruf et al., 2022).[16]

The investment costs for thermal storage are used to evaluate the profitability of thermal storage from the perspective of the heat pump owner. Based on data from Frings and Helgeson (2022) and own research of industry data, the annualized costs are on average 88 EUR/a for a 400 l storage, 105 EUR/a for an 800 l storage, and 134 EUR/a for a 1500 l storage. The discount rate is set to 5% and a technical lifetime of 30 years is assumed (c.f. Frings and Helgeson, 2022).

3.2.3. Scenarios and numerical model setup

The analysis examines the combination of heat pumps with thermal storage in Germany in six scenarios: The three heat pump distributions described above are analyzed within two different model setups described in the following.

The first model setup represents the current market design in Germany with a uniform wholesale electricity price, i.e. one market zone. This means that physical restrictions on electricity flows within the market area are not taken into account in the market clearing. This is addressed in the model setup by defining the market zone m as one zone for the whole of Germany. The dispatch run calculates the market clearing and is complemented by a subsequent redispatch run. Grid restrictions are taken into account as part of the redispatch and it is checked whether physical grid restrictions are violated after market clearing. If this is the case, the dispatch results require curative redispatch measures, which in practice are carried out by the grid operators. Within the redispatch run, the zonal net trade positions are fixed and generation adjustments are only possible within one market zone. It is assumed that wind and solar generation

[16] Passive storage, i.e., the buildings' thermal mass, is not considered in the optimization model. It is indirectly captured by the DSO's demand profiles. For further analysis, it could be integrated into the model by allowing a certain temperature band for the heat demand to fluctuate, see for example Marijanovic et al. (2022), Papaefthymiou et al. (2012).

can be curtailed, but not ramped up, within the redispatch run. Furthermore, small-scale storage units, like thermal storage, are not yet part of the redispatch.

Within this model setup, the effects of providing flexibility through thermal storage can be split into their effects on the market result (dispatch) and on the grid (redispatch). However, as thermal storage does not participate in redispatch, only indirect effects of its use on the grid can be analyzed. The analysis of regional effects in this model setup is therefore limited, as the use of thermal storage in dispatch does not differ regionally due to the lack of grid information.

The second model setup considers the first-best benchmark with LMPs in order to show direct, regional effects through an integrated view of the market and the grid. Each transmission grid node represents a market and grid constraints are considered within the price formation. When grid constraints are binding, LMPs differ between nodes. Without any frictions, such a price formation represents the first-best benchmark for efficient coordination of electricity generation, demand and the grid and sets an upper limit for the benefit of providing flexibility through thermal storage.

Hence, the two model setups differ in terms of the amount of information available or, more specifically, in terms of the consideration of transmission constraints, RES curtailment and the participation of thermal storage.

3.3. Numerical model results

This section presents the numerical model results for six scenarios that are a combination of the two model setups for the German electricity system, the uniform and the LMP model setup, and the three heat pump distributions, based on the current geographic locations of heat pumps, the allocation of wind capacity, and the allocation of PV capacity (c.f. Sections 3.2.2 and 3.2.3). For each scenario, three storage sizes (2h, 4h, and 8h shifting potential) are compared with the base case of inflexible heat pumps that operate strictly according to their demand profiles. Total supply costs of each scenario are compared in Table 3.2.

The results show that, across all scenarios and shifting potentials, flexibility provision from thermal storage always reduces total supply costs compared to an inflexible use of heat pumps. The model setup with LMPs consistently achieves lower total supply costs than the uniform model setup, confirming its role as the first-best benchmark. Furthermore, the results show that within the LMP setup, total supply costs fall continuously with increasing shifting potential for all three distributions. This contrasts with the uniform setup, where an increased shifting potential does not generally lead to lower total supply costs. When allocating heat pumps according to the *hp-distribution* and the *pv-distribution*, the 4h shifting potential achieves lower total supply costs than the 8h shifting potential. For these distributions, the redispatch supply costs increase over-proportionally.

Table 3.2.: Percentage change in total supply costs for different heat pump distributions and shifting potentials for the uniform and the LMP setup

Model setup	Heat pump distribution	Inflexible heat pumps [%]	2h [%]	4h [%]	8h [%]
uniform	*hp-distribution*		-1.22	-1.51	-1.09
uniform	*wind-distribution*	-1.97	-3.55	-3.86	-4.20
uniform	*pv-distribution*	-0.37	-1.62	-1.73	-1.68
LMP	*hp-distribution*	-10.75	-12.20	-12.82	-13.28
LMP	*wind-distribution*	-11.42	-12.92	-13.63	-14.21
LMP	*pv-distribution*	-10.91	-12.43	-13.05	-13.54

Note: The base (100 %) for the percentage change is given by the uniform model setup and the *hp-distribution* with inflexible heat pumps.

The following Sections analyze the results in more detail. Section 3.3.1 further elaborates the results under the uniform setup, differentiating between the impact of flexibility provision on the market result (dispatch effects) and the grid result (redispatch effects). Section 3.3.2 examines the regional value of thermal storage by making use of the LMP setup. Section 3.3.3 assesses the profitability of installing thermal storage for system use from the perspective of the individual household.

3.3.1. Impact of flexibility from thermal storage in the uniform setup

Within the uniform setup, total supply costs consist of the market result (dispatch effects) and the grid result (redispatch effects). Although the flexibility provision by thermal storage consistently reduces total supply costs across all heat pump distributions and shifting potentials, the isolated effects on the market and the grid are opposing, presented in Table 3.3 for each heat pump distribution.

Across all distributions, the shifting through thermal storage positively affects dispatch results and therefore lowers dispatch supply costs compared to the inflexible use of heat pumps. The higher the shifting potential of the thermal storage, the lower dispatch supply costs are. For example, given the *hp-distribution*, dispatch supply costs decrease by -2.34%, -3.34%, and -3.74% with a 2h, 4h, and 8h shifting potential, respectively.

However, as the uniform model setup neglects grid constraints within the dispatch, the market result with flexibility provision can either reinforce or mitigate

Table 3.3.: Percentage change in supply costs with flexibility provided by thermal storage compared to supply costs with inflexible heat pumps for each heat pump distribution

Heat pump distribution	Type of supply costs	2h [%]	4h [%]	8h [%]
hp-distribution	Dispatch supply costs	-2.34	-3.34	-3.74
hp-distribution	Redispatch supply costs	2.97	5.35	8.80
hp-distribution	Total supply costs	-1.22	-1.51	-1.09
wind-distribution	Dispatch supply costs	-2.66	-3.42	-4.33
wind-distribution	Redispatch supply costs	2.73	4.29	6.28
wind-distribution	Total supply costs	-1.62	-1.93	-2.27
pv-distribution	Dispatch supply costs	-2.31	-2.97	-3.65
pv-distribution	Redispatch supply costs	2.75	4.74	7.55
pv-distribution	Total supply costs	-1.26	-1.36	-1.32

Note: The base (100 %) for the percentage change is given for each row by the respective base case with inflexible heat pumps.

grid constraints.[17] Table 3.3 shows that redispatch supply costs increase with an increasing flexibility potential for all distributions, i.e. the market results increase the need for grid management. With the *hp-distribution*, the redispatch supply costs increase by 2.97%, 5.35%, and 8.80% with a 2h, 4h, and 8h shifting potential, respectively.

The resulting effect on total supply costs depends on how these two effects balance each other. With the *hp-distribution* and the *pv-distribution*, total supply costs benefit most from a 4h shifting potential. With a 2h shifting potential, the flexibility potential is lower, resulting in a smaller reduction in dispatch supply costs. With an 8h shifting potential, the negative effect on the grid increases over-proportionally such that the total supply costs are above the case with 4h shifting potential. With the *wind-distribution*, the larger thermal storage with 8h shifting potential achieves the lowest total supply costs, as the locations of heat pumps and thermal storage better align with wind locations and generation patterns. Thus, with an increasing shifting potential, the location of the storage becomes increasingly important, as the spatial alignment between RES generation and flexibility provision within the grid becomes a more critical factor relative to the market result.

The spatial alignment between RES generation and thermal storage locations also explains why the allocation of heat pumps following the *wind-distribution* results in the lowest total supply costs among the three distributions. Compared to the *hp-distribution*, the allocation of heat pumps based on the *wind-distribution*

[17] Since thermal storage is not part of the redispatch, the electricity shifting of thermal storage only indirectly affects redispatch results if the dispatch result is physically better or worse for the grid than it would be without the shifting of the thermal storage.

reduces total supply costs by -1.97% in the base case with inflexible heat pumps, and by -3.55%, -3.86%, and -4.20% with 2h, 4h, and 8h shifting potential, respectively (see Table 3.2). A large part of the reduction is already observable in the base case with inflexible heat pumps and is thus the result from the reallocation of heat pump demand from southern to northern Germany. Installing heat pumps close to wind capacity increases demand in northern Germany, which helps mitigating grid bottlenecks between north and south and facilitates onshore wind integration without violating grid restrictions. The cost reductions are therefore largely driven by lower redispatch costs, which, in comparison to the *hp-distribution*, decrease by -10.0% in the base case, and by -10.2%, -10.9%, and -12.1% with 2h, 4h, and 8h shifting potential, respectively.

All in all, the installation of a thermal storage is recommendable from the system perspective independent of the underlying distribution of heat pumps. A recommendation regarding storage size depends on the location of the thermal storage.

The following Sections 3.3.1.1 and 3.3.1.2 explain the driving factors behind the positive impact of thermal storage on the market and the adverse impact on the grid.

3.3.1.1. Dispatch effects

The flexibility provision through thermal storage positively impacts the market result by enabling the temporal shifting of electricity demand. The dispatch effects are shown below exemplarily for the *hp-distribution*.[18] The annual electricity shifted amounts to 6.7 TWh, 10.1 TWh, and 12.3 TWh with a 2h, 4h, and 8h shifting potential, which corresponds to approximately 19.3%, 29.2%, and 35.5% of electricity demand from heat pumps or about 1.1%, 1.6%, and 1.9% of total electricity demand.

The electricity shifting of thermal storage therefore alters the structure of the electricity demand of heat pumps. The corresponding duration curves of electricity demand from heat pumps are depicted in Figure 3.3. While the electricity demand of heat pumps without thermal storage is positive in all 8760 hours, the shifting of thermal storage reduces it to zero in 2778, 3751, and 4224 hours, depending on storage size. Charging increases electricity demand from heat pumps,

[18] In the dispatch, grid restrictions are not considered. Consequently, changes in the distribution of heat pumps and thermal storage do not affect the market result apart from variations in weather profiles across different nodes, which alter electricity demand. These effects are small on an aggregated level and therefore the direction and magnitude of the effects are comparable for *wind-distribution* and *pv-distribution*.

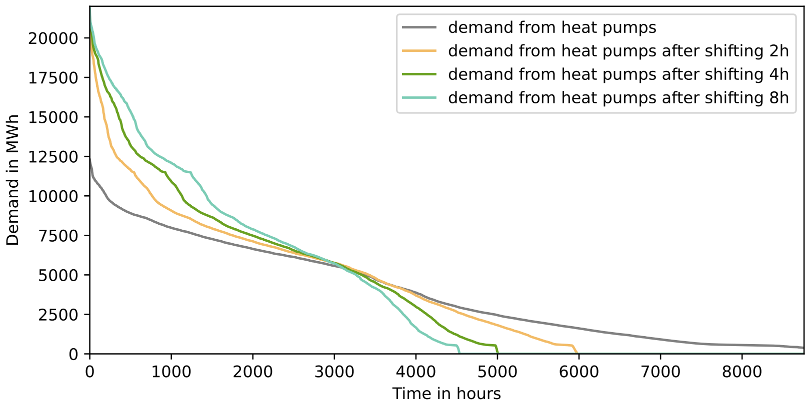


Figure 3.3.: Duration curve of electricity demand from heat pumps in 2030 in MWh

raising peak load from 12.3 GW with inflexible heat pumps to 21.1 GW, 21.5 GW, and 21.9 GW, for 2h, 4h, and 8h shifting potential.[19].

Consequently, the electricity shifting enabled by thermal storage impacts the price formation, reducing price volatility as flexibility increases. Specifically, it shifts electricity demand away from high-price periods and decreases the number of zero-price hours. The average annual electricity price decreases by 0.6%, 1.0%, and 1.2% for 2h, 4h, and 8h shifting potentials, respectively, compared to the average price of 70.5 EUR/MWh for the base case with inflexible heat pumps.

A detailed analysis of the hourly profiles shows the factors that influence the dispatch behavior of thermal storage. Typically, storage charges when electricity prices are low, which often coincides with high RES generation, and discharges when prices are high, reflecting lower RES generation and higher fossil fuel contributions to setting marginal prices.

The results show that thermal storage charging correlates more strongly with PV generation than wind, as PV has a greater impact on electricity prices. The charging of the thermal storage shows a positive correlation with PV generation, reflected in Pearson correlation coefficients of 0.42, 0.51, and 0.54 for 2h, 4h, and 8h shifting potentials, respectively. In contrast, the correlation with wind generation is significantly weaker (0.01, 0.02, and 0.05). This is due to the different feed-in profiles of PV and wind: While wind generation is positively correlated with heat pump demand (0.27 for wind vs. -0.37 for PV), PV generation shows a stronger negative correlation with electricity prices (-0.65 for PV vs. 0.22 for wind). The resulting price reductions from high PV generation incentivize

[19]Note that, the cumulative peak demand from heat pumps that results after the shifting of the thermal storage does not exceed the installed capacity of heat pumps in the model. If this condition does not hold, an extension of the heat pump capacity (and possibly also the grid connection) would be necessary. This would consequently increase the household's annualized investment cost for providing flexibility.

storage charging, whereas wind's weaker price correlation makes its influence on storage charging more ambiguous.

As a result, the flexibility provision by thermal storage leads to an increase in generation from PV, onshore and offshore wind power, and hence a decrease in market based curtailment, while at the same time electricity generation from coal and gas turbines is declining, as listed in the Appendix in Table B.4.

3.3.1.2. Redispatch effects

The impact of flexibility provision through thermal storage on the transmission grid can be evaluated by analyzing the results of the redispatch. Since thermal storage does not actively participate in redispatch, its electricity shifting indirectly affects redispatch results by making the dispatch either more or less compatible with grid constraints compared to the inflexible use of heat pumps.

The results show that, regardless of the distribution of heat pumps and thermal storage, the redispatch volume consistently increases with an increasing shifting potential relative to the inflexible use of heat pumps, as listed in Table 3.4.

Table 3.4.: Redispatch volumes with inflexible heat pumps and percentage changes with thermal storage and different shifting potentials

Heat pump distribution	Inflexible heat pumps [TWh]	2h [%]	4h [%]	8h [%]
hp-distribution	55.0	2.9	4.7	6.0
wind-distribution	52.3	1.9	2.9	3.3
pv-distribution	54.8	2.0	3.6	4.5

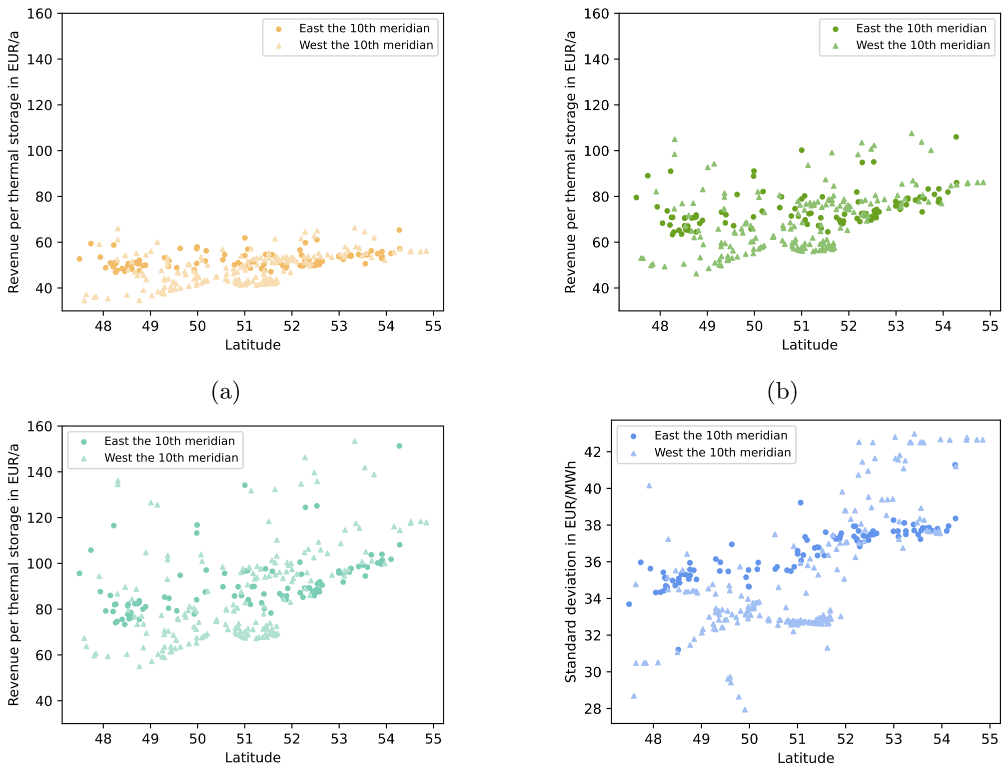
Hence, for all distributions, the market results with flexibility provision through thermal storage require more redispatch measures compared to an inflexible use of heat pumps. The underlying reason is the spatial mismatch between generation technologies and heat pumps combined with thermal storage. This includes increasing curtailment of RES in the redispatch compared to the base case with inflexible heat pumps. RES generation that can be additionally integrated in the market through thermal storage is partially curtailed in redispatch and replaced by fossil fuel-based generation, thus, partly offsetting the environmental and economic benefits of flexibility provision.

Among the analyzed distributions, the *wind-distribution* results in the lowest increase in redispatch volume. This outcome stems from a better spatial alignment between wind generation and heat pumps compared to *hp-distribution* and *pv-distribution*, which also explains why total supply costs are lowest for the *wind-distribution*.

The results suggest that the system value of thermal storage differs between locations, but within the uniform setup these differences cannot be signaled to the market.

3.3.2. Regional value of flexibility from thermal storage

The LMP model setup offers the possibility to analyze the regional differences across Germany in more detail and allows to assess the regional system value of flexibility provision through thermal storage. The regional system value of thermal storage is reflected in the expected revenue depending on its location. Figures 3.4 (a)-(c) illustrate the expected revenue with the *hp-distribution* for each shifting potential by latitude, distinguishing in color shades between nodes west and east the 10th meridian.[20]



(a) (b) (c) (d)

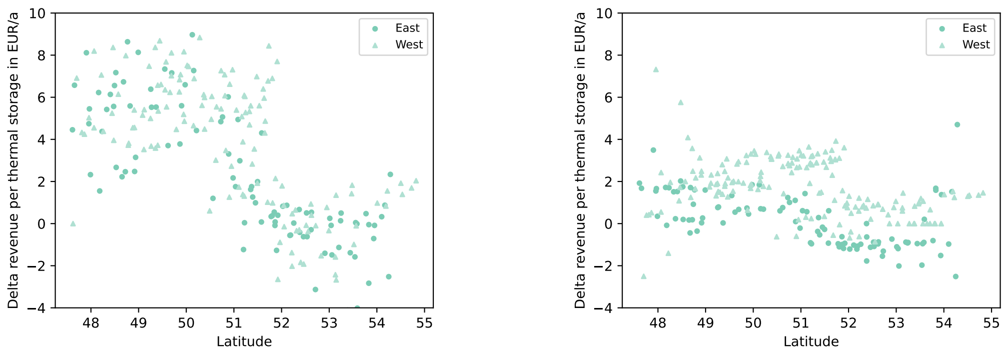
Figure 3.4.: Expected revenues for thermal storage by latitude for (a) 2h shifting potential, (b) 4h shifting potential, (c) 8h shifting potential, and (d) the standard deviation of LMPs in the base case with inflexible heat pumps

[20]The 10th meridian is marked in the maps of Germany in Figure 3.2. To the west of the 10th meridian, most nodes are located in Baden-Wuerttemberg and the federal states of former Western Germany, whereas to the east, they are predominately located in Bavaria and the federal states of former Eastern Germany.

For all three shifting potentials, it can be observed that the regional system value of thermal storage in terms of the expected revenue increases from south to north. In southern Germany, the expected revenues tend to be higher east of the 10th meridian. Further north, with a few exceptions, the regions in eastern Germany follow the upward trend but set the lower limit of expected revenues, while the outliers with relatively high expected revenues are mainly found in western Germany.

The differences in the expected revenues between nodes can be explained by looking at the LMPs in each node. As thermal storage shifts electricity over time, their expected revenue is less dependent on the average level of prices and more dependent on the variation of hourly prices.[21] To illustrate this, the standard deviation of the LMPs per node by latitude is presented in Figure 3.4 (d), showing that higher expected revenues correspond with a greater standard deviation of LMPs.[22] A more detailed examination of the data further reveals that wind and PV generation is relatively high at these nodes, which explains the higher price fluctuations. Consequently, the flexibility of thermal storage is more valuable to the electricity system at these nodes with high RES generation and is utilized more frequently and extensively than at other nodes with lower expected revenues.

In general, these results also apply for the *wind-distribution* and the *pv-distribution*. (see Figure B.3 in the Appendix). Figure 3.5 shows the differences in expected revenues per thermal storage with an 8h shifting potential between the *hp-distribution* and the (a) *wind-distribution* and (b) *pv-distribution*.[23]



(a) (b)

Figure 3.5.: Differences in expected revenues per thermal storage with 8h shifting potential for (a) *wind-distribution* - *hp-distribution* and (b) *pv-distribution* - *hp-distribution*

[21] Figure B.2 in the Appendix shows the average annual LMPs per node by latitude.

[22] Thermal storage has a negligible effect on both the average annual LMPs and their standard deviation. As a result, the base case with inflexible heat pumps is presented.

[23] The effects are most pronounced for the 8h shifting potential. See Figure B.4 in the Appendix for the 2h and 4h shifting potential.

With the *wind-distribution*, expected revenues shift from north to south, especially from above the 51st parallel, with changes ranging from -4 to 10 EUR/a. A reallocation of thermal storage according to the *pv-distribution* yields smaller differences in expected revenues compared to the *hp-distribution*, as the two distributions are more similar. Most nodes show revenue changes between -2 and 4 EUR/a, with mixed impacts in northern and southern nodes. There is a notable shift in expected revenues between eastern and western nodes, with increases predominantly in the west and decreases in the east.

Relating these results to the observed shifts in heat pump demand, expected revenues rise in regions with less thermal storage capacities compared to the *hp-distribution* and fall in regions where more thermal storage is allocated. This suggests that the value of a single thermal storage depends not only on its own location but also on the distribution of other thermal storage capacities. Regions with decreasing thermal storage capacities face higher expected revenues per thermal storage, whereas regions with increasing thermal storage capacities experience lower expected revenues per thermal storage.

3.3.3. Individual household's investment decision

From a system perspective, combining a heat pump with thermal storage reduces total supply costs across all scenarios and shifting potentials. The profitability for individual households is evaluated by comparing expected market revenues with the investment costs of thermal storage, considering stand-alone solutions and storage extensions when installing a new heat pump system.

