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Abstract

In most European countries, taxes and levies, the state-induced components of electricity prices, constitute the major share of electricity prices for consumers and are charged at a fixed rate. This study analyzes whether switching state-induced price components to time varying rates can support the integration of variable renewables (VRE) and, thus, help to efficiently achieve the overarching goal of decarbonizing the energy system. Based on game theory and linear programming, we introduce a novel simulation model of the power market. For a quantitative case study, the model is parametrized to represent a German energy system that meets the political objective to increase the share of renewables (RE) in power generation to 80% in 2050. We find that dynamization supports the integration of VRE into the energy system. Whether dynamization is an efficient instrument to promote decarbonization as well is highly dependent on the policy framework in place.

JEL Classification Nos.: C61, C63, C70, Q42, Q48

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1 Introduction

Compliance with European climate objectives requires a major expansion of VRE like wind and solar (European Commission, 2011: 50). Power generation costs of these technologies have dropped substantially in recent years, but due to their fluctuating nature large-scale integration into the power system continues to pose a challenge (Fürstenwerth et al., 2015: 1).

Charging state-induced price components like taxes and levies based on the time of power consumption could help to address this challenge. In most European countries, state-induced price components constitute the major share of electricity prices for consumers and are charged at a fixed rate, irrespective of the time or place of consumption. Dynamization of these price components would amplify the price signal and encourage consumers to adjust their demand to the supply of VRE.

A technological prerequisite for such an instrument, the mandatory implementation of intelligent metering systems, has been proposed by the European Commission (EC, 2016). In Germany, also the dynamization of several state-induced price components has been proposed (Perner and Zähringer, 2017; Jansen et al., 2015). However, the dynamization of state-induced price components has not been examined scientifically yet, even though such an analysis could contribute to political discussions on smart metering and dynamization. Interestingly, in contrast to dynamization of state-induced price components, passing wholesale prices to consumers, better known as real-time pricing (RTP), has been researched intensively in the context of studies on demand response and demand-side management (DSM). The key difference with dynamization is that, in contrast to RTP, it is not directed towards wholesale prices, but towards state-induced price components charged on top of wholesale prices.

Two key questions emerge regarding the potential of dynamization in the context of decarbonization: First, can the dynamization of state-induced price components help to integrate VRE into the power system and is it therefore a policy instrument to be considered for efficient decarbonization of the energy system? Second, which interactions exist between the dynamization of state-induced price components and other technological or regulatory instruments discussed to decarbonize the energy system? Do dynamization and other instruments complement or exclude one another based on economic efficiency? Examples for these other policy measures include carbon pricing, subsidies for renewable energy sources, intensified coupling of the heat, power and mobility sectors or a ban of certain power plant technologies.

In order to provide an answer to these research questions, in this paper the effects of dynamization on decarbonization and integration of VRE are quantitatively simulated and
evaluated from a welfare economics perspective. Based upon these results, it is possible to assess whether future research and policy making should consider dynamization of state-induced price components as an instrument to support decarbonization.

The entire analysis presented here is restricted to the time dimension and excludes costs and constraints associated with the distribution of electricity, but focuses on the costs and constraints associated with generation and consumption of electricity. Within national borders, costs of transporting electricity from generators to consumers are ignored in this study. As a result, any form of dynamization aiming to reflect the marginal costs of transporting electricity to optimize grid utilization is ignored, because it would require a spatial dimension as well.

All quantitative analysis in this paper focuses on the German power system and assumes a regulatory framework based on an energy-only market with scarcity pricing, carbon pricing and subsidies for renewable energies and storage technologies. In the relevant literature these assumptions are commonly made for the foreseeable future in Germany. The parameters used for quantifying effects are taken from various consistent sources and are relevant for a German power system that meets policy objectives set out for the reference year 2050. Furthermore, operational barriers and practical aspects of introducing dynamization are not considered due to the welfare economics approach adopted.

Within the field of welfare economics, theory concerning market failures and government market intervention is used to set out why the dynamization of state-induced price components might be beneficial in general. To achieve an accurate simulation of the power market, the more detailed quantitative analysis relies on a game-theoretic model of the power market developed as a part of this study. In contrast to models already existing, our game-theoretic model is capable of representing both the own-price elasticity and substitution elasticity of demand and the influence of state-induced price components on demand. This model consists of two stages that are repeatedly processed. The first stage represents the short-term power market and simulates the dispatch of exogenously determined generation capacities using linear programming. The second stage represents the long-term power market and simulates investment decisions into capacities for an exogenously determined market outcome in the short-term via backward induction. An iterative algorithm carries out these steps until both have reached a consistent Nash equilibrium.

First of all, the research this thesis builds upon is outlined. First, the economic theory behind the regulation of energy markets is summed up. Next, two indicators, integration costs and decarbonization costs, for quantifying the effects of dynamization are introduced. Thirdly, former research that performed welfare economic analysis on the RTP of electricity
is summarized. Section 3 gives a detailed description of the particular case-study, which was used to obtain all numerical results. On this basis, the analysis of dynamization is carried out in section 4. After a general analysis of dynamization, a detailed simulation model is developed and parametrized to quantify effects. Finally, results of the model-based calculations are presented. In section 5, results are interpreted to answer the initial research questions. It is discussed to what extent the results of the particular case study can be generalized and how future research could provide additional insights. In conclusion, implications for policy making in the context of decarbonization are derived.

2 Theoretical background

2.1 Economics of regulation

In economic theory, an efficient allocation of goods exists if marginal costs of production equal the marginal benefits of consumption. Any inefficient allocation of goods is called market failure. In environmental and energy economics, the most relevant causes of market failure are externalities. Externalities occur as soon as the market fails to reflect all costs and benefits associated with the production and consumption of a good. For instance, the emission of greenhouse gases is known to bring about climate change. Climate change causes costs, yet emitters of greenhouse gases do not have to bear those costs. In conclusion, the market fails to reflect the true costs of production, because the costs of climate change are not internalized. Government policy can address externalities by establishing a regulatory framework that corrects market failure. Any regulatory framework that leads to an efficient or first-best market outcome is referred to as a first-best framework. In the case of greenhouse gas externalities, a first-best framework is to charge a price for the emission of greenhouse gases that is equal to the marginal damage caused by emissions. If a first-best policy is realized, any additional form of government intervention is inefficient and causes market failure again (Fees and Seeliger, 2013).

However, a lot of research suggests that in real energy markets a first-best setting cannot be reached for two reasons: First, greenhouse gas externalities are not the only market failure energy markets are subject to. Local air pollution, learning spillovers or network effects are further externalities. State-induced price components differing from the Pigouvian tax level, subsidies for renewable energies, or not passing wholesale prices to consumers cause further distortions (Linares and Labandeira, 2010: 6-8). Lastly, the public good character of a secure supply of electricity creates market failure, too. A good is considered as public if it cannot be allocated to a specific consumer, but only to all consumers equally. Since it is physically
impossible to just withhold electricity from selected consumers in the case of a congested power grid, the security of electricity supply is a public good (Abbott, 2001: 31). Secondly, the implementation of a first-best policy might lack the required political support due to undesirable distributional effects or the influence of certain interest groups (Kalkuhl et al., 2013: 218).

If, given these constraints, the first-best setting turns out to be unachievable, the next-best realizable market outcome is called second-best (Meade, 1955). The required regulatory framework to achieve the second-best market outcome may include the simultaneous use of various policy instruments, most of which would have been inefficient in a first-best setting. This might include renewable energy subsidies or the dynamization of state-induced price components. In a second-best setting, the efficiency of policy instruments is dependent on one another and cannot be evaluated in isolation anymore (Bennear and Stavins, 2007: 125). For example, a previously efficient level of renewable energy subsidies might become inefficient as soon as the carbon price changes. Therefore, evaluating the dynamization of state-induced price components in a second-best setting requires some assumptions regarding the remaining regulatory framework. Kalkuhl et al. (2013: 232-233) assume carbon prices to be below first-best levels in the future, because higher levels are not politically enforceable due to the resulting energy prices. On this basis, various additional policy instruments are evaluated by Kalkuhl et al. with respect to their welfare losses compared to the first-best setting. The results suggest that renewable energy subsidies are an efficient additional instrument if carbon pricing exists, but is below first-best levels. This kind of regulatory framework, carbon prices below first-best levels, combined with renewable energy subsidies, is also installed in many European countries (Held et al., 2014).

2.2 Indicators to measure the effects of dynamization

2.2.1 Integration costs

Decarbonization imposes certain challenges upon an energy system: In general, it requires to switch from fossil fuels to renewable forms of energy like wind, solar, biomass, hydro power, and nuclear energy. Since in many countries the potential of biomass and hydro power is just as limited as the public acceptance of nuclear power, in most decarbonization scenarios wind and solar provide the largest share of energy (Edenhofer et al., 2013: 4). This poses a challenge, because energy from thermal power plants and energy from solar panels or wind turbines are not perfect substitutes. Although physically, all provide electrical energy, thermal power plants are able to produce at any desired point in time, while production from VRE
like wind and solar is dependent on the weather (Hirth et al., 2016: 4). For this reason, VRE incur costs that go beyond their direct investment costs and can be interpreted as opportunity costs, for example because of curtailment of variable generation or continued need for thermal backup capacities. These costs are often referred to as “integration costs”.

Diminishing integration costs is a key challenge for decarbonization, which is why the collective term “integration options” has been coined for all instruments serving this purpose. Typical examples discussed in the academic literature are active participation of the demand side in the market, increased cross-border trade of electricity, energy storage or intensified coupling of the heat, power and mobility sector (Ueckerdt et al., 2013: 21). The concept of integration costs this study builds upon is taken from former interrelated research and includes a rigorous definition and decomposition. Ueckerdt et al. (2013: 5) define integration costs as follows: “Integration costs of VRE are all additional system costs induced by VRE that are not directly related to their generation costs.” Integration costs are highly dependent on the generation share of VRE (Ueckerdt et al., 2013: 15). Ueckerdt et al. (2013: 5) provides a formula to compute the total amount of integration costs $C_{int}$ from the results of a power market simulation:

$$ C_{int} = \left( \frac{C_{resid}}{E_{resid}} - \frac{C_{tot(0)}}{E_{tot(0)}} \right) E_{resid}; $$

where $C_{resid}$ refers to the deployment and investment costs of all technologies except VRE, i.e. fossil and nuclear thermal power plants and energy storage. $E_{resid}$ is the amount of energy supplied by these technologies, $E_{tot(0)}$ is the total amount of energy supplied in an energy system without any VRE. $C_{tot(0)}$ refers to the total costs of an energy system without any VRE and serves as a reference point. The formula is derived by comparing the specific costs of generation from thermal power plants between an energy system with and without VRE (for details see Ueckerdt et al.); the derivation assumes demand to be perfectly inelastic.

Note that according to the definition of integration costs, investment costs of VRE are not included in the formula. As a result, estimates of integration costs can be compared even if the underlying assumptions on the future development of investment costs of VRE, which is a question subject to great uncertainty, differ. Finally, it is important to keep in mind that decreasing integration costs is not an end in itself. Economic efficiency of a regulatory framework depends on the costs of avoiding GHG emissions and not on the costs of integrating VRE (Haller, 2012: 68). Nevertheless, evaluation of integration costs provides fundamental insights into market mechanisms and enables comparisons among integration options.
2.2.2 Decarbonization costs

Decarbonization costs, often referred to as abatement or mitigation costs, is the second indicator, next to integration costs, used to evaluate dynamization. In contrast to integration costs, it is a well-established and straightforward metric. Decarbonization costs are defined as the social costs of avoiding GHG emissions within the energy system (Valverde et al., 1999: 91). According to this definition, Growitsch et al. (2014: 3) provide the following formula:

\[ c_{\text{decar}} = \frac{K_g - K_{\text{ref}}}{CE_{\text{ref}} - CE_g}; \]  

where \( CE_g \) and \( CE_{\text{ref}} \) refer to the total sum of carbon emission in the considered case and in a reference case, respectively. \( K_g \) and \( K_{\text{ref}} \) denote the total costs in the considered case and in a reference case. Just like the marginal costs of integrating VRE, the marginal costs of decarbonization rise steeply when the total sum of avoided GHG emissions increases. High sensitivity regarding future investment costs of VRE makes it difficult to compare decarbonization costs from different sources.

2.3 Real-time pricing and dynamization

The basis for RTP is a liberalized energy market, where wholesalers and generators trade electricity. For each time period, the power market determines a price for electricity that reflects the marginal costs of generating electricity at that respective point in time. But if wholesalers do not pass the wholesale prices to consumers and charge an averaged uniform price instead, consumer prices do not reflect the true marginal costs of providing electricity and the market is inefficient (Kirschen, 2003: 520). From this idea, the introduction of dynamic prices was first proposed by Schweppe (1988). The paper suggests the introduction of dynamic prices in a way that the allocative efficiency of the market is increased, because that way prices reflect marginal costs. Otherwise, a first-best setting, where marginal costs of production equal the marginal benefits of consumption, could not be reached (Desrosiers, 2014: 2).

While the topic of our study, a welfare economics analysis of the dynamization of state-induced price components in the context of decarbonization, has not been researched yet, similar research has been done on the closely related topic of RTP. In the following, methods

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1The proposal was actually not limited to passing wholesale prices to consumers, whereas explicitly included dynamization of state-induced price components as well, but following research just focussed on wholesale prices (Desrosiers, 2014: 10). Interestingly, the paper also predicts that technical progress in information technology will allow consumers to easily measure, manage and monitor their power consumption (Desrosiers, 2014: 24). This prediction turned into reality in the course of the development of smart home technology.
and results of this research are briefly summed up to serve as a starting point for our own work.

