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On the Role of Risk Aversion and Market Design in Capacity Expansion Planning

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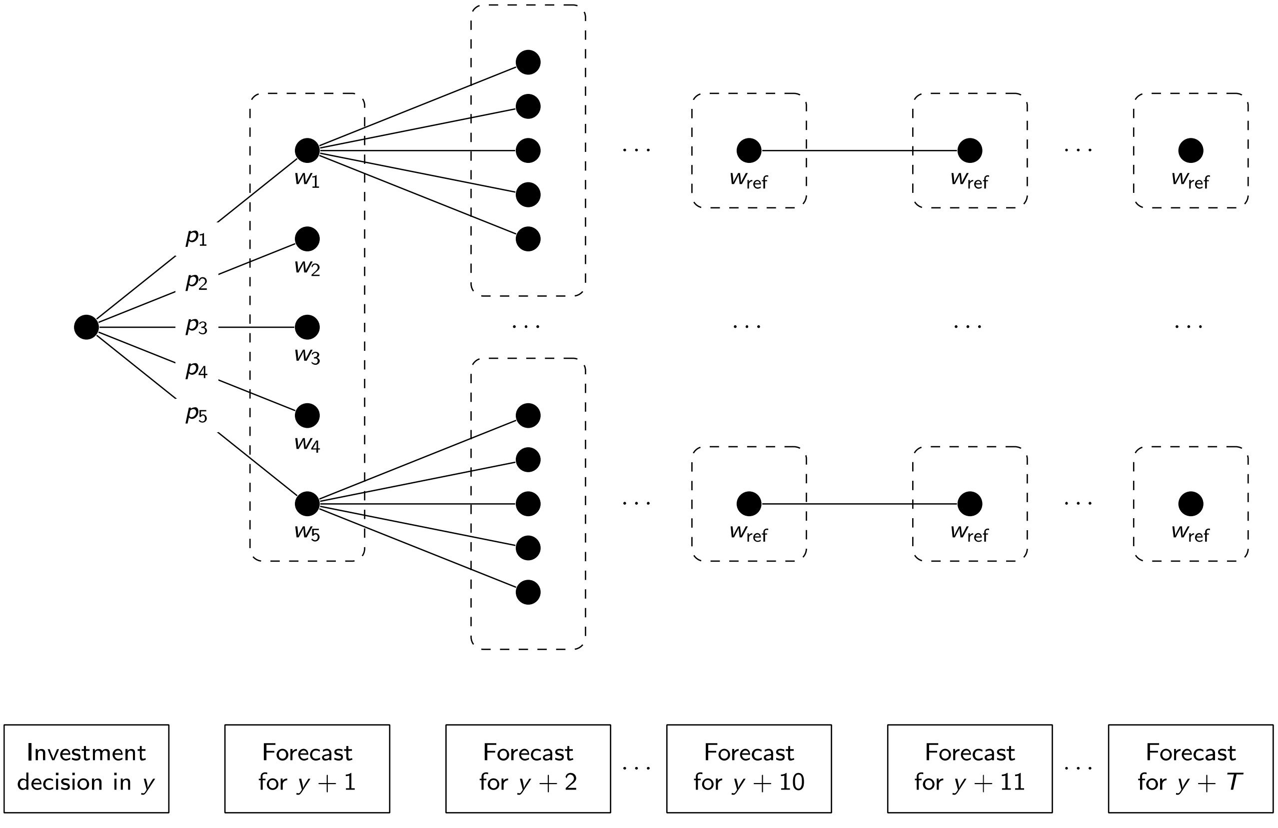

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Investment decisions in competitive power markets are based upon thorough profitability assessments. Thereby, investors typically show a high degree of risk aversion, which is the main argument for capacity mechanisms being implemented around the world. In order to investigate the interdependencies between investors' risk aversion and market design, we extend the agent-based electricity market model PowerACE to account for long-term uncertainties. This allows us to model capacity expansion planning from an agent perspective and with different risk preferences. The enhanced model is then applied in a multi-country case study of the European electricity market. Our results show that assuming risk-averse rather than risk-neutral investors leads to slightly reduced investments in dispatchable capacity, higher wholesale electricity prices, and reduced levels of resource adequacy. These effects are more pronounced in an energy-only market than under a capacity mechanism. Moreover, uncoordinated changes in market design may also lead to negative cross-border effects.

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Abstract

Investment decisions in competitive power markets are based upon thorough profitability assessments. Thereby, investors typically show a high degree of risk aversion, which is the main argument for capacity mechanisms being implemented around the world. In order to investigate the interdependencies between investors' risk aversion and market design, we extend the agent-based electricity market model PowerACE to account for long-term uncertainties. This allows us to model capacity expansion planning from an agent perspective and with different risk preferences. The enhanced model is then applied in a multi-country case study of the European electricity market. Our results show that assuming risk-averse rather than risk-neutral investors leads to slightly reduced investments in dispatchable capacity, higher wholesale electricity prices, and reduced levels of resource adequacy. These effects are more pronounced in an energy-only market than under a capacity mechanism. Moreover, uncoordinated changes in market design may also lead to negative cross-border effects.