In the uniform setup with the *hp-distribution*, a household earns 53 EUR/a with a thermal storage with 400 l (2h shifting potential), 77 EUR/a with 800 l (4h shifting potential), and 96 EUR/a with 1500 l (8h shifting potential).[24] For stand-alone installations, average annualized investment costs of 88 EUR/a (2h shifting potential), 105 EUR/a (4h shifting potential), and 134 EUR/a (8h shifting potential) exceed the expected revenues. For storage extensions, upgrading a 400 l storage to 800 l, i.e. providing a 2h shifting potential for market use, costs an additional 17 EUR/a, and 29 EUR/a for upgrading an 800 l storage to 1500 l, providing a 4h shifting potential. These extensions yield profits of 36 EUR/a and 48 EUR/a, respectively, making them cost-efficient decisions for individual households.[25]

In the LMP setup, the value of flexibility is highest in northern Germany, particularly above the 53rd latitude, where expected revenues consistently exceed those in the uniform setup, reaching up to 66 EUR/a, 108 EUR/a, and

[24]Revenues are the same for the *pv-distribution* and slightly higher for the *wind-distribution* (54 EUR/a, 79 EUR/a, and 99 EUR/a, respectively).

[25]Additional revenues from providing flexibility in other markets, e.g. the intraday market or ancillary services, could improve profitability, especially if price fluctuations are greater than in the wholesale market. However, a detailed analysis of multi-market participation is beyond the scope of this paper, as it alters thermal storage operational patterns.

153 EUR/a, for 2h, 4h, and 8h shifting potentials, respectively. While stand-alone installations still remain unprofitable, storage extensions to either 800 l (2h shifting potential) or 1500 l (4h shifting potential) are profitable across all nodes. The storage extensions yield profits that range between 18 EUR/a and 49 EUR/a for a 2h shifting potential, and between 17 EUR/a and 79 EUR/a for a 4h shifting potential.

Given the heat pump expansion target for 2030, the majority of heat pumps will have to be built in the coming years. It is therefore reasonable to assume that most investment decisions will be made when installing new heat pump systems. At this stage, installing a thermal storage with increased capacity for market-oriented flexibility is a profitable decision, assuming that wholesale price signals are visible on the individual household level as discussed in Section 3.4.3.

3.4. Discussion

In order to understand the results, it is important to be aware of the underlying methodology and to critically assess it. This Section discusses the model assumptions (Section 3.4.1), the data (Section 3.4.2), and the results in the light of existing literature and its policy implications (Section 3.4.3).

3.4.1. Model assumptions

The numerical model uses idealizing assumptions which may lead to results deviating from reality. The model assumes perfect foresight, fully rational economic behavior, and perfect coordination among storage installations. In reality, achieving such a frictionless market participation is challenging and highlights the importance of aggregators and technical necessities like smart meters.

Additionally, the model assumes that flexibility from thermal storage on household level can be fully utilized in the transmission grid, even though they are installed at the distribution grid. Including the distribution grid into the analysis could provide further insights: First, it could accentuate regional differences due to the heterogeneous distribution networks in Germany. Second, interactions between distribution and transmission grid levels could either intensify or mitigate transmission congestion. While bottlenecks in the distribution grid may limit storage availability for the transmission grid, offering flexibility at the distribution level could also create an additional revenue stream for heat pump owners, potentially increasing the profitability of thermal storage.

Furthermore, this paper assumes that only the additional thermal storage capacities are operated in a system-friendly manner. This provides a lower bound for the flexibility potential. The analysis does not determine if 'technical storage capacities' can be utilized for system-use when not required for technical optimization, or if reducing technical operational levels could increase revenues from system-use. In particular, thermal storage meeting §14a EnWG criteria may allow system-friendly optimization without incurring extra costs as this storage is designed for two-hour shifting and likely exceeds technical needs.

Despite possible deviations due to the idealized assumptions, the results indicate that thermal storage offers considerable shifting potential that can be effective even if only partially activated, particularly if it is located in grid-beneficial locations. As shown in Section 3.3 this is particularity the case if heat pumps are allocated close to onshore wind capacity.

3.4.2. Data

The current extrapolation of heat pump demand profiles to 2030 disregards potential changes in heat pump types, technological advancements, and variations in building characteristics like insulation. These factors could reshape future electricity demand profiles and current assumptions on the efficiency (COP) of heat pumps. While advancements in technology and insulation are expected to increase efficiency, the installation of heat pumps in less insulated buildings may lower efficiency. Presently, heat pumps are mainly installed in single-family homes, but broader adoption in multi-family buildings could either level out or intensify demand peaks as usage increases simultaneously. Additionally, a deeper understanding of heat pump operation in practice and thus improved technical optimization could smooth out demand profiles over the course of the day.

Furthermore, this paper investigates the impact of the regional allocation of heat pumps and thermal storage on the electricity market and the grid by analyzing three exemplary distributions. The results are robust with respect to the different distributions, as the core results and the direction of the effects remain essentially unchanged if the distribution assumption is changed. Future studies could aim to improve the predictive quality for heat pump distribution in 2030, similar to the detailed analysis by Arnold et al. (2023) on the expansion of electric vehicles in Germany.

3.4.3. Results and policy implications

This section briefly summarizes the results, embeds them in the literature, and discusses key policy implications concerning the spatial distribution of new heat pump and thermal storage installations as well as the impact of flexibility provision by thermal storage on market effects and grid dynamics.

With regard to the installation of new heat pumps combined with thermal storage, allocating them near wind capacities proves most beneficial for the overall system, achieving the lowest total supply costs. This outcome is primarily driven by the reallocation of heat pump demand, as most of the cost reduction is already observable in the base case with inflexible heat pumps. Shifting demand to northern Germany relieves the grid and reduces redispatch costs compared to installing heat pumps in southern Germany. These results suggest that policymakers should prioritize to incentivize heat pump installations in northern regions to align new demand with local renewable generation and reduce grid constraints — a target applicable to other sources of demand as well.

When considering the impact of flexibility provision by thermal storage, the results show its consistent potential to lower total supply costs independent of the chosen distribution of heat pumps. Unlocking flexibility from thermal storage mitigates RES curtailment and substitutes fossil fuel generation. These results align with the findings in previous studies (e.g., Bauknecht et al., 2024, Bloess et al., 2018, Büttner et al., 2024, Roth et al., 2024, Schöniger et al., 2024).

To fully utilize the flexibility potential of thermal storage, it is recommendable to incentivize equipping heat pumps with thermal storage and ensuring their flexibility is accessible to the market. A practical first step could involve integrating existing thermal storage, built in accordance to §14a EnWG, into the electricity market during periods when it is unused for this purpose or for other technical optimization of the heat pump. To facilitate market participation, existing market barriers should be addressed, in particular the distortions between wholesale price signals and retail prices. Heat pump owners often lack access to real-time electricity prices, limiting their ability to optimize electricity demand based on market conditions. Moreover, the addition of taxes, levies, and network fees distorts wholesale price signals, complicating effective household responses to price fluctuations. Regional variations in retail electricity prices, driven by network tariffs unrelated to grid congestion, add further complexity. The structure of retail electricity prices should therefore continue to be part of the political debate. Agora Energiewende (2023) and Eicke et al. (2024) recently explore various policy instruments such as dynamic retail pricing and time-varying network tariffs, to enable the use of decentralized flexibilities in Germany.

Regarding the size of the thermal storage, the results show that smaller systems with 2h or 4h shifting potential consistently lower total supply costs, independent of the underlying heat pump distribution. However, with an 8h shifting potential, thermal storage provides additional cost reductions only when allocated close to wind capacities. The larger storage size better aligns with wind generation patterns and grid constraints in northern Germany. This finding extends the existing literature, as previous studies (e.g., Roth et al., 2024, Schöniger et al., 2024) focus on market effects of thermal storage but neglect grid impacts.

Concerning the impact of flexibility provision on the grid, the results emphasize the need for locational signals. In the uniform setup, which represents the German electricity system, thermal storage reduces total supply costs through its positive market effects, but at the same time it increases redispatch costs. Unlike aggregated studies of decentralized flexibilities (e.g., Bauknecht et al., 2024, Büttner et al., 2024, Heitkoetter et al., 2022), this analysis highlights the grid impacts of heat pumps with thermal storage. The results suggest that with the introduction of flexibility from thermal storage, taking grid constraints into account becomes increasingly important in order to utilize the flexibility for the market without violating grid constraints. This applies in particular to larger shifting potentials. Although idealized LMPs are not directly applicable, they show the benefits of integrated price signals. Policy makers should ensure that heat pumps are operated with consideration for their impact on the grid. Current proposals for an electricity market reform in Germany, e.g. by the Federal Ministry for Economic Affairs and Climate Action, acknowledge the need for locational signals but have, so far, left out storage technologies (BMWK, 2024b).

Overall, creating a cohesive regulatory framework that integrates both market and grid dynamics will be essential to fully realize the economic potential of heat pumps combined with thermal storage. Policymakers should incentivize the installation of thermal storage and ensure its participation in the electricity market. This particularly includes addressing distortions between wholesale price signals and retail prices. Additionally, locational signals should be implemented that account for both market conditions and grid constraints, ensuring that flexibility provision maximizes its system-wide benefits.

3.5. Conclusion

This paper analyzes the impact of heat pumps combined with thermal storage on the electricity system, accounting for market and grid dynamics. It evaluates the system value of the flexibility provided through thermal storage when taking grid restrictions into account. Six scenarios combine two model setups, a uniform and a LMP model setup, with three heat pump distributions, based on the current geographic locations of heat pumps, the allocation of wind capacity, and the allocation of PV capacity. Each scenario is compared for three storage sizes (2h, 4h, and 8h shifting potential) with the inflexible use of heat pumps.

The results show that across all scenarios and shifting potentials, flexibility provision through thermal storage reduces total supply costs compared to an inflexible use of heat pumps. In the uniform model setup, the provision of flexibility improves the market results but at the same time increases the necessity for grid management. The extent to which these two opposing effects outweigh each other depends on the shifting potential. When heat pumps are allocated based on their current locations or PV capacity, the 4h shifting potential results in lower total supply costs than the 8h shifting potential, as redispatch supply costs increase over-proportionally for these distributions. Allocating heat pumps and thermal storage near wind capacity in northern Germany leads to the largest reduction in total supply costs, which, in contrast to the other two distributions, benefit most from the 8h shifting potential. Thus, spatial proximity to wind generation enhances the benefits of the flexibility provision through thermal storage. The regional analysis within the LMP model setup supports these findings and shows that the regional system value of flexibility provided by thermal storage is highest in northern Germany. The results therefore suggest that the consideration of grid restrictions becomes more important with the introduction of flexibility from thermal storage in order to utilize the flexibility for the market without violating grid constraints. This applies in particular to larger shifting potentials.

The magnitude of effects depends on the model parametrization and data assumptions regarding the market and grid. Particularly, the effects of thermal storage depend on the assumptions about other flexibility options as they interact with the flexibility provided by technologies such as electrolyzers and batteries. Further studies for other countries or other scenarios, e.g. on the impact of heat pump demand profiles, the expansion of RES and other storage technologies, can therefore contribute to further understand the driving factors. In addition, future research could analyze the impact of the location of heat pumps and thermal storage with endogenous investment decisions to further extend the analysis of the different heat pump distributions used in this paper.

In conclusion, unlocking the flexibility potential of heat pumps in combination with thermal storage offers economic benefits for the electricity system across all scenarios. Policymakers are advised to incentivize the market deployment of thermal storage. This should be coupled with locational price signals to align market incentives with grid requirements, thereby ensuring that the benefits of the flexibility are fully realized across the electricity market and the grid. The question of how locational price signals can best be implemented within a uniform setup remains an ongoing topic of public and scientific debate.

4. Network Tariffs under Different Pricing Schemes in a Dynamically Consistent Framework

4.1. Introduction

The transition towards a decarbonized energy system requires investments in new electricity consumption technologies, like power-to-gas facilities or electric heating systems. In liberalized electricity systems, investment and operation decisions are private and based on price signals. Therefore, adequately designed prices are of great importance to efficiently coordinate the network and decisions of supply and demand. Increasingly decentralized investments and rising network costs make spatial price signals even more relevant. In many electricity systems, however, prices for consumers do not include spatial signals, and in most cases, they contain several price components that are not necessarily aligned. While the demand-side has traditionally been perceived as price-inelastic, with new demand-side technologies entering the system, consumers can participate more actively in electricity markets. Therefore, misaligned price signals can have an increasingly negative impact on welfare and the system's efficiency. The adequacy of price signals depends on the design of several components, including the spot market pricing scheme and regulatory price components, like network tariffs. In many countries, network tariffs account for a significant part of the consumer price. In addition to the sum of price components that directly affect the consumers' decision-making, the individual price components can interact with each other. These interactions depend on the design of the individual components.

In this paper, we analyze the interactions of price components by combining different spot market pricing schemes and network tariff designs. We derive static and dynamic effects within each regulatory setting and analyze how regulatory changes impact efficiency by ranking the regulatory settings in terms of overall welfare. The analysis particularly accounts for network tariffs' economic efficiency, including their function to recover network costs for the network operator and their ability to ensure a dynamically consistent allocation of demand investments.

We develop a theoretical two-node model, including a spot market and the network tariff setting of a transmission system operator (TSO).[26] The TSO decides on welfare optimal network tariffs that must recover the network costs. She anticipates the dynamic effects of price signals and optimizes network tariffs such that upcoming demand investments are efficiently allocated. Subsequently, the spot market clearing follows, if necessary, accompanied by congestion management measures. We apply the model in four different regulatory settings - the combination of two spot market pricing schemes and two network tariff designs. As pricing schemes, we consider zonal and uniform pricing because they represent two contrasting approaches to incorporate network constraints in the market clearing.[27] As network tariff designs, we consider fixed and volume-based network tariffs. Economic theory on efficient pricing suggests fixed network tariffs as they do not distort market price signals (c.f. Pérez-Arriaga and Smeers, 2003). In contrast, volume-based tariffs increase the per-unit price for consumers. If consumers react to prices, volume-based network tariffs induce a deadweight loss. Ramsey-Boiteux prices minimize this deadweight-loss and constitute the least-distorting volume-based network tariffs (c.f. Wilson, 1993).

The regulatory setting with zonal pricing and fixed network tariffs achieves the highest welfare. Without reducing the static welfare, the TSO can ensure a dynamically consistent allocation of demand investments by restricting the feasible cost allocation between the two nodes. In the regulatory setting with uniform pricing and fixed network tariffs, the TSO also achieves a dynamically consistent allocation of demand investments without reducing the static welfare. However, the cost allocation is further restricted, as the network tariffs are the only possibility for spatial price signals. Additionally, the introduction of uniform pricing leads to inefficiency from congestion management, as we assume a cost-based redispatch mechanism of generators. With volume-based network tariffs, the inefficiency from the congestion management reduces, if the TSO includes a correction term into the network tariff, which imitates zonal prices. Under both pricing schemes, volume-based network tariffs induce a deadweight loss as they increase per-unit prices and, therefore, impact the spot market outcome. In contrast to fixed network tariffs, optimal volume-based network tariffs can lead to an additional loss in static welfare when considering a dynamically consistent allocation of demand investments.

Comparing the four regulatory settings shows that deviating from the regulatory setting of zonal pricing and fixed network tariffs leads to inefficiencies.

[26] In the following, we refer to the transmission network only. However, due to the stylized representation of network constraints, this does not necessarily exclude our model's application in the context of distribution networks.

[27] We use the term zonal pricing as a general approach for spatially differentiated prices within one regulated region. This definition includes all pricing schemes in which the spot market sends locational price signals to the market participants. The concept of zonal pricing preserves the possibility that several nodes of a network constitute a zone, while prices may differ between the zones of one region. Within our two-node model, nodal or zonal prices are equivalent.

Under uniform pricing, additional costs occur due to congestion management, and the use of volume-based network tariffs results in a deadweight loss due to price distortion. If there is only one source of inefficiency, welfare increases by adjusting the respective price component, i.e., changing either to fixed network tariffs or zonal pricing. However, suppose both sources of inefficiency are present. In that case, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of only one aspect can have unintended effects on overall welfare. If optimal volume-based network tariffs structurally reduce congestion management costs, switching to fixed network tariffs does not necessarily increase market efficiency. This result is important considering that current electricity systems often use a combination of uniform pricing and mainly volume-based network tariffs. Hence, we demonstrate the importance of addressing the interactions between price components when changing the regulatory setting.

This paper contributes to the broader literature on network cost recovery, focusing on the interactions with different spot market pricing schemes in a dynamic context. Electricity networks constitute a natural monopoly and typically face large, fixed network costs. Thus, competitive pricing at short-run marginal costs does not generate enough revenue to cover total costs (c.f. Joskow, 2007, Pérez-Arriaga et al., 1995). Therefore, cost recovery is necessary independently of the spot market pricing scheme and requires an appropriate network tariff design (c.f. Brunekreeft et al., 2005). Borenstein (2016) comprehensively discusses the aspect of fixed cost recovery in natural monopolies and the economic principles of tariff setting in electricity markets. Furthermore, Batlle et al. (2020) and Schittekatte (2020) conceptually discuss options for residual cost allocation, with a special focus on residential consumers and distributional effects of network tariffs. This strand of literature is expanded by empirical studies on the distributional effects, e.g., by Burger et al. (2020) and Ansarin et al. (2020), as well as numerical simulation models, that analyze the effects of different network tariffs on different consumer groups, e.g., Fridgen et al. (2018) and Richstein and Hosseinioun (2020).

In a dynamic context, the demand-side has received relatively little attention so far, as consumers' investment decisions have long been considered not being influenced by electricity price signals. In their recent work on prosumers, Schittekatte et al. (2018) and Schittekatte and Meeus (2020) analyze the effect of network tariffs on consumers' investment incentives and the installation of residential PV. Gautier et al. (2020) contribute to the discussion on investment incentives by taking the presence of heterogeneous prosumers into account and Castro and Callaway (2020) simulate the impact of different network tariffs on demand's investment decisions in a numerical model. Though, these analyses do not consider the spatial dimension and locational choices. While Ambrosius et al. (2018) do analyze spatial demand investments under different spot market pricing schemes, they do not consider multiple network tariff designs. In comparison, the literature acknowledging the spatial dimension and the impact of network tariffs on location-based price signals is currently limited to the supply side. Tangerås and Wolak (2019) analytically show how locational marginal network tariffs can be designed to incentivize efficient supply-side investments. Bertsch et al. (2016) analyze different pricing schemes in a dynamic numerical framework. They consider the interactions of network tariffs (specifically a g-component) and the pricing scheme. Similarly, Grimm et al. (2019) apply regionally differentiated network tariffs under different pricing schemes for the German electricity market. Ruderer and Zöttl (2018) account for the interaction of congestion management methods and network tariffs by examining the impact of volume- and capacity-based network tariffs on generators' investment decision in an analytical model. The importance of efficient cost recovery mechanisms is also highlighted by Chao and Wilson (2020). In a numerical model they find volume-based Ramsey-Boiteux tariffs to be close to the social optimum.

To the best of our knowledge, the paper at hand is the first, which explicitly considers different network tariff designs and pricing schemes in a consistent dynamic framework to analyze the effect on spatial demand-side decisions. Although each of these topics has been studied extensively from an isolated perspective, integrated approaches are relatively scarce. Borenstein and Bushnell (2018) empirically analyze the interaction of network tariffs and the pricing of externalities in the US. The authors show that if prices are affected by more than one distortion, the effects can level each other out. We contribute to the discussion by developing an analytical framework in which we provide insights into the interaction of the two price components, their potential inefficiencies and the requirements for a dynamically consistent allocation of demand-side investments.

The remainder of this paper is structured as follows: Section 4.2 introduces our model set-up, and Section 4.3 analyzes the optimal network tariffs under different pricing schemes in a dynamic context. Section 4.4 examines the effects of the regulatory settings on overall welfare. Section 4.5 discusses political implications and summarizes concluding remarks.

4.2. The model framework

This section introduces the basic model setup to analyze different pricing schemes and network tariff designs in the presence of a congested transmission network. We consider a two-node model with two nodes called *north* and *south* denoted by $i \in \{n, s\}$ with respective generation technologies with constant marginal costs c_i. Further, we assume that the generation technology in the north is strictly cheaper, i.e., $c_n < c_s$. Both technologies have an unrestricted generation capacity. Further, we assume perfect competition in both nodes. Thus producer surplus is equal to zero in all regulatory settings. The aggregated market demand in each node is denoted by $D_i(p_i)$, which is decreasing in price, i.e., $\partial D_i(p_i)/\partial p_i < 0 \; \forall \, i$. We assume a positive number of ω_i identical consumers in each node. The total number of consumers is therefore given by $\Omega = \omega_n + \omega_s$.

Electricity generation q_i in both nodes needs to cover total demand, i.e., $\sum_i q_i = \sum_i D_i(p_i)$. Further, the two nodes are connected by a transmission line, with power flows l and a limited capacity of $\overline{L}$, illustrated in figure 4.1. We focus on congested networks and hence demand exceeds the limited transmission line capacity, i.e., $\overline{L} \leq D_i(p_i) \; \forall \; i$. Since we assume that generation costs are lower in the north, electricity flows from north to south. The transmission system operator (TSO) is responsible for the physical feasibility of the market outcome, which, if necessary, also comprises congestion management.

In our analysis, we consider two pricing schemes - zonal and uniform pricing that differ regarding their congestion management. Under zonal pricing, the spot market clearing simultaneously considers network restrictions, while under uniform pricing, ex-post congestion management of the TSO is necessary. After the spot market clearing, the TSO performs a redispatch of supplied quantities q_i until the transmission constraint $\overline{L}$ is fulfilled.

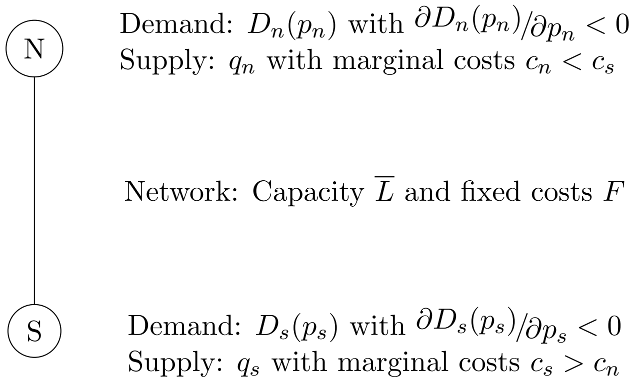


Figure 4.1.: The two-node model.

We assume a redispatch mechanism with incomplete participation. That means, the TSO considers only producers for redispatch, while the demand-side is excluded.[28] This reflects the common practice in many electricity systems and is, in particular, due to the complexity of remunerating the demand for a redispatch measure. With a cost-based redispatch, the TSO compensates generators outside the spot market based on their marginal costs.[29]

Additionally, the operation of the transmission network is associated with fixed costs of $F \in \,]0, \infty[$. We assume that the fixed costs are smaller than the consumer surplus given the generation costs in each node, i.e., $F \leq \int_{c_i}^{\infty} D_i(z)dz \; \forall \; i$. This assumption ensures the participation constraint of consumers in all settings. Fixed network costs cannot be attributed to individual network users. Therefore, the principle of cost causality cannot be applied to recover these costs. The

[28] Noteworthy, under the assumption of full participation, uniform pricing with redispatch achieves the welfare optimal result (Bjorndal et al., 2013).