Borenstein and Holland (2005a) analyze the potential benefits of expanding RTP to more customers. They stress the great impact that the assumed elasticity of demand has on the results, which is why their study includes a fairly wide range of elasticities. The model used is a two-stage simulation model, where the first stage represents the short-term and the second stage the long-term market equilibrium. The short-term equilibrium is determined by equating demand and supply for every hour of the year. The long-term equilibrium is obtained by isolating the capacity decision for a specific technology from the capacity decision for technologies with lower marginal costs. The algorithm is explained in detail in Borenstein (2005b: 5). The resulting benefits of expanding RTP are estimated to be around 5-10% of wholesale energy costs, depending on the elasticity of demand (Borenstein and Holland, 2005a: 470). The whole analysis does not account for VRE as a supply technology and neglects the requirement for reserve power plants. Furthermore, the model does not include other integration options such as cross-border trade of electricity, energy storage or coupling of the heat, power and mobility sector. The representation of the demand side is limited to the own-price elasticity of demand. Gambardella et al. (2016) and Allcott (2012) extend the approach developed by Borenstein and Holland (2005a) in the course of their research on RTP.

Mills and Wiser (2014) evaluate RTP in the context of decarbonization as well, but take a different modeling approach. They assume a policy framework characterized by an energy-only market with scarcity pricing, exogenously given shares of VRE and carbon prices. The main research question is how the market value of VRE is affected by the implementation of various integration options like for example RTP. Since market value and integration costs are closely correlated, market values are often used as a more comprehensible alternative to integration costs. High market values correspond to low integration costs (Hirth, 2013: 16). In contrast to the research presented above, Mills and Wiser (2014) use a highly-detailed simulation of the short-term market to compute their results (Mills and Wiser, 2013: 88-93). The simulation model is based on linear programming and not only able to represent reserve requirements and energy storage, but also technical limitations of thermal power plants and effects resulting from the uncertainty of generation from VRE. However, it does not consider integration options like cross-border trade of electricity and coupling of the heat, power and mobility sector and neglects the substitution elasticity of demand. The model is also distinct regarding the computation of the long-term equilibrium. In contrast to Borenstein and Holland (2005a), the long-term equilibrium is defined as the point where profits from
the short-term market (revenues minus variable operating costs) equal investment and fixed operating costs. It is determined by an algorithm that estimates how social welfare depends on the installed generation capacities (see Mills and Wiser (2013: 28) for details). The results show a substantial increase in market values, when RTP is implemented. In line with results of the research presented previously, positive effects of RTP tend to rise if the share of VRE increases.

In conclusion, two different approaches to analyze RTP from a welfare perspective can be found in the relevant literature: The first approach was originated by Borenstein and Holland (2005a), and expanded in further research. The second approach was first presented by Mills and Wiser (2013). Both approaches have in common that simulation of the energy system is divided into a long-term perspective, the investment in generation capacities, and a short-term perspective, the dispatch of existing generation capacities. They differ in the level of detail applied to simulate the short-term market and how the long-term equilibrium is defined. Still, none of these approaches model cross-border trade of electricity, coupling of the heat, power and mobility sector, substitution elasticity of demand or the effect of state-induced price components on demand.

The model developed for this paper to investigate the dynamization of state-induced price components can best be compared to the model used by Mills and Wiser (2013). Fundamentally, both models are based on linear programming. Unlike Mills and Wiser (2013) our model incorporates all aspects listed earlier, but neglects some aspects less relevant to the matter in question. Furthermore, the model we developed uses game-theoretic definition of the long-term equilibrium and introduces a novel approach inspired by Borenstein and Holland (2005a) to fit this definition.

Although quantitative results cannot be compared due to differences in parametrization and different research questions, two qualitative insights on RTP can be gained from the reviewed literature on RTP and referred to later on: Benefits of RTP are highly dependent on carbon prices and increase with the share of VRE.

3 Case study description

We examine an energy system in Germany that has been decarbonized to a large extent and meets the political objective to reduce GHG emissions by 80% until 2050, compared to 1990 levels (UBA, 2013: 4). Such a scenario is selected because a great reduction in GHG emissions implies high shares of VRE. Since research finds that effects of RTP are most apparent in the case of high VRE shares, the same is likely to apply to dynamization (Gambardella...
et al., 2016: 32). The case study does not analyze the process of transforming the energy system, but instead focuses on the transformed energy system in the long-term equilibrium in a representative year. Although the scope of this study includes the entire energy system, the quantitative analysis is focused on the power market, because other parts of the energy system are not well suited for dynamization.

Besides high shares of VRE, decarbonization also requires measures like reinforced cross-border trade of electricity, expansion of energy storage or an intensified coupling of the heat, power and mobility sector (European Commission, 2011). Utilization of these integration options must be included in the case study. Otherwise, the dynamization of state-induced price components would be the only option to improve the integration of VRE and its effects would be overestimated. In order to correctly represent the effects of dynamization on the demand side, both the own-price and the substitution elasticity of demand have to be included in the case study.

The assumed policy framework consists of an energy-only market with scarcity pricing, carbon prices below first-best levels and subsidies for RE and storage systems. Scarcity pricing enables peak-load plants to earn revenue in the short-term market and thus cover their investment costs (Hogan, 2005: 7-15). While investment in thermal power plants is driven by mechanisms of the energy-only market, generation capacities for RE and storage are set by government support programs. This policy framework matches the current framework in force in Germany except for the subsidies for storage systems. Government subsidies are assumed, because research shows that energy storage systems can contribute to efficient decarbonization but in an energy-only market the welfare-optimal level of storage capacity is not reached (Ehlers, 2011: 111). According to the research presented in subsection 2.1, the assumed policy framework is also economically reasonable in the case of a second-best setting.

For our analysis two types of state-induced price components are distinguished: Taxes, which accrue to the general government budget and can be used freely by the government, and levies, which are raised for and spent on a particular purpose (Nowotny and Zagler, 1991: 116). In Germany, an example for taxation is the general consumer tax, whereas the EEG levy is an example for the levies.

In our case study we assume that subsidies for RE and storage units are financed by a levy on the consumption of electricity to recover their full costs; further, the dynamization of state-induced price components is limited to this levy. All other state-induced price components remain at constant levels. Dynamization is achieved by varying the amount of the levy depending on the price of electricity in the liberalized market. Other forms of dynamization
will not be evaluated here, because their practical implementation seems extremely difficult.

Note that the whole case study is fully deterministic and neglects all effects caused by uncertainty, which means demand and generation from VRE do not deviate from forecasts. As a result, there is only one market for electricity opposed to reality, where electricity is traded on three markets with different time horizons (Futures, Day-ahead, and Spot market). Furthermore, the case study is restricted to the time dimension and excludes costs and constraints associated with the distribution of electricity, but focuses on the costs and constraints associated with generation and consumption. Within national borders, costs of transporting electricity from generators to consumers are ignored. As a result, any form of dynamization aiming at reflecting the marginal costs of transporting electricity and thus to optimize grid utilization, is not studied, because it would require a spatial dimension as well. Operational barriers and practical aspects of introducing dynamization of state-induced price components are not considered due to the chosen welfare economics approach. Also, such studies already exist (e.g. frontier and BET, 2016; Jahn and Praetorius, 2014). Lastly, the case study assumes rational behavior of market participants, perfect information, absence of market power abuse, no barriers to enter or exit the market and no transaction costs. These assumptions form the basis for the mathematical simulation of the short- and long-term market.

4 Analysis and results

4.1 Qualitative analysis

In order to create a general understanding of the market mechanisms affecting dynamization and to explain why dynamization might be beneficial as an additional instrument of regulation, the research questions considered are first discussed qualitatively.

Theory on the first-best setting from subsection 2.1 already provides a partial answer to the research questions: if the emission of greenhouse gases is the only externality in an energy market and is perfectly internalized by a carbon price, dynamization of state-induced price components is inefficient. Carbon pricing at the first-best level and the dynamization of state-induced price components substitute one another based on economic efficiency. This underlines the key difference between RTP and dynamization: While RTP is always efficient and a prerequisite for a first-best setting, dynamization can only be beneficial in a second-best setting. The same applies to any other energy policy instrument like renewable energy subsidies, efficiency standards, or a ban of certain technologies and carbon pricing at first-best levels.

Therefore, in our study dynamization is only evaluated in a second-best setting.
it is a regulatory and not a technological instrument, the dynamization of state-induced price components can be described as an integration option, because it seeks to decrease the costs of integrating VRE. To understand how dynamization could decrease integration costs, its impact on the market outcome is discussed next. Therefore, the effects of dynamization on the short-term market are visualized by a linear demand curve and a merit order supply curve. Having zero marginal costs, VRE lie on the very left of the merit order curve. The rest of the merit order represents thermal power plants with heterogeneous marginal costs that are all greater than zero. The effects of dynamization can best be explained by looking at two market situations being exemplary for energy systems with high shares of VRE.

The first situation is illustrated in the upper row of Figure 1 and characterized by low demand for and high production from VRE. Figure 1(a) depicts the case without dynamization, which means that the level of state-induced price components remains constant regardless of the point in time. In this case, state-induced price components inflicted upon the consumption of electricity further decrease demand such that some of the generation from VRE must be curtailed. Curtailment implies declining utilization of VRE. A decline in utilization raises integration costs of VRE, because less energy from VRE is used while generation costs remain constant. Dynamization can resolve this issue by reducing state-induced price components to trigger an increase in demand. In the case depicted in Figure 1(b) dynamization increases demand such that curtailment can be avoided completely. Furthermore, reducing state-induced price components also decreases welfare losses caused by state-induced price components. On the downside, parts of the increase in demand are covered by thermal power plants and cause additional GHG emissions, which were supposed to be avoided in the first place.

The second situation is contrary to the first situation and illustrated in plots (c) and (d) of Figure 1. In this case, high demand meets low production from VRE. Figure 1(c) depicts the case without and the illustration 1(d) with dynamization. Since the average level of state-induced price components should remain constant, state-induced price components must be increased in this situation to compensate for the decrease in the first situation. The increase of the state-induced price is at the expense of the allocative efficiency of the short-term market. This implies that welfare losses increase, because thermal power plants on the right end of the merit order are not utilized anymore, although the marginal benefit of consumption would have exceeded their marginal costs. These losses must be weighed against welfare gains from decreasing state-induced price components in the first situation and both effects must be factored in when computing integration and decarbonization costs. On the upside, the decrease in demand also leads to a decrease in the emission of greenhouse gases. Fur-
ther positive effects can be expected in a long-term perspective, since the frequency of load peaks is reduced and thus the load profile becomes more evenly distributed and less volatile. As a result, expensive peak-load power plants will be replaced by less expensive mid-load technologies.

In conclusion, dynamization decreases the curtailment of VRE in the first situation and the generation from peak-load power plants in the second situation. Both situations taken together show a shift from peak-load power plants to plants with smaller marginal costs. Effects on welfare losses and GHG emissions are opposed in the first and second situation. However, the shift from peak-load plants to plants with smaller marginal costs allows one statement on GHG emissions. In the case of extremely high carbon prices, marginal costs and emissions are highly correlated and, therefore, this shift would imply a decrease in GHG emissions. In the absence of carbon prices this effect would be contrary. Gas-fueled plants with low emission factors would be replaced by coal-fired plants with greater emission factors because of
their respective marginal costs.\textsuperscript{2} In summary, the effects of dynamization can strongly vary depending on carbon prices. This observation confirms what was said about second-best policy frameworks earlier: In a second-best setting, the efficiency of policy instruments is dependent on one another and cannot be evaluated in isolation anymore.

The dynamization of state-induced price components has both positive and negative effects on the integration of VRE and decarbonization. On the basis of the qualitative analysis performed here, it can be assumed, but not generally proven, that benefits outweigh negative effects under certain conditions. Depending on the properties of supply and demand, carbon prices and other elements of the power markets like energy storage or cross-border trade that have not been considered yet, effects of dynamization will differ from case to case. To capture these aspects, a meaningful analysis of dynamization regarding integration of VRE and decarbonization must be based on a specific case study and a detailed quantitative model.

4.2 Model

4.2.1 General methodology

Before the methodology is unfolded, the general requirements of a model for the quantification of the impact of dynamization on the integration of VRE and on decarbonization are listed. A quantitative analysis of dynamization should capture both, the short- and long-term effects of such a policy instrument. In power markets, “short-term relates” to the dispatch of generation capacities and the “long-term” to decisions on investment in generation capacity.

Furthermore, an appropriate model has to take a simulation and not an optimization approach. An optimization model determines the ideal market outcome by maximizing social welfare regardless of imperfections or externalities existing in the real world. Therefore, it is fundamentally unfit to capture the effects of market failures or policy instruments like dynamization.\textsuperscript{3}

The following game-theoretic perspective on power markets offers a sound economic basis for a model fulfilling all these requirements: Referring to game theory, the power market can be interpreted as a repeated game, where each repetition of the games consists of two stages. In the first stage, which represents the short-term market, generators decide on how to dispatch their generation capacity and consumers decide on consumption. In the second stage, which represents the long-term market, generators decide on their generation capacities. The players of the game are all market participants, both generators and consumers.

