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We assess the effect of different capacity market design options in three scenarios: 1) no capacity market, 2) a capacity market for new capacity only, and 3) a capacity market for new and existing capacity. We compare the results along the three key dimensions of electricity policy – affordability, reliability, and sustainability.

In a Great Britain case study we find that a capacity market increases generation adequacy since it provides incentives for new generation investments. Furthermore, our results show that a capacity market can lower the total bill of generation because it can reduce lost load and the potential to exercise market power. Additionally, we find that a capacity market for new capacity only is cheaper than a capacity market for new and existing capacity because it remunerates fewer generators in the first years after its introduction.

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Capacity market design options: a dynamic capacity investment model and a GB case study

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1. Introduction

Conventional electricity generation is increasingly unprofitable in several European markets. The major reason is that increasing feed-in from renewable energy sources (RES) decreases revenues of conventional generation through decreasing electricity prices and load factors—often referred to as the merit order effect of renewable energy (Sensfuß et al., 2008). At the same time, conventional generation is still needed to ensure security of supply due to the intermittency of RES. This challenge currently leads to a resurgence of the discussion around capacity mechanisms as a suitable measure to ensure generation adequacy[1].

Renewable energy is growing in major markets worldwide. It has reached a share of total electricity generation of 11% in Great Britain, 13% in the U.S., and 22% in Germany in 2012. Most important in terms of renewable capacity growth are intermittent sources, namely wind (onshore and offshore) and solar photovoltaic (PV). An essential characteristic of these sources is that the total cost is almost entirely driven by capital costs and that marginal costs are close to zero. As a consequence, in an energy-only market, RES push conventional generation out of the money, if they are available. Hence, the load factors of conventional generators decrease, along with average wholesale electricity prices[2], and generators become unprofitable. In 2012 for example, gas-fired generation was unprofitable in Germany, France, and the Netherlands, while it was only barely profitable in Great Britain (Bloomberg, 2013a; Platts, 2013; Reuters, 2013).

Due to the intermittency of RES however, these sources are not able to fully replace conventional generation[3]. Moreover, studies of VDE (2012) show that the need for conventional generation capacity stays almost unchanged with rising levels of feed-in from RES. They find that the required conventional peak capacity stays the same with increasing renewable feed-in, only the need for energy from conventional generation decreases (in terms of power generated).

The contradiction between lower profitability of conventional generation, which causes

[1] Additionally, there are other factors creating fear of capacity shortage and therefore reinforcing the discussion: 1. Several large power plants that were built during the 1970s and 1980s have reached the end of their economic lifetime and are scheduled to be retired; 2. Coal fired power plants are soon to be forced out of the market due to the EU large combustion plant directive (EU, 2001) 3. In Germany, all nuclear power plants are scheduled to be decommissioned by 2022 at the latest (German Federal Government, 2011).

[2] (short- and medium-term)

[3] As long as there is no cost-efficient grid scale storage for electricity available.

investors to stay away from new investment, and continuously high demand for reliable capacity puts generation adequacy at risk. Different capacity mechanisms have been discussed to ensure supply adequacy. The three most important ones are strategic reserves, capacity payments, and capacity markets. What distinguishes the three schemes most clearly is the question of who sets the price of capacity and who sets the quantity that is being supplied: a strategic reserve is realized through the regulator determining system critical power stations and paying these specific plants the fixed costs necessary to keep them available for times of capacity shortage. In contrast to that, a capacity payment is a market-wide fixed price set by the regulator, while the quantity is subsequently determined by the market (the market will determine how much capacity is profitable to be supplied at the given price). A capacity market reverses the logic of a capacity payment as the regulator sets the quantity necessary for generation adequacy and auctions that quantity in the market. Hence, the market sets the price that is required to provide the quantity needed to fulfill generation adequacy needs. Additionally, the schemes differ in terms of market clearing: with strategic reserves, the regulator pays for capacity of selected generators only[4]. In a capacity payment scheme, all generators receive a fixed payment per MW installed. Whereas in a capacity market, the regulator auctions the capacity needed for generation adequacy annually. From their design, some benefits and downsides of each mechanism can easily be detected: strategic reserves are a very flexible measure that can be adjusted quickly by the regulator, but the existence of strategic reserves distorts price signals in periods of shortage—i.e., hindering investment in new capacity. A capacity payment allows for the option of different payments per technology but bears the risk that setting the price too low or too high leads to a lack of capacity or to overcapacity. The capacity market is most focused towards fulfillment of the regulator's goal to ensure the required capacity at the lowest possible price. On the downside, it significantly increases market complexity because it introduces an additional market that is interdependent with the electricity market. Our brief qualitative discussion shows that there are differences between these policy schemes and that all of the schemes exhibit individual strengths and weaknesses. Hence, it is not obvious what the effects of the introduction of such a mechanism are in a specific case. Therefore, we enrich the qualitative discussion by a model

[4]Selection is mostly done by location, i.e., if a plant is located in a region of shortage, or by profitability, i.e., if a plant would be unprofitable without a strategic reserve payment.

to quantify the expected effects in the specific market where the mechanism might be introduced.

All schemes are in use in some markets[5], but the current regulatory discussion is mostly focused on capacity markets: examples are the U.K. where a capacity market is currently in the process of legislation and implementation and the discussions in France, Germany, and Texas. Therefore, we focus on the capacity market scheme to facilitate this discussion through a quantification of effects of different capacity market design options on market prices and generation mixes. To the best of our knowledge, the paper is the first to quantify the difference between three scenarios: 1) an energy-only market, 2) a capacity market for new capacity only and 3) a capacity market for new and existing capacity through a dynamic capacity investment model. We apply this model in a GB case study to show its practicality in a case where exactly these policy decisions are currently discussed. At the same time, we set up the model in a way that it could easily be transfered to any other market as well. The findings are of value to three groups. First, regulators discussing the introduction and the possible effects of a capacity market scheme in their market. Second, investors planning to invest in markets with such a scheme[6]. Third, all other market participants such as grid operators, equipment manufacturers, and utilities evaluating possible future regulatory impact.

The remainder of the paper is structured as follows. In Section 2, we provide a brief overview of the literature regarding capacity mechanisms in liberalized electricity markets in general, of qualitative discussions of capacity markets, and of quantitative simulation and capacity expansion models. Section 3 describes our capacity investment model. In Section 4, we present the assumptions and results of our GB case study. Section 5 provides general policy recommendations that can be derived from our findings, while Section 6 concludes and provides suggestions for further research.

2. Literature review

Two streams of literature are important as the foundation to our research. First, the literature around capacity mechanisms in liberalized electricity markets in general and

[5]Strategic reserves exist in Finland, Germany, and Sweden; Capacity payments in Ireland, Portugal, and Spain; Capacity markets in several markets in the U.S.—e.g., in the PJM (Pennsylvania-Jersey-Maryland Interconnection) and in New England.

[6]Either already implemented or in regulatory discussion.

of capacity markets in particular, and second, modeling techniques such as quantitative project valuation, market simulation and capacity expansion models.

Capacity mechanisms—especially capacity markets—in liberalized electricity markets. Generation adequacy and capacity mechanisms have been discussed in the literature for many years. Oren (2005) and Hogan (2005) state that capacity mechanisms should not be necessary in a liberalized electricity market because generators should be able to balance their expenditures through bidding higher than marginal costs in hours of supply shortage. However, they argue that market imperfections such as price caps and other market power mitigation interventions can suppress this effect—even though it is required for the functioning of the energy-only market. Cramton and Stoft (2005) and Joskow and Tirole (2007) emphasize that there will always be imperfections in the energy-only market leading to, e.g., price spikes and exercise of market power, because the demand side does not actively participate in the market and conclude that there is a need for a different market scheme with the goal to ensure generation adequacy, e.g., a capacity market. In line with that, Cramton and Stoft (2005) describe how a capacity market should be designed to ensure adequate capacity while reducing the market power. They argue that, if designed sensibly, a capacity market can ensure generation adequacy while eliminating much of the potential to bid strategically. Baldick et al. (2005) provide a survey on the field of designing efficient generation markets. They emphasize that many arguments mentioned by Oren (2005), Cramton and Stoft (2005) are valid, but specific market design options require more testing through quantitative models such as equilibrium models, sophisticated dynamic models and agent-based modeling. Cramton et al. (2013) argue that RES aggravate the adequacy problem because they can be seen as entirely price-inelastic negative demand (due to marginal costs close to zero). Through this characteristic, RES intensify demand fluctuations and thereby price fluctuations. They add that with rising RES feed-in, conventional investments—due to lower load factors—get less attractive. In this situation, according to their argumentation, increased market coordination—e.g., through a capacity market scheme—is necessary. Whether or not to pay existing generation when introducing a capacity market, Cramton et al. (2013) state that all generation should be paid because an energy-only market would also pay all generation. They reason that the strategy of not paying existing generation[7] might work once, if investors are surprised but afterwards

[7] Which they also call a regulatory taking or expropriation.

would lead to investors requiring additional protection from future unequal treatments and a risk premium. Hence, there is no clear consensus to be derived from a purely qualitative assessment. Therefore, we follow the suggestion of Baldick et al. (2005) and quantitatively analyze the effects entailed by the introduction of capacity markets.

Quantitative project valuation, market simulation and capacity expansion models. Three major groups of models are used in the existing literature to assess long-term electricity capacity investments and to address policy questions regarding generation adequacy (Ventosa et al., 2005). First, single project valuation models that consider a certain type of investment in detail but simplify market feedback—e.g., real options valuation. Second, capacity expansion models that determine competitive market equilibria[8]. And third, dynamic capacity investment models that include market feedback, often strategic behavior and approximate future market developments through methods such as Monte Carlo simulation.

Single project valuation models. Fuss et al. (2012) use a real options analysis to assess the effect of uncertainty on investments in alternative energy technologies at a plant level, which allows them to derive optimal technology portfolios for low emissions targets. The results suggest that investors will focus on robust technology mixes that are most likely to perform well also under the undesirable scenarios. Boomsma et al. (2012) analyze investments in wind park projects under different renewable energy support schemes, such as feed-in tariffs (FiT) and renewable energy certificates (REC). They find that FiTs lead to earlier investment, while a REC market leads to larger project sizes. Hach and Spinler (2014) also use a single project real options approach to assess the impact of capacity payments on investments in gas-fired generation. They find that capacity payments are especially important with increasing levels of intermittent feed-in from RES, as renewables lead to lower load factors of gas-fired generation.