[29] Other congestion management methods are comprehensively discussed in DeVries and Hakvoort (2002), Holmberg and Lazarczyk (2015) and Weibelzahl (2017).

TSO's total network costs C^{TSO} contain the fixed costs F as well as potential congestion rents. Depending on the pricing scheme, congestion rents can be either positive or negative. We introduce the TSO as a benevolent agent who recovers her costs by charging network tariffs. We consider two different network tariff designs: a volume-based tariff $\boldsymbol{\tau} := (\tau_n, \tau_s)$, and a fixed network tariff $\boldsymbol{f} := (f_n, f_s)$. Volume-based network tariffs can be interpreted as an additional demand tax that directly influences the demand decision on the spot market. Fixed network tariffs can be interpreted as an access charge for being connected to the network. These tariffs constitute two extreme cases for network cost recovery. We do not apply general non-linear tariffs, e.g., multi-part tariffs. In both cases, we assume that only consumers pay network tariffs, as is the case in many electricity systems in practice. The TSO can differentiate between consumers in the north and south but cannot distinguish between consumers within one node. Consequently, network tariffs can vary between the two nodes, but not between consumers within a node.

For the network tariff setting, the TSO wants to ensure a dynamically consistent allocation of demand investments. By definition, new consumers choose the location of their investment depending on the prices in each node. We define a pricing schedule P_i^I that includes two price components: the payments at the spot market for each unit demanded and the network tariff payments. The pricing schedule is given by $P_i^I = p_i\overline{D} + f_i$, where $\overline{D}$ is a fixed additional demand for new consumers.[30] If volume-based network tariffs are applied, the per unit price p_i also includes the network tariff τ_i. The TSO aims at achieving a dynamically consistent allocation of demand investments. From a welfare perspective, dynamic consistency is achieved if the new demand investments are in line with the welfare-maximizing result in future periods. As we consider a congested network with lower generation costs in the north, consumers should place new demand investments into the north. The demand invests in the north, if and only if, the pricing schedule is lower in the north compared to the south, i.e., iff $P_n^I \leq P_s^I$, which is:

$$p_n(\boldsymbol{c}, \boldsymbol{\tau}) \cdot \overline{D} + f_n \leq p_s(\boldsymbol{c}, \boldsymbol{\tau}) \cdot \overline{D} + f_s \tag{4.1}$$

The TSO anticipates the rationale of the demand's investment decision and, therefore, accounts for the pricing schedule (4.1) when setting the network tariffs. The structure of this constraint holds in each setting and only the spot market price and the network tariff may change depending on the regulatory setting.[31]

[30] By assuming a price-inelastic demand, we ignore quantity effects, which additionally restrict the optimal solution, but do not change our main results.

[31] We simplify the investment decision by only considering the costs in both nodes and add the investment decision to the pricing problem of the TSO. If the investment decision is modeled endogenously in a sequential setting, i.e., by maximizing the consumer surplus of the invested demand, the rationale slightly differs between the settings, but our main results do not change.

4.3. The interactions of network tariffs and pricing schemes considering dynamic consistency

We analyze the interactions between the different combinations of pricing schemes and network tariff designs and their effect on a dynamically consistent allocation of demand investments. The model set-up consists of two steps.

At first, the benevolent TSO introduces a vector of network tariffs for the current time period that can either be fixed ($\boldsymbol{f}$) or volume-based ($\boldsymbol{\tau}$). The TSO has perfect foresight and anticipates the impact of network tariffs on the spot market outcome and possible network congestion while ensuring the dynamic consistency of the pricing schedule.[32]

Second, the spot market clearing takes place, which depends on the pricing schemes. Under zonal pricing, the spot market clears with a cost-minimal dispatch considering the transmission constraint. The solution is equal to the optimal dispatch of a social planner, as we show in C.1. Production is equal to $q_n^* = D_n(p_n) + \overline{L}$ and $q_s^* = D_s(p_s) - \overline{L}$. Prices differ among nodes and reflect marginal costs of generation, with $p_n^* = c_n$ and $p_s^* = c_s$. The spot market clearing under zonal pricing yields a positive congestion rent $(c_s - c_n)\overline{L}$. The TSO anticipates this rent and offsets fixed costs F with it. Under uniform pricing, both nodes belong to the same bidding zone. In contrast to zonal pricing, both nodes trade irrespective of network constraints. Consequently, the generation in the north is dispatched to fully cover the demand in both nodes at marginal costs of c_n. The resulting spot market prices are $p_n^* = p_s^* = c_n$.[33] The spot market clearing requires a production of $q_n = D_n(c_n) + D_s(c_n)$, which is technically not feasible as it requires the producer at node n to export more than $\overline{L}$. The TSO is responsible for ensuring the system's physical feasibility by conducting congestion management measures. To do so, the TSO performs a redispatch of suppliers. The TSO instructs the producer at node n to reduce generation to $q_n = D_n(c_n) + \overline{L}$ and instructs the producer at node s to increase generation to $q_s = D_s(c_n) - \overline{L}$. The TSO compensates the producers outside the spot market for redispatching their generation. This leads to additional costs of $(c_s - c_n)(D_s(p_s^*) - \overline{L})$. In the following, we use these spot market results to determine the optimal network tariffs.

4.3.1. Fixed network tariffs under zonal pricing

The TSO maximizes welfare by setting the fixed network tariffs under zonal pricing (4.2a). The optimization is subject to the budget constraint (4.2b) to

[32] The assumption regarding the TSO's benevolence is critical for the formulation of the optimization problem. Otherwise, the TSO would only consider her budget and neglect the impact on consumer surplus or dynamic consistency.

[33] With volume-based network tariffs, the per-unit price in each node also includes τ_n and τ_s, respectively, and hence, in sum p_i may differ between both nodes. However, the spot market price component is the same, regardless of the network tariff design.

ensure full network cost recovery. Due to the positive congestion rent under zonal pricing, the TSO has to recover the following costs $C^{TSO}_{ZP,f} = F - (c_s - c_n)\overline{L}$. Further, the TSO anticipates the impact of network tariffs on the dynamic allocation of demand investments. Therefore, the optimization is additionally restricted by (4.2c).

$$\max_{\boldsymbol{f}} W_{ZP,f}(\boldsymbol{p}^*, \boldsymbol{f}) = \int_{p_n^*=c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_s}^{\infty} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L} \tag{4.2a}$$

$$s.t. \quad \sum_i \omega_i f_i - F + (c_s - c_n)\overline{L} = 0 \tag{4.2b}$$

$$c_n\overline{D} + f_n \leq c_s\overline{D} + f_s \tag{4.2c}$$

The fixed network tariffs do not impact the welfare function and the TSO only has to ensure, that the constraints (4.2b) and (4.2c) hold. See C.2 for a proof and the derivation of possible solutions for the optimization problem (4.2a-4.2c). As consumers are homogeneous and fixed costs do not exceed consumer surplus in each node, fixed network tariffs cannot exceed the individual consumer surplus. Hence, the participation constraint holds for each consumer. Thereby, fixed network tariffs do not change the cost-minimal dispatch of supply and demand and thus, do not distort welfare. This is a well-known result from the literature on fixed cost recovery in network industries (e.g. Borenstein, 2016, Joskow, 2007, Wilson, 1993). Within the boundaries of constraints (4.2b) and (4.2c), the TSO can allocate the costs freely among the nodes.[34] Allocating network costs equally among consumers in all nodes would be a practical solution that ensures a dynamically consistent allocation of demand investments. In practice, this approach is often called *horizontal cost allocation*. Such a simple allocation rule would ensure that network tariffs do not distort spatial price signal from the spot market while fully recovering the fixed network costs.

4.3.2. Fixed network tariffs under uniform pricing

Under uniform pricing, the optimization problem of the TSO changes to (4.3a-4.3c). First, the spot market prices differ from zonal pricing, and second, the budget constraint of the TSO (4.3b) changes. Since redispatch comes with additional costs for the TSO, she has to recover total costs of $C^{TSO}_{UP,f} = F + (c_s - c_n)(D_s(p_s^*) - \overline{L})$. Again, the TSO ensures the dynamic consistency for the allocation of future demand investments (4.3c). As the per-unit spot price is equal

[34] We ignore income and distribution effects in our model. Considering these effects may change the socially desirable cost allocation, e.g. if additional restrictions are included in the optimization problem. See for example Batlle et al. (2020) for a discussion on this topic and a proposed alternative to fixed network tariffs.

in both nodes, the additional demand quantity $\overline{D}$ cancels out.

$$\max_{\boldsymbol{f}} W_{UP,f}(\boldsymbol{p}^*, \boldsymbol{f}) = \int_{p_n^*=c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_n}^{\infty} D_s(z)\,\mathrm{d}z - F - \left[(c_s - c_n)(D_s(p_s^*) - \overline{L})\right] \tag{4.3a}$$

$$s.t. \quad \sum_i \omega_i f_i - F - \left[(c_s - c_n)(D_s(p_s^*) - \overline{L})\right] = 0 \tag{4.3b}$$

$$f_n \leq f_s \tag{4.3c}$$

Proposition 4.3.1. *With fixed network tariffs and homogeneous consumers, the TSO can ensure dynamic consistency without impacting static welfare by restricting the feasible cost allocation between the two nodes. Under uniform pricing, the cost allocation between the nodes is further restricted compared to zonal pricing.*

Again, the fixed network tariffs do not affect welfare and the TSO only has to ensure that the constraints (4.3b) and (4.3c) are met.[35] However, under uniform pricing, the solution to the optimization problem is more constrained by the dynamic consistency condition compared to the setting under zonal pricing. The boundary on network tariffs changes from $c_n\overline{D} + f_n^* \leq c_s\overline{D} + f_s^*$ under zonal pricing to $f_n^* \leq f_s^*$ under uniform pricing. Thus, to ensure a dynamically consistent allocation, the TSO has to choose network tariffs that compensate for the spot market's missing spatial price signals under uniform pricing.

4.3.3. Volume-based network tariffs under zonal pricing

As in section 4.3.1, spot market prices differ between the nodes and reflect the respective marginal costs. However, unlike fixed network tariffs, volume-based network tariffs constitute a levy on consumption and directly influence the demand decision at the spot market. The total price, that consumers pay per unit, is the marginal costs of generation c_i plus the network tariff τ_i, i.e. $p_i = c_i + \tau_i$. The demand-side reduces demanded quantities accordingly.

The TSO maximizes welfare by choosing the optimal vector of volume-based network tariffs (4.4a-4.4c). The optimization is subject to the TSO's break-even constraint (4.4b).[36] The TSO accounts for the positive congestion rent from zonal pricing, and consequently, recovers costs of $C_{ZP,\tau}^{TSO} = F - (c_s - c_n)\overline{L}$.

[35] It is straightforward to see that the solution of this optimization resembles to the solution of the previous chapter, which is depicted in C.2.

[36] Note that the TSO is unbundled. Unlike the case of a classical, vertically integrated natural monopoly, the TSO does not increase the spot market price to recover her fixed cost but introduces a separate network tariff. The difference is that network tariffs are a payment from consumers to the TSO. Therefore, the congestion rent $(c_s - c_n)\overline{L}$ and producer profits are not affected by the network tariffs and remain constant.

Additionally, the optimization is restricted by the dynamic consistency constraint (4.4c). With volume-based network tariffs, the constraint is independent of the fixed additional demand of new consumers ($\overline{D}$) and only depends on the per unit price $p_i(c_i, \tau_i)$.

$$\begin{aligned}\max_{\boldsymbol{\tau}} W_{ZP,\boldsymbol{\tau}}(\boldsymbol{p}^*(\boldsymbol{\tau})) = &\int_{p_n^*=c_n+\tau_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_s+\tau_s}^{\infty} D_s(z)\,\mathrm{d}z \\ &+ \sum_i \tau_i D_i(p_i^*) - F + (c_s - c_n)\overline{L}\end{aligned} \tag{4.4a}$$

$$s.t. \quad \sum_i \tau_i D_i(p_i^*) - F + (c_s - c_n)\overline{L} = 0 \quad \longrightarrow \quad \lambda \tag{4.4b}$$

$$c_n + \tau_n \leq c_s + \tau_s \quad \longrightarrow \quad \mu \tag{4.4c}$$

Proposition 4.3.2. *If the dynamic consistency constraint is binding, the network tariffs deviate from the optimal static volume-based network tariffs. In this case and under the assumption of constant marginal costs, a dynamically consistent allocation of demand investments lowers static welfare since consumer surplus in the north increases less than consumer surplus in the south decreases.*

To solve the TSO's optimization problem we derive the first-order condition of the Lagrangian ${}^{\partial L}\!/_{\partial \tau_i}$. Rearranging for τ_n^* and τ_s^* yields

$$\tau_n^* = \frac{\lambda}{1+\lambda} \cdot \frac{D_n(c_n + \tau_n^*)}{-\partial D_n(c_n + \tau_n^*)/\partial \tau_n^*} - \frac{\mu}{1+\lambda} \cdot \frac{1}{-\partial D_n(c_n + \tau_n^*)/\partial \tau_n^*} \tag{4.5}$$

and

$$\tau_s^* = \frac{\lambda}{1+\lambda} \cdot \frac{D_s(c_s + \tau_s^*)}{-\partial D_s(c_s + \tau_s^*)/\partial \tau_s^*} + \frac{\mu}{1+\lambda} \cdot \frac{1}{-\partial D_s(c_s + \tau_s^*)/\partial \tau_s^*} \tag{4.6}$$

We distinguish between two cases:[37] First, assume that the constraint for dynamic consistency (4.4c) is non-binding and $\mu = 0$. Then, the optimal network tariff in both nodes is equal to:

$$\tau_i^* = \frac{\lambda}{\lambda+1} \cdot \frac{D_i(c_i + \tau_i^*)}{-\partial D_i(c_i + \tau_i^*)/\partial \tau_i^*} \tag{4.7}$$

In this case, the optimal network tariff (4.7) can be interpreted as a modified version of the Ramsey-Boiteux inverse elasticity rule (see C.3.1). A high variation in demand in response to a variation in price leads to lower network tariffs. To solve for the optimal network tariffs, we define the *quasi-elasticity* ρ_i, insert it

[37] There exists a third case where $\mu = 0$ and the constraint is binding. This case leads to the same solution as our first case.

into (4.7) and equate for both nodes. We obtain the following relation:

$$\frac{\tau_n^*}{\tau_s^*} = \frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} \quad \text{with} \quad \rho_i(\tau_i^*) = -\frac{\partial D_i(c_i + \tau_i^*)/\partial \tau_i}{D_i(c_i + \tau_i^*)} \tag{4.8}$$

The relationship between the network tariffs in the two nodes corresponds to the relationship between the quasi-elasticities. By using the relationship from (4.8) and the budget constraint of the TSO (4.4b), we solve for the optimal network tariff in the south:

$$\tau_s^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} D_n(c_n + \tau_n^*) + D_s(c_s + \tau_s^*)} \tag{4.9}$$

The result can be derived analogously for τ_n^*. Similar to the Ramsey-Boiteux inverse elasticity rule, we see that when the ratio of the quasi-elasticities between the south and the north decreases, i.e., when the price sensitivity of the north increases compared to the south, demand in the south covers a higher share of the residual network costs and vice versa. In this case, the condition for dynamically consistent allocation is already met without any further adjustments to the network tariffs. The optimal static volume-based network tariffs thus provide dynamic consistency by themselves.

Second, assume that (4.4c) is binding and $\mu > 0$. This is the case if the optimal static network tariffs reverse the ratio of price schedules between the two nodes so that the north would become more expensive than the south. This depends on the ratio of the demand functions, particularly the quasi-elasticities, in the two nodes (see (4.8)). We denote the resulting network tariffs with $\hat{\tau}_i$.[38] As $\mu > 0$ it follows from (4.5) and (4.6) that $\hat{\tau}_i$ deviate from τ_i^*. In the north, the optimal volume-based network tariff decreases due to the latter part of (4.5), i.e. $\hat{\tau}_n < \tau_n^*$. The opposite effect occurs in the south. From (4.6) it follows that $\hat{\tau}_s > \tau_s^*$. By setting $\hat{\tau}$ instead of τ^* the TSO deviates from the optimal static (unconstrained) volume-based network tariffs.

Consequently, this creates a deadweight loss in the current period to benefit the dynamically consistent allocation of future demand investments. While network tariffs rise in the south and, thus, lower consumer surplus there, network tariffs in the north decrease and increase consumer surplus. However, the increase in consumer surplus in the north does not compensate for the decrease in the south. The adjustments are not equal because of the ratio of the two demand functions, which would lead to higher (lower) network tariffs in the north (south) without the constraint for a dynamically consistent allocation of demand investments. For example, consider a situation where the demand function of the north is almost perfectly inelastic, and there is very price-sensitive demand in the south. Without the requirement for dynamic consistency, consumers in the north would

[38] In C.3.2, we solve for the optimal network tariffs for the case that the constraint is binding and derive at what point the constraint restricts the optimal static network tariffs for dynamic consistency.

bear most of the fixed network costs, while network tariffs in the south would be low. If the difference in network tariffs exceeds the difference in marginal generation costs, dynamic consistency is violated. In order to ensure dynamic consistency, the TSO reduces the network tariffs in the north. However, due to the inelastic demand in the north, consumer surplus increases only slightly. Conversely, increasing network tariffs in the south lead to a significant loss of consumer surplus.

4.3.4. Volume-based network tariffs under uniform pricing

In a regulatory setting with uniform pricing, the spot market clearing results in $p_i = c_n + \tau_i$. Total prices p_i may differ between the two nodes depending on the network tariffs τ_i.

The TSO maximizes welfare, anticipating the spot market result, her own budget and the dynamic consistency constraint (4.10a-4.10c). Due to uniform pricing, the spot market result is physically infeasible, and the TSO is obligated to redispatch generators. From this, the TSO bears additional costs that sum up to $C^{TSO}_{UP,\tau} = F + (c_s - c_n)(D_s(c_n + \tau_s^*) - \overline{L})$. In contrast to the other regulatory settings, the TSO's network costs depend on the network tariffs, because volume-based network tariffs impact the quantities demanded and they, in turn, impact redispatch costs.

$$\begin{aligned} \max_{\boldsymbol{\tau}} W_{UP,\boldsymbol{\tau}}(\boldsymbol{p}^*(\boldsymbol{\tau})) = &\int_{p_n^*=c_n+\tau_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{p_s^*=c_n+\tau_s}^{\infty} D_s(z)\,\mathrm{d}z \\ &+ \sum_i \tau_i D_i(p_i^*) - F - (c_s - c_n)(D_s(p_s^*) - \overline{L}) \end{aligned} \tag{4.10a}$$

$$s.t. \quad \sum_i \tau_i D_i(p_i^*) - F - (c_s - c_n)(D_s(p_s^*) - \overline{L}) = 0 \longrightarrow \lambda \tag{4.10b}$$

$$\tau_n^* \leq \tau_s^* \quad \longrightarrow \quad \mu \tag{4.10c}$$

The first-order conditions of the Lagrangian ${}^{\partial L}/_{\partial \tau_i}$ are no longer identical between north and south. The optimal network tariff in the north has the same structure as under zonal pricing, shown in (4.5). For the south, the optimal network tariff slightly changes to:

$$\tau_s^* = \frac{\lambda}{1+\lambda} \cdot \frac{D_s(c_s + \tau_s^*)}{-\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*}} + \frac{\mu}{1+\lambda} \cdot \frac{1}{-\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*}} - c_n + c_s \tag{4.11}$$

Compared to the structure derived under zonal pricing (4.6), the network tariff in the south consists of an additional component, which functions as a correction-term for redispatch. Under uniform pricing, the optimal volume-based network tariffs mimic zonal prices and partially correct for the inefficiency of the pricing scheme. Plugging equation (4.11) into the demand function of the south $D_s(c_n +$

τ_s^*) yields a similar result as under zonal pricing, i.e. $D_s(c_s + \tau_s)$. However, the result is not equivalent to the setting under zonal pricing, as the values of the network tariffs τ_i differ.

Under uniform pricing, the ratio between the network tariffs not only depends on the ratio of the quasi-elasticities but also on the generation costs in the respective nodes. We derive the optimal network tariffs in C.3.3 and show the relationship in detail. Like in the setting under zonal pricing, the TSO might adjust the optimal static network tariffs if the dynamic consistency constraint is binding. The rationale is the same as under zonal pricing: Deviating from the optimal static (unconstrained) volume-based network tariffs creates a deadweight loss in the current period to the benefit of the dynamically consistent allocation of future demand investments. However, under uniform pricing, missing dynamic consistency is even more severe, as network tariffs are the only possibility of creating spatial price signals. Investments in the south would amplify the system costs by increasing redispatch and additionally increase the burden from network cost recovery for the consumers in the north.

4.4. Welfare implications of the different regulatory settings

In this chapter, we compare the four combinations of network tariffs and pricing schemes in terms of their static welfare. This way, we can show how different regulatory price components affect static efficiency and interact with each other. Based on the results of section 4.3, we further discuss the results for the static welfare in the context of a dynamically consistent allocation of demand investments. From sections 4.3.1- 4.3.4, we derive the optimal static welfare for each regulatory setting:
Fixed network tariffs and zonal pricing:

$$W^*_{ZP,f} = \int_{c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_s}^{\infty} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L}, \tag{4.12}$$

Fixed network tariffs and uniform pricing:

$$W^*_{UP,f} = \int_{c_n}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_n}^{\infty} D_s(z)\,\mathrm{d}z - F - \left[(c_s - c_n)(D_s(c_n) - \overline{L})\right] \tag{4.13}$$

Volume-based network tariffs and zonal pricing:

$$W^*_{ZP,\tau} = \int_{c_n+\tau_n^{ZP*}}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_s+\tau_s^{ZP*}}^{\infty} D_s(z)\,\mathrm{d}z \tag{4.14}$$

Volume-based network tariffs and uniform pricing:

$$W^*_{UP,\tau} = \int_{c_n+\tau_n^{UP*}}^{\infty} D_n(z)\,\mathrm{d}z + \int_{c_n+\tau_s^{UP*}}^{\infty} D_s(z)\,\mathrm{d}z. \tag{4.15}$$

With volume-based network tariffs, the TSO's costs are indirectly displayed in the lower bounds of the integrals as per definition they are refinanced by the sum over all τ_i-payments. Note that the volume-based network tariffs are not identical under the two pricing schemes.

First, we analyze the isolated effects of changing either the pricing scheme or the network tariff design. Comparing zonal and uniform pricing with the same network tariff design, we show the inherent inefficiency that results from the incomplete redispatch scheme under uniform pricing. With fixed network tariffs, the difference in welfare under zonal and uniform pricing is equal to:

$$\begin{aligned}\Delta W^*_{ZP,f-UP,f} &= (4.12) - (4.13) \\ &= (c_s - c_n)D_s(c_n) - \int_{c_n}^{c_s} D_s(z)\,\mathrm{d}z \\ &= \int_{c_n}^{c_s} D_s(c_n) - D_s(z)\,\mathrm{d}z > 0 \implies W_{ZP,\boldsymbol{f}} > W_{UP,\boldsymbol{f}}\end{aligned} \tag{4.16}$$

The result is always greater than zero as demand decreases in price. It is straightforward to show that the same relation holds with volume-based network tariffs, i.e. $W_{ZP,\boldsymbol{\tau}} > W_{UP,\boldsymbol{\tau}}$. Thus, regardless of the network tariff design, zonal pricing is welfare-superior to uniform pricing. Consumption at the spot market is higher under uniform pricing, as market-participants neglect transmission capacities. The TSO corrects the spot market result ex-post. Due to restricted participation of the supply-side, redispatch induces additional costs. The resulting welfare loss is depicted in the shaded triangle in the south in figure 4.2.