\textsuperscript{2}This only holds true under the assumption that the relation of gas and coal prices does not greatly diverge from current levels.

\textsuperscript{3}Due to this requirement, the majority of power market models used in research or industry are not suited for the purpose of our analysis.
The rules of the game reflect the technical constraints of power generation and distribution and the assumed policy framework. The long-term equilibrium to be computed for analyzing dynamization corresponds to the concept of the Nash equilibrium in game theory. A Nash equilibrium is defined as a state, where no player has anything to gain by changing his decisions. The Nash equilibrium is self-enforcing in the long-run, if market participants behave rational and possess perfect information, which both was assumed within the case study (Fudenberg and Tirole, 2007).

Since a model based on this game-theoretic approach meets the requirement of being a simulation model and representing the two stages of power markets, computing a Nash equilibrium in the power market is the general methodology chosen for the development of the model that follows. The modeling approaches outlined in subsection 2.3 will serve as a starting point for development and are fully consistent with a game-theoretic perspective, but do not refer to game theory as their economic basis at any point. Nevertheless, a game-theoretic perspective on the power market is not superfluous, because it provides a guideline for modeling and facilitates understanding for the reader. For this reason, we will repeatedly resort to basic game-theoretic concepts in the following sections. As explained in the case study, analyzing dynamization should incorporate elements of the power market like cross-border trade of electricity, energy storage or intensified coupling of the heat, power and mobility sectors or substitution elasticity of demand, which is why none of the approaches presented in subsection 2.3 can be adopted without modifications to evaluate dynamization.

4.2.2 Model of the short-term market

4.2.2.1 Modeling approach

The approach adopted to model the short-term market is a mathematical optimization approach based on linear programming similar to the one used by Mills and Wiser (2013). Compared to other approaches described in subsection 2.3, mathematical optimization has the advantage of allowing to accurately model the demand side of the market, the impact of state-induced price components on demand and integration options like cross-border trade, energy storage or coupling of the heat, power and mobility sector. According to the reasons given in the case study, a precise model has to be capable of incorporating all these aspects.

At first glance, it seems inconsistent to use an optimization method, whereas in the previous section it was stressed that optimization is fundamentally unfit to capture the effects of the dynamization of state-induced price components. For this reason, we shortly want to shed light on this misconception. First of all, mathematical optimization is a tool to minimize or
maximize a given objective function given certain constraints. Power market models based on an optimization approach use this tool to minimize the short- and long-term costs of the power system regardless of other externalities or imperfections. Models aiming to simulate the short-term market use this tool to maximize social welfare, assuming allocative efficiency of the market in the short-term. Efficiency in the short-term implies rational behavior of market participants, perfect information, absence of transaction costs and no exercise of market power and is, therefore, in line with the assumptions made within the case study.\footnote{These assumptions also seem plausible, especially given the facts that digitization allows trading at very low costs, and that regulation forbids the exercise of market power in the power market.} Using mathematical optimization to simulate power markets in the short term is widely used in energy economic research including, Mills and Wiser (2013), Bruninx et al. (2012), Richter (2011), and Šumbera and Dlouhý (2015).

Maximizing social welfare is based on the supply and demand curve. While it is standard practice to display the supply curve in power markets, the so-called merit order, as a step function, the demand function is usually assumed to be isoelastic (Borenstein, 2005b: 4). Nevertheless, in this case an isoelastic demand function has to be approximated by a step function for the optimization problem in order to remain linear. Furthermore, to model cross-border trade of electricity, import and export were added to the supply and demand curve, respectively. The import and export curves are computed by an independent model (Appendix A.2). For a given time period $t$ the curves of demand, supply, import and export are illustrated exemplarily in Figure 2 in order to explain the mechanics of the modeled optimization problem.

The objective function seeks to maximize social welfare, which relates to the difference between the area below the demand curve minus the area above the supply curve, and to satisfy the first constraint of the optimization problem: quantities supplied must equal quantities demanded. Therefore, the optimization will always lead to a state corresponding to the interception of the supply and demand curve. According to the rules of an energy-only market the market price equals the largest marginal costs of all operating power plants. It can be shown that this results represents a Nash equilibrium: if any generator changed his quantities supplied, he would either produce (not produce), although prices do not cover (exceed) his marginal costs. Likewise, if any consumer changed his quantities demanded, he would either consume, although prices exceed his willingness to pay (WTP), or not consume, although prices are below his WTP. In conclusion, nobody has anything to gain by changing the strategy, which meets the definition of a Nash equilibrium.

The simulation still is at a Nash equilibrium if the mechanism of price formation changes
in scarcity events. Since the model aims to represent an energy-only market with scarcity pricing, in scarcity events prices exceed the marginal costs of any power plant and rise to the maximum benefit of consumption of consumers minus state-induced price components to avoid a blackout. This maximum benefit of consumption is also referred to as the value of lost load (VOLL). In this paper, a situation of scarcity is defined as a point where all available power plants produce at maximum capacity, up to the point where the demand with the highest WTP is covered. Such a situation is illustrated in Figure 3. The model developed in our study and the model developed in Mills and Wiser (2013) differ in the additional elements of the power market they include. In order to address the specific needs resulting from our research questions regarding some elements of the power market, we devoted more effort than Mills there, while less relevant elements have been neglected.

First technical restrictions regarding the flexibility of thermal power plants are neglected. Existing research on integration costs presented in subsection 2.2.1 and other research only show small effects arising from the technical restrictions of thermal power plants (Kraemer, 2014). Furthermore, effects can be assumed to be small in the case study considered, because it mainly relies on gas-fired thermal power plants, which offer a high level of flexibility compared to other technologies. Therefore, these effects can be treated generally and are not included into the model.

Secondly, we neglect uncertainty and assumed perfect information. On the one hand, considering uncertainty could provide additional insights on dynamization, because the ability of
dynamization to accurately respond to certain situations in the power market as described in subsection 4.2.1 is highly dependent on the accuracy of forecasts. On the other hand, modeling uncertainty requires a lot of computational effort, especially when simulating the dispatch of energy storage systems. For this reason, uncertainty in general is not studied to keep computation time of the model and the scope of the study within reasonable limits. Neglecting technical restrictions of thermal power plants and uncertainty also frees computational resources to represent the demand side of the market, integration options, and the impact of state-induced price components more thoroughly. This results in the objective function (3) and balancing equation (4).

\[
\begin{align*}
\max & \sum_{\text{con},t} D_{\text{DoQ},\text{con},t} \cdot (D_{\text{DB},\text{con},t} - D_{\text{DT},\text{con},t}) - \sum_{\text{gen},t} S_{\text{SQ},\text{gen},t} \cdot M_{\text{CG},\text{gen},t} + \\
& \sum_{\text{ex},t} E_{\text{EXQ},\text{ex},t} \cdot E_{\text{WX},\text{ex},t} - \sum_{\text{im},t} I_{\text{MQ},\text{im},t} \cdot I_{\text{MC},\text{im},t} + \\
& \sum_{\text{conS},t} U_{\text{SQ},\text{conS},t} \cdot D_{\text{xB},\text{conS},t} - D_{\text{SQ},\text{conS},t} \cdot D_{\text{xT},\text{conS},t} \\
\sum_{\text{con}} D_{\text{Q},\text{con},t} + \sum_{\text{ex}} E_{\text{XQ},\text{ex},t} + \sum_{\text{conS}} D_{\text{SQ},\text{conS}} + \sum_{\text{st}} S_{\text{In},\text{st},t} + E_{\text{Q},t} + C_{\text{HP},\text{Q},t} \\
+ P_{2\text{GQ},t} &= \sum_{\text{gen}} S_{\text{SQ},\text{gen},t} + \sum_{\text{im}} I_{\text{MQ},\text{im},t} + \sum_{\text{st}} S_{\text{Out},\text{st},t} \cdot \eta_{\text{out},\text{st}}, \forall t
\end{align*}
\]

Appendix A.1 provides the complete mathematical formulation of the optimization problem.
including variables and indices used in eqs. (3) and (4).

4.2.2.2 Substitution elasticity in the short-term simulation

While the own-price elasticity of demand has simply been implemented into the model by a stepped demand curve, the approach we developed for implementing the substitution elasticity of demand is more complicated.

Based on Neenan and Eom (2008: 17) the substitution elasticity of demand is defined as the change in consumption in a time period $t$ caused by a change in prices in another time period $t'$. The substitution elasticity is of particular relevance if demand can be shifted between time periods under certain technical restrictions. For example, the electricity needed to charge the battery of an electric car could be demanded any time the car is plugged in, as long as it is fully charged when the car is used again. As a result, demand will shift to periods with the lowest consumer prices. Technologies allowing demand to be shifted in time are often referred to as DSM technologies. Examples besides car batteries include electric heat pumps, heat storage, energy-intensive industrial processes, and more. Many of these technologies play a key role for the intensified coupling of the heat, power, and mobility sector.

Analogously to own-price elasticity, substitution elasticity is usually represented by a single number for two specific time periods $t$ and $t'$. However, in a year consisting of 8,760 h or time periods, factoring in every substitution elasticity for a given technology would require $8,760 \cdot 8,760 = 76,737,600$ values. Computing and implementing such a high number of substitution elasticities does not seem practical, which is why a different method was deployed: Instead of computing substitution elasticities that reflect the restrictions shifting demand in time is subjected to, and then working these elasticities into the model, we decided to directly represent the restrictions of shifting demand within the model. To this end, eqs. (5) - (7) provide the constraints to the optimization problem.

$$ DU_s Q_{conS,t} = $$

$$ DU_s Q_{conS,t-1} \cdot \gamma_{shift,conS,t} - U_s Q_{conS,t} + D_s Q_{conS,t} \cdot \eta_{shift,conS,t}, \forall conS, t \quad (5) $$

$$ 0 \leq \sum_{T_{conS,t}} U_s Q_{conS,t} - DU_s Q_{conS,t}, \forall conS, t \quad (6) $$

$$ DU_s Q_{max_{conS,t}} \geq \sum_{T_{conS,t}} U_s Q_{conS,t}, \forall conS, t \quad (7) $$

A detailed summary of all sets, parameters and variables used in eqs. (5) - (7) can be found...
in Appendix A. In the model, every substitution-elastic consumer group $\text{conS}_t$ aggregates on particular DSM technology. Since demand from these technologies comes from many small units, it is assumed to be infinitely divisible. To provide a better understanding of the approach, the variables, parameters and sets as well as the corresponding constraints are explained using the example of a car battery again.

The variables $D_sQ_{\text{conS},t}$ and $U_sQ_{\text{conS},t}$ are counterparts. One represents the quantity demanded and the other the quantity utilized in each time period $t$. Returning to the example $D_sQ_{\text{conS},t}$ gives the amount of electricity the battery is being charged with, and $U_sQ_{\text{conS},t}$ the amount of electricity used for driving. Both are interrelated by the variable $DUsQ_{\text{conS},t}$ relating to the currently shifted quantity or the current charging level of the battery.

Again, every variable has a lower limit of zero and individual upper limits set by constraints not listed here. These upper limits vary depending on the time period $t$ to create a temporal profile. For example, the temporal profile of $D_sQ_{\text{conS},t}$ reflects at what times the car battery is plugged in and the profile $U_sQ_{\text{conS},t}$ corresponds to when the car is being used. The upper limit of $DUsQ_{\text{conS},t}$ is $DUsQ_{\text{max conS},t}$ and is also used directly within the constraints. In the example it refers to the maximum capacity of the car battery. Due to conversion losses of the battery, not the whole electricity demanded can be utilized for driving, which is factored in by the efficiency of shifting quantities, $\eta_{\text{shift,conS},t}$. Further losses caused by the self-discharge rate of the battery can be modeled by the loss rate, $\gamma_{\text{conS},t}$. $T_{\text{S conS},t}$ determines a time frame within which demanded electricity has to be utilized. In the example, this means that after a defined number of time periods electricity charged to the battery must be used for driving. $TR_{\text{conS},t}$ limits the frequency of utilizing the DSM technology by determining a number of subsequent time periods within which the maximum time-shiftable quantity $DUsQ_{\text{max conS},t}$ can only be utilized once. In terms of the example, the amount of electricity corresponding to a single charge of the battery can only be used for driving once in a defined time frame.

The set of constraints makes sure that $D_sQ_{\text{conS},t}$ and $U_sQ_{\text{conS},t}$ always comply with the technical restrictions outlined above. Eq. (5) ensures under consideration of all losses that $DUsQ_{\text{conS},t}$ always correctly reflects the quantity currently shifted. Due to the constrained formulated by eq. (6), the quantity shifted is always utilized within the required time frame $T_{\text{S conS},t}$. Eq. (7) solves the purpose to control the DSM technology is not utilized too often. While the framework so far was always applied to the battery of an electric car as an example, it can be used to model any type of substitution-elastic demand technology. To explain how the framework can be transferred to other technologies, two idealized types of substitution-elastic demand are defined. They are distinguished by the way the utilization of electricity is
restricted. In order to not further complicate these examples, energy losses from $\eta_{\text{shift}\, conS,t}$ and $\gamma_{conS,t}$ and the maximum time frame for shifting demand $TS_{conS,t}$ are put aside.