Keywords: Agent-based simulation; Capacity expansion planning; Risk aversion; Electricity market design; Energy-only market; Capacity mechanism

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1 Introduction

In competitive power markets, investment decisions are based upon thorough profitability assessments. Thereby, investors typically show a high degree of risk aversion due to the capital intensity of large-scale generation and storage facilities, and the corresponding long-term investment horizons (Vàzquez et al., 2002). The significant increase of renewable electricity generation in countries around the world further exacerbates the situation. Even under very high shares of renewables, a certain amount of dispatchable capacity will still be required to compensate for the intermittency of solar and wind power. Yet, the small number of (expected) operating hours as well as price volatility increase the risk of investments in the required firm capacity.

Against this background, *capacity remuneration mechanisms* (CRMs) have been implemented in several regions of the world as an extension to an *energy-only market* (EOM), in which capacity providers are solely compensated for the amount of electricity they sell on the markets (Bublitz et al., 2019). CRMs aim to reduce the risks for new investments by offering capacity providers supplementary income on top of the earnings from selling electricity on the market. The additional firm capacity is then expected to help improve resource adequacy, i.e., avoid shortage situations.

These developments illustrate that the interdependencies between investors' risk aversion and market design are crucial when analyzing transformation pathways of electricity systems. However, existing capacity expansion planning[1] models do not cover all aspects relevant for a realistic representation of real-world electricity markets, which are amongst others characterized by heterogeneous risk-averse actors

[1]In the literature, the term *generation expansion planning* is often used to describe models that aim to determine a future generation technology mix subject to the future electricity demand, renewable feed-in and cross-border transmission capacities. Since we also consider a model-endogenous expansion of storage capacities, we use the more generic term *capacity expansion planning*.

and – particularly in the European case – cross-border effects of asymmetrical market design implementations.

In our article, we therefore extend the agent-based electricity market model PowerACE to account for long-term uncertainties, such that capacity expansion planning can be carried out from an agent perspective and with diversified risk preferences. For this purpose, we construct model-endogenous scenario trees and implement a new decision metric that comprises the expected profitability and the corresponding *conditional value at risk* (CVaR) of a potential investment. The enhanced model is then applied in a case study covering multiple interconnected market areas with diverging market designs. This allows us to quantify the impact of risk aversion on capacity expansion, wholesale electricity prices, and resource adequacy for both, a European EOM design as well as asymmetrical CRM implementations.

The remainder of the article is structured as follows. In Section 2, we briefly review the relevant existing literature and outline how it is complemented by our analysis. Section 3 introduces the applied simulation model as well as all relevant extensions carried out for this article. We then describe the data and major assumptions of our case study in Section 4. The subsequent Section 5 presents and discusses the results of our simulations. Finally, Section 6 concludes and derives policy implications of our analysis.

2 Literature Review and Research Gap

Capacity expansion planning is one of the traditional problems in electricity system design which is reflected by the several review papers available in the literature (e.g., Sadeghi et al., 2017; Koltsaklis and Dagoumas, 2018; Babatunde et al., 2019). In the following, we first summarize previous work on the role of risk aversion in capacity expansion planning. We then define several requirements for models that aim to represent real-world electricity markets in a realistic fashion. Based on this, we outline in what sense existing approaches fail to meet these criteria and how our work therefore complements the literature.

Originally, optimization models from the perspective of a central planner that aims to maximize social welfare by minimizing total system cost were mostly applied for capacity expansion planning. Over time, this model class was extended to consider uncertainties (e.g., Swider and Weber, 2007; Spiecker et al., 2013; Fürsch et al., 2014; Scott et al., 2021) and even risk aversion (e.g., Möbius et al., 2021). However, such optimization models are not able to adequately represent competitive electricity markets, where investment decisions are made by individual market players based on market price expectations under imperfect information (Weber et al., 2021; Anwar et al., 2022).

For this reason, equilibrium models have recently gained popularity. In these models, the individual profit maximization problems faced by the different market players are simultaneously solved in order to find an equilibrium with no incentive for any of the actors to unilaterally deviate. Equilibrium models generally allow to represent uncertainties (e.g., Schröder et al., 2013) as well as risk aversion (e.g., Ehrenmann and Smeers, 2011; Fan et al., 2012; Mays et al., 2019). However, this type of models is particularly challenging to solve, so typically only small-scale systems can be investigated (Anwar et al., 2022).