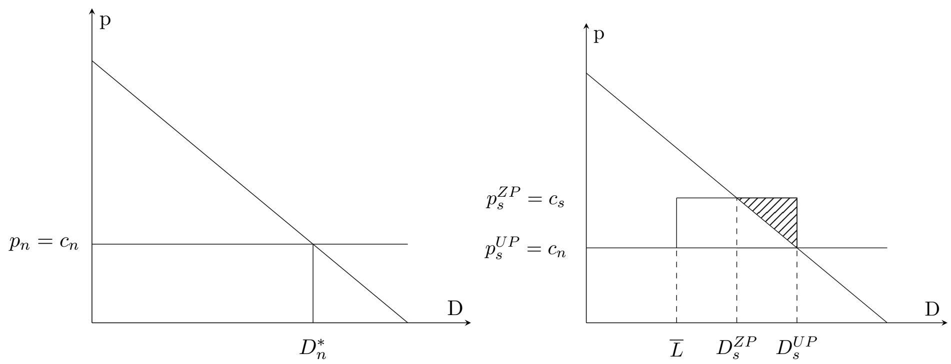


Figure 4.2.: Additional costs from redispatch under uniform pricing compared to zonal pricing; both with fixed network tariffs.

Comparing welfare under zonal pricing with either fixed or volume-based network tariffs, we derive the inefficiency of volume-based network tariffs. Under zonal pricing, the difference in welfare with fixed and volume-based network tariffs yields:

$$\begin{aligned}
&\Delta W^*_{ZP,f-ZP,\tau} = \text{(4.12)} - \text{(4.14)} \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - F + (c_s - c_n)\overline{L} \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - \sum_i \tau_i^{ZP*} D_i(c_i + \tau_i^{ZP*}) \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z) - D_n(c_n + \tau_n^{ZP*})\,\mathrm{d}z + \int_{c_s}^{c_s+\tau_s^{ZP*}} D_s(z) - D_s(c_s + \tau_s^{ZP*})\,\mathrm{d}z \\
&>0 \implies W_{ZP,f} > W_{ZP,\boldsymbol{\tau}}
\end{aligned} \tag{4.17}$$

Since $z < c_i + \tau_i$ and demand decreases in price, the welfare difference must always be positive. According to economic theory, fixed network tariffs are welfare-neutral from a static perspective, whereas volume-based network tariffs cause a deadweight-loss. Figure 4.3 depicts the deadweight loss in the static setting, which is in both nodes depicted in shaded triangles.

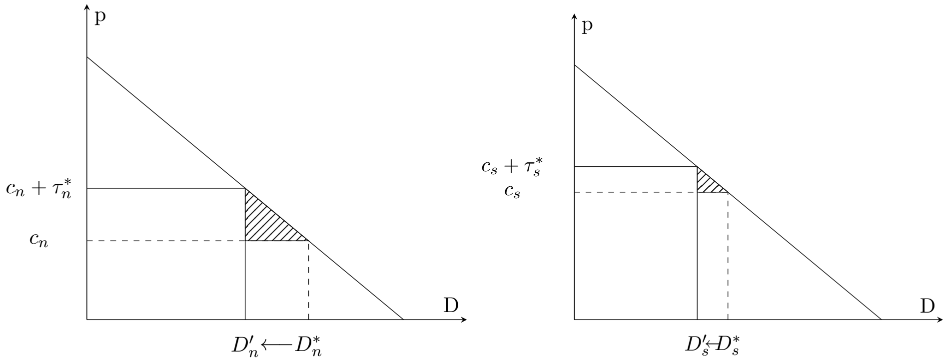


Figure 4.3.: Deadweight loss associated with volume-based network tariffs under zonal pricing.

One could now assume that when applying uniform pricing, the relationship between the network tariffs is identical with the one under zonal pricing, or the inefficient pricing scheme even increases the inefficiency of the network tariff design. However, when both sources of inefficiency are present, it is not so clear-cut, as the following comparison between uniform pricing with fixed tariffs and volume-based network tariffs shows:

$$
\begin{aligned}
&\Delta W^*_{UP,f-UP,\tau} = (4.13) - (4.15) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z)\,\mathrm{d}z - F - (c_s - c_n)(D_s(c_n) - \overline{L}) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z)\,\mathrm{d}z - \sum_i \tau_i^{UP*} D_i(c_n + \tau_i^{UP*}) \\
&\quad - (c_s - c_n)(D_s(c_n) - Ds(c_n + \tau_i^{UP*})) \\
&= \int_{c_n}^{c_n+\tau_n^{UP*}} D_n(z) - D_n(c_n + \tau_n^{UP*})\,\mathrm{d}z + \int_{c_n}^{c_n+\tau_s^{UP*}} D_s(z) - D_s(c_n + \tau_s^{UP*})\,\mathrm{d}z \\
&\quad - (c_s - c_n)(D_s(c_n) - D_s(c_n + \tau_s^{UP*}))
\end{aligned}
\tag{4.18}
$$

The result can be either positive or negative, meaning that the welfare effect is ambiguous. On the one hand, fixed network tariffs do not impact the spot market result, while volume-based network tariffs induce a deadweight loss. On the other hand, equation (4.18) shows that the redispatch costs differ between the two network tariff designs. Since the quantity demanded in the south is lower with volume-based network tariffs, the market outcome requires less redispatch than the setting with fixed network tariffs. However, this is not only due to the general demand reduction associated with the higher prices in both nodes. As shown in equation (4.11), the optimal volume-based network tariff in the south includes a correction term that accounts for the difference in marginal generation costs between both nodes and, therefore, structurally reduces demand in the south. If the welfare-enhancing effect of reducing redispatch costs exceeds the deadweight loss, volume-based network tariffs can increase overall welfare. Whether this is the case depends on the particular demand functions.

Proposition 4.4.1. *If multiple market inefficiencies are present through the pricing scheme and network tariff design, it may not be sufficient to offset only one distortion. Uniform pricing with volume-based network tariffs can outperform a regulatory setting of uniform pricing and fixed network tariffs if the redispatch costs outweigh the deadweight loss of volume-based tariffs. Vice versa, the higher the fixed costs of the network, the more likely it is that regulation with fixed network tariffs is welfare superior.*

We analyze the interactions if both the network tariff design and the pricing scheme are varied between the two settings. To do so, we compare the welfare under uniform pricing and fixed network tariffs with the welfare under zonal pricing and volume-based network tariffs:

$$
\begin{aligned}
&\Delta W^{*}_{UP,f-ZP,\tau} = (4.13) - (4.14) \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z)\,\mathrm{d}z + \int_{c_n}^{c_s+\tau_s^{ZP*}} D_s(z)\,\mathrm{d}z - F - (c_s - c_n)(D_s(c_n) - \overline{L}) \\
&= \int_{c_n}^{c_n+\tau_n^{ZP*}} D_n(z) - D_n(c_n + \tau_n^{ZP*})\,\mathrm{d}z + \int_{c_n}^{c_s+\tau_s^{ZP*}} D_s(z) - D_s(c_s + \tau_s^{ZP*})\,\mathrm{d}z \\
&\quad - (c_s - c_n)D_s(c_n)
\end{aligned}
\tag{4.19}
$$

The result can also be either positive or negative. In this case, the overall effect on welfare depends on whether the deadweight loss from volume-based tariffs, i.e., the inefficiency of the welfare inferior network tariff design, or the redispatch costs under uniform pricing, i.e., the inefficiency of the welfare inferior pricing scheme, predominates.

If the redispatch costs are high enough, they can exceed the deadweight loss from volume-based network tariffs, making zonal pricing with volume-based network tariffs welfare superior. Hence, the higher the inefficiency of redispatch is, the more important the pricing scheme is to manage congestion. Vice versa, if fixed network costs rise, it becomes more likely that the fixed network tariffs become welfare superior as the inefficiency of volume-based network tariffs outweighs the redispatch costs in $W^{*}_{UP,f}$. Using (4.19), we can show that with rising F, the welfare difference between the two network tariff designs increases, i.e. $\partial\Delta W^{*}_{UP,f-ZP,\tau}/\partial F > 0$. From equation (4.9), we can derive that with increasing fixed network costs F, the network tariffs in both nodes increase, too, i.e., $\partial\tau_i^{ZP*}/\partial F > 0\ \forall i$. It is straightforward to show that $\partial\Delta W^{*}_{UP,f-ZP,\tau}/\partial\tau_i^{ZP*} > 0$. Therefore, with volume-based network tariffs, the deadweight loss increases as fixed network costs rise. Thus, from a welfare perspective, the higher the fixed network costs F rise, the more advantageous the application of fixed network tariffs becomes.

For the sake of completeness, the difference between $W^{*}_{ZP,f}$ and $W^{*}_{UP,\tau}$ can be derived from the results above:

$W^{*}_{UP,\tau} < W^{*}_{ZP,\tau} < W^{*}_{ZP,f}$ and thus, $\Delta W^{*}_{ZP,f-UP,\tau} > 0$.

Figure 4.4 summarizes the findings.

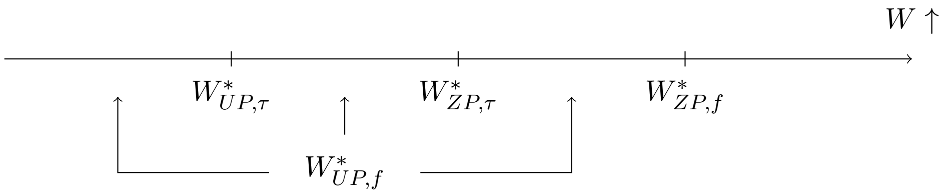


Figure 4.4.: Welfare comparison of the different regulatory settings.

Ranking the regulatory settings in terms of static welfare demonstrates the importance of addressing the interactions between price components. Contrary to the first intuition, there is no clear order regarding the four analyzed settings. Our analysis finds that the distortions of one regulatory element can either amplify or compensate for the distortions of another element. If either the pricing scheme or the network tariff design leads to inefficiencies, it is best addressed by restructuring the respective price component. However, suppose both sources of inefficiency are present. In that case, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of only one aspect can have unintended, welfare-adverse effects. As optimal volume-based network tariffs structurally reduce redispatch costs, it is impossible to ensure that switching to fixed network tariffs increases market efficiency. Due to this compensation effect, the two inefficiencies can perform better than a regulatory setting with only one inefficiency in place. This compensation effect is particularly relevant for the static welfare, the higher the costs for redispatch are.

As section 3 shows, the static welfare of the four regulatory settings interacts with the requirements for dynamic consistency. The interaction can be divided into two main effects. The first interaction occurs in regulatory settings with volume-based tariffs. The TSO reduces static welfare in the regulatory settings with volume-based network tariffs if it is necessary to adjust the optimal (static) network tariffs to ensure dynamic consistency. Under zonal pricing, this adjustment only increases the deadweight loss. Under uniform pricing, this adjustment additionally increases the compensation effect. The redispatch costs decrease as the volume-based network tariffs in the south increase to ensure dynamic consistency. This effect partially makes up for the increase in deadweight loss. However, the overall static welfare still decreases due to the adjustment of the volume-based network tariffs. In contrast, the TSO can adjust fixed network tariffs without impacting the static welfare to ensure dynamic consistency. Hence, the welfare-ranking of the regulatory settings changes if the TSO must adjust the volume-based network tariffs to ensure dynamic consistency. It becomes more likely that the regulatory setting with fixed network tariffs and uniform pricing is welfare superior to the regulatory settings with volume-based network tariffs. Second, the importance of dynamically consistent network tariffs increases with the difference in generation costs, regardless of the network tariff design. Under zonal pricing, misaligned demand-side investments, i.e., investments in the south, would lead to higher generation costs in the future and, therefore, lower consumer surplus. Under uniform pricing, costs for redispatch would increase. To prevent congestion from being further exacerbated in the future, investment decisions should be made dynamically consistent. Thus, there is a bi-directional relationship between dynamic consistency of network tariffs and static welfare that policymakers should account for when changing the regulatory setting.

4.5. Conclusion

The transformation of the energy system from mainly inelastic consumers towards active market participants challenges the principles of network tariff design. If appropriately designed, network tariffs can serve as a coordination mechanism between the network operator and market participants. Otherwise, network tariffs can distort efficient price signals.

In an analytical model, we examine different regulatory settings, consisting of alternative spot market pricing schemes and network tariff designs, while considering a dynamically consistent allocation of demand investments. In our analysis, we assess the interactions of spot market pricing schemes and network tariff designs. The regulatory setting with zonal pricing and fixed network tariffs yields the highest welfare. A deviation of either the pricing scheme or the network tariff design leads to inefficiency. While under uniform pricing, additional costs occur due to redispatch, the application of volume-based network tariffs leads to a deadweight loss at the spot market. If both sources of inefficiency are present, i.e., the combination of uniform pricing and volume-based network tariffs, an adjustment of one single aspect can have unintended effects on overall welfare. As optimal volume-based network tariffs structurally reduce redispatch costs, it is not possible to ensure that market efficiency increases by switching to fixed network tariffs. Besides the network tariff design, network operators must pay additional attention to the allocation of network costs. It affects spatial price signals and, therefore, the dynamic allocation of demand investments. The restrictions on cost allocation are tighter under uniform pricing, as network tariffs are the only spatial price signal. However, under both pricing schemes, the TSO can ensure a dynamically consistent allocation of demand investments with fixed network tariffs without adversely affecting welfare. In contrast, with volume-based tariffs, the case may arise where the TSO must trade off between static welfare and dynamic consistency. The TSO can adjust the volume-based network tariffs deviating from the optimal static network tariffs to ensure dynamic consistency. By doing so, the TSO reduces static welfare in benefit of a dynamically consistent allocation of demand investments.

In current political debates, pricing schemes and network tariffs are often discussed separately. Our results highlight the relevance of jointly assessing network tariffs and pricing schemes for policymakers and regulating authorities. Our results are important, considering that today's electricity systems often use a combination of uniform pricing and mainly volume-based network tariffs. In such a regulatory setting, it seems advisable to identify the predominating inefficiency instead of partly adjusting the regulatory setting. Especially when a change to zonal pricing and fixed network tariffs seems unlikely, regulators could consider the possibility of using volume-based tariffs in favor of their steering possibilities. Our analysis suggests that an integrated regulatory framework is important to avoid unintended distortions.

Moreover, regulators tend to use simplified rules for cost allocation in practice, which are not aligned with spot market prices and typically do not consider dynamic consistency. Spatial price signals become more important in a system under transition as they impact investment decisions. Therefore, these cost allocation rules have an essential impact on static welfare and dynamic consistency, especially in regulatory settings with uniform pricing.

Future research could include other network tariff designs such as general nonlinear tariffs. Those tariffs could improve system efficiency and compensate for the frictions of distorted price components. The analytical model could further be expanded by including concerns on zonal pricing in practice, e.g., market power and illiquid markets. In addition, empirical studies could complement our theoretical findings to distinguish between the ambiguities that we found in our theoretical model and measure the associated welfare loss for the static and dynamic effects.

5. How Prices Guide Investment Decisions under Net Purchasing - An Empirical Analysis on the Impact of Network Tariffs on Residential PV

5.1. Introduction

Solar photovoltaic (PV) is generally expected to have a substantial share in the future electricity generation mix around the globe (IEA, 2020). In Germany, residential PV systems already count for around 1.2 million installations in 2020 (Bundesnetzagentur, 2021b). These PV systems are typically installed by individual households and, thus, distributed decentrally. To limit network expansion and reduce congestion costs, an efficient coordination of these investments is essential. Recent findings suggest that economic factors are among the main drivers for PV adoption in the residential sector (e.g. Jacksohn et al., 2019). In principle, households can use the self-generated PV electricity to either feed it into the grid or replace electricity consumption from the grid. The profitability of these options depends on the regulatory framework. In Germany, a net purchasing system is in place for residential PV installations, which is also the predominant metering scheme in Europe (Gautier et al., 2018). That is, grid feed-in and grid consumption are metered separately and billed at two different prices. The remuneration of grid feed-in is based on the feed-in tariff, which is the main subsidy for residential PV in Germany, granted under the Renewable Energy Sources Act (EEG.). The value of self-consumption depends on the consumption costs, which households can reduce for each kilowatt-hour (kWh) of grid consumption substituted with self-generated PV electricity.

Higher tariffs for grid consumption increase the consumption costs of the household and raise the incentive for self-consumption and residential PV installations. This relationship is unambiguous under net metering, where grid feed-in and grid consumption are billed at the same price (c.f. Gautier and Jacqmin, 2020). Under net purchasing, the same rationale should apply, although the incentive structure also depends on the remuneration for grid feed-in. In particular, the effect should increase the more profitable self-consumption is compared to the revenue from grid feed-in (c.f. Jägemann et al., 2013).

Additionally, tariffs follow a nonlinear pricing schedule. The investment decision should be incentivized only by the volumetric price rather than the fixed price component or an average price calculated from both. Empirical findings suggest that consumers confuse nonlinear price schedules, which contrasts with the theoretical expectation (Ito, 2014). Such an effect would raise concerns regarding the effect of regulatory changes in electricity price components on residential PV installations. In Germany, for example, reform proposals for the network tariff system plan to shift network costs from predominantly volumetric network tariffs to a more substantial share of fixed network tariffs. Other proposals aim for a change in the EEG-levy that is currently paid exclusively on a volumetric basis. Knowing whether and how consumers respond to the different price components is crucial to assess the consequences of such policy reforms on PV adoption.

We empirically investigate whether and how price signals impact the adoption of residential PV installations in Germany. More specifically, we analyze the impact of network tariffs on PV adoption and exploit the fact that network tariffs are a considerable part of retail tariffs and the decisive driver for their regional variation. The heterogeneity of network tariffs allows us to identify the impact of price signals on a high regional resolution. In contrast, the other components of the retail tariff depend on markets and regulations that are equal across Germany. We use a panel data set of PV installations, network tariffs, and socioeconomic covariates on postcode level covering the years of 2009-2017 and apply a Poisson quasi-maximum likelihood estimator (PQMLE) with fixed effects to capture unobserved heterogeneity across regions and time.

We find evidence that network tariffs significantly impact PV investments across Germany. An increase in network tariffs by one within standard deviation (0.34 eurocent per kWh) is estimated to increase PV installations by 2 %, all else equal. This effect has grown, supporting the hypothesis that the incentive for self-consumption has increased over time. Furthermore, it is indeed the volumetric network tariff that impacts PV adoption rather than the average price. Our results provide valuable insights into the driving forces of residential PV adoption in Germany, which allows evaluating upcoming policy reforms regarding the regional allocation of PV installations and the structure of electricity prices.

The paper is organized as follows. Section 5.2 provides an overview of the empirical literature on residential PV adoption. Section 5.3 outlines the policy framework and the economic rationale for investment in residential PV installations in Germany. Section 5.4 introduces the empirical strategy while section 5.5 presents our panel data set. Our results are shown and discussed in section 5.6 and we discuss our findings and conclude in section 5.7.

5.2. Literature review

Our analysis contributes to two streams of the literature: first, the drivers of residential PV expansion, and second, the impact of nonlinear tariff structures on investment decisions in the residential energy sector.

The main drivers for residential PV investments can be classified by socio- and techno-economic factors, behavioral factors, and economic factors.[39] The first and most extensively researched category are socioeconomic factors such as education, per capita income, environmental awareness, and techno-economic factors, such as solar irradiance and specific house characteristics. Schaffer and Brun (2015) conduct a comprehensive analysis on the drivers for adopting residential PV in Germany between 1991 and 2012. They find strong effects for solar irradiance, house density, home-ownership, and per capita income, while the environmental awareness hardly affects PV investments.[40] Subsequent studies, for example, Dharshing (2017), Baginski and Weber (2019), Jacksohn et al. (2019) and Gutsche et al. (2020), generally confirm these findings: environmental awareness has only little explanatory power, while the other socio- and techno-economic factors are important drivers of residential PV adoption in Germany.

Second, behavioral factors, such as myopia, inertia, or peer effects, are also likely to drive PV adoption in the residential sector. For example, regarding peer effects, i.e., the impact of previously installed PV in a surrounding area on the current investment decision of an individual household, findings in the empirical literature are mixed. In their seminal work, Bollinger and Gillingham (2012) examine peer effects on residential PV expansion in the US and find a significant impact. Rode and Weber (2016) conduct a similar analysis for Germany and confirm the impact of imitative adoption behavior. Though Baginski and Weber (2019) also find regional dependencies in their analysis, social imitation does not seem to be the main driver of the regional spillover effects. Similarly, Rode et al. (2020) find that the impact of previously installed PV on current adoption decreases over time and might be mistaken with the regional concentration of craft skills or solar initiatives.

The third category contains literature on the influence of economic factors, i.e., expected costs and revenues of the PV installation.[41] We observe a growing research interest regarding the economic factors due to two simultaneous developments. First, Palm (2020) suggests that in the first stage of the diffusion process, early adopters have fewer concerns for costs or concrete financial benefits. In contrast, in the later stages, the economic factors become more decisive. Hence, the impact of socioeconomic and behavioral factors on PV investments should decrease over time as these factors become less pivotal during the diffusion process of new technologies. Second, in the early years of PV expansion in Germany, a PV installation has been financially attractive mainly due to the feed-in tariffs granted as a subsidy for PV deployment. Ossenbrink (2017), and

[39] Comprehensive reviews on the adoption of building-scale renewable energy systems in European countries can be found in, for example, Heiskanen and Matschoss (2017) and Selvakkumaran and Ahlgren (2019). In this literature review, we mainly focus on analyses for Germany to derive a better understanding of the empirical case for the reader. However, most findings of the literature also apply to other regions.

[40] Balta-Ozkan et al. (2015) find similar factors for the UK.

[41] Intuitively, cost and revenues also depend on techno-economic factors, like irradiance. However, we think of economic factors as monetary metrics.

Germeshausen (2018) analyze the impact of feed-in tariffs in Germany and, in particular, the impact of (changes in) the policy framework on PV adoption. Jacksohn et al. (2019) analyze the impact of the costs of PV panels and revenues from feed-in tariffs in Germany from 2008 to 2015 on the individual household level. They find that these economic factors mainly drive the investment decisions in PV installations and solar thermal facilities. Also in other countries, economic factors impact households' PV investment decisions. As for the case of feed-in tariffs in Germany, governmental pricing policies play a substantial role for the PV adoption in many countries. Best et al. (2019) quantify the impact of Australia's spatially-differentiated small-scale renewable energy scheme on residential PV investments using postcode-level data. Their results indicate that postcodes receiving a higher subsidy factor have significantly more residential PV investments, after controlling for solar exposure and spatial patterns in the data. Similarly, de Groote et al. (2016) find that local policies have a significant impact on PV adoption in Flanders. Focusing on the residential PV adaption in California, e.g., Hughes and Podolefsky (2015), show a significant regional effect of upfront rebates on PV investments, exploiting variation in rebate rates across electric utilities over time. Similarly, Crago and Chernyakhovskiy (2017) show that rebates have the biggest impact among financial incentives on residential PV adoptions in the Northeast. They further indicate positive impacts of electricity prices.[42] With the increasing attraction of self-consumption, the economic rationale of residential PV installations is further influenced by the costs for electricity consumption and, therefore, not only by the feed-in tariff but also by the retail tariff. Klein and Deissenroth (2017) show that the overall German residential PV expansion is impacted by the anticipation of profitability, including both feed-in and retail tariffs in their analysis. Sahari (2019) analyzes the choice of heating systems in Finland. She finds a significant impact of electricity prices on long-term technology choices. Further and closest to our analysis, Gautier and Jacqmin (2020) analyze the impact of volumetric network tariffs on PV investments under a net metering system in Wallonia. They find a positive and significant effect of network tariffs on PV installations. In a similar vein, de Freitas (2020) analyzes PV investments in Brazil. Both regions currently apply net metering systems, where grid feed-in and self-consumption are both valued at the retail tariff. Therefore, higher retail tariffs should encourage higher PV investments. In a net purchasing system, the incentive is two-fold and depends on the remuneration for grid feed-in, which is determined separately (see section 5.3).