Regarding the first idealized type, utilization is only restricted by the temporal profile given for the upper limit of $UsQ_{conS,t}$. The frequency of utilizing the DSM technology defined by $TR_{conS,t}$ is unconstrained. Consequently, $DsQ_{conS,t}$ will adjust to cover all quantities of $UsQ_{conS,t}$ at the lowest consumer costs possible, as long as these costs do not exceed the marginal benefits $DsB_{conS,t}$ of the substitution-elastic consumer group. All continuously used DSM technologies like, again, electric car batteries or electric heating systems, can serve as an illustration for this type. The second idealized type is contrary to the first. The temporal profile of $UsQ_{conS,t}$ is unconstrained above, but the frequency of utilizing the quantity $DUsQ_{\max\, conS,t}$ is constrained. As a result, $DsQ_{conS,t}$ adjusts to cover $DUsQ_{\max\, conS,t}$ at the lowest cost possible, which corresponds to shifting all quantities into the time periods with the lowest consumer prices. Any DSM technologies that are only used at selected times such as washing machines in private households or flexible industrial processes, are examples of this type. Of course, most technologies in the real world cannot be assigned to either of these two idealized types, because both kinds of restrictions might apply at some point. In this case, these technologies can be modeled by the given framework as a superposition of both idealized types. To illustrate this idea for a given time frame, in Figure 4 $UsQ_{conS,t}$ and $DsQ_{conS,t}$ are taken from actual model results and plotted for a technology of the first type, the second type, and a superposition of both.

The illustration very clearly demonstrates the difference between the first and the second idealized type. In the first case, quantities utilized, $UsQ_{conS,t}$ (shown in the left array) are always covered up to their upper limit. The costs depend on when the utilized electricity is demanded, which is displayed in the right-hand side plots. Demand is subjected to technical restrictions like the maximum time-shiftable quantity and the upper limit of demand. Therefore, not all energy can be demanded when costs are lowest. In the second case, the upper limit of $UsQ_{conS,t}$ is unbound, but of course the quantity defined by $DUsQ_{\max\, conS,t}$ can only be utilized once in a given time frame. As a result, the whole quantity is demanded at once, when costs are lowest. The third case is a superposition of both previous cases. Both, the upper limit of $UsQ_{conS,t}$ and $DUsQ_{\max\, conS,t}$, are binding constraints at some point. The particular profile illustrated could represent an industrial cooling systems requiring a certain amount of electricity per day, but at the same time available cooling capacity varies depending on the time of day due to changing outdoor temperatures.

After the constraints regarding substitution-elastic demand have been discussed, notice that apart from these constraints the substitution elasticity is worked into the objective func-
Figure 4: Types of substitution-elastic demand in the model
Source: Own illustration

Since they are adopted from previous research and are not as elaborate as methods deployed in the rest of the model, the remaining constraints and elements of the short-term simulation model are collectively summarized in Appendix A.3.
4.2.3 Model of the long-term market

4.2.3.1 Investment in renewables and storage

According to the assumed policy framework generation capacities of RE and storage are set and subsidized by the government and subsidies are financed by a levy on the consumption of electricity. Therefore, generation capacities of RE and storage are not determined within the long-term model, whereas the level of the levy is. The revenue generated by the levy equals the subsidies for RE and storage. This follows from the fact that according to the case study a levy might only be used for a specific purpose. In a Nash equilibrium, subsidies summed up with market revenues of RE and storage must equal the full costs of RE and storage. This can be shown as follows: If the sum of market revenues of RE and storage and subsidies exceeds full costs, the government has an incentive to decrease subsidies in order to achieve the same political objectives at lower costs. In turn, if full costs exceed the sum of market revenues and subsidies, the government is obliged to increase subsidies to trigger investment and meet the political objectives. Thus, the condition of a Nash equilibrium concerning the investment in RE and storage within the assumed policy framework can be described as follows:

\[ \sum_{RE} FC_{re} + \sum_{ST} FC_{st} = LR + \sum_{RE} MR_{re} + \sum_{ST} MR_{st} = \text{const}. \]  

Equation (8) says that full costs \( FC \) summed among all RE and storage systems must equal subsidies or levy revenues \( LR \) plus the market revenues \( MR \) summed among all RE and storage systems. Notice that determining a level of the levy corresponding to a Nash equilibrium is not trivial, because all terms on the right-hand side of the equation \( LR, \sum_{RE} MR_{re} \) and \( \sum_{ST} MR_{st} \) are affected by changes of the levy. While the level of the levy has a direct impact on the revenues generated by the levy \( LR \), the market revenue of RE and storage is affected indirectly through the changing outcome of the short-term market. The short-term market outcome changes, because according to the short-term market model consumption patterns are linked to tax levels. Since generation capacities of RE and storage (and as a result full costs) are fixed, the left-hand side of the equation always remains constant.

To address the described difficulty in the long-term model, the level of the levy-satisfying condition formulated in eq. (8) is determined by an iterative approach. After each iteration, the level of the levy for the next iteration is estimated based on the impact of a marginal change in the level of the levy until a Nash equilibrium is reached. To avoid extremely long calculation times the iteration process will end as soon as the condition is satisfied with a set accuracy of 0.1%. State-induced price components not used to subsidize RE and storage are
kept constant throughout the entire model. Figure 5 summarizes the simulation model; now, effects from the investment in RE and storage are incorporated and, therefore, the level of state-induced price components no longer is an input, but determined endogenously within the model. Before we proceed to explain how the investment in thermal power plants is covered, note that the part of the model described in this section is where dynamization of state-induced price components is implemented. For this purpose, the temporal profile of the iterated levy used to finance subsidies for RE and storage is changed from a flat profile to a profile coupled to the market price for electricity.

4.2.3.2 Investment in thermal power plants

According to the assumed policy framework, investment in thermal power plants, unlike investment in RE and storage, is not regulated by the government, but solely depends on mechanisms of the energy-only market. For the thermal power plant portfolio resulting from these mechanisms in the long-term, the RTP literature fallback on two different definitions.:

Borenstein and Holland (2005a) define the long-term equilibrium as the state where an additional increase in capacity of a specific technology would cause profits for all units of the specific technology to be negative. This definition was also adopted in our study, because it matches the definition of a Nash equilibrium, which says that no market participant has an incentive to change his strategy. This can be shown as follows: If additional capacity causes negative profits for all, no generator has an incentive to increase capacity. Furthermore, there is no incentive to decrease capacity, because the definition implies current profits are zero or greater. In contrast to this, Mills and Wiser (2013) define the long-term equilibrium as the point where for every technology profits are equal to zero, which violates the definition of a Nash equilibrium. Although the Nash equilibrium will lead to a state where most profits are zero or at least close to zero, distinguishing between the definitions is not without difference if the model includes scarcity pricing. In this case peak-load plants earn their full costs when
scarcity events occur, and market prices rise to the VOLL minus state-induced price components. Profits of peak-load plants are very sensitive to the frequency of these events, because they create high revenues in a single time period. As a consequence, peak-load plants can have profits significantly greater than zero at a Nash equilibrium, because a marginal increase of capacity would lead to one scarcity event less and negative profits.

Determining a Nash equilibrium of the thermal power plant portfolio, especially while maintaining the Nash equilibrium of investments in RE and storage, poses a challenge because profits of all generation technologies on the supply side are heavily interrelated with each other. Changing the generation capacity of a single technology might affect the profits of all technologies. Elastic demand and storage technologies adjusting to the supply side of the market add more complexity. To meet these challenges, determining the long-term equilibrium thermal power plant portfolio is implemented as a three-step process based on game-theoretic concepts.

The first step is easy to comprehend and involves excluding dominated strategies from the set of options. In game theory, a strategy is referred to as dominated if another strategy will always achieve better results (Fudenberg and Tirole, 2007). In this case, a thermal power plant technology is dominated if fixed costs and marginal costs of another technology are smaller. Since there is no economic incentive to invest in dominated power plant technologies, they can be excluded from further considerations.

In the second step, a set of necessary conditions for the thermal power plant portfolio to be at a Nash equilibrium is defined and generation capacities satisfying these conditions are derived. The derivation of the conditions is based on an approach introduced in Borenstein (2005b) that corresponds to the concept of backward induction used in game theory (Fudenberg and Tirole, 2007). The approach is based on the idea to first focus on investment in the last relevant technology in the merit order, also referred to as peak-load plants. Corresponding to the concept of backward induction, investments in the next technology to the left in the merit order can be determined using the results obtained for peak-load plants, and so on. Corresponding to their position in the merit order, peak-load plants have the highest marginal costs of all technologies, but at the same time the lowest fixed costs. Any technology with smaller fixed costs would dominate the peak-load technology and, therefore, have been excluded from considerations in the first step. Profits of peak-load plants \( PR_{PL} \) are defined as:

\[
PR_{PL} = MR_{PL} - FC_{PL} = \frac{t_{VOLL}}{a_{SL,VOLL}} \cdot WTP_{VOLL} \cdot P_{PL} \left( \frac{t_{VOLL}}{a_{SL,VOLL}} \cdot MC_{PL} \cdot P_{PL} + fc_{PL} \cdot P_{PL} \right)
\] (9)
where $MR_{PL}$ and $FC_{PL}$ refer to the market revenue and full costs of all peak-load power plants, respectively. The equation can be further decomposed by taking into consideration that peak-load plants earn their full costs in scarcity events as explained earlier. Revenue from these situations can be expressed by multiplying the number of scarcity events, $t_{VOLL}$, the WTP at a scarcity event, $WTP_{VOLL}$, which is the $VOLL$ minus state-induced price components, and the available capacity of peak-load plants at scarcity events. This capacity is expressed as the installed capacity $P_{PL}$ divided by the average availability of peak-load plants at scarcity events, $a_{SL;VOLL}$. The corresponding full costs are composed of costs of deployment in these situations depending on the marginal costs $MC_{PL}$ and the fixed costs, which are expressed using the fixed costs per capacity installed, $fc_{PL}$.

According to the definition of the Nash equilibrium applied investment occurs until an additional increase in capacity causes profits of the technology to become negative. Therefore, at a Nash equilibrium profits are zero or greater, which is why we can draw the following conclusion based on eq. (9):

$$PR_{PL} \geq 0 \iff \frac{t_{VOLL} \cdot WTP_{VOLL}}{a_{SL;VOLL}} \cdot P_{PL} - (\frac{t_{VOLL}}{a_{SL;VOLL}} \cdot MC_{PL} \cdot P_{PL} + f_{cPL} \cdot P_{PL}) \geq 0$$

$$\iff \frac{t_{VOLL} \cdot VOLL}{a_{SL;VOLL}} - (\frac{t_{VOLL}}{a_{SL;VOLL}} \cdot MC_{PL} + f_{cPL}) \geq 0$$

Solving inequality (10) for $t_{VOLL}$ and considering, that there is no such thing as a “half scarcity event”, the following conditions for $t_{VOLL}$ at a Nash equilibrium can be set:

$$\Rightarrow t_{VOLL} \geq \frac{f_{cPL} \cdot a_{SL;VOLL}}{WTP_{VOLL} - MC_{PL}}, \ t_{VOLL} \in \mathbb{Z}.$$  

At the point where a marginal increase in capacity causes profits to become negative, profits are at the smallest non-negative value possible. Transferred to the number of scarcity events $t_{VOLL}$ at a Nash equilibrium this means that profits correspond to the smallest value satisfying the condition. This value can easily be computed by transforming inequality (11) into an equation and rounding up $t_{VOLL}$ to the next larger integer. From now on this value, the number of scarcity events at a Nash equilibrium, is referred to as $t'_{VOLL}$. A number of scarcity events equal to $t'_{VOLL}$ is a necessary but not sufficient condition for investment in peak-load plants to be at a Nash equilibrium. To clarify this, consider the following situation: The number of scarcity events equals $t'_{VOLL}$, but the capacity of peak-load plants can be increased by a further 300 MW, before $t_{VOLL}$ becomes smaller than $t'_{VOLL}$. In this situation a market participant can gain profits by investing in additional peak-load capacity and, therefore, a

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Note that revenues and deployment costs in time periods where market prices equal marginal costs are not included in the equation because they balance each other out.
Nash equilibrium is not reached yet.

$t'_{VOLL}$ is used in the next step of backward induction, where the process applied to peak-load plants is transferred to the next group of power plants in the merit order, which are termed mid-load power plants. Since mid-load power plants earn revenues in scarcity events and in time periods where prices are set by peak-load plants, their profits can be defined as:

$$PR_{ML} = \frac{t'_{VOLL}}{a_{ML, VOLL}} \cdot WTP_{VOLL} \cdot P_{ML} + \frac{t_{PL}}{a_{ML, PL}} \cdot MC_{PL} \cdot P_{ML} -$$

$$\left( \frac{t'_{VOLL}}{a_{ML, VOLL}} \cdot MC_{ML} \cdot P_{PL} + \frac{t_{PL}}{a_{ML, PL}} \cdot MC_{ML} \cdot P_{PL} + f_{cML} \cdot P_{ML} \right)$$

(12)

This equation is completely analogous to eq. (9) in the previous step, except for the fact that it includes revenues and deployment costs in hours where prices are set by peak-load plants: The number of these hours is referred to as $t_{PL}$ and the availability of mid-load plants in these hours is $a_{ML, PL}$. Derived analogously to the previous step, the following condition for $t_{PL}$ at a Nash equilibrium can be defined:

$$\Rightarrow t_{PL} \geq \frac{f_{cML} \cdot a_{ML, PL} - t'_{VOLL} \cdot \frac{a_{ML, PL}}{a_{ML, VOLL}} \cdot (WTP_{VOLL} - MC_{ML})}{MC_{PL} - MC_{ML}}, \quad t_{PL} \in \mathbb{Z}.$$  

(13)

The smallest value satisfying this condition is termed $t'_{PL}$; it is used to define the necessary conditions for a Nash equilibrium: The necessary conditions for investment in mid-load plants to be at a Nash equilibrium are the number of scarcity events equal to $t'_{VOLL}$ and the number of time periods when peak-load plants set the market price equal to $t'_{PL}$. This same process is successively applied to all groups of thermal power plants in the merit order. Analogously to the previous step the number of time periods each technology is setting the market price at a Nash equilibrium is obtained and used to define a set of necessary conditions.