Single project valuation models allow to model specific investments and the particular characteristics of a certain technology. This type of model lacks, however, market feedback and technology competition. Therefore, we can make use of the results for comparative purposes, but for the model we rather focus on a methodology that is capable of reflecting market feedback such as the following two methods.

[8]Which are equivalent to the cost optimal solution under the assumption of perfect information and perfect competition (Hobbs, 1995).

Capacity expansion models. Hobbs (1995) describes an early form of a capacity expansion model using a mixed integer linear program. The model is capable of finding an optimal solution as a cost-optimal market outcome while ignoring rate-feedback (i.e., price elasticity) and uncertainty. MARKAL (acronym for MARKet ALlocation) (Fishbone and Abilock, 1981; Loulou et al., 2004) is a more sophisticated linear programming model for energy system analysis[9]. The primary objective of this project was to build a tool that allows evaluating the role of new technologies in energy systems. MARKAL provides a modeling environment with a long list of features: plant shut-down (scheduled and unscheduled), hydro and pumped hydro representation, fuel processing, combined heat and power, to name just a few. The model has been used for energy system modeling in more than 20 countries as well as by the European Commission and the International Energy Agency. However, MARKAL does not account for strategic bidding and price elasticity since its objective function is cost minimization, neither does it account for ramping constraints since it is a time-collapsed model—not allowing for a granular hour-by-hour evaluation. Ehrenmann and Smeers (2011) formulate a capacity expansion model as a stochastic equilibrium model to assess capacity investments under different risk attitudes with and without capacity markets. With regards to capacity markets they find that risk aversion decreases capacity investments compared to risk-neutrality in an energy-only market with a low price cap.

Capacity expansion models are well suited to reflect market feedback and technology competition through the optimization approach—the solutions represent a market equilibrium. However, due to the complexity of the optimization itself, this type of models lacks—in most cases—one or more of the following features: ramping constraints, strategic bidding, and price elasticity.

Dynamic capacity investment models. Day and Bunn (2001) provide a computational approach to incorporate strategic bidding in competitive electricity markets. They simulate generation companies with profit maximizing behavior and their competition using supply functions. They find that in the 1999 divestment proposal of the regulatory authorities in England and Wales, the level of market power was underestimated. Bunn and Oliveira (2008) develop an evolutionary agent-based computational approach to assess the

[9]Including primary energy flows and consumption in the heating and transportation sector. Hence, it is not only focused on the power sector like all other models discussed here.

dynamic strategic evolution of generation portfolios under regulatory interventions. They use a Cournot representation of the wholesale electricity market and an iterative plant trading game. The authors find that a minimum generation requirement, enforced for example through a capacity market, limits the ability of market participants to exercise market power. Powell et al. (2011) provide a comprehensive stochastic simulation model based on approximate dynamic programming. The model aims to facilitate the multi-scale assessment of energy resource allocation from a short term consideration of dispatch and storage to long-term investment decisions. They include a wide range of technologies and incorporate the energy value chain starting from the different resources and reaching to various service demands. Eager et al. (2012) use a dynamic investment model that encompasses conventional generation investment. They use a Monte Carlo simulation to include stochastic fuel prices, demand growth, and conventional plant construction. Investors are modeled as risk-averse. The authors assess the level of security of supply under increasing—exogenously given—investment in RES. They find for a GB case study, that security of supply is at risk during the years 2020-30. Additionally, they observe that many new investments can recover their fixed costs only during years in which more frequent supply shortages push electricity prices higher as particularly peaking units are even unable to recover their fixed costs. The authors explicitly propose to assess capacity mechanisms such as strategic reserves and capacity markets in a similar model. Cepeda and Finon (2013) focus on electricity generation investments and examine two different market schemes: an energy-only market and a capacity mechanism. Their results show that capacity mechanisms can help to reduce the social cost of large scale wind power development—quantified through a decrease in probability for lost load. Furthermore, they state that in a market-based wind power deployment without any subsidies, wind generators are penalized for insufficient contribution to the system's long-term reliability. This is because there is an implicit reliability constraint in the market that favors reliable conventional generation over unreliable wind power.

Dynamic investment models (as the ones presented above) often include market feedback and technology competition as well as price elasticity, ramping constraints, and strategic behavior of generators that allow these models to properly reflect real-world market dynamics. These features are crucial to our analyses, since they become more important with an increasing share of feed-in from RES due to two effects. First, it aggravates demand fluctuations which make the reflection of ramping constraints more important—they become binding in more cases. Second, it increases the number of positive and negative price spikes. The limitation of dynamic investment models however, is the non-optimality of the solution—there is no indication how close the simulated result is to an optimal solution.

We propose a dynamic electricity market investment model that uses simulative runs with an extensive set of important features. We run the model iteratively for multiple times, until electricity price developments converge, to determine a long-term market outcome that is sufficiently close to an equilibrium. We provide a three-pronged argument that the iterative model leads to the desired results: First, for the periods within one iteration, we receive the desired results because we rely on standard procedures such as merit order bidding, profitability, NPV, etc. to determine reasonable results. Second, over the course of multiple iterations investors can adjust their behavior to decisions made by other market participants. Third, in case of convergence, we reach a situation where it is not desirable for any of the market participants to change their behavior. This type of model thus reflects realistic market conditions and implements investor behavior that is close to real-world decision making processes, by including a first phase focused on determining a sensible starting point for the iteration and a second phase focused on iterating possible market responses. As a consequence, this model allows us to address the following research question:

How does a capacity market affect the three major objectives of electricity policy (affordability, reliability, and sustainability)? To this end, three scenarios are considered: No capacity market (*No CM*); Capacity market for new capacity only (*CM new*); Capacity market for new and existing capacity (*CM new&ex*). We compare the results of the scenarios in terms of the three dimensions of electricity policy as done in several similar studies such as Kavrakoglu and Kiziltan (1983) as one of the first.

To summarize, we extend the existing literature in three ways. First, we develop a dynamic capacity investment model that is capable of reflecting ramping costs and constraints, strategic bidding, and price elasticity. Second, we quantify the effects of different capacity market design options and derive policy recommendations. Third, we calibrate the model to the GB market where a capacity market is currently being implemented.

3. Dynamic capacity investment model

In this section, we describe the dynamic capacity investment model. A description of the model's main building blocks is followed by the details of the model in the second subsection. For a complete list of symbols used in this section and the following, please see Tables 4 and 5 in the appendix.

3.1. Main building blocks

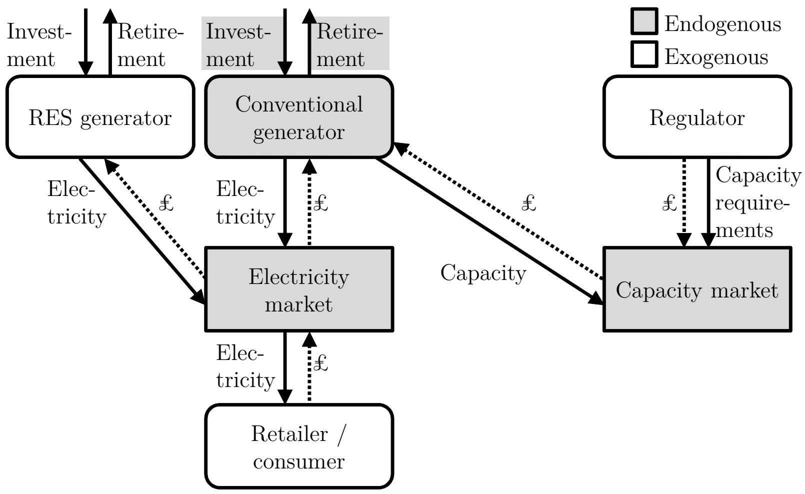

Figure 1: Illustration of market setup with highlighted endogenous components

The primary goal of our model is to assess the impact of capacity market design options on an electricity market. At the same time, the model should reflect the effect of rising intermittent RES generation. Therefore, the model must include the following eight features. 1. Endogeneity of capacity and electricity market. This includes endogenous conventional generators and their investment and retirement decisions, as shown in Figure 1. All other characteristics are assumed to be given exogenously—for example demand patterns, build-up of RES, resource prices and technology characteristics. 2. Inclusion of all major types of generation[10], to reflect competition between these technologies[11] and report long-term generation mixes. 3. Long time horizon T in line with the economic life of generation assets[12] 4. Individual profit-maximizing investors who require expected profitability of all existing generation and new projects. 5. Hourly granularity to track

[10]For the case of GB this is wind, solar, nuclear, coal, and gas. For other markets it can be adjusted accordingly.

[11]We assume a correlation between higher marginal costs in the merit order and higher flexibility. See also Section 4.1.3 where we show that the assumption holds for the empirical data of the GB case study.

[12]Economic asset lifetimes typically range between 20 years for renewable and gas-fired generation and up to 40 (and more) years (DECC, 2010a) for nuclear generation.

detailed price behavior which is crucial in presence of intermittent RES that lead to more pronounced and more frequent price fluctuations. Therefore, the model covers a long time horizon and at the same time calculates market clearing for each hour of each year. 6. Hourly ramping constraints which become increasingly binding with rising renewable feed-in. 7. Allowing generators to bid strategically, i.e., above marginal costs, in times of tight capacity (Newbery, 2002), because tightness may be expected to occur more often with increasing supply fluctuation in the presence of ramping constraints. 8. Reflection of price elasticity of demand to include not only investment but also consumer behavior and possibly increasing capacities of demand response and electricity storage—depending on the assumptions made in the specific case.

In order to accommodate the aforementioned eight features we build a model that works in two phases—the *initial forecast* phase to create a starting value and the *actual iteration* phase in which market outcomes are iterated for multiple times until convergence is reached. Therefore, the model begins with the forecast and subsequently determines the expected reactions of market participants to that possible price development and derives the first iteration result—a new generation portfolio development. However, market participants' investment and divestment decisions may differ from the previous iteration in sight of this new electricity price development. Hence, we repeat the process of reiterating the calculation of portfolios and prices based on results of previous runs to derive a converged generation portfolio. In case of convergence, this represents a likely market outcome as market participants have no incentive to change their actions in response to expected outcomes anymore. This general modeling logic can also be used to develop approaches to assess other electricity market policies and dynamics as in (Ritzenhofen et al., 2014) who compare different RES support schemes.