Moreover, we extend the analysis of price signals by examining how the non-linear tariff structure influences investment decisions. In his seminal work, Ito (2014) analyzes the price perception of consumers in US electricity markets. His results suggest that consumers are short-sighted in their response to electricity prices by deciding on their electricity bill of the past rather than current tariffs or

[42] See Ossenbrink (2017), for a comparison of the impact of feed-in tariff designs and their interplay with retail electricity prices between Germany and California.

future expectations. Further, Ito (2014) examines the impact of nonlinear multi-tier tariffs on electricity consumption, and Shaffer (2020) conducts a similar analysis for British Colombia. The authors analyze whether consumers respond to nonlinear tariffs in the way microeconomic theory suggests, i.e., whether they respond to the marginal price rather than the fixed or an average price. Both find that consumers respond to average rather than marginal prices, which contrasts with the theoretical expectation. However, a further analysis by Ito and Zhang (2020) for heating usage in China finds that consumers do indeed respond to the marginal price in the context of a simpler tariff form, i.e., a two-part tariff.

To the best of our knowledge, we are the first to empirically analyze the impact of price signals on PV adoption in a net purchasing system. We use the regional variation in network tariffs in Germany to investigate whether and how prices impact PV investments. We examine whether the incentives for self-consumption have become more relevant in recent years and conduct the first empirical study that analyzes how the price components of a nonlinear tariff impact residential PV adoption.

5.3. Residential PV in Germany: policy framework and investment incentives

PV installations enable individual households to generate their own electricity so that they no longer participate in the market only as consumers.[43] To illustrate the economic rationale behind residential PV adoption in Germany, we derive the microeconomic foundation of the investment incentives for an individual household. The regulatory framework in Germany is a net purchasing system. In contrast to a net metering system, where one single price for electricity consumption from the grid (imports) and grid feed-in (exports) exists, these two options are measured separately (c.f. Gautier et al., 2018).

The PV installation offers two options for the household how the self-generated electricity (q_{PV}) can be used:

$$q_{PV} = q_{togrid} + q_{self} \tag{5.1}$$

The household can feed the electricity into the grid (q_{togrid}) or use it for self-consumption (q_{self}), i.e., substitute electricity consumption that is otherwise imported from the grid (d_{total}).[44] We structure the economic incentives by ana-

[43] As households with PV installations both produce and consume electricity, the term prosumer has also been established. Prosumers are of general interest in recent literature, seeking to understand their decision-making and how regulatory policies impact them in more detail, (e.g. Gautier et al., 2018).

[44] To fully reflect the potential temporal discrepancy of PV generation and the household's electricity consumption, an (hourly) time index could be introduced (see e.g. Ossenbrink (2017) for a more detailed representation). However, for simplicity and without loss of generality, we refrain from this issue in the following representation.

lyzing the net present value (NPV)[45] of the PV installation in equation (5.2):

$$NPV = -C_I + \sum_{t=0}^{T} \frac{R(q_{togrid}) - C(d_{total} - q_{self}) - c_{OM}}{(1+r)^t} \tag{5.2}$$

One-time costs occur due to the initial investment C_I. Once the PV system is installed, continuous costs for operation and maintenance c_{OM} incur and the PV installation offers the opportunity to generate revenue by selling electricity to the grid ($R(q_{togrid})$) and to reduce electricity costs by self-consuming electricity from the PV installation ($C(d_{total} - q_{self})$). By assumption, costs and revenues are constant over time, but discounted on a yearly basis t at an interest rate r. We briefly describe the institutional and regulatory framework in Germany and discuss the incentives for PV investments over the years.

5.3.1. Regulatory framework for residential PV in Germany

The grid feed-in of a residential PV installation is regulated under the EEG, and residential PV owners receive a feed-in tariff, paid for each kilowatt-hour (kWh) of electricity fed into the grid. The feed-in tariff varies depending on the date, size, and type (roof-top or ground-mount) of the installation.

Feed-in tariffs are determined administratively by the government, and the level and the categorization are regularly adjusted for new installations. Residential PV installations with 10 kW or smaller have always been eligible to receive the highest possible feed-in tariff. In contrast, larger installations have been subject to some changes in the definition of their support categories over the years. Adjustments of the level of feed-in tariffs are mainly based on the development of PV investment costs which has led to a declining trend over the past years (see figure 5.1). While the feed-in tariff was about 43 ct/kWh in 2009, this has been reduced to about 12 ct/kWh by 2017. In addition to the feed-in tariff, from 2009 until 2012, the EEG granted an additional remuneration for self-consumption. Although this remuneration was lower than the feed-in tariff, e.g., 25 ct/kWh compared to a feed-in tariff of 43 ct/kWh in 2009, households benefited from self-consumption on top of the savings from reduced electricity consumption costs (Bundesnetzagentur, 2021a).

5.3.2. Retail electricity tariffs and the incentive for self-consumption

The value of self-consumption depends on the consumption costs that can be reduced for each kWh of grid consumption substituted with self-generated PV

[45] We focus on the economic rationale in terms of cash flows and do not consider the utility function of the household. One can think of factors that increase the utility beyond the financial aspects, e.g. environmental preferences, and those that have a negative impact, e.g. behavioral biases like inertia or myopia.

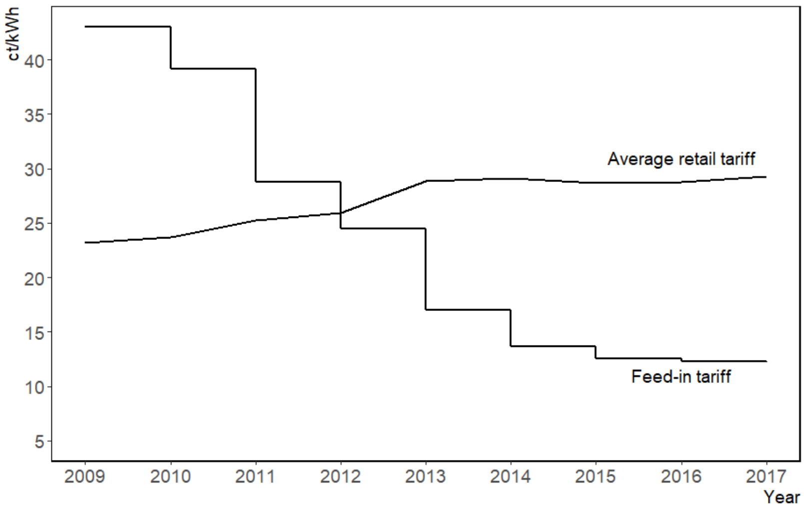


Figure 5.1.: The development of feed-in tariffs for PV installations < 10 kW and average retail tariffs for households in Germany between 2009 and 2017. Own illustration based on data from Bundesnetzagentur (2021a) and BDEW (2021).

electricity. PV owners can profit from self-consumption because the household's electricity bill in Germany mainly depends on the actual consumption. The retail tariff for grid consumption is nonlinear and consists of a volumetric and a fixed price component, i.e., it constitutes a two-part tariff.

The volumetric price per kWh typically predominates, whereas the fixed component, i.e., the basic price for being served and connected to the network, accounts for a smaller proportion of total retail costs. Furthermore, the retail tariff in Germany comprises of three elements: procurement and sales costs of the retailing firm, network tariffs, and administratively determined taxes, charges, and levies. The latter include, for example, the tax on electricity, the EEG-levy, and the concession fee. In 2017, for instance, these three elements split up into 19 % procurement and sales costs, 26 % network tariffs, and 55 % taxes, charges, and levies (BDEW, 2021). Households do not have to pay the volumetric parts of the network tariff and all taxes, charges, and levies for self-consumption.[46] Following the theory on nonlinear pricing, the fixed price component of the retail tariff should not affect the economic rationale to invest in PV installations. These costs always have to be paid unless the household becomes fully independent and, thus, disconnected from the grid. The volumetric tariff describes the opportunity to purchase electricity from the grid and thus, represents the value of self-consumption.

Furthermore, and in contrast to the feed-in tariff that applies equally for all households across Germany, retail prices vary regionally. While wholesale market prices and taxes, charges, and levies are the same across Germany, the network

[46] Though there were changes regarding the EEG-levy for self-consumption in 2012, residential PV installations with 10 kW or less have always been exempted.

tariff is the only cost component that systematically differs on a regional level.[47] In particular for residential consumers connected to the low-voltage network, network tariffs are increasingly diverging.[48] The regional variation of distribution network tariffs in Germany is due to the allocation mechanism, a so-called vertical mechanism, by which network operators allocate the network costs to network users (c.f. Jeddi and Sitzmann, 2019). In Germany, the network costs are refinanced by electricity consumers. The allocation is based on the principle that costs incurred in a particular network area are borne by consumers connected to the respective network. Network operators calculate the network tariffs on an annual basis, based on their individual, regulated revenue cap. In practice, this regulatory procedure means that network costs of the current year are decoupled from this year's network tariffs and rather passed on to the network tariffs in later years.

5.3.3. The economic rationale for investments in PV installations

The profitability of a PV investment hinges on the the value of self-consumption, the feed-in tariff and the interaction of both options. On the one hand, substituting electricity from the grid reduces electricity costs. On the other hand, each kWh used for self-consumption cannot be fed into the grid, i.e., the PV owner does not receive the feed-in tariff. Therefore, it is not only the absolute level of prices and tariffs compared to the PV installation costs that is decisive, but also the relation of the feed-in tariff to the retail electricity price. We apply the regulatory setting in Germany to equation (5.2). The expected revenue consists of the subsidization of grid feed-in via feed-in tariffs (p^{fit}), self-consumption via a reduction of electricity consumption costs valued at the volumetric tariff (p^{retail}), plus, if applicable, the additional subsidy for self-consumption (p^{self}):

$$NPV = -C_I + \sum_{t=0}^{T} \frac{q_{togrid} \cdot p^{fit} - [(d_{total} - q_{self}) \cdot p^{retail} + q_{self} \cdot p^{self} - c_{OM}]}{(1+r)^t} \tag{5.3}$$

Equation (5.3) shows that as soon as the volumetric retail tariff (p^{retail}) rises above the feed-in tariff (p^{fit}), self-consumption becomes financially more profitable compared to grid feed-in.

The feed-in tariff has been continuously decreasing to accommodate the declining costs of PV installations and technological developments. Contrarily, the average retail tariff across Germany has been increasing in most years. Both developments are depicted in figure 5.1 for the period between 2009 and 2017. Since 2012, the average retail tariff is higher than the feed-in tariff by a constantly in-

[47]The concession fee can also vary depending on the network area. However, the magnitude is legally fixed, so that the differences are minor compared to the variation in network tariffs.
[48]See e.g. Hinz et al. (2018) and Schlesewsky and Winter (2018) for further investigations.

creasing margin. Therefore, we expect the investment incentives for residential PV adoption to be increasingly affected by the incentive for self-consumption rather than the feed-in tariff. If this holds, the impact of price signals should have become more relevant since 2012. The abolition of the explicit subsidy for self-consumption in 2012 should have further strengthened the influence of the implicit incentive of the retail tariff.

However, one should keep in mind that self-consumption is attractive only if the household can use the electricity when the sun shines or if a storage opportunity exists. Installation numbers of batteries in households only recently begin to increase as storage is still relatively costly (Figgener et al., 2021). If storage opportunities become economically attractive, the incentive for self-consumption might increase in the upcoming years. Thus, it could become interesting to distinguish between PV systems with and without battery storage.[49]

In principle, the economic incentives of PV adoption apply equally to all households. The feed-in tariff does not vary regionally across Germany, and thus, all else equal, it should have a similar impact on the investment decision. In contrast, network tariffs of the distribution grid vary throughout Germany and over time. Therefore, the implicit investment incentive from self-consumption can differ between regions. As summarized in section 5.3.2, network tariffs are the only price component, which varies substantially between regions, and, therefore, are the main driver for regional retail price variation in Germany. Our empirical strategy takes advantage of this heterogeneity to investigate the impact of price signals on PV investments in Germany.

5.4. Empirical strategy

Our objective is to identify whether network tariffs influence investments in PV installations. Therefore, we set up our analysis on postcode-specific panel data for Germany and exploit the regional variance of network tariffs across Germany. Our dependent variable, the number of new PV installations ($Y_{i,t}$) per postcode (i) and year (t), is a count variable, i.e., it follows a non-negative distribution and can only take on integer values. Given the characteristic of the dependent variable and the panel data structure, we employ a Poisson quasi-maximum likelihood estimator with multiple fixed effects (PQMLE) (c.f. Wooldridge, 2010). The consistency of the estimator neither requires that our dependent variable follows a Poisson distribution nor any additional assumptions concerning the distribution of our dependent variable. As part of the estimation procedure, we calculate robust standard errors. By clustering the standard errors at a regional level, we accommodate for arbitrary correlation across clusters. The choice of

[49] Due to the low number of installed batteries and data availability, we refrain from including batteries in this analysis. Predictive simulations for the development of combined PV and storage systems in Germany can be found, for example, in Kaschub et al. (2016), Fett et al. (2021) and Günther et al. (2021).

the PQMLE approach as our preferred estimation method is in line with recent research by Gautier and Jacqmin (2020) and de Freitas (2020), who apply it in a similar setting.

The formulation of our preferred estimation model is as follows:

$$Y_{i,t} = exp(\beta \cdot tariff_{i,t-1} + \gamma \cdot X_{i,t} + \phi_t + \mu_i + \theta_i \cdot t) \cdot \epsilon_{i,t} \tag{5.4}$$

, where $tariff_{i,t-1}$ is our primary explanatory variable, $X_{i,t}$ is a vector of postcode-specific covariates, ϕ_t are year-specific fixed effects, μ_i are postcode-specific fixed effects and θ_i are postcode-specific time trends. $\epsilon_{i,t}$ is an error term.

In our preferred model specification, we lag our primary explanatory variable by one year. Although fully rational households should form an expectation about future electricity costs, in practice, it may be reasonable to assume that households are rather short-sighted and base their expectation on the currently observed electricity costs (c.f. de Groote and Verboven, 2019, Ito, 2014). In Germany, households pay their electricity bill annually and ex-post, which results in a time lag of one year between the temporal validity of the network tariff and the cost realization. In addition, some time passes between the investment decision and the actual PV installation, e.g., due to administrative reasons. Therefore, we assume that households are more likely to respond to the previous year's tariff than the current one and use the network tariff lagged by one year as our explanatory variable.[50] We check the robustness of our assumption against the current network tariff $tariff_{i,t}$ in Section 5.6 and for tariffs further in the past, i.e., $tariff_{i,t-2}$ and $tariff_{i,t-3}$, in D.2.

An advantageous effect of using the time lag is that it helps us to alleviate the strict exogeneity assumption of our primary explanatory variable. The endogeneity concerns arise because, in recent years, network tariffs increase mainly due to network expansion costs which in turn are due to the integration of renewable energy sources, including residential PV installations (c.f. Just and Wetzel, 2020). However, PV adoption in the current year does not affect the network tariffs of the previous year. Therefore, based on our choice of lagged network tariffs as our explanatory variable and because network tariffs reflect historical network costs, we suggest that reverse causality is not a concern in our setting.

We further include a vector of covariates to control for observable heterogeneity of postcode areas. This vector contains the average income and age of the population, the share of detached and semi-detached houses in the building stock, and the number of residential buildings.

[50] Our assumption is supported, for example, by an empirical analysis regarding electricity consumption behavior by Bushnell and Mansur (2005), who find that households respond more strongly to recent past electricity bills than to new retail tariff price information, even when the new tariff has already been announced. Also, Gautier and Jacqmin (2020) find the assumption of using a lagged network tariff to be justified in their analysis on the effect of network tariffs on PV installations under a net metering scheme in Wallonia.

The fixed effects approach takes advantage of the panel data structure of our data and allows us to control for unobserved heterogeneity. By applying multiple fixed effects, we can isolate and identify the impact of our primary explanatory variable on the dependent variable based on the within-postcode variance in our data. A random effects model would not be consistent as we expect a correlation between the individual effects and the independent variables.[51] By including year-specific fixed effects, we control for overall developments over time. Examples are declining prices for solar modules, overall trends in electricity demand[52] or national policy changes, in particular changes in feed-in tariffs. Another aspect covered by these effects is the development of retail price components that do not vary across Germany, such as the EEG-levy or wholesale electricity prices. Postcode-specific fixed effects account for factors that regionally differ between postcode areas but are constant over time, e.g., socioeconomic aspects and solar irradiance.[53] Postcode-specific time trends control for any linear postcode-specific development over time that is not addressed by the nationwide year-specific fixed effects. Examples of such trends include local demographic change or local economic growth.

In addition to the PQMLE, other commonly used models in count data applications are, for example, negative binomial regression models or OLS models with a logarithmized dependent variable. We include these models as robustness checks for our main findings.

To analyze the effect of the nonlinear pricing schedule, we apply the encompassing approach by Davidson and MacKinnon (1993), which can be used to identify a preferable model specification for non-nested models. We specify the encompassing model as an augmented model of (5.4) and include both alternative explanatory variables, i.e., the volumetric tariff ($tariff_{i,t-1}$) and the average tariff ($\varnothing\text{-}tariff_{i,t-1}$):

$$Y_{i,t} = exp(\beta \cdot tariff_{i,t-1} + \delta \cdot \varnothing\text{-}tariff_{i,t-1} + \gamma \cdot X_{i,t} + \phi_t + \mu_i + \theta_i \cdot t) \cdot \epsilon_{i,t} \quad (5.5)$$

We want to test our hypothesis that the volumetric tariff impacts PV investments rather than the average tariff. Hence, we expect that as long as the model accounts for the volumetric tariff, the coefficient of the average tariff δ is statis-

[51] A Hausman test rejects the null hypothesis that there is no significant correlation at the significance level of 1 %, which supports the choice of a fixed effects approach.

[52] In Germany, the overall electricity demand has decreased over the past years, which is covered by the year-specific fixed effects. If spatial heterogeneity in demand exists, this is covered by the postcode-specific fixed effects. We do not expect substantial variation in both dimensions, as we see no indication that energy efficiency gains should vary significantly across regions over time.

[53] Generally, solar irradiance is a decisive variable influencing residential PV investments. However, we assume that households do not account for the (relatively small) solar irradiance variation over time. Instead, we expect that households consider it as a spatial component, such as whether one lives in a generally sunnier region. Therefore, we do not include solar irradiance as a covariate in our model, as it is reflected in the postcode-specific fixed effects.

tically insignificant, i.e., not influencing the number of PV installations, and we can check this hypothesis with a standard F-test (c.f. Greene, 2003).

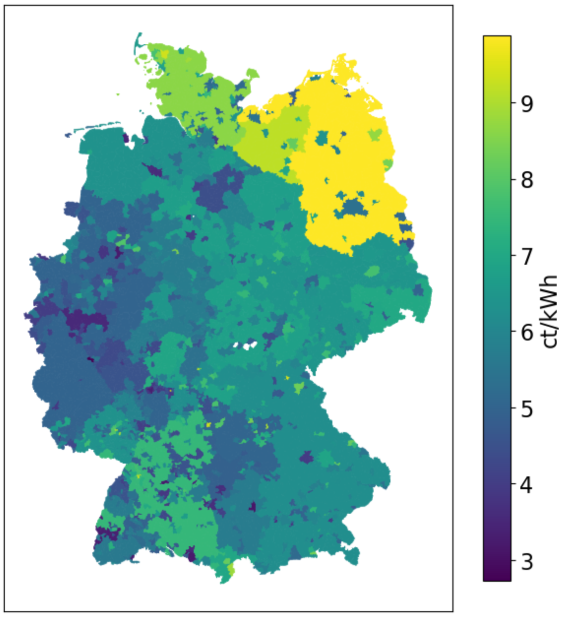
5.5. Data

For our analysis, we use a unique panel data set at the German postcode level. The panel data set covers 8,148 postcodes (PLZ) for 2009-2017, a total of 72,672 observations. For our dependent variable we rely on data from the Marktstammdatenregister (MaStR) (Bundesnetzagentur, 2021b). For each unit, the MaStR documents the energy carrier, the installed capacity, the postcode, the installation date, and various additional information. In this paper, we focus on PV installations with a size up to 10 kW as this is the typical size installed on residential buildings. Our data consists of 708,555 PV installations commissioned between 2009 and 2017. By aggregating the number of new PV installations per year and postcode, we receive our dependent variable (*# of PV*).

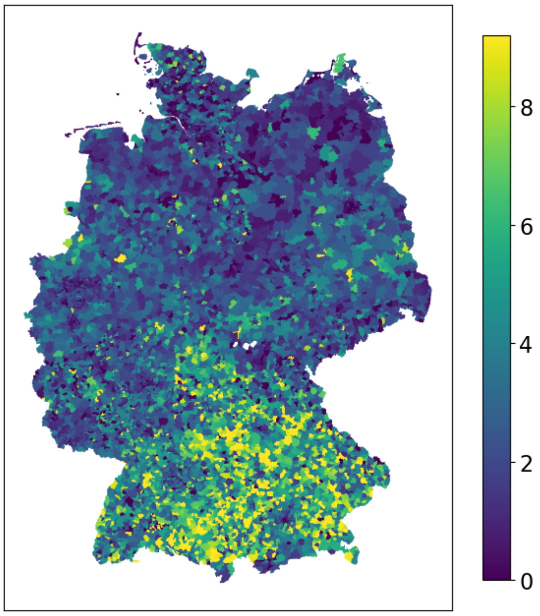
Furthermore, we use detailed data on annual network tariffs on postcode level from ene't, a German data provider for the electricity industry (ene't, 2021). The data contains information on the annual fixed component of network tariffs (*fixed_tariff*, in Euro/year) and the volumetric component (*tariff*, in ct/kWh). For our investigation of price perception, we use both components to calculate an average tariff (*∅-tariff* in ct/kWh) by assuming a reference load profile of 3,500 kWh annual consumption. Figure 5.2 illustrates the regional distribution of the volumetric network tariff and the number of PV installations per 1000 residential buildings for the year 2017. The maps show regional heterogeneity for both variables. The volumetric tariffs are highest in north-east and south-west Germany, driven by the high wind penetration, especially in the north. PV installations per 1000 buildings concentrate in the southern regions, which is in line with the general expectations, as these regions show the highest solar irradiance. Note that the fixed effects of our estimation approach capture this persistent difference between regions. The spatial heterogeneity of the variables differs over time, shown in further illustrations of the temporal variation of our data in D.1.