Figure 6 shows how generating capacities that satisfy the necessary conditions can be obtained if three different power plant technologies are considered and an exogenously given residual demand curve is assumed. The third generation technology has been termed base-load. The illustration shows the ordered duration curve of residual demand. Residual demand is the share of demand to be covered by thermal power plants, computed by subtracting generation of VRE from original demand. Thus, generation of VRE exceeds demand in hours of negative residual demand. A point on the duration curve gives the total installed generation capacity required to cover demand in the respective time period. Therefore, the duration curve can be used to obtain installed generation capacities satisfying the necessary conditions for $t'_{PL}$, $t'_{ML}$, and $t'_{BL}$.

However, in the model the residual demand curve and the thermal power plant portfolio
used are highly interrelated, because according to the objective function (3) of the short-term model, elastic demand and storage systems adjust to the supply side. For this reason, the existing iteration process to achieve a Nash equilibrium regarding investment in RE and storage was extended with an additional superordinate iteration process in order to determine a thermal power plant portfolio that meets the necessary conditions. The inner process of the nested iteration provides the level of state-induced price components at a Nash equilibrium for a given thermal plant portfolio, as described in the previous section. The outer process iterates generation capacities for each generation technology separately, based on the bisection method until the necessary conditions are satisfied.

In the third step, the model goes from necessary conditions to sufficient conditions. The sufficient conditions are met if a marginal increase in capacity of any technology causes profits of the respective technology to become negative. In the model this condition is relaxed by replacing the marginal increase with an adjustable step size (usually set to 50 MW). Every generation capacity obtained in the previous step is successively increased by this step size until the necessary condition is violated again. At this point, the previous value corresponds to the Nash equilibrium.

The developed model is capable of achieving a long-term equilibrium of the power market corresponding to a Nash equilibrium by simulating the investment in RE, storage and thermal power plants based on a nested iteration, as depicted in Figure 7. The nested iteration has the effect that the optimization problem simulating the short-term market is solved very often in a single run of the model. Therefore, the whole practical implementation of the model aims at reducing computational time of the optimization. Although data pre-processing, iterating and evaluating results is done in Matlab, linear programming to solve the optimization problem

![Figure 6: Derivation of thermal power plant portfolio](image)

Source: Own illustration
is handled in GAMS to improve model performance. Furthermore, using the solution to the optimization problem from the previous iteration as a starting point for the optimization of the following iteration significantly decreases running time. Final model outputs are written to an Excel file and the input data is supplied as a SQL database.

4.3 Model parametrization

To ensure maximum consistency of the input data, as many assumptions as possible have been adopted from the same source, a study mapping out a largely decarbonized German energy system in 2050 (Gerhardt et al., 2015). All essential parameters like quantities demanded and installed generation capacities of VRE and storage systems are taken from this study. All time series data - such as temperature, demand, availability of thermal power plants or generation from VRE - are for Germany in the year 2016. The considered time span is one year, i.e. 8,760 h. A detailed description of the parametrization is provided in Appendix B. Among all inputs, results are probably most sensitive to the characteristics of demand, but at the same time the characteristics of demand are also subject to the greatest uncertainty. For this reason the parametrization of demand is presented in more detail here.

Although the pre-processing part of the model allows to incorporate different groups of consumers, with different demand patterns, own-price elasticities, and levels of state-induced price components imposed on them, only one uniform consumer group was modeled due to a lack of suitable data. In line with existing research, we assume an isoelastic demand function (Borenstein, 2005b: 4) of the form:

$$Q_t(p_t) = Q_{0,t} \cdot \left(\frac{p_t}{p_{0,t}}\right)^{\varepsilon \cdot x}, \quad p_t \in (0, VOLL].$$  \hspace{1cm} (14)

The function says that in hour $t$ demand $Q_t$ depends on the price $p_t$, the reference point set
by \( Q_{0,t} \) and \( p_{0,t} \), and the own-price elasticity \( \epsilon_t \) scaled by factor \( x \).

The smallest possible value of \( p_t \) corresponds to almost zero and the largest to \( VOLL \).\(^6\) The estimate of \( VOLL \) used is 2,190 €/MWh and taken from a study of the German energy system (Growitsch et al., 2007: 8). In every hour \( Q_t(p_t = VOLL) \) represents the inelastic share of demand. Reference quantities \( Q_{0,t} \) are obtained by applying the temporal profile of German demand in 2016 to the total conventional demand assumed in Gerhardt et al. (2015), which excludes demand from the heat and mobility sector (ENTSO-E, 2017). German day-ahead prices in 2016 plus the average level of state-induced price components in 2016, which is 152.48 €/MWh, serve as reference prices \( p_{0,t} \) (EPEX, 2017; Ecke and Göke, 2017). \( \epsilon_t \) varies depending on the hour of the day, taken from a study measuring the own-price elasticity of demand in the German market in 2015 (Knaut and Paulus, 2016: 15). The factor \( x \) is introduced to scale these elasticities to a desired level.

One might intuitively guess that the effects of dynamization strongly depend on the elasticity of demand and this intuition is supported by the research on RTP presented in section 2.3. Estimating future elasticities is difficult because, on the one hand, they depend on technological developments like the implementation of intelligent metering systems or DSM technologies, whereas, on the other hand, they are also influenced by the policy framework. For example, the expansion of RTP or dynamization itself can be expected to increase elasticity, because they create an additional incentive for flexibility. While all studies agree that elasticity in a decarbonized energy system will exceed current levels, absolute values differ by a factor of 20. Figure 8 gives an overview of the elasticities assumed in the reviewed literature. In this study, we assume that own-price elasticities are on the lower end of the

![Figure 8: Range of elasticities assumed in earlier research](image)

Source: Own illustration, based on references cited

range, for two reasons: First, proving economic benefits at low elasticities strongly suggests economic benefits at high elasticities. Second, the elasticities displayed refer to the whole

\(^6\)Zero itself is not included, because the isoelastic demand function for the value of zero is undefined.
demand and not just the conventional share of demand parametrized at this point, where elasticities can assumed to be lower. The values used are -0.0029, which corresponds to what Knaut and Paulus (2016) measure for Germany in 2015 on average, -0.025 and -0.05, which serve as a base-case assumption.

The demand curves derived using these values and eq. (14) are modified in order to ensure that the inelastic share of demand remains at the level computed for an elasticity of -0.0029. How and why this is done can be explained using Figure 9. If the inelastic share of demand remains unmodified, increasing elasticity dramatically diminishes the share of demand with the highest WTP. Mathematically, this results in a steep decline of consumer surplus if elasticity is increased, which, however, contradicts economic logic. To resolve this distortion, WTP is automatically increased to VOLL (red curve), until the quantity demanded exceeds $Q_t(p_t = VOLL, x = 1)$. Lastly, the computed isoelastic demand function is approximated by a step function (dotted line) that is used within the linear optimization model.

4.4 Results

4.4.1 General effect of dynamization

The general effects of dynamization are demonstrated in a base-case scenario, which assumes an average elasticity of -0.05 and a carbon prices of $100 \frac{\epsilon}{tCO_2}$. The results of the following analysis hold true, unless the relation of gas and coal prices extremely diverges from the assumed levels. Different scenarios considered later lead to different numerical results, but show the same mechanism, which is outlined next.
Dynamization alters consumer prices, which are comprised of the market price for electricity and state-induced price components, taxes and levies. Before dynamization is introduced, only the market price changes depending on the point of time, but after the introduction of dynamization also the levy to subsidize RE and storage is coupled to the market price. Thus, dynamization reinforces the market price signal for consumers, which results in the change of the price curve displayed in Figure 10 for an interval of 72 hours. Figure 10 shows that the introduction of dynamization also affects the market price and, therefore, the supply side and market outcome. In section 4.1 it was argued that these effects will lead to a decrease in curtailment of VRE on the one hand, and to a shift from peak-load towards mid-load power plants on the other hand. The numerical model results displayed in Figure 11 illustrate this statement.

Figure 10: Change of consumer prices from dynamization
Source: Own illustration, based on model results

Figure 11: Change in generation from dynamization
Source: Own illustration, based on model results

Overall, dynamization causes an increase in generation by 4 TWh, which is composed of a decline in curtailment by 2.5 TWh, an increase in generation from mid-load power plants by 3.2 TWh, and a drop in generation from peak-load plants by 1.7 TWh. The rise in consumption due to dynamization amounts to 5.2 TWh because, in addition to increased generation,
the electricity trade balance shifts towards import by 1.2 TWh. Changed consumer prices and consumption quantities result in the change of social welfare created in the market illustrated in Figure 12. Two effects can be observed concerning consumer surplus: First, the additional consumption, which is part of the own-price elastic demand, creates an additional consumer surplus of €206 million. Second, dynamization causes strong distributional effects among the demand already covered before dynamization was introduced. The social welfare from substitution-elastic demand, which is able to shift towards low-price hours, increases at the expense of inflexible own-price elastic demand, which strongly decreases. These effects are consequences of the price curve displayed in Figure 10 and nearly balance each other out, so that the total rise of consumer surplus amounts to €200 million. Producer surplus drops by €23 million. As explained in depth in subsection 4.2.3.2, in the long-term equilibrium profits of thermal power plants deviate from zero due to revenues from scarcity events. These revenues depend on the difference between the VOLL and state-induced price components according to eq. (9). Since state-induced price components at these events are raised by dynamization, producer surplus declines. The rise in government revenues almost entirely results from revenues created by fixed state-induced price components imposed on a higher amount of consumption. A small share also results from a net increase in GHG emissions that are taxed with the carbon price by the government. This change in GHG emissions induced by dynamization is displayed in Figure 13. Corresponding to the shift of generation

---

7Total social welfare roughly amounts to 1,000 billion Euro and is not a meaningful measure, because unlike the changes in social welfare considered here, it is highly sensitive to the assumed VOLL.
from peak-load plants towards mid-load plants, GHG emissions of peak-load plants drop by 700,000 t CO$_2$, whereas those of the mid-load plants increase by 1,000,000 t CO$_2$. So, overall emissions avoided by peak-load power plants are overcompensated by rising emissions from mid-load plants, resulting in a net increase. The magnitude of this effect varies, depending on the respective mid-load and peak-load technology. In the considered base-case scenario, mid-load corresponds to combined-cycle gas turbine (CCGT) and peak-load to gas-turbine (GT) power plants.

In conclusion, the impact of dynamization on utilization of VRE and social welfare corresponds to the objective of efficiently integrating VRE into the energy system, but is accompanied by an increase in GHG emissions.

### 4.4.2 Integration and decarbonization costs

The formula used to compute integration costs is an extension of eq. (1) that provided integration costs assuming perfectly inelastic demand. If this assumption is relaxed, the formula must account for welfare losses or gains associated with VRE as well. Therefore, we added a second term to the formula where $N_{tot(VRE)}$ and $N_{tot(0)}$ refer to the consumer welfare in an energy system with and without VRE, respectively. In addition, we added a third analogous term, consisting of $G_{tot(VRE)}$ and $G_{tot(0)}$ to reflect a change in government revenue:

$$C_{int} = \left[ \frac{C_{resid}}{E_{resid}} - \frac{C_{tot(0)}}{E_{tot(0)}} \right] E_{resid} + (N_{tot(0)} - N_{tot(VRE)}) + (G_{tot(0)} - G_{tot(VRE)})$$  \hspace{1cm} (15)

The resulting formula now incorporates all components of social welfare. $C_{int}$ is divided by the total energy supplied by VRE $E_{VRE}$, yielding the specific integration costs $c_{int}$:

$$c_{int} = \frac{C_{int}}{E_{VRE}}$$  \hspace{1cm} (16)
The formula to compute decarbonization costs is based upon eq. (2), but adapted slightly to reflect changes in social welfare. In order to provide consistency with integration costs, an energy system without VRE serves as a reference point for calculating the decarbonization costs:

\[ c_{\text{decar}} = \frac{W_{\text{tot}(0)} - W_{\text{tot}(VRE)}}{CE_{\text{tot}(0)} - CE_{\text{tot}(VRE)}}, \]  

Where \( CE_{\text{tot}(VRE)} \) and \( CE_{\text{tot}(0)} \) refer to the total sum of carbon emissions in a system with VRE and in a reference system without VRE, respectively, and \( W_{\text{tot}(VRE)} \) and \( W_{\text{tot}(0)} \) relate to social welfare, the sum of consumer surplus, producer surplus, and government revenue.

These formulas are applied to determine how integration and decarbonization costs are affected by the introduction of dynamization. For this purpose, the assumed own-price elasticity of demand and the policy framework, in particular carbon prices and available technologies, are varied. The reference point always represents a scenario without any VRE according to eq. (1), but with the same own-price elasticity and the same policy framework as the scenario analyzed. This is opposed to studies which, unlike this study, do not evaluate a certain policy instrument within a given framework, but the policy framework for decarbonization as a whole. These studies, consequently, choose a scenario without any decarbonization efforts as a reference.