3.2. Iteration cycle

Figure 2 illustrates the steps included in the model. The goal of the initial forecast is to provide a starting point as an initial "best guess" forecast for the core of the model. In the first actual iteration, we start by calculating electricity prices using that initial portfolio. These electricity prices can then be used as an expectation for the first profitability assessments. Afterwards, we conduct—in case there is a capacity market scheme in place—a

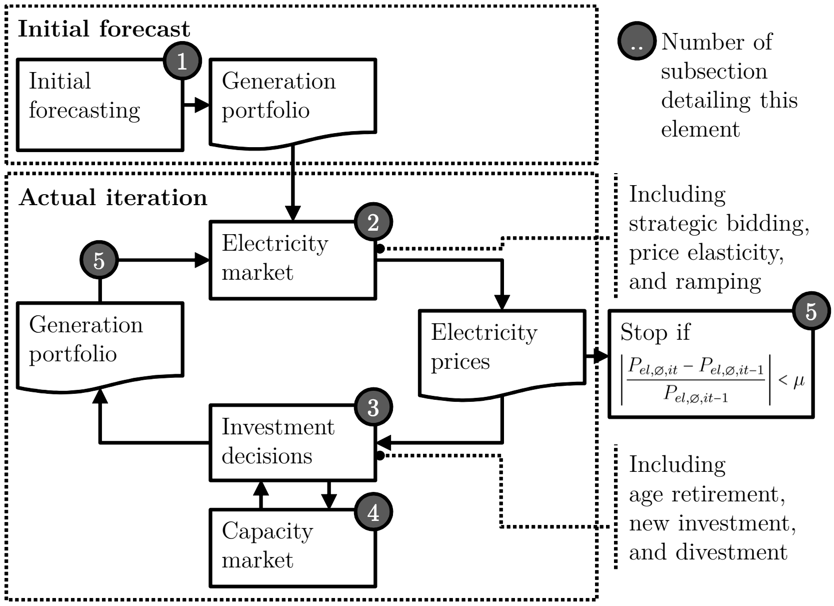

Figure 2: Model steps

capacity auction in which generators bid their profitability gap[13], while expecting electricity prices as provided by the initial forecast. With the resulting capacity prices and the expected electricity prices, investors have all the necessary data to make investment decisions with respect to their generation portfolio. Investors take three decisions: age retirement—if plants have reached the economic lifetime, divestment—if an existing plant is not profitable anymore, it is retired before it has reached the economic lifetime, and new investment—if an investment in a new plant is promising. We limit the model to these decisions and do not include mothballing and refurbishment of existing plants for two reasons. One, these only represent intermediate steps of retirement and new investments[14]. Two, this enhances the clarity and traceability of the investors' decisions. Based on the aforementioned three decisions, we derive a new generation portfolio which is the last step of the first actual iteration and an input to the next iteration. The second iteration then follows the same procedural steps.

We run these iterations multiple times for all years until changes in the average electricity price (over all years and hours) are sufficiently small and longitudinal electricity price developments are sufficiently similar (measured by the Pearson correlation). The convergence criterion of the change in average electricity prices is shown in 1 with μ being

[13]The profitability gap is the delta between the earnings from the energy-only market and the investors' profitability expectation. These expectations are defined by an NPV threshold in case of a new investment and by a profitability threshold in case of an existing plant.

[14]Since for example, a series of refurbishments of an existing plant is in terms of costs almost equivalent to the construction of a new plant.

a predetermined convergence limit.

$$\left| \frac{P_{el,\varnothing,it} - P_{el,\varnothing,it-1}}{P_{el,\varnothing,it-1}} \right| < \mu. \tag{1}$$

It turns out that 10 to 20 runs are in most cases sufficient to meet these criteria. We choose the electricity price development as the convergence criterion because, most importantly, it directly influences investors' key investment and divestment determinant in every year because it feeds into the cash flow calculations. Additionally, it implicitly reflects changes in the overall generation portfolio.

3.2.1. Initial forecasting

As the starting point for investors' expectations of electricity price developments, the initial generation portfolio is calculated in three steps. These are the same for all three scenarios. We use the following four index sets: 1) g for the generation technology, $g \in \{1, ..., G\}$, 2) h to specify the hour within a period, $h \in \{1, ..., 8760\}$, 3) t for the year, $t \in \{1, ..., T\}$, and 4) it for the iteration, $it \in \{1, ..., it_{converged}\}$.

Conventional demand. On the demand side, the conventional (also called residual) load ($D_{t,h}^{CONV}$) is calculated for each hour by subtracting all intermittent RES feed-in ($K_{t,h}^{disp,REN}$) from the total load ($D_{t,h}$). We assume that $D_{t,h}^{CONV}$ cannot be negative and argue that excess RES generation would either be curtailed or exported,

$$D_{t,h}^{CONV} = max(D_{t,h} - K_{t,h}^{disp,REN}; 0) \ \forall \ t, h. \tag{2}$$

Subsequently, the conventional (residual) load curve is ordered by quantity in descending sequence and thus we obtain the residual load duration curve (RLDC).

Screening curve. On the supply side, the screening curve (SC) is determined to find the least cost technology for each load level. For this, we calculate the total cost per technology $C_t^{Tot,g}$ depending on its utilization κ by considering total capital $C_t^{C,g}$, total fixed $C_t^{F,g}$, and marginal costs $C_t^{M,g}$,

$$C_t^{Tot,g}(\kappa^g) = C_t^{C,g} + C_t^{F,g} + C_t^{M,g} * \kappa^g * 8760. \tag{3}$$

Using $C_t^{Tot,g}(\kappa^g)$, we can determine SC as the least cost combination of the total cost curves of all technologies. Hence, it is a stepwise linear function of the following form:

$$SC_t(\kappa) = \min[C_t^{Tot,g}(\kappa^g)] = \begin{cases} C_t^{Tot,1}(\kappa), & \text{if } ub_1 \geq \kappa > lb_1 \\ C_t^{Tot,2}(\kappa), & \text{if } ub_2 \geq \kappa > lb_2 \\ ..., & ... \\ C_t^{Tot,g}(\kappa), & \text{if } ub_g \geq \kappa > lb_g. \end{cases} \tag{4}$$

Where lb_x and ub_x represent the lower bound and the upper bound of the utilization range where technology x is most cost-efficient generation technology with $lb_G = 0$, $ub_1 = 1$, and $lb_x = ub_{x+1}\ \forall\ x = 1...(G-1)$.

Initial generation portfolio. We determine the initial generation portfolio by mapping the SC onto the RLDC. The SC yields the most cost-efficient conventional types of generation for all capacity utilization rates, while the RLDC provides the capacity requirements for all capacity utilization rates. Hence, by combining both, we can determine the cost-optimal capacity mix. This initial portfolio, however, abstracts from existing capacities and hence only represents a good starting point for the iteration—it does not represent an optimal market outcome.

3.2.2. Electricity market

Based on the initial generation forecast, the actual iterations are run. The first step is to derive a forecast of electricity prices from a given generation portfolio.

Electricity market clearing with ramping and price elasticity. The electricity prices result from the given residual load and the conventional generation portfolio. This is done by matching the merit order of supply and demand for each hour. Thus, the load is matched with the merit order based on the marginal costs of all available generation—accounting for ramping constraints and price elasticity. The most expensive generator, necessary to fulfill demand, sets the market price for that hour. The model accounts for price elasticity, i.e., for consumption to be reduced in times of high prices and to be increased in times of low prices. We implement this by allowing for sloped, not fully vertical demand curves. The slope of the demand function is defined as β while the maximum demand at a price of 0 is described by $D_{0,t,h}$. The realized demand $D_{t,h}$ is hence defined as a function of the price in the respective period $P_{el,t,h}$

$$D_{t,h}(P_{el,t,h}) = D_{0,t,h} - \beta * P_{el,t,h}. \tag{5}$$

If existing generation is not sufficient, the model determines a loss of load occasion and sets the price to the exogenously given value of lost load (VOLL). We run this matching mechanism for each hour in all years and obtain an electricity price development over the whole time frame (T). Since we run the mechanism for each hour in chronological order, ramping constraints can also be accounted for. To do that, the model compares for each hour h and each technology g the required capacity for that hour with the utilized capacity in the previous hour $h-1$. In case the delta (i.e., the ramp) between these two values is too high (i.e., too steep) the ramping constraint comes into effect and the ramp cannot be realized. In case of a ramp-up, the next more expensive technology in terms of marginal costs has to jump in. This leads to a change in the merit order because one technology can effectively only provide a smaller amount of capacity than expected and hence gives way to the next technology. Hence, the available capacity of a certain generator $K_{t,h}^{avail,g}$ is the minimum of its actual capacity and the capacity taking its ramping constraint into account.

$$K_{t,h}^{avail,g} = min(K_{t,h}^{g}; K_{t,h-1}^{disp,g} * \varrho_u^g) \tag{6}$$

In case of a ramp-down, on the other hand, a binding ramp-down constraint leads to some plants continuing to run even though they are not needed to match demand. In that situation, cycling cost $C^{Cy,g}$ come into effect to reflect the additional cost that are incurred by slowly ramping the plants down to avoid damage to the machinery, e.g., turbines and boilers. These costs are added to the marginal costs,

$$C_{t,h}^{M,g} = \begin{cases} C_t^{fuel,g} + C_t^{CO_2,g} + C_t^{M-other,g} + C^{Cy,g}, & \text{if } \varrho_d^g \text{ is binding} \\ C_t^{fuel,g} + C_t^{CO_2,g} + C_t^{M-other,g}, & \text{if } \varrho_d^g \text{ is not binding.} \end{cases} \tag{7}$$

Where C_t^{fuel} and $C_t^{CO_2}$ are the fuel and CO_2 cost and $\eta^{fuel,g}$ and $\eta^{CO_2,g}$ the respective technology specific fuel and CO_2 intensities, while $C_t^{M-other,g}$ are other marginal costs (such as variable maintenance costs).