To analyze whether network tariffs had a greater impact on the number of PV installations after 2012, we define two binary dummy variables: One that takes on the value 1 for all years before 2012 ($d_{<2012}$), and one that takes on the value 1 otherwise ($d_{\geq 2012}$).

We further control for the heterogeneity of postcode areas by including socioeconomic drivers of PV expansion that have been identified in the literature described in section 5.2. We use yearly and postcode-specific data for these socioeconomic covariates from RWI-GEO-GRID, a data set from the Leibniz Institute for Economic Research (RWI) (RWI and Microm, 2020). First, we consider the average purchasing power of households per capita (*income*, in Euro/year).



(a)



(b)

Figure 5.2.: Regional resolution of (a) the volumetric network tariff and (b) # of PV per 1000 residential buildings, both for the year 2017.

Table 5.1.: Descriptive statistics, 2009-2017 (N = 73,329)

Variable	Mean	Median	SD	Min	Max	Source
Dependent variable						
# of PV	9.66	6	11.57	0	184	MaStR
Independent variables						
tariff (ct/kWh)	5.29	5.08	1.04	2.38	9.90	ene't
fixed_tariff (Euro/year)	21.56	18.00	17.72	0	95.00	ene't
∅-tariff (ct/kWh)	5.90	5.65	1.24	2.67	11.55	ene't
income (log of)	9.95	9.95	0.19	9.30	11.01	RWI
housetype (% of 1- and 2-family homes)	58.32	63.64	20.69	0.30	100	RWI
age	43.74	43.58	2.35	35.11	58.48	RWI
buildings (log of)	7.40	7.46	0.92	0.69	9.80	RWI

We expect a positive impact of the purchasing power of households on PV expansion as the investment costs of the installation are more likely to be afforded by more affluent people. The variable *age* denotes the average age of inhabitants in a specific postcode area. One would assume that a younger population is more aware of the possibility to invest in PV, thus leading to a negative influence of average age on our dependent variable. For the number of residential buildings (*buildings*), which is closely correlated with the number of inhabitants, we would expect a positive effect on our dependent variable as more buildings in a postcode mean more opportunities for PV investments. Further, we include the share of detached and semi-detached houses in the building stock (*housetype*, in %). Detached and semi-detached houses are well suited for residential PV installations, for example, due to the unity of electricity consumer and investor. Therefore, we would expect a positive impact of the housetype on our dependent variable. Another factor that could have an influence on PV investments but is not included in our analysis is environmental awareness. Election results, i.e. the proportion of green voters, are usually taken into account as a measure of environmental awareness. There is no continuous annual data for this, so the approach conflicts with the panel-based fixed-effects approach of our model. Moreover, the existing literature shows that environmental awareness has little to no effect on PV investment (see Chapter 5.2).

5.6. Results

We estimate the impact of network tariffs on residential PV installations in Germany within our preferred model specification, described in section 5.4. Further, we analyze whether the incentives for self-consumption have become more relevant in recent years compared to the early years of PV adoption and how the nonlinear pricing schedule affects PV adoption. Using additional model specifications, we also check the robustness of our results.

We present our main results regarding the impact of network tariffs on PV adoption in table 5.2. Regression (1) shows our preferred model specification (c.f. equation 5.4), which estimates the impact of lagged network tariffs on the number of new PV installations, controlling for socioeconomic covariates. Our estimation suggests that network tariffs have a positive and significant impact on the number of PV installations. All else equal, an increase of one within standard deviation (0.34 eurocent per kWh) in network tariffs is estimated to increase the number of PV installations by 2 %.[54] The magnitude of this effect is in line with the findings of Gautier and Jacqmin (2020) for PV investments in Wallonia. The results further confirm the findings of Frondel et al. (2019), who show that households in Germany are aware of yearly price variations and change their electricity consumption respectively. Furthermore, the impact of the other covariates in our model is not statistically different from zero. The fixed effects absorb their impact due to their relatively low within-variance, which is depicted in D.3.

We further examine whether the incentives for self-consumption have become more relevant in recent years compared to the early years of PV adoption. Therefore, we analyze how the change in the economics of PV investments from 2012 onward has affected the impact of network tariffs on PV installations in Germany (c.f. section 5.3). We include an interaction term between our binary dummy variables ($d_{<2012}$ and $d_{\geq 2012}$) and the network tariff in regression (2). This estimation allows us to compare the effect of network tariffs before and after 2012. The results suggest that network tariffs did not significantly impact PV adoption before 2012, while they do afterward. We estimate that, since 2012, an increase in network tariffs of one standard deviation (0.34 eurocent per kWh) increases PV installations by 2.4 %. A Chow test confirms the difference between the estimates of the two time-subsets, revealing significance at the 1 % level. Hence, we can confirm our hypothesis that self-consumption has gained importance since 2012 when rising retail tariffs started to exceed declining feed-in tariffs.

We further examine how the different price components of nonlinear tariffs impact PV installations. We make use of the volumetric and the fixed component of network tariffs and test the theoretical expectation that PV adoption should only be affected by the volumetric tariffs. In a first step, we estimate the impact of average instead of the volumetric tariffs in regression (3). This

[54] Within standard deviation refers to the variation of the network tariffs that is not accounted for by the applied fixed effects. The model results show an increase by 5.8 % for one cent per kWh increase in network tariffs. However, we cannot make reliable statements about the effect of a shift of that magnitude, because the within standard deviation of network tariffs in the model is significantly lower than one cent per kWh. We include a more detailed discussion in D.3.

Table 5.2.: Main results

Model:	(1)	(2)	(3)	(4)
Dependent Variable:	# of PV	# of PV	# of PV	# of PV
tariff_{t-1}	0.0578***			0.0914***
	(0.0061)			(0.0208)
$\text{d}_{<2012} \times \text{tariff}_{t-1}$		0.0112		
		(0.0083)		
$\text{d}_{\geq 2012} \times \text{tariff}_{t-1}$		0.0707***		
		(0.0064)		
$\varnothing\text{-tariff}_{t-1}$			0.0577***	-0.0386*
			(0.0066)	(0.0224)
income (log of)	-0.0334	0.0230	-0.0374	-0.0332
	(0.1497)	(0.1488)	(0.1502)	(0.1495)
housetype	0.0041	0.0050	0.0037	0.0042
	(0.0042)	(0.0042)	(0.0042)	(0.0042)
age	0.0168	0.0184	0.0160	0.0171
	(0.0136)	(0.0136)	(0.0137)	(0.0136)
buildings (log of)	-0.1225	-0.1363	-0.0988	-0.1287
	(0.1688)	(0.1688)	(0.1687)	(0.1689)
Fit statistics				
observations	64,531	64,531	64,531	64,531
AIC	330,230	330,094	330,271	330,225
BIC	476,772	476,644	476,812	476,776
Log-Likelihood	-148,967	-148,898	-148,987	-148,963

Robust standard errors clustered at the postcode level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

estimation yields similar results compared to our preferred model specification with the volumetric tariffs in regression (1). In a second step, we jointly test the two alternatives in the encompassing model (c.f. equation 5.5). In regression (4), we include both the volumetric ($tariff_{t-1}$) and the average tariff ($\varnothing$-$tariff_{t-1}$). The coefficient of the volumetric tariff is still positive and statistically significant, while the average tariff does not have a statistically significant impact on the number of PV installations. Thus, the encompassing test confirms the theoretical expectation that volumetric tariffs drive PV investments. The results indicate that consumers differentiate between the price components of the two-part tariff, which contributes to the empirical evidence on consumers' perception of nonlinear pricing. Consumers may understand the taxonomy of the two-part tariff and base their investment decision on the volumetric rather than an average tariff. However, given the aggregate nature of our data, this finding should be complemented by further analysis of microeconomic data.

In table 5.3, we provide several robustness checks regarding our model specification and our estimation strategy. In regression (5), we check our assumption that PV adoption is impacted by the lagged network tariff rather than the contemporary one by using the contemporary tariff ($tariff_t$) as our explanatory variable instead of the lagged network tariff ($tariff_{t-1}$). The results indicate a positive effect of the current network tariff on PV adoption. However, the coefficient is smaller compared to the impact of the lagged network tariff in regression (1). Moreover, in regression (5), the values of the two information criteria, AIC and BIC, increase while the value of the log-likelihood decreases compared to regression (1), implying that the explanatory power of our preferred model specification is higher. This finding supports our assumption that households respond to their electricity bill rather than current tariffs and, thus, may have a rather short-sighted perception of prices.[55]

We aggregate our data to the next higher regional level (NUTS-3) in regression (6) to check whether our results remain valid at a higher regional aggregation. The estimation suggests that, even under a higher regional aggregation, network tariffs positively and significantly impact PV investments, supporting the results derived from postcode-level data.[56] In regression (7), we estimate our preferred model specification without the postcode-specific time trends. We observe that the positive and significant impact of network tariffs persists. Further, as expected, income has a significantly positive and age a significantly negative impact on the number of new PV installations. Hence, in our preferred model specification, the postcode-specific time trends do indeed capture the assumed postcode-specific demographic change and local economic growth.

To further check the robustness of our results, we apply alternative estimation strategies to determine the impact of network tariffs on the number of PV installations. First, regression (8) assumes a linear relationship, using an OLS regression. To accommodate for the non-negative nature of our count data, we take the log of the dependent variable to which we add one unit due to the presence of zero outcomes. Second, we estimate a negative binomial regression (9). Negative binomial regressions make stronger assumptions regarding the distribution of the dependent variable, which do not fully hold for our data. However, the results can provide a robustness check. Overall, both results confirm the finding of our preferred model specification, that higher network tariffs lead to more PV installations.

Finally, we perform another robustness check of our hypothesis by replacing the dependent variable with a sample of PV systems that should not be affected by network tariffs. Regression (10) shows the results of such a placebo test. The dependent variable is defined as the number of PV installations larger than 300 kW. PV systems with this size can be assumed to be commercial systems, i.e., installed on non-residential buildings or ground-mounted. Al-

[55] An additional robustness check on tariffs further in the past can be found in D.2.

[56] In D.2 we further analyze whether the impact of network tariffs may differ between regions and include a regression on state-specific effects of network tariffs on PV investments.

Table 5.3.: Robustness checks

Model: Dependent Variable:	(5) # of PV	(6) # of PV	(7) # of PV	(8) log(# of PV+1)	(9) # of PV	(10) # of PV >300 kW
tariff_t	0.0351***					
	(0.0056)					
tariff_{t-1}		0.0725***	0.0540***	0.0478***	0.0550***	-0.0468
		(0.0153)	(0.0047)	(0.0056)	(0.0045)	(0.0520)
income	-0.1770	-1.320**	0.6786***	-0.0810	0.7198***	0.6676
(log of)	(0.1468)	(0.5806)	(0.1241)	(0.1462)	(0.1140)	(1.2350)
housetype	0.0152***	0.0286**	0.0017	0.0051	0.0027	-0.0690 *
	(0.0038)	(0.0144)	(0.0030)	(0.0036)	(0.0028)	(0.0342)
age	-0.0043	0.0547	-0.0997***	0.0153	-0.1025***	0.2476*
	(0.0131)	(0.0571)	(0.0076)	(0.0116)	(0.0070)	(0.1202)
buildings	-0.1371	-0.5982	0.1874	0.0796	0.2362*	-0.8075
(log of)	(0.1543)	(0.5511)	(0.1379)	(0.1386)	(0.1285)	(1.3720)
Fixed effects						
PLZ	Yes+slope		Yes	Yes+slope	Yes	Yes+slope
year	Yes	Yes	Yes	Yes	Yes	Yes
NUTS-3		Yes+slope				
Distribution	PQMLE	PQMLE	PQMLE	OLS	Neg.Bin.	PQMLE
Fit statistics						
observations	72,672	3,192	64,531	65,179	64,531	27,595
AIC	375,142	32,949	338,674	91,389	330,167	42,126
BIC	523,758	37,864	411,999	239,563	403,492	98,980
Log-Likelihood	-171,406	-15,664	-161,257	-29,384	-157,003	-14,151

Robust standard errors clustered at the regional level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

though non-residential network users are also required to pay network tariffs, self-consumption should generally not be the driving factor for PV investments in these cases. Rather, investment decisions should be motivated by potential revenues from the sale of electricity. Therefore, we expect network tariffs not to affect investment decisions for PV installations larger than 300 kW. The regression results confirm this hypothesis, as they do not show a significant impact of network tariffs on PV installations larger than 300 kW.

5.7. Conclusion

Within a net purchasing system, investment incentives for residential PV arise from feed-in tariffs and the value of self-consumption. With the latter becoming the dominant economic driver, network tariffs, which constitute a substantial part of the consumption costs, are expected to gain importance. By exploiting the regional heterogeneity of network tariffs, we investigate whether network tariffs encourage to invest in PV systems using a unique panel data set at the German postcode level over the period 2009-2017. We further evaluate how the nonlinear tariff structure impacts residential PV adoption.

We use a Poisson quasi-maximum likelihood estimator with conditional fixed effects and provide additional robustness checks for various distributional assumptions and the regional aggregation level. All else equal, an increase in network tariffs by one standard deviation (0.34 eurocent per kWh) is estimated to increase PV installations by 2 %. Thus, our results indicate that network tariffs impact PV adoption across Germany. We find evidence that the impact of network tariffs has increased over time, supporting our expectation that the economic incentives for self-consumption have become more important in recent years. Furthermore, our analysis of the different price components indicates that the volumetric network tariff drives PV adoption rather than the average price.

For policymakers, our results provide essential insights for upcoming reforms of electricity price components. Our results suggest that households do react to price signals and that prices effectively guide investments. The current incentive for self-consumption is a side effect of the retail tariff design in Germany. Due to taxes, levies and the network tariff design, retail tariffs contain various price components that are not necessarily aligned and, thus, may distort the investment decision of the household in a way that is economically inefficient. If the retail tariff is higher than economically efficient, the incentives for PV investments are distorted. For instance, a feedback effect, as discussed in Jägemann et al. (2013), arises when rising retail tariffs lead to rising residential PV expansion and rising PV expansion, in turn, leads to increasing retail tariffs. Therefore, from an economic point of view, it is essential to create price signals in the least distorting way. In Germany, reform proposals are currently considered for the network tariff system and include a shift from predominantly volumetric network tariffs to a more substantial fixed network tariff. Other proposals aim for a change in the EEG-levy that is currently paid exclusively on a volumetric basis. Consequently, these reforms influence not only household consumption behavior but also investment incentives for PV installations.

The regional variation of price signals may explain at least part of the present heterogeneity of PV installations in Germany. However, as we use fixed effects to control for unobserved heterogeneity between regions, our analysis is limited in this regard. Further analyses could examine the impact of economic factors on the regional heterogeneity across Germany in more detail. Furthermore, declining costs for storage technologies, such as batteries, will further strengthen the case for self-consumption in the residential sector. Therefore, future empirical research could investigate the incentives that drive households to invest in combined PV and storage systems. In a similar vein and in the light of currently increasing adoption rates of electric vehicles and electric heating systems in the residential sector, future empirical analyses could shed light on the impact of price signals on these technologies. Finally, our analysis focuses on the influence of price signals on the initial decision to invest in a PV installation. Another promising field would be to supplement our results with empirical studies on consumption profiles to provide insights into the short-term price sensitivity of households with PV installations.

A. Supplementary Material for Chapter 2

A.1. Notation

Throughout the paper at hand, the notation presented in table A.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table A.1.: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m, n \in M$		Markets
$l \in L$		Transmission Grid Lines
$c \in C$		Linear independent cycles of modeled grid
$y, y1 \in Y$		Years
$d \in D$		Representative Days
$h \in H$		Hours
Parameters		
$demand(y, d, h, m)$	[MWh]	Electricity demand
$avail(y, d, h, m, i)$	[-]	Availability of technology
$eff(i, m)$	[-]	Efficiency of technology
$linecap(y, m, n)$	[MW]	Available transmission capacity
$\beta(y)$	[-]	Discount factor
$\delta(y, i)$	[EUR/MW]	Annualized investment cost
$\sigma(i)$	[EUR/MW]	Fixed operation and maintenance cost
$\gamma(y, i)$	[EUR/MWh]	Variable generation cost
$cap_{add,min}(y, m, i)$	[MW]	Capacities under construction
$cap_{sub,min}(y, m, i)$	[MW]	Decommissioning of capacity due to lifetime or policy bans
$l(m, n)$	[-]	Relative transmission Losses
$\kappa(m, l)$	[-]	Incidence matrix
$\phi(l, c)$	[-]	Cycle matrix
Variables		
$CAP(y, m, i)$	[MW]	Electricity generation capacity
$GEN(y, d, h, m, i)$	[MWh]	Electricity generation
$CAP_{add}(y, m, i)$	[MW]	Investments in electricity generation capacity
$CAP_{sub}(y, m, i)$	[MW]	Decommissioning of electricity generation capacity
$TRADE(y, d, h, m, n)$	[MWh]	Electricity trade from m to n
$TRADE\_BAL(y, d, h, m)$	[MWh]	Net trade balance of m
$FLOW(y, d, h, l)$	[MWh]	Power flow along line l
TC	[EUR]	Total costs
$FC(y)$ / $VC(y)$	[EUR]	Yearly fixed or variable costs

A.2. Power market model

Basic model

The central planner invests into new power plants and dispatches generation capacities such that the net present value of the variable (VC) and fixed costs (FC) is minimized, where β represents the discount factor.

The objective is hence:

$$min!\ TC = \sum_{y \in Y} \beta(y) \cdot [VC(y) + FC(y)]. \tag{A.1}$$

Installed electricity generation capacities (CAP) are modeled endogenously: The model invests in new generation capacities (CAP_{add}) and decommissions capacities (CAP_{sub}), which are not profitable. For a realistic depiction of European energy markets, existing as well as under construction capacities ($cap_{add,min}$) and decommissioning due to end-of-lifetime or technology bans ($cap_{sub,min}$) are given exogenously. These parameters serve as lower bounds for building or decommissioning capacities, respectively. The fixed costs per year comprise the annualized investment costs (δ) plus fixed operation and maintenance costs (σ) per installed capacity. The following equations describe these interrelations.

$$CAP(y,m,i) = CAP(y-1,m,i) + CAP_{add}(y,m,i) - CAP_{sub}(y,m,i) \tag{A.2}$$

$$CAP_{add}(y,m,i) \geq cap_{add,min}(y,m,i) \tag{A.3}$$

$$CAP_{sub}(y,m,i) \geq cap_{sub,min}(y,m,i) \tag{A.4}$$

$$FC(y) = \sum_{m \in M, i \in I} CAP(y,m,i) \cdot \sigma(i) + \sum_{\substack{y1: y-y1 \\ < econ\_lifetime(i)}} CAP_{add}(y1,m,i) \cdot \delta(y,i)$$
$$\forall y \in Y, \forall m \in M, \forall i \in I \tag{A.5}$$

Electricity generation (GEN) in each market, day (d) and hour (h) has to level the (inelastic) *demand* minus the trade balance ($TRADE\_BAL$), which depicts the net imports of trade flows ($TRADE$) from other markets. Availability of power plants ($avail \cdot CAP$), which, e.g., considers maintenance shutdowns limit their generation. Trade flows between markets are limited by interconnection capacities (*linecap*). Yearly total variable costs (VC) result from the generation per technology times the technology-specific variable operation costs (γ), which mainly comprise costs for burnt fuel and required CO_2 allowances.

$$\sum_{i \in I} GEN(y,d,h,m,i) = demand(y,d,h,m) - TRADE\_BAL(y,d,h,m) \tag{A.6}$$

$$GEN(y,d,h,m,i) \leq avail(y,d,h,i) \cdot CAP(y,m,i) \tag{A.7}$$

$$\begin{aligned} TRADE\_BAL(y,d,h,m) = \sum_{n} &(1 - l(n,m)) \cdot TRADE(y,d,h,n,m) \\ &- TRADE(y,d,h,m,n) \end{aligned} \tag{A.8}$$

$$TRADE(y,d,h,m,n) \leq linecap(y,m,n) \tag{A.9}$$

$$\forall y \in Y, \forall m,n \in M \;\; \& \;\; m \neq n, \forall i \in I$$

$$VC(y) = \sum_{\substack{m \in M, i \in I, \\ d \in D, h \in H}} GEN(y,d,h,m,i) \cdot \gamma(y,i) \tag{A.10}$$

Storage equations

The charging level of storage ($STORLEVEL$) is determined by the level in the previous time step and the net-balance of electricity charged and withdrawn. The level cannot exceed the storage volume which is given by the installed capacity and an exogenous ratio of capacity and volume (vol_factor).

$$\begin{aligned} STOR\_LEVEL(y,d,h,m,i) &= STOR\_LEVEL(y,t-1,m,i) \\ &- eff(m,i) \cdot GEN(y,d,h,m,i) + eff(i,m) \cdot GEN(y,d,h,i,m) \end{aligned} \tag{A.11}$$

$$STOR\_LEVEL(y,d,h,m,i) \leq STOR\_VOL \tag{A.12}$$

$$STOR\_VOL = avail(y,d,h,i) \cdot vol\_factor(i) \cdot CAP(y,m,i) \tag{A.13}$$

$$\forall y \in Y, \forall d \in D, h \in H, \forall m \in M, \forall i \in I_{Storage}$$

The amount of energy which can be shifted between typedays (DAY_SALDO) is limited according to the number of days that a typeday represents (d_rep). The total of the energy shifted by storage must add up to zero.

$$DAY\_SALDO(y,d,m,i) = \sum_{h \in H} (GEN(y,d,h,i,m) - GEN(y,d,h,m,i)) \tag{A.14}$$

$$DAY\_SALDO(y,d,m,i) \cdot d\_rep(d) \leq STOR\_VOL(y,m,i) \tag{A.15}$$

$$DAY\_SALDO(y,d,m,i) \cdot d\_rep(t) \geq -STOR\_VOL(y,m,i) \tag{A.16}$$

$$\sum_{d \in D} DAY\_SALDO(y,d,m,i) = 0 \tag{A.17}$$

$$\forall y \in Y, \forall d \in D, \forall m \in M, \forall i \in I_{Storage}$$

A.3. Assumptions on technologies, demand and fuel prices

Table A.2.: Considered technologies and their generation efficiency, assumptions based on scenario *Stated Policies* in World Energy Outlook 2021 (IEA, 2021) and Knaut et al. (2016)

Technologies	Efficiency
Nuclear	0.33
Lignite	0.4
Coal	0.45
Combined Cycle Gas Turbines (CCGT)	0.5
Open Cycle Gas Turbines (OCGT)	0.38
Oil	0.4
Biomass	0.3
PV	1
Wind Onshore	1
Wind Offshore	1
Hydro	1
Pumped Storage	0.78
Battery Storage	0.95

Table A.3.: Development of fuel and carbon prices [EUR/MWh_{th}], based on scenario *Net Zero Emissions* in World Energy Outlook 2022 (IEA, 2022)

Fuel	2019	2030
Uranium	3.0	3.0
Lignite	3.9	4.0
Coal	7.9	7.7
Natural Gas	13.6	25.9
Oil	33.1	44.9
Biomass	21.0	23.0
Carbon [EUR/tCO2]	24.9	95.0