The upper row of plots in Figure 14 show the change in the integration and decarbonization costs if dynamization is introduced, for different own-price elasticities and carbon prices. Appendix C provides the underlying absolute values of integration and decarbonization costs that these graphs are based on.

As shown for the base-case scenario in subsection 4.4.1, dynamization increases social welfare and the utilization of VRE, which is why dynamization decreases integration costs in every scenario considered. Integration costs can be reduced by up to 3.4 €/MWh, which corresponds to 4% of the total integration costs in the particular scenario. Additional consumer surplus and tax revenues represented by \( N_{\text{tot}} \) and \( T_{\text{tot}} \) in eq. (17) provide the greatest contribution to decrease integration costs.

The results show that higher own-price elasticities, as already presumed in section 2.3, amplify the effects of dynamization, because they increase the amount of generation shifted as displayed in Figure 11. This shift of generation, in particular the shift from peak-load to mid-load power plants, also causes the effect of carbon prices on dynamization: Welfare gains resulting from this shift increase if the difference of marginal costs between mid-load and peak-loads is high. For example, at a carbon price of 150 €/t CO₂ mid-load means CCGT power plants and peak-load refers to GT. Since CCGT emits 0.32 tons of carbon per MWh of
electricity generated, while GT emits 0.44, the difference in marginal costs grows if carbon prices rise to 200 €/tCO₂. As a result shifting generation from peak-load to mid-load plants becomes more beneficial and integration costs drop when rising carbon prices. This effect is reversed if an increased carbon price narrows the gap between marginal costs of mid-load and peak-load plants. For example, at a carbon price of 0 €/tCO₂ hard-coal power plants, assumed to emit 0.82 tons of carbon per MWh of electricity, represent the mid-load technology and peak-load still corresponds to GT power plants emitting 0.44 tons of carbon per MWh of electricity. As a result, raising the carbon price to 50 €/tCO₂ decreases the effect of dynamization. The magnitude of the effect increases if higher own-price elasticities amplify the amount of generation shifted. At low elasticities this effect is overcompensated by welfare gains from substitution-elastic demand discussed in subsection 4.4.1.

While dynamization always decreases integration costs, because utilization of VRE and social welfare increase in every case considered, the effects on decarbonization as the overar-
ching goal are dominated by two opposite effects. The numerator in the decarbonization cost formula reflects changes in social welfare, which is always increased by decarbonization, as discussed above. The denominator represents GHG emissions, which, due to increased thermal generation, rise in every scenario considered, if dynamization is introduced. But the extent of this rise again strongly depends on the specific emissions of the mid-load and peak-load technologies. If carbon prices are below $100 \frac{€}{t \text{CO}_2}$, mid-load corresponds to hard-coal power plants, and the shift of generation towards mid-load triggered by dynamization increases emissions by 6.5% on average. If carbon prices are above $100 \frac{€}{t \text{CO}_2}$, the mid-load technology switches to CCGT power plants, which has considerably lower specific emissions than hard-coal plants.\footnote{Results for a carbon price equal to $100 \frac{€}{t \text{CO}_2}$ are in between both cases. Although hard-coal power plants still have lower marginal costs than CCGT power plants, they are only utilized in the reference scenario without VRE. After the introduction of VRE hard-coal power plants are not able to recover their full costs any more and are replaced by CCGT.} As a result, the net increase in GHG emissions induced by dynamization only amounts to 1.3%.

The revenue of RE and storage increases when carbon prices rise from $0 \frac{€}{t \text{CO}_2}$ to $200 \frac{€}{t \text{CO}_2}$ and as a result the required subsidies for RE and storage drop by up to 50%. Consequently, also the level of the levy, which is coupled to the market price in the case of dynamization, drops by 50% when carbon prices rise. However, the results suggest that the impact of dynamization is not adversely affected. This is because most of the shift in consumption is already achieved at moderate changes of state-induced price components in the flat part of the isoelastic demand curve displayed in Figure 9.

The lower row of Figure 14, again, displays the change of integration and decarbonization costs, but is limited to the reference level of the own-price elasticity and varies the policy framework by excluding hard coal as a generation technology. The underlying absolute values are provided in Appendix C as well. If hard-coal power plants are not included, CCGT is always the mid-load technology, and the gap between marginal costs of mid-load and peak-load power plants decreases compared to scenarios without a coal phase-out. Therefore, the effect on integration costs induced by dynamization slightly drops at low carbon prices, if hard coal is excluded as a generation technology. On the contrary, effects on decarbonization costs increase substantially in these scenarios. If hard-coal power plants are phased out, the negative impact on decarbonization costs caused by a shift towards mid-load power plants is avoided. Therefore, decarbonization costs considerably decline even at low carbon prices, but total GHG emissions still slightly increase 1.2% on average.

Evaluating this trade-off, a substantial decrease of decarbonization costs against a slight increase in emissions is difficult. An exact assessment would require the incremental costs of
abating carbon within the energy system at the point considered, which the developed simulation model is fundamentally unfit to provide. Therefore, we will rely on a rough assessment based on the simulation model to evaluate this trade-off: In the base-case scenario, the increase of surplus induced by dynamization amounts to €600 million and carbon emission rise by 276,000 t\textsubscript{CO\textsubscript{2}}. If a portion of €100 million of welfare gains is invested in additional lead-acid batteries, GHG emissions drop by 297,000 t\textsubscript{CO\textsubscript{2}}. This example shows that investing a small share of social welfare gained by dynamization into decarbonization easily compensates the slight increase in GHG emissions.

In conclusion, dynamization of state-induced price components does reduce integration costs in every scenario considered. The effect on decarbonization costs depends on the policy framework, and is always accompanied by additional GHG emissions. In the case of a policy framework that does not include hard coal as a generation technology, decarbonization costs are always decreased, and model results strongly suggest a positive impact on efficient decarbonization, which is the overarching objective.

5 Conclusions

Satisfying climate objectives requires expansion and integration of VRE into the energy system on a large scale. This study analyzed whether the dynamization of state-induced price components imposed on the consumption of electricity can support the integration of VRE and, thus, help to efficiently achieve the overarching goal: decarbonization of the energy system. Dynamization in our approach means coupling the level of state-induced price components to the wholesale market price of electricity, instead of charging them at a fixed rate.

As a start, we reviewed the literature on efficiency in energy markets, indicators to evaluate dynamization, and research on the closely related topic of RTP. On this basis, we then carried out a qualitative analysis to identify general effects arising from dynamization. Aiming to quantify these effects, we developed a deterministic simulation model of the power market tailored to address the requirements resulting from the research questions. At the heart of the model is a detailed simulation of the short-term market based on linear programming. The inputs to the simulation are adapted iteratively until the long-term market outcome reaches a Nash equilibrium. For a quantitative case study, the model was parametrized in order to represent a German energy system that meets the political objective of reducing GHG emissions by 80% in 2050, compared to 1990 levels. The case study is based on a policy framework that is characterized by an energy-only market with scarcity pricing, carbon pricing and subsidies for renewable energies and energy storage technologies.
Model results confirm the effects of dynamization identified by qualitative analysis: if state-induced price components are coupled to the market price of electricity, curtailment of VRE decreases and generation from thermal power plants shifts from peak-load towards mid-load power plant technologies. Overall, generation and consumption of electricity rise, which results in higher GHG emissions, but also creates additional consumer surplus and government revenue. Furthermore, distributional effects among consumers arise from dynamization: Consumers able to shift their demand to low-price hours profit at the expense of inflexible consumers. Since a long-term equilibrium corresponds to producer profits close to zero, the changes in producer surplus are negligible.

In every scenario considered in the case study, dynamization supports the integration of VRE into the energy system and decreases integration costs by up to 4%. If dynamization is an efficient instrument to promote decarbonization as well, highly dependents on the policy framework in place: if the policy framework does not prevent the utilization of hard-coal power plants as a mid-load technology, welfare gains from dynamization are accompanied by a substantial rise of GHG emissions, which render dynamization unfavorable. In case the policy framework prevents utilization of hard-coal power plants, regardless of whether this is achieved by a market-based instrument like high carbon prices or a command-and-control instrument like a coal phase-out, model results strongly suggest efficiency gains from introducing dynamization. Positive impacts of dynamization are found to rise if the gap between marginal costs of mid-load and peak-load power plants widens and also if the own-price elasticity of demand increases. Furthermore, model results indicate that applying dynamization to only a small share of state-induced price components is sufficient to achieve a considerable impact.

The results of the case study can be transferred to any energy system that is characterized by VRE and fulfils ambitious decarbonization targets. Results of this study are a conservative estimate of the benefits arising from the dynamization of state-induced price components for two reasons: First, as illustrated in Figure 8, the own-price elasticity of demand assumed in the base-case scenario is at the lower end of assumptions in the respective literature. Numerical results show that positive effects increase at higher own-price elasticities. Second, long-term adjustments to the introduction of dynamization on the supply side are likely to create additional benefits. Due to the observed distributional effects from dynamization, consumers have an incentive to invest in technologies that enable them to shift their demand towards low-price hours. This creates additional flexibility and has positive effects on the system level. However, if the share of VRE is smaller and decarbonization targets are less ambitious, the effects of dynamization are likely to decline. Effects of dynamization are di-
minished as well if integration options such as intensified coupling of the heat, power and mobility sector or energy storage provide enough flexibility to avoid curtailment or the utilization of peak-load plants.

Results of this study could be interpreted as an argument for a roll-out of smart metering systems. Consumers cannot be exposed to time-varying prices without their implementation, which is why smart metering systems are a technical prerequisite for gaining benefits from dynamization. So far, the main argument for a roll-out of intelligent metering systems was the expansion of RTP. Furthermore, the results of this study provide an additional argument in favor of a coal phase-out. Numerical results of the simulation model demonstrate that the benefits of dynamization are outweighed by adverse effects on GHG emissions, as long as hard-coal is used as a mid-load technology.

Future research could contribute to a more comprehensive understanding of the dynamization of state-induced price components. How demand adjusts to dynamization in the long-term, the effects of dynamization if decarbonization targets are less ambitious, and the potential of dynamization to optimize the utilization of the power grid, are questions not researched yet and thus left for future research.

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**Appendix**

**A Description of the short-term model**

**A.1 Mathematical formulation**

**Sets**

- $conO$: Groups of own-price elastic consumers
- $conS$: Groups of substitution-elastic consumers
- $gen$: Groups of generator
- $genT$: Groups of thermal generators, subset of $gen$
- $st$: Groups of storage technologies
- $ex$: Groups of exports
- $im$: Groups of imports
- $t$: Time period

$TS_{conS,t}$: Time frame for the demand shift of substitution-elastic consumer group $conS$, assigns a number of subsequent time periods to time period $t$

$TR_{conS,t}$: Time frame to not repeat the demand shift of substitution-elastic
consumer group $conS$, assigns a number of subsequent time periods to time period $t$

**Parameters**

- $DoB_{conO,t}$: Benefit of consumption of own-price elastic consumer group $conO$ in time period $t$
- $DoT_{conO,t}$: State-induced price components imposed on own-price elastic consumer group $conO$ in time period $t$
- $DsB_{conS,t}$: Benefit of consumption of substitution-elastic consumer group $conS$ in time period $t$
- $DsT_{conS,t}$: State-induced price components imposed on substitution-elastic consumer group $conS$ in time period $t$
- $MCG_{gen,t}$: Marginal costs of generator $gen$ in time period $t$
- $EXW_{ex,t}$: WTP of export group $ex$
- $IMC_{im,t}$: Marginal costs of import group $im$
- $DUsQ_{- maxconS,t}$: Maximum time-shiftable quantity of substitution-elastic consumer group $conS$ in time period $t$
- $SQ_{- maxgen,t}$: Maximum quantity supplied by generator $gen$ in time period $t$
- $StOut_{- maxst,t}$: Maximum quantity supplied by storage technology $st$ in time period $t$
- $StIn_{- maxst,t}$: Maximum quantity demanded by storage technology $st$ in time period $t$
- $EQ_t$: Quantity demanded by the electrification of the heat sector in time period $t$
- $CHPQ_t$: Quantity supplied by CHP in time period $t$
- $P2GT$: Total quantity demanded by Power-to-Gas processes
- $RR_{pos,t}$: Positive reserve requirement in time period $t$
- $RR_{neg,t}$: Negative reserve requirement in time period $t$
- $\eta_{out, st}$: Efficiency of storage technology $st$ when supplying electricity
in time period $t$

$\eta_{in, st}$: Efficiency of storage technology $st$ when demanding electricity in time period $t$

$\eta_{shift, cons, t}$: Efficiency of shifting quantities of substitution-elastic consumer group $cons$ in time period $t$

$\gamma_{cons, t}$: Loss rate of quantities demanded per time period of substitution-elastic consumer group $cons$ in time period $t$

Variables

$DoQ_{dem, t}$: Quantity demanded by own-price-elastic consumer group $conO$
in time period $t$, $DoQ_{dem, t} \in [0, DoQ_{max, dem, t}]$

$SQ_{gen, t}$: Quantity supplied by generator $gen$
in time period $t$, $SQ_{gen, t} \in [0, SQ_{max, gen, t}]$