Strategic bidding. In addition to the previously described merit order logic, we need to account for strategic bidding of market participants. This type of bidding behavior has two different facets. On the one hand, it can help the marginal bidder to cover investment and fixed cost. Hence, this reduces the number of hours during which the price needs to increase to VOLL because it provides a way to recover fixed costs and investment for marginal generators and therefore less need for prices at the VOLL. On the other hand, it represents a form of exercise of market power and leads to additional profits of generators. As indicated by several studies for the GB market (Pöyry, 2009) and for other markets (Sioshansi and Oren, 2007; Bushnell et al., 2008; Borenstein et al., 1999), liberalized electricity markets provide opportunities for the exercise of market power and generators indeed try to bid strategically and exercise market power. One of the best known examples is the one of the Californian energy crisis in 2000 (Joskow and Kahn, 2001). As seen in California, the effect occurs mostly at times of capacity shortage and can rise to an enormous magnitude. Therefore, we follow Eager et al. (2012) in accounting for strategic behavior by introducing a price markup function $\omega(K_{t,h}^{marg})$. Based on this function, the extent of market power is described as a function of the available capacity margin $K_{t,h}^{marg}$—the margin between demand and available capacity at a certain point in time. $K_{t,h}^{marg}$ is defined as

$$K_{t,h}^{marg} = \frac{\sum_{g=1}^{G} K_{t,h}^{avail,g} - D_{t,h}}{\sum_{g=1}^{G} K_{t,h}^{avail,g}}. \tag{8}$$

The markup function $\omega(K_{t,h}^{marg})$ would typically be expected to be defined as 0 as long as the capacity margin is sufficiently large, e.g., greater than 20% and to steeply rise to a high markup for a capacity margin of 0-20%. In this way, we preserve the convexity of the price function even in the presence of strategic behavior thus preserving concavity of the profit function. With a given capacity margin, $\omega(K_{t,h}^{marg})$ yields the markup factor that increases the electricity price $P_{t,h}^{El,e,g}$ as follows

$$P_{t,h}^{El,e,g,\omega}(K_{t,h}^{marg}) = P_{t,h}^{El,e,g} * (1 + \omega(K_{t,h}^{marg})). \tag{9}$$

3.2.3. Investment decisions

Age retirement. The model checks the age of all power plants against their economic lifetime (LF^g) and retires all plants for which the age exceeds the lifetime,

$$K_t^g = K_{t-1}^g - K_t^{g,age-ret}. \tag{10}$$

Retirement of unprofitable existing generation. The model calculates the profitability ($\Pi_t^{g,e}$) for all existing plants e in year t. In terms of revenue, the average[15] price of electricity ($P_{el,avg,it}^{g,e}$) multiplied by the expected dispatched capacity ($K_{el,t,h}^{disp,g,e}$) is summed up over all hours. In terms of cost, the fixed ($C_t^{F,g}$) and marginal costs ($C_t^{M,g}$) of the type of technology are subtracted,

$$\Pi_t^{g,e} = \sum_{h=1}^{8760} ((P_{el,t,h,it}^{g,e} - C_t^{M,g}) * K_{el,t,h}^{disp,g,e}) - C_t^{F,g}. \tag{11}$$

[15] Average over the future years of operation.

Investors combine two pieces of information to forecast the expected electricity price $P^{g,e}_{el,t,h,it}$. First, the price that has been observed in the previous year in the current iteration and second, the price for the current year in the previous iterations. This is reasonable, because an investor would equally consider current price levels and also factor in the expectations of future price developments. In line with exponential smoothing, these two pieces are weighed with the factor α and $(1-\alpha)$ to obtain $P^{g,e}_{el,t,h,it}$. In addition, the application of exponential smoothing supports convergence as multiple previous market outcomes are included in investors' decision making processes and hence they are less likely to overreact on a specific recent market situation. Subsequently, all existing generation that exceeds a given unprofitability threshold (Γ^g) is retired to reflect that investors withdraw from their investments (as described in Bloomberg (2013b); Platts (2013)), if a given level of unprofitability is reached.

Investment in new generation. In terms of new generation, the NPV of new investments (n^g_t) of technology g in year t is determined over the entire economic lifetime (LF^g). Therein, initial investments $C^{I,g}$, expected profits (see above) of all years, and the discount rate r are considered

$$NPV^{n^g,g}_t = -C^{I,g} + \sum_{i=t}^{t+LF^g} (\Pi^{n^g,g}_i * (1+r)^{-(i-t)}). \tag{12}$$

Based on these results, investors invest in NPV-positive projects and reject NPV-negative ones. They invest in the order of the NPV—starting with the most positive ones. The model limits the maximum buildup to $b^{n^g,g}_{max}$ of plants per year per technology. This is to reflect constraints in manufacturing as well as project development and construction capacities of the market. Hence, the investor undertakes the considered investment if

$$NPV^{n^g,g}_t > 0 \text{ and } n^g \leq b^{n^g,g}_{max}. \tag{13}$$

Therefore, the decisions are made in a way prescribed by a greedy algorithm—the most profitable investments are pursued first until one of the constraints is binding.

3.2.4. Capacity market

Capacity market for new capacity only (CM new). In this scenario, we introduce a capacity market for new capacity only as part of the investor decision making. The *CM new* is an auction that matches previously determined capacity demand and supply (given by the participants' bids).

On the demand side, we determine the required new capacity by taking the given peak demand plus the reserve margin ϕ and subtracting the existing plants that will be divested due to unprofitability and age. The reserve margin ϕ, set by the regulator, is the required capacity that is needed on top of expected peak demand to ensure generation adequacy. It is un-derated, i.e., the rate does not include expected maintenance of generation capacities. We obtain the unprofitable existing plants with the same logic as in 3.2.3.

On the supply side, the model collects all bids and runs the capacity auction that, in this scenario, allows all reliable *new* generation to bid. We assume that all investors bid the annuity[16] of the profitability gap. The capacity market thus ensures a payment at the level of the auction clearing price over multiple years[17]. Therefore, we calculate the NPVs of all new generation (see 3.2.3) and, in case the NPV is negative, each project bids the annual payment $B_t^{CM_{new},n,g}$ necessary to increase the negative NPV to 0. In case the NPV is already positive without a capacity market, the investor bids 0,

$$B_t^{CM_{new},n,g} = max\left(0; -\frac{-C^{I,g} + \sum_{i=t}^{t+LF^g}\left(\Pi_i^{g,n} * (1+r)^{-(i-t)}\right)}{\sum_{i=1}^{t_{pay}}\left((1+r)^{-i}\right)}\right). \tag{14}$$

Subsequently, all bids are put in ascending order and form the supply curve that is matched with the demand. Hence, the market is cleared and all generation that is required to fulfill demand receives the clearing price as a certain payment over a number of years t_{pay} (e.g. 10).

For the capacity market we assume no strategic bidding. As argued by Cramton and Stoft (2005), this can be realized through a sensible design of the demand curve with two important elements. First, there should be a price cap that can, for example, be set to the annualized investment and fixed cost of an OCGT power plant[18]. Second, a price-sensitive reserve margin (ϕ) should be used with a minimum and maximum range. Determined through these two regulatory assumptions, the demand curve can be established. With that type of demand curve, "much of strategic bidding can be eliminated" (Cramton and Stoft, 2005) and thus we abstract from it. We assume the use of a demand curve that is similar to the one also proposed in DECC (2013a) (also shown in Figure 3).

Capacity market for new and existing capacity (CM new&ex). The *CM new&ex* scenario works similarly to the *CM new* scenario. We also adjust the investor decision-making by

[16] For example a 10 year annuity in case the payment is guaranteed for 10 years.
[17] See for example DECC (2013a) where the price is planned to be contracted for 10 or more years.
[18] Which could be built by the regulator if the provided bids are too high.

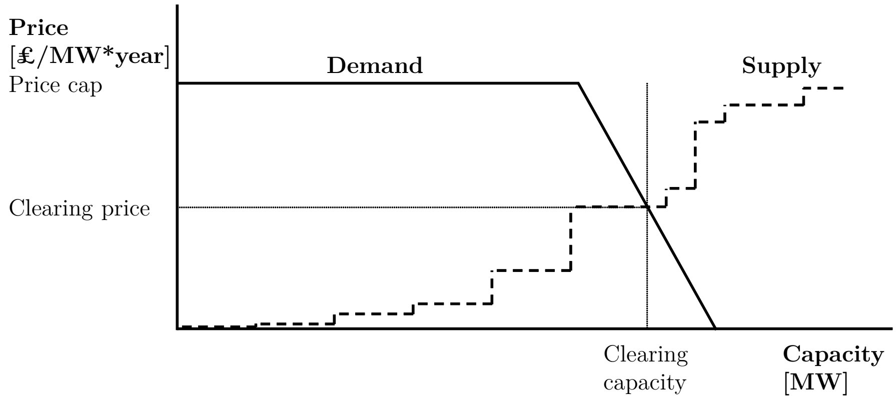

Figure 3: Illustrative capacity demand and supply curves (DECC, 2013a)

introducing a capacity market for *new and existing* generation. The *CM new&ex* is very similar to the *CM new* with only one simplification. Where, in the *CM new* scenario, the regulator had to anticipate plant retirements, we now only take the expected demand at peak, plus the given reserve margin ϕ to determine the required capacity to be provided from all existing and new generation,

$$D_t^{CMnew\&ex} = D_t^{EL,peak} * (1 + \phi). \tag{15}$$

The capacity market itself uses the same logic but allows bids from existing generation as well. These generators bid their profitability gap and neglect investments since these are sunk. This means, that if a generator who misses money to cover its fixed cost and who does not receive any capacity payments will retire the plant—according to the divestment logic explained previously. Hence, we have the following two forms of bids:

$$B_t^{CM_{new\&ex},e,g} = max\left(0; -\left(\sum_{h=1}^{8760}((P_{el,t,h}^{g,e} - C_t^{M,g}) * K_{el,t,h}^{disp,g,e}) - C_t^{F,g}\right)\right) \tag{16}$$

$$B_t^{CM_{new\&ex},n,g} = max\left(0; -\frac{-C^{I,g} + \sum_{i=t}^{t+LF^g}(\Pi_i^{g,n} * (1+r)^{-(i-t)})}{\sum_{i=1}^{LF^g}((1+r)^{-i})}\right). \tag{17}$$

All bids of existing as well as new generation are brought in ascending order and the supply curve is matched with the demand. Subsequently, all generation left of demand receives the capacity clearing price. In case it is new generation for 10 years, otherwise for only one year.

3.2.5. Iteration, feedback, and convergence

Calculation of prices and technology mixes for all years. We conduct the previous steps (2-4)—i.e., electricity price clearing, investor decisions, and generation portfolio determination—for all years until t=T. By reaching this point, the model has considered all periods of one iteration and can obtain a new electricity price development and a new average electricity price.

Feedback and convergence. After an iteration, we check the average electricity price against the one of the previous iteration. If the values differ (see Equation 1) by more than a certain percentage value (μ), we proceed to the next iteration and steps 2-4 are repeated another T times (i.e., for all years) until a new electricity price development has been determined. In that case, the electricity price development of the current iteration is used as the price forecast for the following iteration. Hence, we use this as the feedback mechanism of the model. If the difference is smaller than μ and the longitudinal electricity price developments are highly correlated, we consider the results as converged and interpret the result as a likely market outcome as investors have no incentive to change their investment behavior anymore.