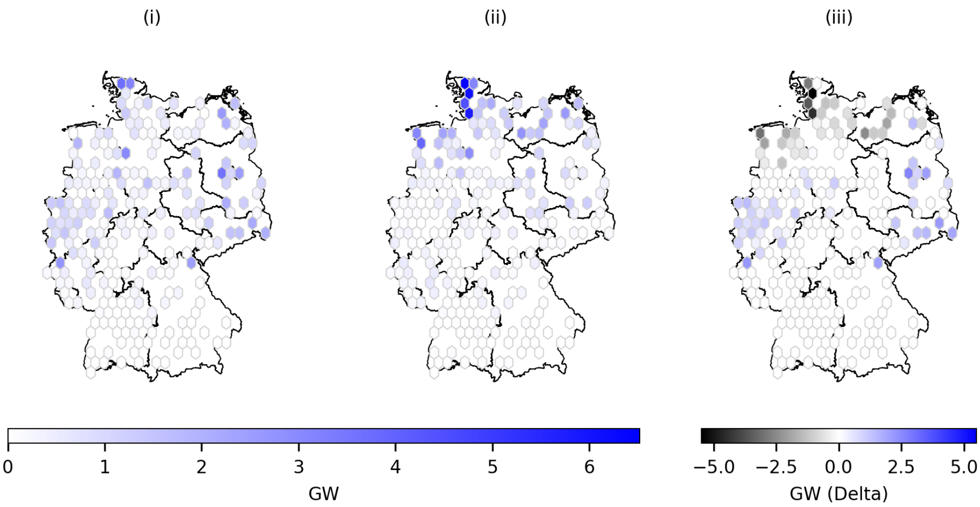
Table A.4.: Development of demand [TWh], for Germany based on Bundesministerium für Wirtschaft und Klimaschutz (BMWK) (2022) and for all other countries on scenario *National Trends* in ENTSO-E (2020a)

Country	2019	2025	2030
AT	67	77	79
BE	85	87	91
CH	62	62	61
CZ	63	73	78
DE	524	600	715
DK	35	52	46
FR	456	496	486
NL	114	114	119
PL	156	181	182

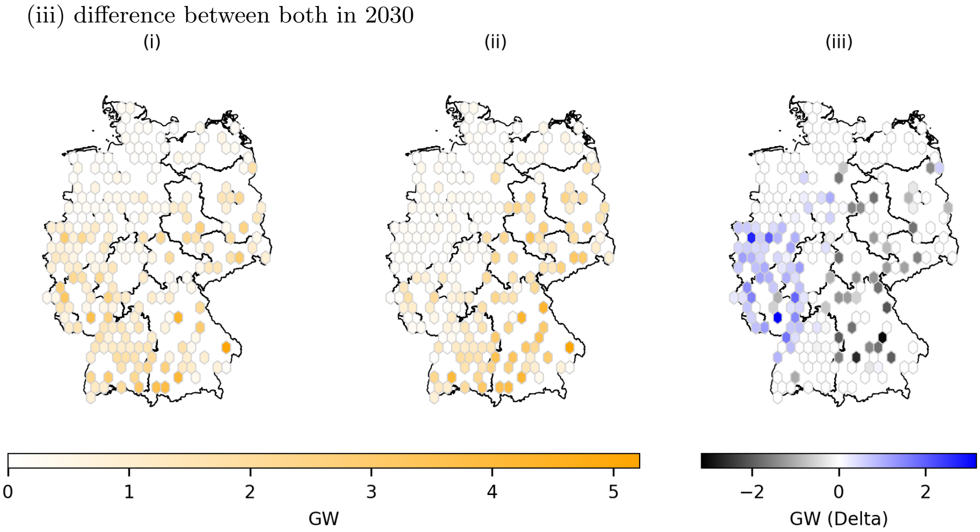
A.4. Additional results and sensitivity analyses

Renewable allocation

Solar and wind power allocation is primarily driven by the consideration of transmission capacity. In the nodal setting, grid constraints are considered when siting new capacity. However, in the uniform case, investment decisions depend mainly on resource quality and, to a lesser extent, on feed-in patterns and resulting balancing effects. As a result, wind and solar capacity are distributed more broadly and closer to demand under the nodal setup. At the same time, it is concentrated at sites with high resource quality in the uniform setting. Figures A.1a and A.1b compare the spatial distribution of wind and solar capacity in both cases. Total capacity is exogenous for both settings and reflects Germany's 2030 capacity targets.



(a) Spatial distribution of wind capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030



(b) Spatial distribution of solar capacity expansion in the (i) nodal and (ii) uniform setting and (iii) difference between both in 2030

Figure A.1.: Spatial distribution of wind and solar capacity expansion in the nodal and uniform setting

In the nodal setting, wind capacity peaks in the very north of the country, where resource quality is high. The rest of the capacity is widely distributed above the 50th parallel. Solar capacity is relatively evenly distributed below the 52nd parallel, despite higher resource quality in the south of Germany. All in all, significant shares of wind and solar capacities are allocated close to the demand centers in western Germany.

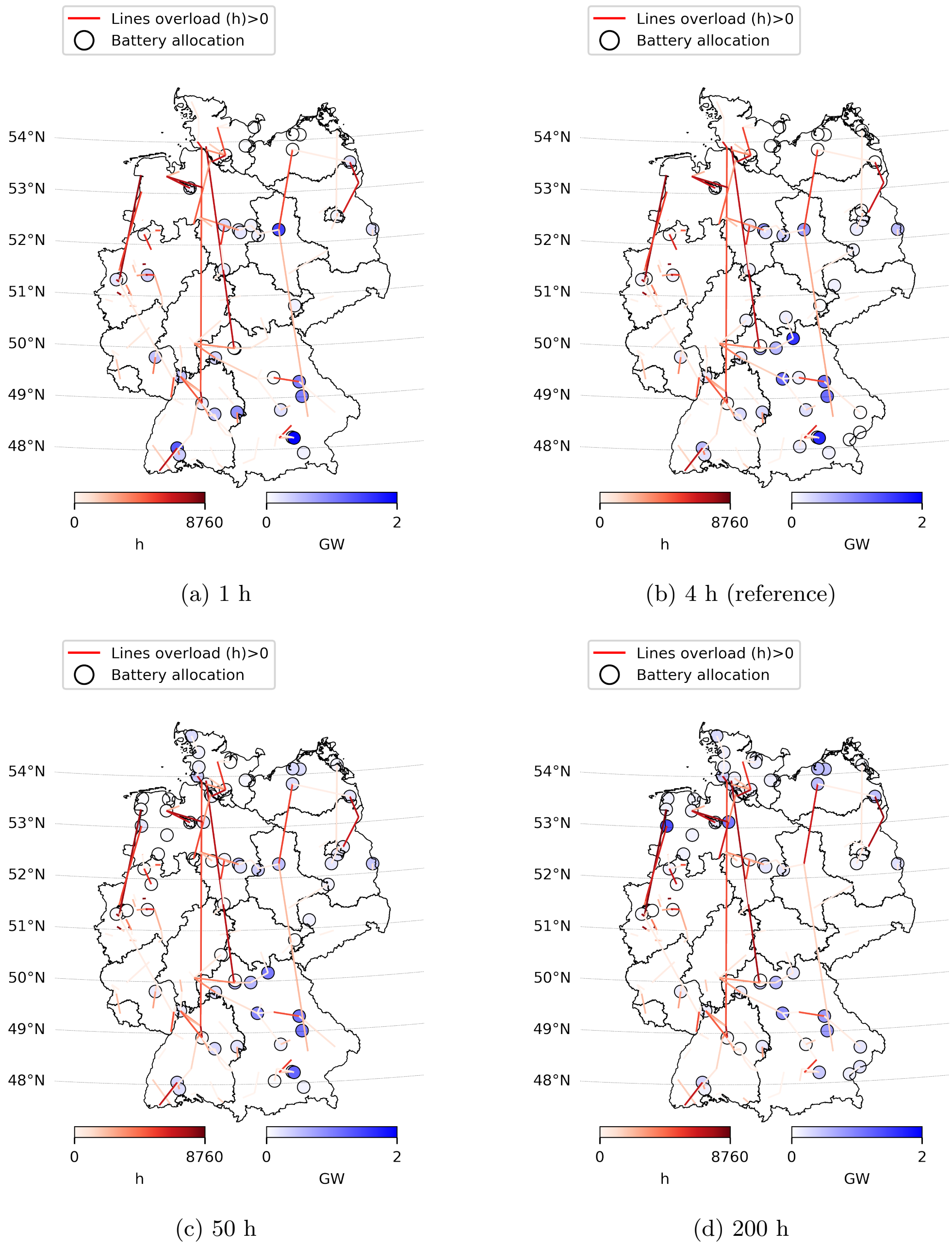
In the uniform setting, investment in wind power concentrates above the 53rd parallel. Solar capacity concentrates in Germany's south and east, with the majority of capacity installed below the 50th parallel. The lack of coordination of renewable feed-in and grid bottlenecks under the uniform setup leads to high curtailment. This especially affects wind power, which is separated from demand by a structural north-south grid bottleneck. In total, 109 TWh of renewable electricity are curtailed under the uniform setup in 2030, compared to only 30 TWh under the nodal setup.

Volume factor

Figure A.2 shows variations of the volume factor, i.e., the ratio between connected power (GW) and the energy volume (GWh) of a storage technology. Low volume factors correspond to battery storage, while higher factors can be seen for technologies using a different energy carrier for storage, e.g,. hydrogen. Storage allocation depends significantly on the volume factor. For higher volume factors (¿4h), storage moves northwards and closer to wind generation. Here, they buffer volatile wind generation and increase utilization of the congested lines along the structural grid bottleneck. However, even for higher volume factors, significant capacities are allocated in the south of Germany. Even when volume factors are above 100h and the majority of storage is located above the 52nd parallel, storage is needed to buffer volatile PV infeed in the south.

Battery capacity

Figure A.3 shows sensitivity analyses for the total installed capacity of batteries for a given distribution of wind and solar generation according to the nodal setting. The allocation of batteries close to grid bottlenecks along the 53rd parallel as well as in the south of Germany is robust. In the case of 15 and more GW of batteries, saturation in those areas leads to an allocation in the north, close to wind generation centers. The sensitivity analyses, therefore, highlights again the role of batteries in balancing short-term volatility from demand and solar feed-in time series as opposed to wind generation that requires longer storage of electricity.



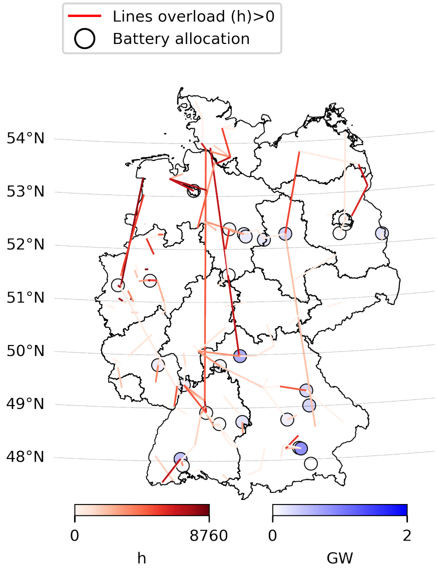
(a) 1 h

(b) 4 h (reference)

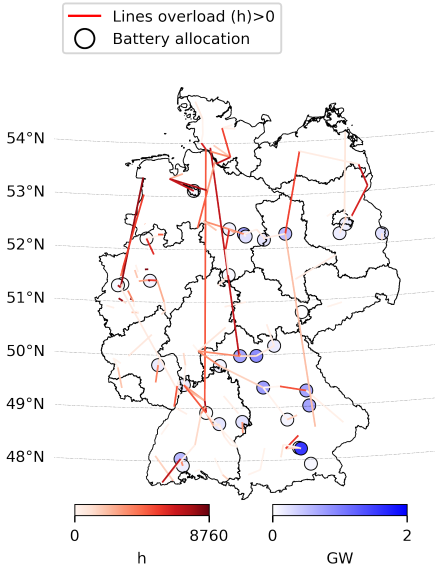
(c) 50 h

(d) 200 h

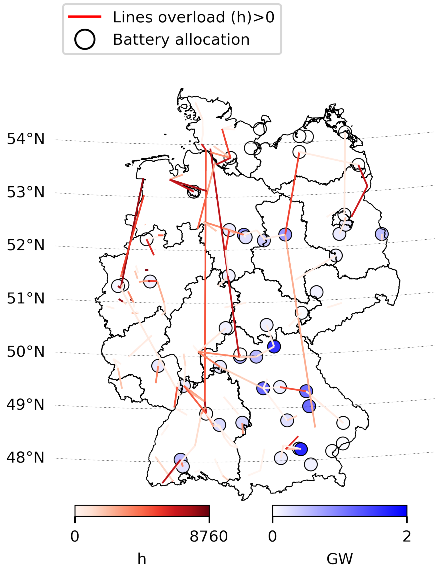
Figure A.2.: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery volume factors



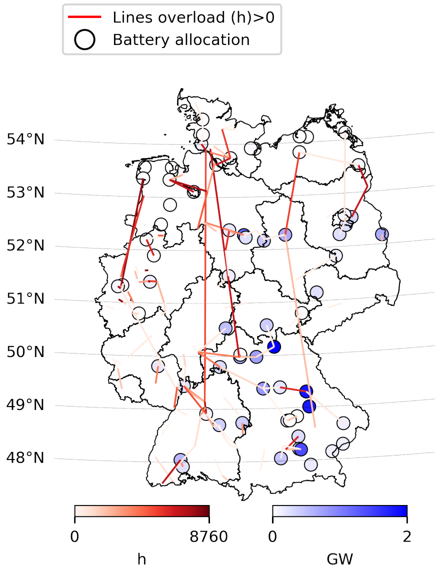
(a) 5 GW



(b) 10 GW



(c) 15 GW (reference)



(d) 20 GW

Figure A.3.: Optimal battery allocation based on the distribution of wind and solar in the uniform setting for different battery capacities

B. Supplementary Material for Chapter 3

B.1. Notation

Throughout the paper at hand, the notation presented in table B.1 is used. To distinguish (exogenous) parameters and optimization variables, the latter are written in capital letters.

Table B.1.: Sets, parameters and variables

Sets		
$i \in I$		Electricity generation and storage technologies
$m \in M$		Markets
$t \in T$		Timesteps
Parameters		
$demand_{t,m}$	[MWh]	Electricity demand
$demand_{t,m}^{heatpump}$	[MWh]	Electricity demand from heat pumps
ϵ^{static}	[-]	Static efficiency
$\epsilon^{dynamic}$	[-]	Dynamic efficiency
$\gamma_{t,i}$	[EUR/MWh]	Variable generation cost
cap_m	[MW]	Installed capacities of thermal storage
vol_factor	[-]	Volume factor
$cop_{t,m}$	[-]	Coefficient of performance
Variables		
VC	[EUR]	Yearly variable costs
$GEN_{t,m,i}$	[MWh]	Electricity generation
$CON_{t,m,i}$	[MWh]	Electricity consumption
$STOR\_VOL_m$	[MWh]	Storage volume
$STOR\_LEVEL_{t,m}$	[MWh]	Storage level

B.2. Additional model data

B.2.1. Assumptions on installed capacities, fuel and carbon prices

The data on the existing power plant capacities and on capacity developments as well as the allocation of power plant capacities on transmission nodes are taken from Zinke (2023). The capacity developments in Germany are based on current legal and political targets. EEG (2023) and WindSeeG (2023) set the legal targets for the expansion of wind onshore, offshore and solar energy. The phase-out of German nuclear, lignite, and hard coal power plants follows the path defined in KVBG (2020) and Bundesministerium für Wirtschaft und Klimaschutz

(BMWK) (2022). While the capacity development of H2 electrolyzers is based on political targets set in Bundesministerium für Wirtschaft und Klimaschutz (BMWK) (2023), the development of batteries follows the *Global Ambition* scenario in ENTSO-E and ENTSO-G (2022). The assumed capacity developments are shown in Table B.2. Furthermore, Table B.3 shows the assumptions made on the development of fuel and carbon prices.

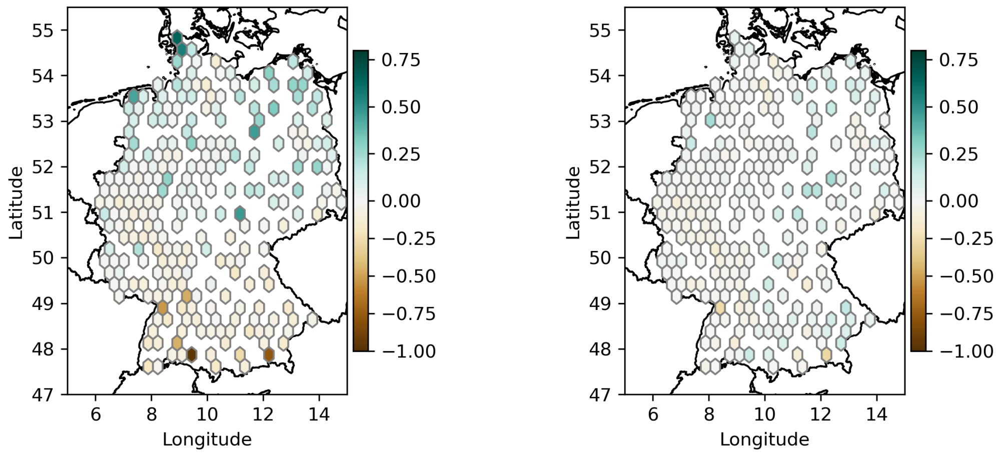
Table B.2.: Assumptions on installed capacities [GW] in Germany

Technology [GW]	2021	2030
Wind Onshore	54.5	115.0
Wind Offshore	7.8	29.6
Solar	53.3	215.0
Hard Coal	23.5	8.4
Lignite	20.5	8.9
Gas	31.9	47.0
Nuclear	8.1	-
Batteries	0.0	14.6
H2 Electrolyzers	-	10.0
Others	27.5	27.5

Table B.3.: Development of fuel and carbon prices, based on scenario *Stated Policies* in World Energy Outlook 2022 (IEA, 2022)

Fuel [EUR/MWh_{th}]	2021	2030
Uranium	5.5	5.5
Lignite	4.5	5.0
Coal	15.3	7.7
Natural Gas	28.8	25.8
Oil	37.7	44.8
Biomass	20.0	22.0
Carbon [EUR/tCO2]	54.0	100.0

B.2.2. Heat pump distributions



(a) (b)

Figure B.1.: Differences in annual electricity demand from heat pumps between the *hp-distribution* and (a) *wind-distribution* and (b) *pv-distribution*, in TWh

B.3. Additional results

Table B.4.: Electricity generation with inflexible heat pumps and percentage changes with thermal storage and different shifting potentials based on the *hp-distribution*

	Inflexible heat pumps [TWh]	2h [%]	4h [%]	8h [%]
PV	217.5	0.4	0.6	0.9
Onshore wind	179.0	1.1	1.4	1.9
Offshore wind	115.8	0.4	0.7	1.0
Gas	86.0	-1.2	-2.1	-3.1
Coal	5.5	-5.6	-8.1	-9.8
Others	52.4	0.4	0.7	1.0
Total	656.2	0.2	0.3	0.5

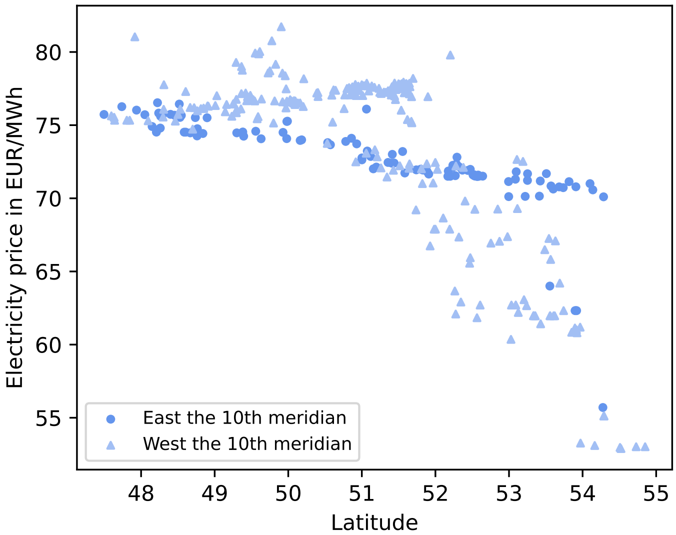


Figure B.2.: Average LMPs by latitude in the base case with inflexible heat pumps based on the *hp-distribution*

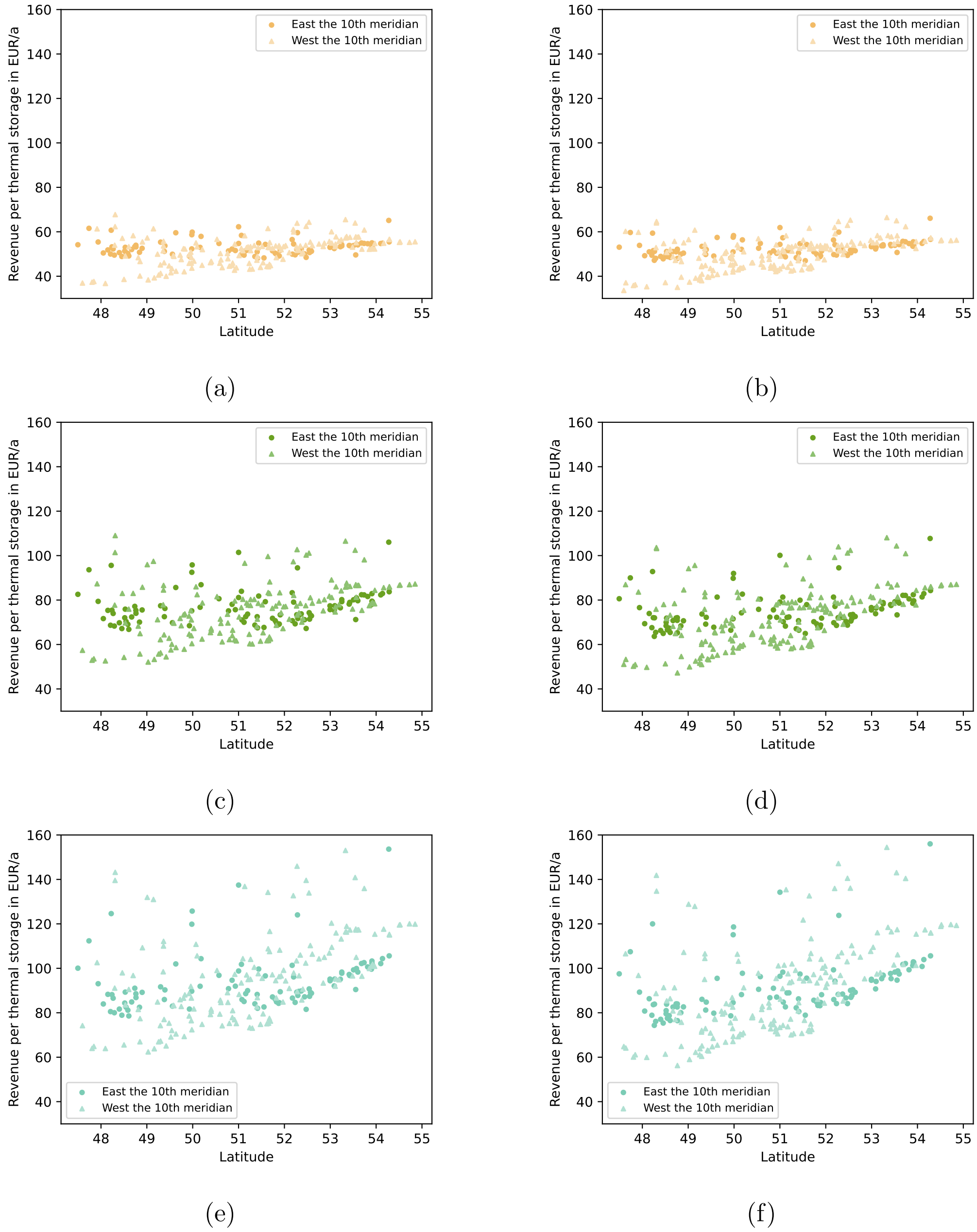
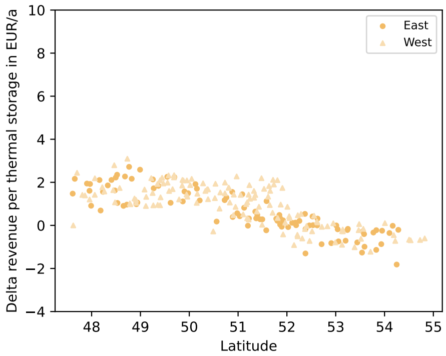
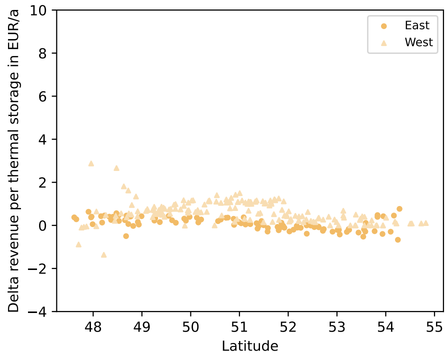