$EXQ_{ex, t}$: Quantity exported by export group $gen$
in time period $t$, $EXQ_{ex, t} \in [0, EXQ_{max, ex, t}]$

$IMQ_{im, t}$: Quantity imported by import group $gen$
in time period $t$, $IMQ_{im, t} \in [0, IMQ_{max, im, t}]$

$DsQ_{cons, t}$: Quantity demanded by substitution-elastic consumer group $cons$
in time period $t$, $DsQ_{cons, t} \in [0, DsQ_{max, cons, t}]$

$StIn_{st, t}$: Quantity demanded by storage technology $st$ in time period $t$,
$StIn_{st, t} \in [0, StIn_{max, st, t}]$

$StOut_{st, t}$: Quantity supplied by storage technology $st$ in time period $t$,
$StOut_{st, t} \in [0, StOut_{max, st, t}]$

$P2GQ_t$: Quantity demanded for the production of synthetic gases $t$
in time period $t$, $P2GQ_t \in [0, P2GQ_{max, t}]$

$StE_{st, t}$: Quantity saved by storage technology $st$ in time period $t$,
$StE_{st, t} \in [0, StE_{max, st, t}]$

$DsQ_{cons, t}$: Quantity demanded by substitution-elastic consumer group $cons$
in time period $t$, $DsQ_{cons, t} \in [0, DsQ_{max, cons, t}]$
\(UsQ_{\text{conS},t}\): Quantity utilized by substitution-elastic consumer group \(\text{conS}\) in time period \(t\), \(UsQ_{\text{conS},t} \in [0, UsQ_{\text{max\ conS},t}]\)

\(DUsQ_{\text{conS},t}\): Quantity currently shifted in time by substitution-elastic consumer group \(\text{conS}\) in time period \(t\),
\(DUsQ_{\text{conS},t} \in [0, DUsQ_{\text{max\ conS},t}]\)

Objective function

\[
\max \sum_{\text{con}, t} DoQ_{\text{conO},t} \cdot (DB_{\text{conO},t} - DT_{\text{conO},t}) - \sum_{\text{gen}, t} SQ_{\text{gen},t} \cdot MCG_{\text{gen},t} + \\
\sum_{\text{ex}, t} EXQ_{\text{ex},t} \cdot EXW_{\text{ex},t} - \sum_{\text{im}, t} IMQ_{\text{im},t} \cdot IMC_{\text{im},t} + \\
\sum_{\text{conS}, t} UsQ_{\text{conS},t} \cdot Db_{\text{conS},t} - DsQ_{\text{conS},t} \cdot Dxt_{\text{conS},t} \\
\Rightarrow \text{maximize social welfare}
\]

Constraints

\[
s.t. \sum_{\text{con}} DQ_{\text{con},t} + \sum_{\text{ex}} EXQ_{\text{ex},t} + \sum_{\text{conS}} DsQ_{\text{conS}} \sum_{\text{st}} StIn_{\text{st},t} + EQ_{t} + CHPQ_{t} + \\
P2GQ_{t} = \sum_{\text{gen}} SQ_{\text{gen},t} + \sum_{\text{im}} IMQ_{\text{im},t} + \sum_{\text{st}} StOut_{\text{st},t} \cdot \eta_{\text{out},st}, \forall t \\
\Rightarrow \text{balancing equation}
\]

\[
DUsQ_{\text{conS},t} = DUsQ_{\text{conS},t-1} \cdot \gamma_{\text{shift,conS},t} - UsQ_{\text{conS},t} + \\
DsQ_{\text{conS},t} \cdot \eta_{\text{shift,conS},t}, \forall \text{conS}, t \\
\Rightarrow \text{substitution elasticity, setting shifted quantity}
\]

\[
0 \leq \sum_{TS_{\text{conS},t}} UsQ_{\text{conS},t} - DUsQ_{\text{conS},t}, \forall \text{conS}, t \\
\Rightarrow \text{substitution elasticity, control time frame of shifting}
\]

\[
DUsQ_{\text{max\ conS},t} \geq \sum_{TR_{\text{conS},t}} UsQ_{\text{conS},t}, \forall \text{conS}, t \\
\Rightarrow \text{substitution elasticity, control frequency of shifting}
\]

\[
StE_{st,t} = StE_{st,t-1} \cdot \gamma_{\text{stor,st},t} + StIn_{st,t} \cdot \eta_{\text{in,st},t} - StOut_{st,t}, \forall st, t \\
\Rightarrow \text{storage equation}
\]

\[
P2GT = \sum_{T} P2GQ_{t} \\
\Rightarrow \text{cover Power-to-Gas demand}
\]
\begin{align*}
RR_{pos,t} & \leq \sum_{genT} SQ_{max,gen,t} - SQ_{gen,t} + \sum_{st} StOut_{max,st,t} - StOut_{st,t} \\
+ \sum_{st} StIn_{st,t}, \forall t \\
\Rightarrow & \text{ satisfying positive reserve requirement} \\
RR_{neg,t} & \leq \sum_{genT} SQ_{gen,t} + \sum_{st} StOut_{st,t} + \sum_{st} StIn_{max,st,t} - StIn_{st,t}, \forall t \\
\Rightarrow & \text{ satisfying negative reserve requirement}
\end{align*}

A.2 Import and export in the short-term simulation

In order to obtain the part of demand and supply stemming from the import or export of electricity, first a very generalized simulation of the power market in all neighboring countries of the country actually considered is performed. To do so, the optimization problem used for the short-term market in the model is reduced to the objective function and the balancing equation. In addition, demand is assumed to be inelastic and, therefore, the objective function has to be changed to minimize costs instead of maximizing social welfare. This results in the following optimization problem:

\begin{equation}
\min \sum_{gen,cr,t} SQ_{gen,cr,t} \cdot MCG_{gen}
\tag{18}
\end{equation}

\begin{equation}
DQ_{cr,t} = \sum_{gen} SQ_{gen,cr,t}, \forall cr, t
\tag{19}
\end{equation}

Newly introduced sets, parameters and variables are given in Table A.1.

\begin{table}[h]
\centering
\begin{tabular}{|l|l|l|}
\hline
Name & Description & Type \\
\hline
$cr$ & Group of neighbouring countries & Index \\
$DQ_{cr,t}$ & Inelastic demand of country $cr$ in time period $t$ & Parameter \\
$SQ_{gen,cr,t}$ & Quantity supplied by generator $gen$ in country $cr$ in time period $t$ & Variable \\
\hline
\end{tabular}
\caption{Definition of sets, parameters and variables in the European model}
\end{table}

In the following step, the outcome of the optimization problem is used to derive the quantities a neighboring country is willing to export or import and at what price and in which time period. The process applied for this purpose can be explained using Figure 15. The illustration shows the market outcome for a given time period $t$ and country $cr$. The inelastic demand curve is a vertical line whose interception with the merit-order supply curve gives the market equilibrium and the market price. Import of electricity takes place if the price of importing undercuts marginal costs of utilized generation capacities. The maximum quantity depends on the installed cross-border capacity available for importing $ImpC_{cr}$ between the country actually considered and the respective neighboring country $cr$. Export of electricity takes
place if the revenue of exports exceeds the marginal costs of generation. Again, the quantity exported is limited by the cross-border capacity available for exporting $ExpC_{cr}$. The potential import of the neighboring country is added to the export curve of the country focused on, whereas the potential export of the neighboring country is added to the import curve. The mechanics of the objective function (3) of the short-term market model ensure that electricity is only imported from the neighboring country, if the market price of the neighboring country undercuts the market prices of the country focused on, or exported from the neighboring country in the opposite case.

A.3 Additional elements of the short-term simulation

First, we want to address how the model incorporates the energy storage capacity used for generating arbitrage revenue. From an economic perspective, energy storage systems used for arbitrage purposes and energy storage systems owned by consumers - like an electric car battery - are fundamentally different and thus treated differently in the model, although technically both might be identical. Energy storage systems used for arbitrage purposes need electricity when prices are low, and seek to resell electrical energy at a profit later. Thus, they create an economic value beyond their own profits and do not have any state-induced price components imposed on their demand within the model (Ehlers, 2011: 111). In contrast, storage systems owned by consumers are not used for reselling purposes, but to shift their own demand. The variables representing demand and supply from storage technology $st$ in time period $t$, $StIn_{st,t}$ and $StOut_{st,t}$, have already been introduced when the balancing eq.
(4) was presented. In addition, the variable \( StE_{st,t} \) relates to the amount of energy saved by storage technology \( st \) in time period \( t \). As before, every of these variables has a lower limit of zero and an individual upper limit. The upper limits of \( StIn_{st,t} \) and of \( StOut_{st,t} \) represent the maximum power capacity of demand or supply of storage technology \( st \) in time period \( t \), respectively. The upper limit of \( StE_{st,t} \) corresponds to the total storage capacity. In the simulation, those three variables are interconnected by the following constraint:

\[
StE_{st,t} = StE_{st,t-1} \cdot \gamma_{stor,conS,t} + StIn_{st,t} \cdot \eta_{in,stor,t} - StOut_{st,t}, \forall st, t
\]  

(20)

where \( \gamma_{stor,conS,t} \) factors in the self-discharging rate of storage technologies and \( \eta_{in,stor,t} \) serves the purpose of modeling conversion losses when energy is transferred into the storage system. Apart from eq. (20) the short-term model does not constrain the behavior of energy storage operators in any way. Therefore, according to the objective function (3) energy storage is dispatched to maximize social welfare within technical restrictions. Note that this is only in line with the general methodology of the model if the welfare-maximizing dispatch of storage corresponds to a Nash equilibrium of storage operators. Sioshansi (2014) mathematically proofs that this is the case if no market participant can exercise market power, which is assumed as part of our case study. Next, we discuss how the coupling of the heat, power and mobility sector is reflected by the model. In general, the quantities demanded or supplied from coupling these sectors are not determined within the model, but exogenously given. These quantities can either be modeled as own-price or substitution-elastic demand with state-induced price components imposed on, as described earlier, or as demand without state-induced price components imposed on, which is described now. The parameter relating to the quantity \( EQ_t \) demanded for electrical heating in time period \( t \) was already introduced as part of the balancing equation. Since storage of heat is not cost-effective in most cases, the temporal profile of heat demand is inflexible and set externally. As the name suggests Power-to-Gas (PtG) refers to the concept of using electricity to create synthetic gases, which can be used in the heat or mobility sector. The quantity demanded by PtG processes within the time frame \( T \) covered by the model is referred to as \( P2GT \). In contrast to \( EQ_t \), the quantity of electricity demanded by PtG processes \( P2GQ_t \) in time period \( t \) is a variable and determined within the model, because gas can be stored at low costs. \( P2GQ_t \) has a lower limit of zero and an upper limit corresponding to the installed input capacity of PtG processes. \( P2GT \) and \( P2GQ_t \) are interrelated by eq. (21):

\[
P2GT = \sum_T P2GQ_t.
\]  

(21)
The supply from CHP is treated analogously to the demand for electrical heating. It is exoge- 

ously determined and passed on to the model as the parameter $CHPQ_t$, corresponding to 

quantities supplied by CHP in time period $t$. This approach implicitly assumes that dispatch 

of CHP is dictated by the demand for heat and, therefore, not simulated within the model. 

The presented framework achieves the purpose of modeling the impact of intensified coupling 

of the heat, power, and mobility sector. Yet, especially compared to the way own-price and 

substitution-elastic demand was modeled, these elements of the power system are treated 

rather generally, because a more detailed simulation faces two obstacles: First, a detailed 

simulation needs to include state-induced price components imposed on all types of energy 

and not just electricity. The state-induced price components depend on the general policy 

framework for coupling these sectors in a decarbonized energy system, which seems hard 

to predict from today’s perspective. Second, a representation in more detail would not just 

require a simulation of the power market, but an integrated simulation of the heat, power, 

and mobility market, which is beyond the scope of this paper. The last constraints of the 

simulation model to be introduced are related to the requirement for reserve capacities in 

power markets. Reserve requirements are not to be confused with peak-load power plants 

needed to cover demand at peak consumption times. The need for reserve capacities arises 

because differences between supply and demand for electricity must be kept within narrow 

bounds at any time to ensure the stability of the transmission grid. Therefore, grid operators 

take measures to balance deviations, if actual supply or demand differs from planned supply 
or demand. In the short-term simulation, these measures are represented by the two following 

constraints loosely based on Brouwer et al. (2016):

\[
RR_{pos,t} \leq \sum_{genT} SQ_{\max gen,t} - SQ_{gen,t} + \sum_{st} StOut_{\max st,t} - StOut_{st,t} + \sum_{st} StIn_{st,t}, \forall t \tag{22}
\]

\[
RR_{neg,t} \leq \sum_{genT} SQ_{gen,t} + \sum_{st} StOut_{st,t} + \sum_{st} StIn_{\max st,t} - StIn_{st,t}, \forall t \tag{23}
\]

The first constraint (22) ensures grid stability if unexpectedly demand exceeds supply. It 
guarantees that, in sum, thermal power plants and storage operators can increase supply or 
storage operators can decrease demand to meet $RR_{pos,t}$ in each time period $t$. $RR_{pos,t}$ repre-
sents the positive net change in grid load needed to ensure grid stability in a worst-case sce-
nario. The second constraint (23) serves the same purpose in the case supply unexpectedly 
exceeds demand and a negative net change in grid load is required. Regarding the objective
function (3), this approach implicitly assumes that grid operators manage to provide grid stability at the lowest social costs possible. Since reserve requirements can be assumed to not have a major impact on the research questions dealt with in this paper, it seems reasonable to not spend a lot of modeling effort on them. Consequently, it is not considered how the demand side could contribute to providing reserve capacities. Furthermore, only the effect of providing reserve capacities is modeled. Effects on the market caused by the utilization of these reserves, if demand and supply differ unexpectedly, are not incorporated. The latter would require a non-deterministic model able to represent effects of uncertainty.