4. GB case study

We choose the GB market for our case study, because the introduction of a capacity market is currently in the process of legislation and implementation in this market. The latest plans include a first capacity auction in 2014 (for capacity available in 2018). In order to reflect the situation in this market as closely as possible, we make several assumptions which we discuss in the first subsection. Subsequently, we present our results in the second subsection. We report all numbers (assumptions as well as results) in 2013 real terms, i.e., we abstract from inflation. In case references report earlier numbers, we inflate them by an average rate of 3% (Trading Economics, 2014) per year to reach 2013 terms.

4.1. Assumptions

4.1.1. General market and model parameters

We report results for a 20 year time frame (2014-2034) but run the model in the background for 60 years to omit distortions from an end of horizon effect—cf. Dantzig et al. (1978). We assume a development of fuel prices for coal, gas, and oil according to the expectations of UKERC (2013) and of carbon prices according to the Department of Energy and Climate Change (DECC) central case (DECC, 2013b). We report these developments in Figure 4 (center and left). We set the value of lost load (VOLL) according to London Economics (2013) to £10,000/MWh. The model stops the iteration if prices change by less than 1% from one iteration to the next one—i.e., $\mu = 0,01$. Sensitivities of μ show that a decrease to $\mu = 0,001$ reduces the speed of convergence by 20-40% (depending on the exact input value). Hence, it only leads to a limited number of additional iterations. The weighting factor of current prices (α) and expected future prices ($1 - \alpha$) is set to $\alpha = 0.75$ and $(1 - \alpha) = 0.25$ respectively. The parameter alpha can only be estimated, there are no sources available for the validation of this assumption. Therefore, we conduct sensitivity analyses on alpha and do not observe structural changes in results as long as alpha does not reach either of the extreme ends of the [0;1] interval. However, values close to 0 or 1 are not sensible from an economic point of view because they imply that investors only focus on either future or current prices respectively.

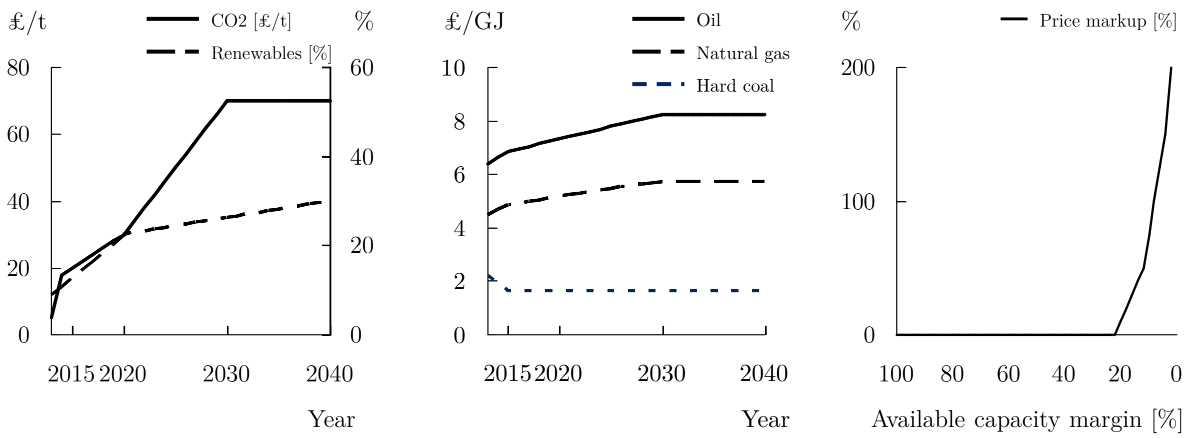

Figure 4: Carbon price and renewable quota (left), fuel prices (center), strategic bidding price markup (right)

For the capacity market scenarios, the regulator sets an un-derated capacity margin ϕ of 10%—however, we also run a sensitivity analysis for 15%. This capacity margin is used in the capacity market to determine the amount of capacity that is to be secured in the capacity auction. For intermittent RES, we assume a worst case availability of 0, as done in the GB market. Hence, these are not allowed to participate in the capacity market. However, the model can easily be adjusted to equally allow RES to bid, e.g., their expected load factor at peak—as done in markets such as PJM in the U.S.. The price markup function $\omega(K_{t,h}^{marg})$ is implemented as depicted in Figure 4 (right). Markups start at an available capacity margin of 10%, reach 50% at 10% available capacity margin, and 200% at 0% available capacity margin—below that, the price is set to the VOLL.

	$C^{I,g}$ Invest £/MW	$C^{F,g}$ Fixed £/MW*yr	$C_1^{M,g}$ Marginal £/MWh	η_{fuel}^g Fuel int. GJ/MWh	$\eta_{CO_2}^g$ CO_2 int. t/MWh	$C^{M-other,g}$ Other marg. £/MWh
Nuclear	4,295,250	72,000	10.6	0.00	0.00	10.6
Coal	1,647,700	51,750	33.2	9.20	0.73	1.0
CCGT	668,900	23,182	37.6	7.20	0.33	0.1
OCGT	598,500	23,000	47.2	8.78	0.495	0.0
Oil	1,647,700	23,000	96.9	13.29	0.73	0.0

Table 1: Technology cost parameters

	K_0^g Init. cap. MW	Q^g Capacity MW/plant	U_0^g Plants #	Age 0-4 #	5-9 #	10-14 #	15-19 #	20-29 #	30-40 #
Nuclear	9,946	1,105	9	0	0	0	1	4	4
Coal	23,072	1,538	15	0	0	1	0	14	-
CCGT	33,113	808	41	7	2	14	13	5	-
OCGT	2,151	307	7	0	1	2	3	1	-
Oil	2,338	102	23	0	0	11	12	-	-

Table 2: Technology parameters—initial portfolio

4.1.2. Investment decision parameters

Investors are assumed to apply a discount rate r of 8% to their investments. The maximum buildup (in plants per year) for the GB market is set to 1 plant for the nuclear technology, 2 for coal, and 5 for CCGT, 20 for OCGT, and 5 for oil. This is derived from capital intensity (see Table 1 for details) and complexity of the respective technology. Similar to the maximum buildup there is also a maximum divestment per year. The model limits the amount of divestment per year to three units of the smaller OCGT and oil plants and to one unit of the larger CCGT, coal, and nuclear plants. This is due to the fact that investors have an incentive not to divest all plants in the same year and rather keep the optionality and wait for the market to develop. Before a divestment is actually executed, a divestment threshold (Γ^g) must be reached - this has been suggested in several discussions with private investors. Therefore, we set Γ^g to 50% of $C^{F,g}$, i.e., the fixed cost of the respective technology arguing that an investor would only consider divestment if the yearly loss is larger than 50% of the plant's fixed annual costs.

	LF^g Econ. life Years	ξ Availability Percent	ϱ_u^g Ramp up %/(plant*h)	ϱ_d^g Ramp down %/(plant*h)	$C^{Cy,g}$ Cycling costs £/MW
Nuclear	40	90	55	55	67,34
Coal	30	90	70	70	50,62
CCGT	20	95	100	100	33,67
OCGT	20	98	100	100	15,57
Oil	20	98	100	100	15,57

Table 3: Technology parameters on lifetime, availability, and ramping

4.1.3. Technology parameters

We use three groups of technology data—cost parameters, initial portfolio characteristics, and parameters regarding lifetime, availability, and ramping. First, the cost parameters, shown in Table 1, are based on an industry report by Parsons Brinckerhoff (2011) and validated with experts from the SIEMENS power division.

Second, the information regarding the current GB generation portfolio is derived from DECC (2013a) and shown in Table 2. In some cases we found plants that already exceed the expected economic lifetime—in these cases we normalized the data[19].

Third, all parameters with regards to lifetime (LF^g), availability, and ramping are presented in Table 3. The ramping parameters ϱ_u^g and ϱ_d^g represent the share of capacity that can be ramped up or down within one hour in a warm start scenario, ϱ_u^g and ϱ_d^g are derived from Vuorinen (2009), Chiodia et al. (2010), and VDE (2012) while the ramping costs can be found in Kumar et al. (2012). Combining the information on ramping constraints and on marginal costs, we see that the assumption of a correlation between higher marginal costs in the merit order and a higher flexibility holds true for the empirical data of our GB case study.

4.1.4. RES technology and demand data

We assume RES to be exogenous to the model because our model is focused on assessing the effect of the introduction of capacity markets. We consider the discussion around renewable energy support schemes as a different field of research. Hence, we treat the

[19]Using the following procedure: we reduced the plant age by 10 years and checked whether the age falls into the expected economic lifetime. If yes, we kept that age, if not, we repeated the process. This procedure reflects a major plant overhaul which needs to be done at the end of the economic lifetime to allow the plant to run for a certain number of additional years.

build-up of renewables as exogenous to the model as it is determined by a different set of regulatory instruments. We employ three components to determine renewable electricity production over 60 years in an hourly granularity. First, we use RES production profiles for sample years in hourly granularity to include realistic fluctuation and distributions. For onshore and offshore wind, we include GB capacity factor data of the sample year 2005 from Green and Vasilakos (2010). For solar PV capacity factors, we make use of German data from Gemsjaeger (2012) due to the lack of publicly available GB data. This inaccuracy is bearable, because solar PV only represent a very small share of GB's (renewable) electricity generation and the German capacity factors are very similar to the ones in GB. Second, In the case of all intermittent RES generation, we multiply these capacity factors by the installed capacity. The current (2013) generation capacity is reported in DECC's DUKES report (DECC, 2013a) at 5,900 MW for wind onshore, 3,000 MW for wind offshore, and 1,700 MW for solar PV. Third, we scale these generation capacities up, according to the government's policy targets for renewable energy production. These include a buildup from 11% of electricity generation in 2013 to 30% in 2020 and 35% in 2030 as depicted in Figure 4 (left) (DECC, 2010b, 2011). Sensitivity analyses on lower/higher build-up of renewables show that all design options are similarly affected through a lower/higher share of renewable generation but there are no structural changes in the comparison between the design options.

On the demand side we also use a 2005 demand profile with an hourly granularity from Green and Vasilakos (2010)—consistent with the wind profiles. The model allows this to be equally scaled as done with RES feed-in. However, we leave demand stable over time due to the expectation that demand growth and efficiency gains level out. Additionally, we incorporate the short-term price elasticity of demand that could be realized through demand response programs. We set β_t it to the low value of 0.1 £/(MWh)^2, however, because we do not yet expect high shares of demand to be included in demand response programs.