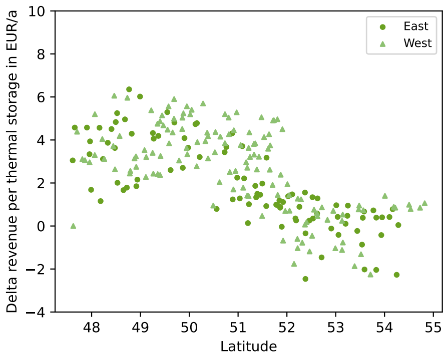
Figure B.3.: Expected revenue per thermal storage with (a) *wind-distribution* and 2h shifting potential, (b) *pv-distribution* and 2h shifting potential, (c) *wind-distribution* and 4h shifting potential, (d) *pv-distribution* and 4h shifting potential, (e) *wind-distribution* and 8h shifting potential, and (f) *pv-distribution* and 8h shifting potential



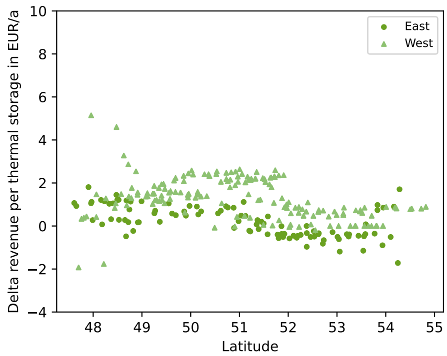
(a)



(b)



(c)



(d)

Figure B.4.: Delta between the expected revenues per thermal storage for (a) *wind-distribution* - *hp-distribution* and 2h shifting potential, (b) *pv-distribution* - *hp-distribution* and 2h shifting potential, (c) *wind-distribution* - *hp-distribution* and 4h shifting potential, and (d) *pv-distribution* - *hp-distribution* and 4h shifting potential

C. Supplementary Material for Chapter 4

C.1. Optimal spot market result

Consider a social planner solving the optimization problem (C.1a-C.1e). The social planner maximizes overall welfare, consisting of the consumer surplus from the participation at the spot market minus the electricity generation costs. Thus, she jointly optimizes the cost-minimal dispatch at the spot market level. The solution is constrained by the equilibrium condition, which requires supply to equal demand (C.1b-C.1c) and the restriction of the transmission line (C.1d).

$$\max_{l,\mathbf{q},\mathbf{D}} W = \int_0^{D_n} [p_n(z)]\,\mathrm{d}z + \int_0^{D_s} [p_s(z)]\,\mathrm{d}z - \sum_i c_i q_i \tag{C.1a}$$

$$s.t. \quad D_n + l = q_n \tag{C.1b}$$

$$D_s - l = q_s \tag{C.1c}$$

$$|l| \leq \overline{L} \tag{C.1d}$$

$$q_n, q_s, D_n, D_s \geq 0 \tag{C.1e}$$

The optimal solution yields a node-specific result. The optimal level of generation in each node is given by (C.2) and depends on the spatial choice of the demand investment.

$$q_i^* = \begin{cases} D_n^* + \overline{L} & \text{for } i = n \\ D_s^* - \overline{L} & \text{for } i = s \end{cases} \tag{C.2}$$

Since by assumption, generation costs are higher in the south and demand exceeds the capacity limit of the transmission line, the network is congested and fully utilized up to the capacity limit, i.e. $l^* = \overline{L}$. The prices reflect the marginal costs at the respective nodes with $p_n^* = c_n$ and $p_s^* = c_s$ and thus, producer surplus equals zero. Due to the price difference between the nodes and the quantity transmitted from node n to node s, a positive congestion rent $(c_s - c_n)\overline{L}$ results, which is accounted to the TSO budget.

C.2. Fixed network tariffs

The first-order conditions of the Lagrangian of the optimization problem (4.2a-4.2c) are:

$$\frac{\partial L}{\partial f_n} = \lambda\omega_n - \mu = 0 \tag{C.3}$$

$$\frac{\partial L}{\partial f_s} = \lambda\omega_s + \mu = 0 \tag{C.4}$$

$$\frac{\partial L}{\partial \lambda} = \sum_i \omega_i f_i - F + (c_s - c_n)\overline{L} = 0 \tag{C.5}$$

$$\mu\frac{\partial L}{\partial \mu} = \mu[c_s\overline{D} + f_s - c_n\overline{D} - f_n] = 0 \tag{C.6}$$

$$\frac{\partial L}{\partial \mu} = c_n\overline{D} + f_n \leq c_s\overline{D} + f_s \tag{C.7}$$

$$\mu \geq 0 \tag{C.8}$$

The complementary slackness condition (C.6) is true if either (1) $\mu = 0$, (2) $c_n\overline{D} + f_n = c_s\overline{D} + f_s$, or (3) both.

Case 1: $\mu = 0$. Plugging $\mu = 0$ into the first two equations yield $\lambda = 0$, as $\omega_i > 0$. The fixed network tariffs $\boldsymbol{f}$ can take every possible values that satisfy equation (C.5) and (C.7).

Case 2: $\mu > 0$ and $c_n\overline{D} + f_n = c_s\overline{D} + f_s$. Using the equality, we can solve for the fixed network tariffs, e.g. $f_s = \frac{F-(c_s-c_n)(\overline{L}+\overline{D}\omega_n)}{\omega_n+\omega_s}$. In addition, $\lambda = \frac{-\mu}{\omega_s}$ and $\lambda = \frac{\mu}{\omega_n}$. We can rule this case out, as it would require $\omega_n = -\omega_s$.

Case 3: $\mu = 0$ and $c_n\overline{D} + f_n = c_s\overline{D} + f_s$. Again, we can solve for the fixed network tariffs, e.g. $f_s = \frac{F-(c_s-c_n)(\overline{L}+\overline{D}\omega_n)}{\omega_n+\omega_s}$. Again, plugging $\mu = 0$ into the first equation yields $\lambda = 0$.

Hence, cases 1 and 3 are possible solutions of the optimization and both require $\lambda = 0$. As the shadow variable of the budget constraint is zero, the constraint (and the fixed network tariffs) has no influence on social welfare. Hence, fixed network tariffs can be considered as a welfare neutral payment.

C.3. Volume-based network tariffs

C.3.1. Deriving the Ramsey-Boiteux inverse elasticity rule

We use equation (4.7), substitute $p_i = c_i + \tau_i$ on the right-hand side and make use of the relationship $\tau_i = p_i - c_i$ to expand the equation. We denote the elasticity of demand with

$$\epsilon_i(p_i) = -\frac{\partial D_i(p_i)/\partial p_i}{D_i(p_i)/p_i} \tag{C.9}$$

Plugging the elasticity in, we then obtain the Ramsey-Boiteux formula, which is the classical inverse elasticity rule:

$$\frac{p_i - c_i}{p_i} = \frac{\lambda}{\lambda + 1} \cdot \frac{1}{\epsilon_i(p_i)} \tag{C.10}$$

We can see that a change in price ∂p_i is equivalent to a change in network tariff $\partial \tau_i$.

C.3.2. Solution for restricted volume-based network tariffs and boundary for binding dynamic consistency constraint

To solve for the optimal volume-based network tariff with a binding dynamic consistency constraint, we use the relation of network tariffs from (4.4b) and (4.4c). As (4.4c) is binding, it follows that $\tau_n = \tau_s + c_s - c_n$. Using the budget constraint (4.4b), we yield

$$\hat{\tau}_s = \frac{F - (c_s - c_n)(\overline{L} + D_n(c_n + \hat{\tau}_n))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_n)} \tag{C.11}$$

and

$$\hat{\tau}_n = c_s - c_n + \frac{F - (c_s - c_n)(\overline{L} + D_n(c_n + \hat{\tau}_n))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_n)}. \tag{C.12}$$

To derive the boundary at which the dynamic efficiency constraint is binding, we plug in the optimal static volume-based network tariff (4.9) into $c_n + \tau_n^* = c_s + \tau_s^*$:

$$c_n + \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)} D_s(c_s + \tau_s^*) + D_n(c_n + \tau_n^*)} = c_s + \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)} D_n(c_n + \tau_n^*) + D_s(c_s + \tau_s^*)}, \tag{C.13}$$

which simplifies to

$$\frac{\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*} D_n(c_n + \tau_n^*) - \frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*} D_s(c_s + \tau_s^*)}{\frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*} D_s(c_s + \tau_s^*)^2 + \frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*} D_n(c_n + \tau_n^*)^2} = \frac{c_s - c_n}{F - (c_s - c_n)\overline{L}}. \tag{C.14}$$

The solution depends on the costs that need to be recovered, the relation of the generation costs and the relation of the demand functions in the respective nodes.

C.3.3. Volume-based network tariffs under uniform pricing

To solve for the case that the dynamic efficiency constraint is non-binding, i.e., $\mu = 0$, we make use of equation (4.11) and substitute the quasi-elasticity ρ_i.

$$\tau_s^* = \frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)}\tau_n^* + c_s - c_n \tag{C.15}$$

It still holds that the elasticity in one node affects the network tariff in the other node. In addition, the network tariffs also depend on marginal generation costs. Again, we can solve for the respective network tariffs using the budget constraint of the TSO. The network tariff in the south is equal to:

$$\tau_s^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_s(\tau_s^*)}{\rho_n(\tau_n^*)}D_n(c_n + \tau_n^*) + D_s(c_n + \tau_s^*)} + c_s - c_n, \tag{C.16}$$

while the structure of the solution for the north is similar to the one under zonal pricing:

$$\tau_n^* = \frac{F - (c_s - c_n)\overline{L}}{\frac{\rho_n(\tau_n^*)}{\rho_s(\tau_s^*)}D_s(c_n + \tau_s^*) + D_n(c_n + \tau_n^*)} \tag{C.17}$$

For the case that the dynamic efficiency constraint is binding, we can use (4.10b) and (4.10c). This yields:

$$\hat{\tau}_s = \hat{\tau}_n = \frac{F - (c_s - c_n)(\overline{L} + D_s(c_s + \hat{\tau}_s))}{D_s(c_s + \hat{\tau}_s) + D_n(c_n + \hat{\tau}_s)} \tag{C.18}$$

We can check when the dynamic efficiency constraint gets binding, by substituting (C.16) and (C.17) into $\tau_n \leq \tau_s$:

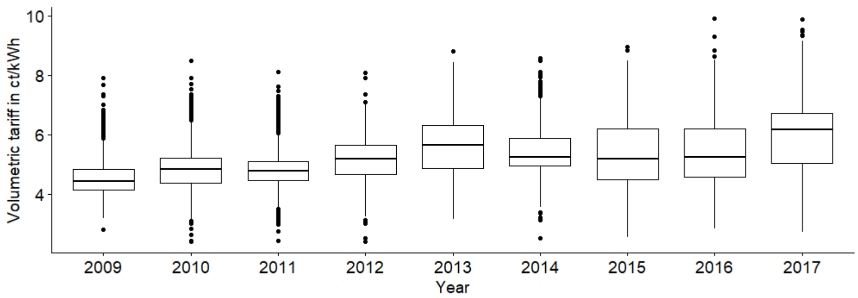
$$\begin{aligned} &D_n(c_n + \tau_n^*)\frac{\partial D_s(c_s+\tau_s^*)}{\partial \tau_s^*}[R + (c_n - c_s)D_s(c_s + \tau_s^*)] \leq \frac{\partial D_n(c_n+\tau_n^*)}{\partial \tau_n^*}D_s(c_s + \tau_s^*)[R + (c_n - c_s)D_n(c_n + \tau_n^*)] \\ &\text{with} \quad R = F - (c_s - c_n)\overline{L} \end{aligned} \tag{C.19}$$

The result is similar to the regulatory setting with zonal pricing and depends on the costs that need to be recovered, the relation of the generation costs and the relation of the demand functions in the respective nodes.

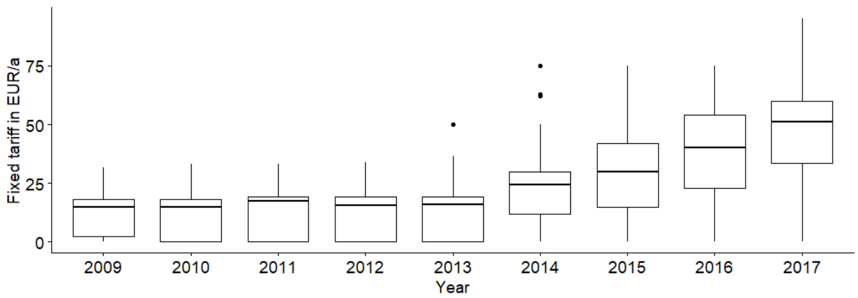
D. Supplementary Material for Chapter 5

D.1. Further data statistics

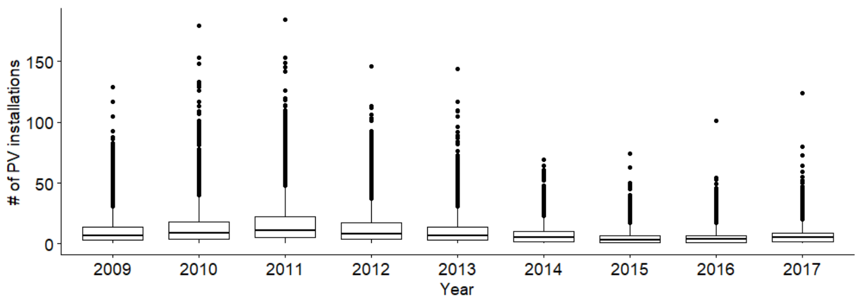
Figure D.1 illustrates the variation of the volumetric network tariffs, the fixed network tariff and the number of PV installations between the years 2009 and 2017.



(a)



(b)



(c)

Figure D.1.: Temporal variation of (a) the volumetric network tariffs, (b) the fixed network tariff, and (c) the number of PV installations

As shown in figure D.1 (a) and (b) network tariffs have risen steadily over the period under consideration. In particular, the median fixed tariff more than doubled between 2009 and 2017. In addition, one can see that for both the volumetric and fixed tariff the regional dispersion in the 25th to 75th percentile across postcode areas has increased substantially, while the regional dispersion of the number of PV installations has tended to decrease (see figure D.1 (c)).

D.2. Further robustness checks

With the following robustness checks in table D.1, we additionally check our assumption that households respond to the previous years' tariffs, i.e., $\mathit{tariff}_{i,t-1}$, by including tariffs further in the past. We test a regression with $\mathit{tariff}_{i,t-2}$ and one alternative with $\mathit{tariff}_{i,t-3}$ instead of $\mathit{tariff}_{i,t-1}$.

Table D.1.: Further robustness checks: time lags

Model:	(11)	(12)	(13)
Dependent Variable:	# of PV	# of PV	# of PV
tariff_{t-1}			0.0231^{**}
			(0.0086)
tariff_{t-2}	0.0245^{***}		-0.0107
	(0.0071)		(0.0091)
tariff_{t-3}		-0.0050	-0.0031
		(0.0081)	(0.0082)
income (log of)	-0.1004	-0.4194	-0.4253
	(0.2140)	(0.3182)	(0.3184)
housetype	-0.0014	0.0034	0.0038
	(0.0047)	(0.0054)	(0.0054)
age	0.0366^{*}	0.0331	0.0336^{*}
	(0.0155)	(0.0170)	(0.0171)
buildings (log of)	-0.0403	0.01267	0.1075
	(0.1839)	(0.2178)	(0.2186)
Fit statistics			
observations	56,269	48,084	48,083
AIC	282,959.3	235,622.8	235,605.7
BIC	426,858.3	376,482.9	376,483
Log-Likelihood	-125,380.6	-101,769.4	-101,758.9

Robust standard errors clustered at the postcode level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The results show that the impact of the lagged network tariffs $\mathit{tariff}_{i,t-2}$ and $\mathit{tariff}_{i,t-3}$ decreases compared to the impact of $\mathit{tariff}_{i,t-1}$. An encompassing test further supports this finding. The coefficient of $tariff_{i,t-1}$ is the only significant variable, at least at a 5 percent level, compared to $tariff_{i,t-2}$ and $tariff_{i,t-3}$. Hence, the results further support our assumption.

Table D.2.: Further robustness check: regional results

Model:	(14)
Dependent Variable:	# of PV
BW × tariff_{t-1}	0.1652*** (0.0197)
BY × tariff_{t-1}	0.0290*** (0.0085)
BE × tariff_{t-1}	-0.1352 (0.0929)
BB × tariff_{t-1}	0.0559* (0.0232)
HB × tariff_{t-1}	0.2740** (0.0872)
HH × tariff_{t-1}	0.0659 (0.1405)
HE × tariff_{t-1}	-0.0058 (0.0238)
MV × tariff_{t-1}	0.0869* (0.0368)
NI × tariff_{t-1}	0.0607** (0.0192)
NW × tariff_{t-1}	0.0570** (0.0198)
RP × tariff_{t-1}	-0.0678** (0.0255)
SL × tariff_{t-1}	-0.0508 (0.0624)
SN × tariff_{t-1}	0.1360*** (0.0257)
ST × tariff_{t-1}	0.0678* (0.0300)
SH × tariff_{t-1}	0.1550*** (0.0309)
TH × tariff_{t-1}	0.2682*** (0.0432)
income (log of)	-0.0273 (0.1487)
housetype	0.0044 (0.0043)
age	0.0158 (0.0136)
buildings (log of)	-0.1350 (0.1685)
Fit statistics	
observations	64,531
AIC	329,958
BIC	476,636
Log-Likelihood	-148,816

Robust standard errors clustered at the postcode level.
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

In another model variation (14, table D.2), we include an interaction term between binary dummy variables for the 16 German states and the network tariff. This estimation allows us to compare the regional effect of network tariffs on PV investments. The model specification is based on the assumption that while the effect of the network tariffs differs between states, the effects of the covariates and time-specific fixed effects do not. The results suggest that network tariffs significantly impact PV investments in a selection of states (BW, BY, SN, SH, TH), with the highest effect being in HB and the lowest in BY. An explanation for the different sizes of the effect could be differences in awareness for PV investments in different states. A reason why we cannot identify a significant effect for most states could be the low within-variance of network tariffs in the respective state. Because of the low within-variance of the state-specific tariffs and because the results depend on the assumptions made about the effects of the covariates and the annual fixed effects, the results should be treated with caution. Therefore, we interpret the results as indicative of the existence of regional differences in the effect of network tariffs on PV investments. However, a detailed analysis of these differences is outside the scope of this paper and remains subject to future research.

D.3. Within-variance of the covariates in our sample

Using a fixed effects approach, we exploit the within-region variation of our explanatory variables to identify their impact on our dependent variable. By including time fixed effects, we control for overall developments over time. While this allows us to isolate the effects under investigation, i.e., the effect of network tariffs on PV investments, it prevents us from making statements about the influence of covariates that have little or no within-region variation after controlling for time fixed effects. By regressing the explanatory variables on our fixed effects, we calculate the variation in these variables used to estimate the coefficients in our fixed effects model. The standard deviations of these residuals, calculated for the preferred specification of our model (1) and the specification without the postcode-specific slope (7), are shown in table D.3. The given values may aid in interpreting and classifying the estimated treatment effects of the explanatory variables. For a detailed analysis on the interpretation of fixed effects, refer to Mummolo and Peterson (2018).

Table D.3.: Within standard deviation

Model:	(1)	(7)
tariff$_{t-1}$ (ct/kWh)	0.34	0.49
income (log of)	0.02	0.03
housetype (%)	0.63	0.96
age	0.18	0.43
buildings (log of)	0.02	0.02

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CURRICULUM VITAE

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PERSONAL DATA

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RESEARCH INTERESTS

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ACADEMIC EDUCATION

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10/2013 - 07/2016	**University of Cologne** Master of Science in Economics
09/2011 - 01/2012	**University of Nottingham, UK** Study abroad
07/2010 - 08/2010	**University of California, Berkeley, US** Study abroad
09/2009 - 02/2013	**University of Mannheim** Bachelor of Science in Economics
06/2009	**Jakob-Grimm-Schule, Rotenburg an der Fulda** Maturity/Abitur

PROFESSIONAL EXPERIENCE

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10/2013 - 08/2016	**Institute of Energy Economics at the University of Cologne (EWI)** Student Assistant
03/2013 - 06/2013	**MVV Energie AG, Department of Energy Economics and Energy Politics, Mannheim** Internship
10/2012 - 12/2012	**German Federal Ministry of Economic Affairs and Technology, Department of Structural Policies and New Federal Laender, Berlin** Internship
07/2011 - 08/2011	**Hessisches Statistisches Landesamt, Department of National Accounts, Wiesbaden** Internship

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PUBLICATIONS

Articles in Peer-Reviewed Journals:

- Arnold, F., Jeddi, S., and Sitzmann, A. (2022). How prices guide investment decisions under net purchasing - An empirical analysis on the impact of network tariffs on residential PV. *Energy Economics*, Vol. 112:106-177. DOI: 10.1016/j .eneco.2022.106177.
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- Hintermayer, M., Sitzmann, A., and Tode, C. (2018). Ökonomische Bewertung des Marktentwicklungsmodells. *EWI study on behalf of ARGE Netz.*

PRESENTATIONS AND TALKS

- The impact of network tariffs on PV investment - An Empirical Analysis on Regionally Different Network Tariffs in Germany. *1st IAEE Online Conference*. June 2021. Online.
- Adjusting or shifting? - The economic differences between demand response and energy storages in a long-run equilibrium model. *16th IAEE European Conference*. August 2019. Ljubljana, Slovenia.