\section*{B Parametrization}

\subsection*{B.1 Substitution-elastic demand}

The only technology modeled as substitution-elastic demand in the case study corresponds to batteries of electric cars. Any other technology cannot be modeled due to a lack of sufficient data. The most relevant data, total quantity demanded and power capacity of electric cars, are again based on Gerhardt et al. (2015). The total quantity demanded is distributed across hours of the year according to average driving profiles taken from a nationwide survey used to obtain the upper limit of $U_s Q_{\text{con}S,t}$ (infas, 2008). The temporal profile for the upper limit of $D_s Q_{\text{con}S,t}$ is taken from appropriate research and scaled by the power capacity to reflect the electric capacity of car batteries connected to the electric grid in each hour (Jacqué, 2013). The discharge duration of a car battery is derived from the literature and projected based on the electric capacity to obtain $D U_s Q_{\text{max} \text{con}S,t}$, i.e. the capacity of all car batteries (Styczynski and Sauer, 2015).

Due to the lack of adequate data the discharging rate $\gamma_{\text{shift,con}S,t}$ is assumed to be unity, but charging the battery a long time in advance is avoided by limiting $T S_{\text{con}S,t}$ to 24 hours. Since the total quantity demanded already reflects conversion losses, $\eta_{\text{shift,con}S,t}$ is set to one as well. $T R_{\text{con}S,t}$ is set to zero, so it will not cause any form of restriction. $D s B_{\text{con}S,t}$ is set to VOLL, thus assuming the demand for mobility is covered in any case.

\subsection*{B.2 Demand without state-induced price components}

The demand without state-induced price components imposed on results from PtG and electrification of the heating sector. The total electricity demanded from PtG processes, $P_{2GT}$, and the upper limit of $P_{2GQ_t}$ equaling the installed input capacity of PtG processes, are again set according to Gerhardt et al. (2015). The total demand resulting from the electrification of the heating sector split up into demand from heat pumps and from electric boilers is drawn
from the same source. The temporal profile of heat demand is assumed to match the gas demand of small customers. This seems reasonable, because small customers only buy gas for heating purposes. The gas demand of small customers in 2016 was derived by distributing daily demand data across the hours of a day, applying standard load profiles and hourly temperature time series data from 2016 averaged across Germany (BDEW, 2011; NetCon, 2017; DWD, 2017). The same temperature time series was used to adjust the profile according to the temperature-dependent coefficient of performance of heat pumps. The adjusted profile is used to distribute the total demand of heat pumps across the hours of the year. The unadjusted profile serves the same purpose for demand from electric boilers. Both profiles are summed up to obtain $EQt$.

### B.3 Characteristics of supply

Gerhardt et al. (2015) consider four renewable technologies, photovoltaics, onshore wind, offshore wind, run-of-river and hydro, and two storage technologies, lead-acid batteries and pumped-storage, whose generating capacities are set accordingly in the model. Any other parameters describing the generation and storage technologies are adopted from the same series of publications, including the storage capacity of lead-acid batteries and pumped-storage (Rech and Elsner, 2016; Reuter and Elsner, 2016; Styczynski and Sauer, 2015; Welker and Elsner, 2016; Elsner and Sauer, 2015; Görner and Sauer, 2016). The values used are average projections for 2050. The thermal power plant technologies for Germany considered in the model are GT, CCGT, hard coal, and lignite. The full costs, $FC$, and the fixed costs per capacity installed, $fc$, are derived from these values and annualized with an internal interest rate of 7.5%, because the time span covered is one year. Marginal costs are based on these values as well, but they also depend on the commodity prices (Öko and ISI, 2015: 98) assumed. Full load hours of VRE are derived from data given in (Gerhardt et al., 2015) and used to scale the generation profiles for Germany in 2016 taken from ENTSO-E (2017), whereas availability curves of thermal power plants in 2016 are taken from online publications (EEX, 2017). The following tables provide an overview of the parameters used.

#### Table B.1: Parameters of thermal power plants

<table>
<thead>
<tr>
<th>Technology</th>
<th>Efficiency [%]</th>
<th>Variable costs [€ MVWh⁻¹]</th>
<th>Fuel price [€ MVWh⁻¹ th]</th>
<th>Emission factor [t CO₂/MWth]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard-coal power plant</td>
<td>50</td>
<td>0</td>
<td>6.14</td>
<td>0.411</td>
</tr>
<tr>
<td>Lignite power plant</td>
<td>50</td>
<td>0</td>
<td>16.25</td>
<td>0.34</td>
</tr>
<tr>
<td>Biomass plant⁹</td>
<td>100</td>
<td>10</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Gas turbine</td>
<td>46</td>
<td>0</td>
<td>50.18</td>
<td>0.202</td>
</tr>
<tr>
<td>Combined-cycle-gas turbine</td>
<td>64</td>
<td>0</td>
<td>50.18</td>
<td>0.202</td>
</tr>
<tr>
<td>Nuclear plant</td>
<td>33</td>
<td>0</td>
<td>2.232</td>
<td>0</td>
</tr>
</tbody>
</table>

Source: Görner and Sauer (2016); Welker and Elsner (2016); Icha (2013); Öko and ISI, 2015

⁹Efficiency and fuel price are reflected in the variable costs.
Table B.2: Investment costs of thermal power plants

<table>
<thead>
<tr>
<th>Technology</th>
<th>Investment costs [€/MW]</th>
<th>Lifetime [a]</th>
<th>O&amp;M [% Invest]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hard-coal power plant</td>
<td>1,400,000</td>
<td>50</td>
<td>2.6</td>
</tr>
<tr>
<td>Lignite power plant</td>
<td>1,800,000</td>
<td>50</td>
<td>3.3</td>
</tr>
<tr>
<td>Biomass plant</td>
<td>5,250,000</td>
<td>10</td>
<td>2.71</td>
</tr>
<tr>
<td>Gas turbine</td>
<td>400,000</td>
<td>20</td>
<td>2.5</td>
</tr>
<tr>
<td>Combined-cycle-gas turbine</td>
<td>900,000</td>
<td>32.5</td>
<td>2.58</td>
</tr>
</tbody>
</table>

Source: Görner and Sauer (2016); Welker and Elsner (2016)

Table B.3: Parameters of VRE

<table>
<thead>
<tr>
<th>Technology</th>
<th>Investment costs [€/MW]</th>
<th>Lifetime [a]</th>
<th>O&amp;M [% Invest]</th>
<th>Full load hours [h]</th>
<th>Installed capacity [MW]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Run-of-river</td>
<td>2,300</td>
<td>50</td>
<td>2</td>
<td>4,577</td>
<td>5,000</td>
</tr>
<tr>
<td>Onshore wind</td>
<td>1,032,000</td>
<td>22.5</td>
<td>3.6</td>
<td>2,250</td>
<td>140,000</td>
</tr>
<tr>
<td>Offshore wind</td>
<td>3,235,000</td>
<td>22.5</td>
<td>2.6</td>
<td>4,200</td>
<td>38,000</td>
</tr>
<tr>
<td>Photovoltaic, roof</td>
<td>577,000</td>
<td>25</td>
<td>1.7</td>
<td>1,000</td>
<td>100,000</td>
</tr>
<tr>
<td>Photovoltaic, open space</td>
<td>460,000</td>
<td>25</td>
<td>2.2</td>
<td>1,000</td>
<td>100,000</td>
</tr>
</tbody>
</table>

Source: Reuter and Elsner (2016); Rech and Elsner (2016); Gerhardt et al. (2015)

Table B.4: Parameters of storage technologies

<table>
<thead>
<tr>
<th>Technology</th>
<th>Efficiency, in [%]</th>
<th>Efficiency, out [%]</th>
<th>Self discharging rate [%]</th>
<th>Installed power capacity [MW]</th>
<th>Installed storage capacity [MWh]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-acid batteries</td>
<td>94.3</td>
<td>94.3</td>
<td>0.99562</td>
<td>18,000</td>
<td>18,000</td>
</tr>
<tr>
<td>Pumped-storage</td>
<td>88</td>
<td>91.5</td>
<td>0.999652</td>
<td>8,000</td>
<td>48,000</td>
</tr>
</tbody>
</table>

Source: Elsner and Sauer (2015); Gerhardt et al. (2015)

Table B.5: Investment costs of storage technologies

<table>
<thead>
<tr>
<th>Technology</th>
<th>Invest. costs in [€/MW]</th>
<th>Invest. costs out [€/MW]</th>
<th>Invest. costs capacity [€/MWh]</th>
<th>Lifetime [a]</th>
<th>O&amp;M [% Invest]</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lead-acid batteries</td>
<td>0</td>
<td>45,000</td>
<td>146,341</td>
<td>30</td>
<td>0.75</td>
</tr>
<tr>
<td>Pumped-storage</td>
<td>350,000</td>
<td>330,000</td>
<td>25,000</td>
<td>40</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Source: Elsner and Sauer (2015)

The total quantity supplied by CHP power plants is found in Gerhardt et al. (2015) and distributed across the year again using the profile of heat demand derived earlier for obtaining $C H P Q_t$.

B.4 Additional input data

According to Brouwer et al. (2016) the requirement for positive and negative reserve are both set to equal the sum of 1% of inelastic demand $Q_t(p_t = V O L L)$ plus 2% of maximum total generation of VRE in a given hour $t$. The share of state-induced price components, which remains constant and is not determined within the long-term model, is set to 68.31 €/MWh, which corresponds to the average level of state-induced price components excluding the EEG levy in Germany in 2016 (Ecke and Göke, 2017). The neighboring countries of Germany considered are: France, Slovenia, Poland, the Netherlands, Denmark, Belgium, Austria, and the Czech Republic. Cross-border capacities are based on future projections (ENTSO-E, 2016). Installed generation capacities and total demand quantities in these countries are based
on the trend scenario of the European Commission in 2050 (EC, 2016). Total quantities were distributed across the hours of the year according to load profiles from ENTSO-E in 2016 (ENTSO-E, 2017).

### C Integration and decarbonization costs

Table C.1: Integration and decarbonization costs by scenario and carbon price, \[ \frac{\epsilon}{MWh} \]

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Carbon price [( \frac{\epsilon}{MWh} )]</th>
<th>0</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
<th>0</th>
<th>50</th>
<th>100</th>
<th>150</th>
<th>200</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Integration</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \epsilon = -0.0029 )</td>
<td></td>
<td>65.7</td>
<td>82.8</td>
<td>113.2</td>
<td>76.7</td>
<td>86.2</td>
<td></td>
<td>65.4</td>
<td>82.2</td>
<td>112.2</td>
<td>75.1</td>
</tr>
<tr>
<td>( \epsilon = -0.025 )</td>
<td></td>
<td>66.9</td>
<td>83.4</td>
<td>113.5</td>
<td>77.5</td>
<td>86.9</td>
<td></td>
<td>65.7</td>
<td>82.5</td>
<td>111.8</td>
<td>75.6</td>
</tr>
<tr>
<td>( \epsilon = -0.05 )</td>
<td></td>
<td>67.4</td>
<td>83.2</td>
<td>112.2</td>
<td>76.8</td>
<td>86.1</td>
<td></td>
<td>65.3</td>
<td>81.4</td>
<td>110.0</td>
<td>74.4</td>
</tr>
<tr>
<td>( \epsilon = -0.05, \text{ no hard coal} )</td>
<td></td>
<td>52.2</td>
<td>62.0</td>
<td>71.2</td>
<td>76.8</td>
<td>86.1</td>
<td></td>
<td>50.6</td>
<td>60.4</td>
<td>69.2</td>
<td>74.4</td>
</tr>
<tr>
<td><strong>Decarbonization</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>( \epsilon = -0.0029 )</td>
<td></td>
<td>65.4</td>
<td>82.2</td>
<td>112.2</td>
<td>75.1</td>
<td>84.1</td>
<td></td>
<td>75.3</td>
<td>78.1</td>
<td>82.0</td>
<td>34.5</td>
</tr>
<tr>
<td>( \epsilon = -0.025 )</td>
<td></td>
<td>65.7</td>
<td>82.5</td>
<td>111.8</td>
<td>75.6</td>
<td>84.2</td>
<td></td>
<td>76.2</td>
<td>78.2</td>
<td>81.8</td>
<td>32.4</td>
</tr>
<tr>
<td>( \epsilon = -0.05 )</td>
<td></td>
<td>65.3</td>
<td>81.4</td>
<td>110.0</td>
<td>74.4</td>
<td>82.8</td>
<td></td>
<td>77.1</td>
<td>78.2</td>
<td>79.2</td>
<td>29.7</td>
</tr>
<tr>
<td>( \epsilon = -0.05, \text{ no hard coal} )</td>
<td></td>
<td>50.6</td>
<td>60.4</td>
<td>69.2</td>
<td>74.4</td>
<td>82.8</td>
<td></td>
<td>20.5</td>
<td>25.5</td>
<td>29.3</td>
<td>29.7</td>
</tr>
</tbody>
</table>

Source: Model results
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