4.2. Results

In the following, we describe the results obtained from running the model with the above-presented parameters and assumptions. The model is implemented in MATLAB version R2012a.

4.2.1. Overview

We compare the three previously described scenarios (*No CM*, *CM new*, *CM new&ex*) along the three dimensions of electricity policy—affordability, reliability, and sustainability. To represent affordability, we report three metrics: first, yearly total bill of electricity generation[20] (this includes all revenues realized by (conventional[21]) generators—from the energy-only market as well as the capacity market), second, average electricity price development, and third, average capacity price development. With regards to reliability, we present electricity price volatility and the number of lost load occasions. Finally, sustainability is represented by the system's yearly CO_2 emissions.

Our case study shows that the introduction of a capacity market has a positive effect on the market in terms of affordability and reliability because the total bill of generation decreases and lost load does not occur as opposed to the *No CM* case. Sustainability is not affected by a *CM new&ex*, while it is positively affected by a *CM new* because this scheme leads to new investments in less CO_2-intensive gas-fired generation instead of existing coal-fired generation. Furthermore, we identify differences between the two design options of capacity markets—a *CM new* leads to a lower total bill of generation than a *CM new&ex*.

To provide more detail behind these overarching statements, we discuss the metrics depicted in Figure 5 one by one. The total bill of generation is higher without a capacity market than with a capacity market. There are two reasons to explain that difference. First, lost load which is priced at a high cost[22] (£10,000/MWh) occurs more frequently due to investors providing less capacity to increase profit per plant. Second, capacity margins that lead to more potential for strategic behavior and bidding above marginal costs get tighter. By contrast, with the introduction of a capacity market, there is always sufficient capacity in the market and hence less potential to exercise market power. The average capacity price of £32,000-41,000 per MW per year leads to cost of roughly £2-4 billion per year but does not outweigh the benefits of mitigating lost load occasions and

[20] One could also consider total welfare as a metric to compare the scenarios in terms of affordability. However, in our perception, regulators, consumers, and policy makers are mostly focused on the bill of generation when discussing capacity markets. Therefore, we focus on this measure and leave an analysis on total welfare to future research. A discussion of economic welfare would also require a more thorough discussion of the demand function and its shape.

[21] We exclude RES because these are exogenous to the model and equal in all three scenarios.

[22] Compared to the marginal cost of expensive peak load generation in the magnitude of £100/MWh

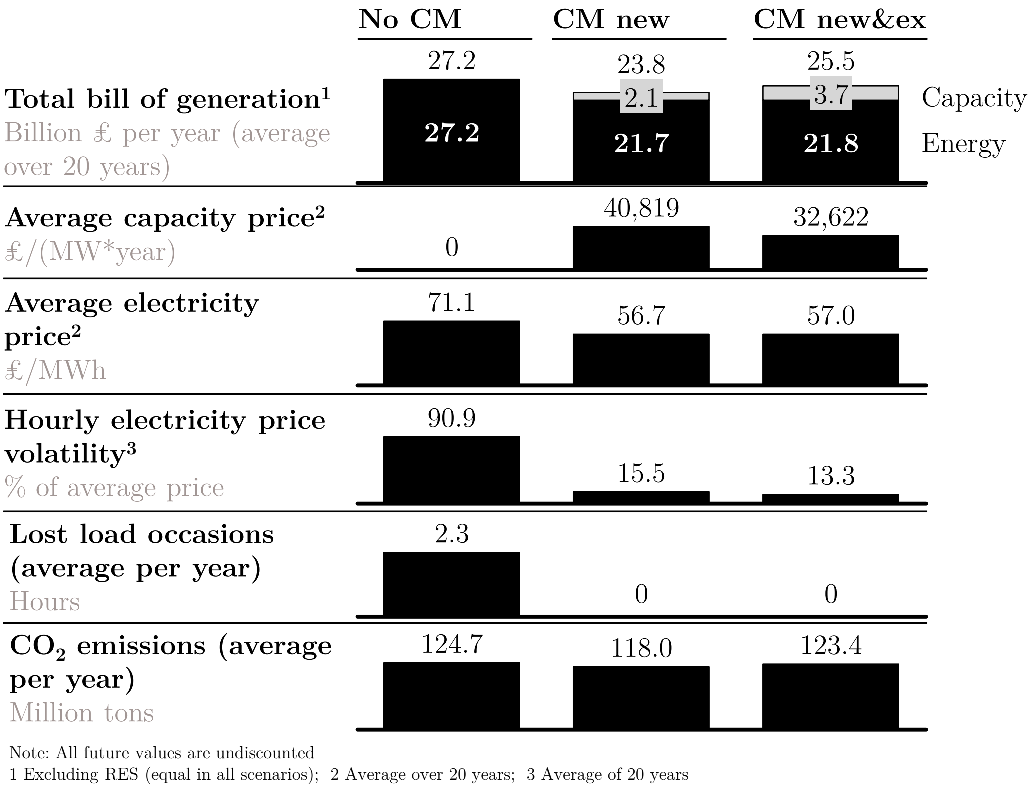

Figure 5: Overview of results

strategic bidding potential. The average electricity prices reflect the difference caused by the presence or absence of a capacity market—without a capacity market, all investment incentives are provided through the electricity price. As limited capacity installations occur, capacity shortages happen more often and lead to higher prices that consequently incentivize investment. Moreover, all results across all three scenarios in terms of costs must be seen in the light of the assumed steeply increasing CO_2 prices. These lead to prices significantly higher than observed in today's market. To give an estimate of the extent of that effect: if we assumed CO_2 prices to stay at £5 per ton throughout the time horizon, the above-presented bill of generation values would decrease by roughly 25-30%. All scenarios are similarly affected by this assumption. However, this only affects the absolute values, but it does not change the structure and the relative differences of the results between scenarios.

The reliability metrics volatility and lost load also show an advantage for the capacity market scenarios. The electricity price volatility is significantly lower with a capacity market (14% as opposed to 91%) and there are no situations of lost load—both due to a larger amount of capacity in the market.

The introduction of a capacity market for new and existing generation does not change

CO_2 emissions. Under a *CM new* however, we observe a decrease in CO_2 emissions of about 5%. This can be explained by the fact that a capacity market for new generation only incentivizes investment in new fuel-efficient gas-fired generation and leads to an earlier retirement of existing inefficient coal-fired generation.

4.2.2. Electricity prices

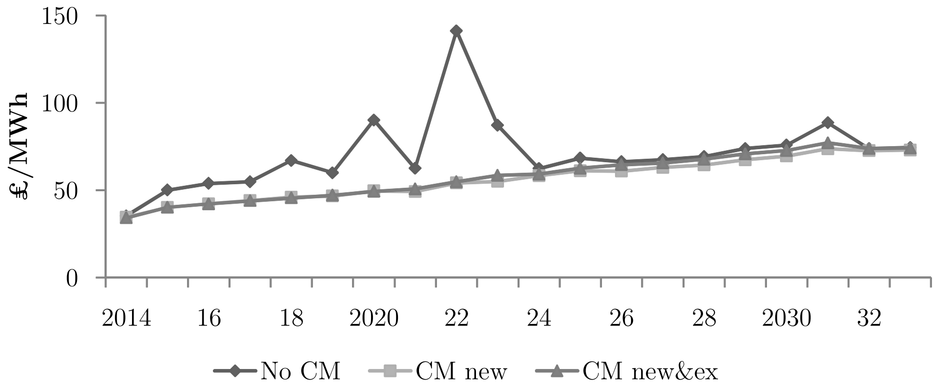

Figure 6: Electricity price development

Looking more closely at the electricity price developments over 20 years visualized in Figure 6, we can make three major observations. First, in all scenarios average prices rise over time. This is due to the rising CO_2 cost as shown in Figure 4 (left). The U.K. government plans to significantly increase cost of CO_2 emissions that will be passed on to consumers through increasing electricity prices.

Second, several years of high prices occur in the *No CM* scenario. These are due to capacity retirements given existing generation not being replaced by new investments because of missing investment incentives. The reduced capacities lead to higher prices and hence, help create sufficient incentives for new investment in the following years. This is the case around year 2020 with several occurrences of lost load. These findings are in line with the simulations of Eager et al. (2012), who also anticipate capacity shortages around the year 2020 in their GB case study.

Third, the electricity price development is stabilized through a capacity market. With a capacity market, an investment can expect revenues from both, the energy-only and the capacity market. As investors bid the profitability gap, the capacity bid is the one that fluctuates as we discuss in the following section. Additionally, the situation of unstable investment incentives under the *No CM* scenario in the years around 2020 also leads to more fluctuations in electricity prices and therefore to more price volatility.

4.2.3. Capacity prices

The capacity prices show strong fluctuations in the rage between 0 and 150,000 £/MW for both design options with an average of 30,000-40,000 £/MW (see Figure 5). This can be explained by the fact that different capacity requirements in each year lead to different types of capacity bids. Market conditions differ from year to year because they depend on demand development and capacity retirement (due to end of economic lifetime or unprofitability). In case of a demand increase and many retirements, a large capacity gap can be expected, whereas decreasing demand and stable existing capacity can even lead to overcapacity. These market conditions determine whether existing capacity is sufficient or new capacity must be built. The bids of generators in the capacity auction depend on two factors. First, whether the marginal bidder is existing or new capacity and second, on the type of technology. Bids are very low, often even zero, if the plant exists already because the necessary costs of keeping the plant running are very low. On the other hand, new generation requires high capacity prices to cover for the investment. The combination of the changing market conditions and different types of bids leads to the jumps in prices. However, we should keep in mind that the contracts are designed in a way that new generation is guaranteed the price of the auction in which it has been cleared for 10 years. Hence, it is independent from fluctuations of capacity prices.

4.2.4. Generation portfolio

The discussion of the generation portfolio can be simplified through two explanatory notes. First, RES generation capacity (i.e., the top three rows in Figure 7) is determined exogenously and therefore identical in all three scenarios. Second, nuclear generation, given the cost assumptions, is an attractive investment target. Therefore, it is being built at the maximum rate which keeps nuclear capacity roughly stable over time due to retirements of the rather old current GB nuclear assets. This effect is identical across all three scenarios. Hence, differences are only seen in coal, gas, and oil fired technologies.

For the *No CM* case we observe a capacity reduction in the first 5 years that leads to the price spikes discussed earlier. From 2018 on, capacity is being gradually increased mainly in gas-fired technologies with an emphasis on OCGT. In contrast, capacity levels with a capacity market are significantly higher. The results show that the mechanism leads to more available gas-fired capacity—mainly OCGT and some additional CCGT. We see that the technology profiting the most from a capacity market is OCGT with its low

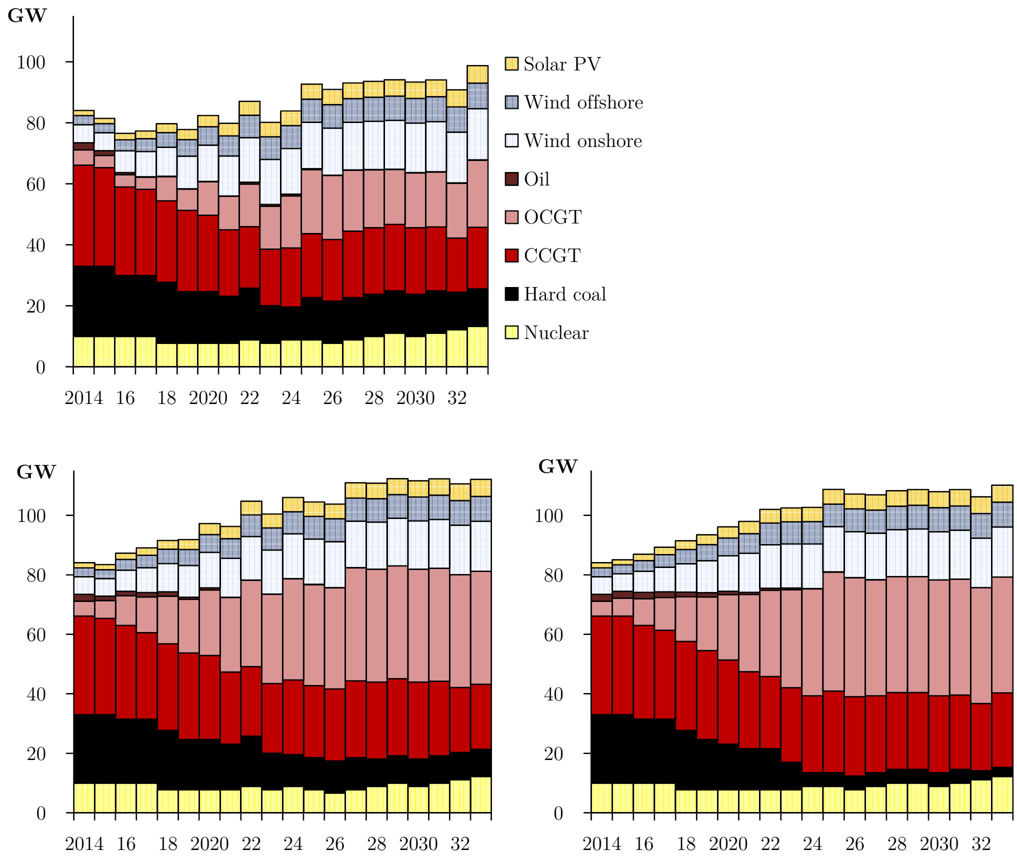

Figure 7: Generation portfolio without a capacity market (top row: *No CM*) and with a capacity market (bottom left: *CM new*, bottom right: *CM new&ex*)

investment and high marginal cost. The plants are mostly constructed to provide sufficient capacity with low load factors.

4.2.5. Model convergence

We reach the convergence criterion in iteration 16 for the *No CM* scenario while both capacity market scenarios converge more quickly—see Figure 8. The rationale is, that the higher level of capacity induced by the capacity market leads to more price stability and therefore to less differences in the reactions of other market participants to outcomes of previous iterations. To show not only convergence of the average electricity price but also of longitudinal electricity price developments, we include Figure 9. We observe that the price development is rather flat in the initial forecast (It0) while it converges towards a development that exhibits peaks as discussed earlier over the iterations (see It4–It16). Additionally, we see that the Pearson correlation (shown in "()" behind the iteration) indeed increases over the iterations. Together, these two criteria allow us to conclude that the market has reached a stable equilibrium.

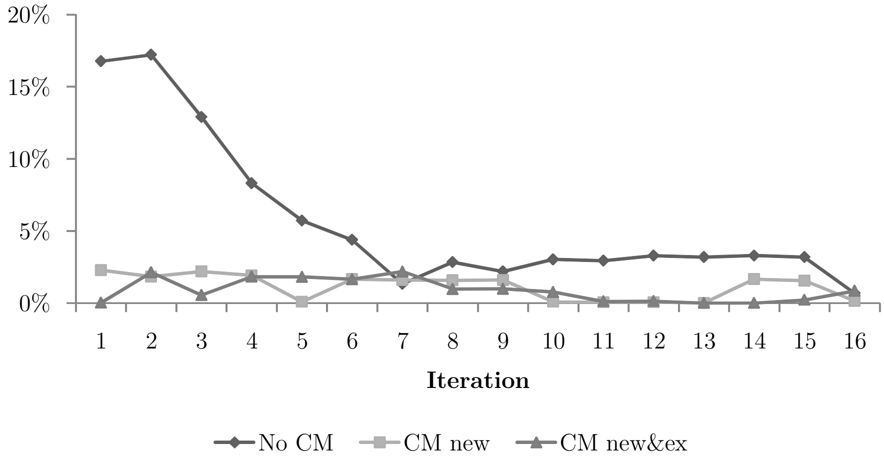

Figure 8: Change in average electricity price over the iterations

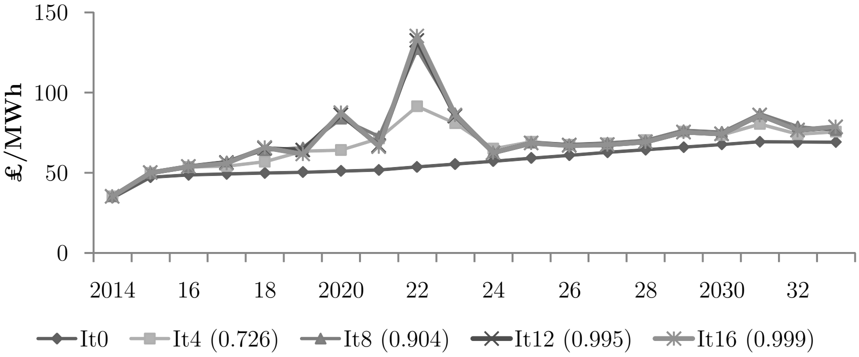

Figure 9: Longitudinal electricity price development (in the *NoCM* scenario) in different iterations (Pearson correlation of electricity price developments)

4.2.6. Sensitivity analyses

In order to check the robustness of the results and to provide more information on controversially discussed assumptions, we run several sensitivity analyses. We show a comparison of the total bill of generation in the sensitivity results compared to the general results in Figure 10.

No strategic bidding. First, we deactivate the opportunity for strategic bidding by setting $\omega(K_{t,h}^{marg}) = 0$ for all levels of residual capacity. We observe that without any potential for strategic bidding, the *No CM* scenario is as cost-efficient as the *CM new*. The reason for this is that both schemes are equally efficient in providing the exact amount of necessary incentives for sufficient new generation investments. In the *No CM* scenario these incentives arise from occasions of lost load that drive up the prices in a limited number of hours per year. While in the *CM new* scenario incentives arise from the capacity market where the payments are guaranteed for 10 years in case of new capacity construction. Consequently, the electricity price volatility is very high without a capacity market 130%

(as opposed 11% in both CM scenarios) and there are on average 3.25 hours of lost load (as opposed to 0 with a CM). The *CM new&ex* scenario is more expensive than the other two scenarios, because it also remunerates existing generation with capacity payments. In conclusion, the absence of strategic bidding diminishes the advantage of the CM scenarios on the affordability dimension, while the benefits in terms of reliability continue to hold.

Stable CO_2 emission cost. Second, we change the assumptions on the CO_2 price development to a stable CO_2 price at £5 per ton instead of the steep increase as currently proposed by the British Government. We find that the total bill of generation falls by roughly 25-30% across all scenarios. Additionally, we observe that prices of electricity do not rise over time anymore but instead are stable at the low level of the beginning. The *No CM* scenario is more positively affected by a lower CO_2 price because it is completely reliant on marginal cost bidding of generators and the CO_2 cost are a part of these marginal costs. In the capacity market scenarios however, a share of the total bill of generation comes from the capacity market that is less influenced by the change in generator's marginal costs. In terms of CO_2 emissions, we see a rise of 1/3 due to a shift in generation and capacities from gas to coal.

Stable fuel prices. Third, we test the effect of stable fuel prices instead of a slightly declining coal price and rising gas and oil prices in our general assumptions. The results show a 10-15% decrease in the total bill of generation across all scenarios as well as an increase in CO_2 emissions by 25%. Again, the *No CM* scenario is more positively affected by the fuel price decrease for the same reasons as stated in the discussion of the previous sensitivity on stable CO_2 emission cost.

Reserve margin at 15% instead of 10%. Fourth, we set the reserve margin to a higher level of 15% instead of 10% and find higher capacity cost in both capacity market scenarios (up by 10%) due to additional capacity payments for the additional 5% of capacity. The new capacity is entirely gas-fired (both, CCGT and OCGT).

VOLL at £2,500 instead of £10,000. Finally, we find that a reduced VOLL slightly lowers the total bill of generation in the NoCM scenario. However, even a reduction of the VOLL to 25% (2,500) of its standard value (10,000) only reduces the total bill of generation in the NoCM scenario by 2%. This is due to the fact, that hours with lost load (and high prices) are needed as an investment incentive. Hence, reducing the VOLL leads to more hours with lost load—thus balancing the lower (VOLL) prices with a higher number of VOLL hours. The CM results are largely unaffected by the changes in VOLL because hours with lost load do (almost) never occur in these scenarios.

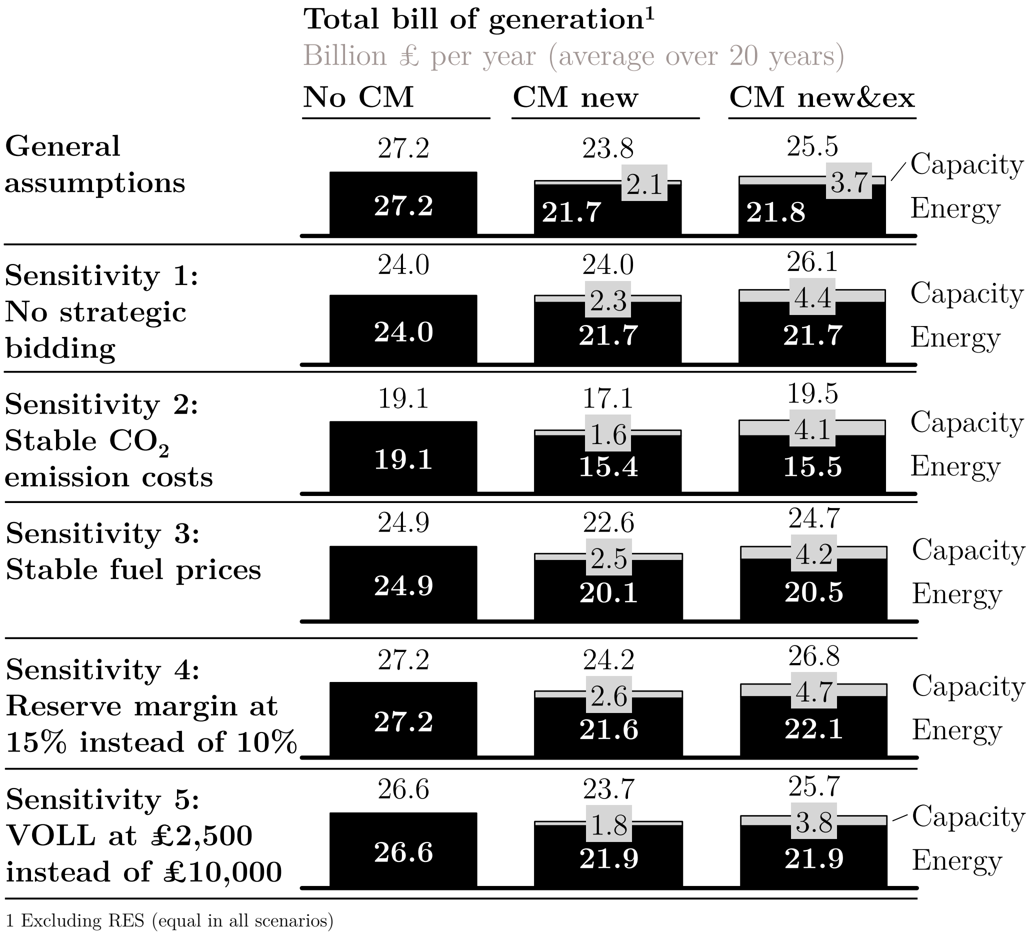

Figure 10: Comparison of sensitivity results with the general results

5. Discussion

5.1. Policy implications

In our case study we make projections of GB market prices and generation mixes that are specific to the properties of the market at hand. However, there are four findings from this study that can be generalized to foster a policy discussion on capacity markets in general because they depend on the overarching electricity market structure and are independent from GB-specifics. First, capacity markets increase generation adequacy. Second, capacity markets do not necessarily increase the total bill of generation. Third, it is cheaper to set up a capacity market for new generation only but risky from a policy perspective. Fourth, a capacity market can be desirable if there is a risk of capacity shortage. However, if there is significant overcapacity during an extended period of time, there is no need for a capacity market.

We find that in the two capacity market scenarios generation adequacy indeed improves significantly by providing incentives for the construction of additional capacity. This is shown by a lower number of lost load occasions as well as by a reduced electricity price volatility. This result was expected as achieving generation adequacy is the major goal of a capacity market.

In capacity market policy discussions around the world, critics of capacity markets argue that capacity remuneration improves generation adequacy at the expense of an increase in the total bill of generation (ACER, 2013; TCAPTX, 2013). Most studies arguing in this way neglect two important factors that we incorporate in our model: First, the interdependency of capacity and electricity markets leading to decreasing electricity wholesale prices if revenues is also obtained from a capacity market. Second, strategic behavior and above marginal cost bidding in an energy-only market resulting in wholesale electricity prices that partially reflect market power in times of shortage rather than marginal costs. Drawing from our results we can argue that this does not always hold true. Moreover, assuming the existence of strategic bidding in the energy-only market and assuming the successful prevention of strategic bidding in the capacity market, the introduction of a capacity market can even decrease the long-term overall the total bill of generation as we observe in our GB case study. In that case, capacity markets add £2-4 billion to the generation bill. However, by providing additional capacity and reducing the potential for lost load and strategic bidding, that addition is overcompensated by £3-5 billion in bill of generation savings. While the extent of this effect is likely to differ across markets, it is important that these secondary effects[23] are taken into account as well. Therefore, a policy discussion should be supported and informed through a quantitative model that is able to reflect such effects.

Should all generation that provides capacity be eligible for capacity remuneration from the capacity market, or only the newly built capacity? We find that it is cheaper to only pay new capacity. With a *CM new* less capacity payments get disbursed in the first years since only new investments need to receive these. Despite this observation, a policy maker should bear two further factors in mind. First, by only paying new generation,

[23]E.g., the impact of a capacity market on strategic bidding and lost load occasions.

investors are incentivized to retire existing generation earlier, because it is not profitable anymore and there is no access to the capacity market. This leads to an earlier need to incentivize investment in new generation through the capacity market. Hence, there is a faster capacity turnaround leading to a situation where a larger number of new generators receive high capacity payments. Second, as argued by Cramton et al. (2013), the strategy of not paying existing generation[24] might work once, if investors are surprised but afterwards would lead to investors requiring additional protection from future unequal treatments and a risk premium. Apart from that, in the long-term both design options converge, because gradually there will be no generation left that existed before the introduction of the CM and all generation is covered by the capacity mechanism. Therefore, regulators should carefully consider, whether the cost reduction is worth the effect of increasing investment uncertainty that results from such an unequal treatment.

Finally, capacity markets are only desirable if the market is relatively close to a capacity shortage. The reason for this is that the major goal of a capacity market is to ensure sufficient capacity in the system at all times. If this is already the case without a capacity market, it should not be introduced. The current situation in Germany shows a market with significant overcapacity (Bloomberg, 2012; Timera Energy, 2013). In that situation a capacity market would induce unnecessary additional cost. For a market like this, it might be, in the short- and medium-term, more desirable to use a strategic reserves scheme that can be easily adjusted and locally focused. However, in the long-term a strategic reserve has other disadvantages (see Section 1 for details), so that this scheme could be transformed into a capacity market as soon as a capacity shortage is looming.

5.2. Limitations

Even though we include a wide range of important features of electricity markets, one should keep in mind when discussing the results of our model, that we also have leave out a number of complexities of these markets. At this point, we abstract from stochasticities, the transmission system, and storage. In terms of stochasticity, we do not include unexpected unavailabilities of conventional generation and long-term uncertainties of renewable energies (while we include short-term renewable fluctuation). With regards to the transmission system, additional features could be the modeling of the grid topology

[24]This unequal treatment can even be called a regulatory taking or expropriation.

(including transmission capacities and transmission losses), locational demand and generation (to determine nodal shortages and exact unit commitment), and interconnections to neighboring countries. These features represent areas for further research and an extension of the presented model. However, we are confident that our major findings with regards to capacity market policy also hold without these features because they would affect all scenarios similarly and not change the structure of the results.

6. Conclusion and further research

We present a dynamic capacity investment model that is well suited for policy assessments regarding capacity mechanisms. It comprises realistic modeling of investor behavior and a broad range of features including an extended time horizon, all major generation technologies, ramping constraints, strategic behavior, and price elasticity of demand.

We apply the model to the GB case, where the introduction of a capacity market is ongoing. We find that a capacity market increases reliability. The results of this case study also suggest that capacity markets can decrease the long-term bill of generation because, through deliberate overcapacity, they prevent loss of load occasions and reduce strategic bidding. Hence, we find that capacity markets can lower the wholesale electricity price and can decrease price volatility. Our findings apply to a market where strategic bidding is present and the results are based on the assumption that strategic bidding can mostly be omitted in a capacity market. We discuss why these are reasonable assumptions, however, we see potential for further research on the extent of strategic behavior in the GB energy-only and capacity market, which is not the focus of this study. Additionally, we compare a capacity market that remunerates new capacity only to one that compensates new and existing capacity. We show that a capacity market for new capacity is only cheaper because it remunerates fewer generators in the beginning. However, there is a significant downside of such an unequal treatment that should be considered when deciding on the design option.

We propose to include additional features in a model similar model, such as stochasticity of conventional plant outages as well as of RES feed-in, grid constraints, and interconnections to neighboring countries. Apart from these specific features, it would also be desirable to compare the presented model with other methods such as simulation models or optimization models. By doing so, one could examine the quality of obtained results, range of features, and usability of these different methods for policy assessment. Finally, we suggest assessing other design options of capacity mechanisms (e.g., technology-focused capacity markets or strategic reserves) with a quantitative model presented here. This could help regulators and market participants to make well informed decisions on future policies and long-term investments.

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List of symbols

Symbol	Description	Symbol	Description
α	Weighting factor of last period against last iteration	ξ	Availability
β	Price elasticity of demand	Π	Profit
Γ	Divestment threshold	ϱ_d	Ramp down factor
η_{CO_2}	CO_2 emission intensity	ϱ_u	Ramp up factor
η_{fuel}	Fuel intensity	ϕ	Reserve margin
κ	Utilization	ω	Price markup
μ	Convergence threshold		

Table 4: List of symbols (Greek characters)

Symbol	Description	Symbol	Description
B^{CM}	Capacity market bid	it	Index for iteration
B^{El}	Electricity market bid	K_0	Initial capacity
b_{max}	Maximum buildup	K^{avail}	Available capacity
C^C	Capital costs	K^{disp}	Dispatched capacity
C^{Cy}	Cycling costs	$K^{disp,REN}$	Capacity of dispatched RES
C^F	Fixed costs	LF	Economic lifetime of plants
C^M	Marginal costs	n	Index for new plants
$C^{M-other}$	Other marginal costs	NPV	NPV of possible new investments
C^{Tot}	Total cost	P_{el}	Electricity price
D	Total demand	Q	Size of plants
D^{CONV}	Conventional demand	r	Plant specific discount rate
D^{EL}	Electricity demand	SC	Screening curve
e	Index for existing plants	T	Number of years considered
G	Number of generation technologies	t	Index for year
g	Index for generation technology	U_0	Initial number of plants
h	Index for hour	$VOLL$	Value of lost load

Table 5: List of symbols (Arabic characters)