The computational challenges of equilibrium models can be mitigated by moving to other model types, such as system dynamics (e.g., Petitet et al., 2017) or agent-based simulations (e.g., Botterud et al., 2007; Anwar et al., 2022). However, while the mentioned articles consider uncertainties and risk aversion, none of them features a geographical scope covering more than a single country.

Existing research shows that both, the flexibility of an electricity system (Möbius et al., 2021) and the market design (Ehrenmann and Smeers, 2011; Petitet et al., 2017) may decide on how big a role risk aversion plays in capacity expansion planning. Thus, given the European Commission's goal of creating an Internal Electricity Market, cross-border effects between interconnected market areas are a major aspect to be considered in European electricity market models. Moreover, several European countries have recently opted to introduce CRMs (Bublitz et al., 2019), which may come along with substantial cross-border effects. Finally, when investigating electricity market designs, it is important to model system transformation pathways in order to account for path dependencies and lock-in effects arising from long investment horizons. Considering multiple investment decision periods is therefore preferable over using a limited number of milestone years as typical for optimization and equilibrium models.

To the best of our knowledge, there exists no approach in the literature that fulfills all of these requirements (cf. Table 1). In this article, we therefore enhance an existing agent-based simulation model, which allows us to adequately represent a dynamic capacity expansion planning in a deregulated market structure with heterogeneous and risk-averse actors. We then apply our approach in a case study covering multiple interconnected market areas with diverging market designs.

3 Methodology

In the following sections, we describe the methodological approach of this article. To start with, Section 3.1 introduces the applied electricity market simulation model PowerACE and provides some details on the previously developed algorithm for capacity expansion planning from the perspective of individual agents. We then

Table 1: Existing modeling studies considering uncertainties in capacity expansion planning. Our article is the first to cover several important features of real-world electricity systems at the same time.

Model type/ Reference	Agent perspective	Risk aversion	Cross-border effects	Transformation pathway	Market design
Stochastic optimization model					
Fürsch et al. (2014)			x	(x)	
Möbius et al. (2021)		x	x	(x)	
Scott et al. (2021)				(x)	
Spiecker et al. (2013)			x	(x)	
Swider and Weber (2007)				x	
Equilibrium model					
Ehrenmann and Smeers (2011)	x	x			x
Fan et al. (2012)	x	x			
Mays et al. (2019)	x	x			x
Schröder et al. (2013)	x		x	(x)	
Simulation model					
Anwar et al. (2022)	x	x		x	
Botterud et al. (2007)	x	x		x	
Petitet et al. (2017)	x	x		x	x
This article	x	x	x	x	x

focus on the extensions to the existing approach that are required in order to account for uncertainties and risk aversion. For this purpose, Section 3.2 describes how the considered long-term uncertainties are modeled, whereas Section 3.3 concentrates on the decision making of the agents under consideration of their risk aversion.

3.1 Overview of the Simulation Model PowerACE

The methodological basis for this work is the established PowerACE model, which has previously been applied for various long-term scenario analyses of the European electricity markets (e.g., Keles et al., 2016; Bublitz et al., 2017; Ringler et al., 2017; Fraunholz et al., 2021a,b; Zimmermann et al., 2021). The focus of PowerACE lies on the simulation of interconnected day-ahead markets and different CRMs, with the relevant market participants – e.g., utility companies, regulators, consumers – represented by agents. In particular, the modeled utility companies decide on the short-term dispatch of their conventional power plants and storage units as well as long-term capacity expansions. Ultimately, the development of the markets emerges from the simulated behavior of all agents. The simulation model is continuously enhanced with new features. A detailed description of the current functionalities can be found in Fraunholz (2021).

PowerACE is a detailed bottom-up simulation model with a time horizon typically covering 30–40 years at a high temporal resolution of 8760 h/a. In order to adequately account for cross-border effects, the model currently covers a total of ten interconnected European market areas. Thus, PowerACE requires substantial amounts of input data, including a database of existing conventional power plants and investment candidates with their respective techno-economic characteristics, assumptions on the future development of fuel and carbon prices as well as hourly time series for renewable feed-in and electricity demand. The major model output comprises hourly day-ahead electricity prices, the corresponding electricity generation by technology as well as long-term changes of the conventional power plant fleets and utility-scale storage capacities for all simulated market areas. The future technology mix emerges from the model-endogenous capacity expansion planning algorithm, which is carried out at the end of each simulation year. In Fig. 1, the principles of this algorithm are sketched and a brief description is provided in the following. For more details, we refer the reader to the original work by Fraunholz et al. (2019).

The modeled investors base their decisions on expectations regarding future electricity prices. These prices are in turn affected by the investment decisions of all investors in all interconnected market areas. Thus, in order to find a stable solution

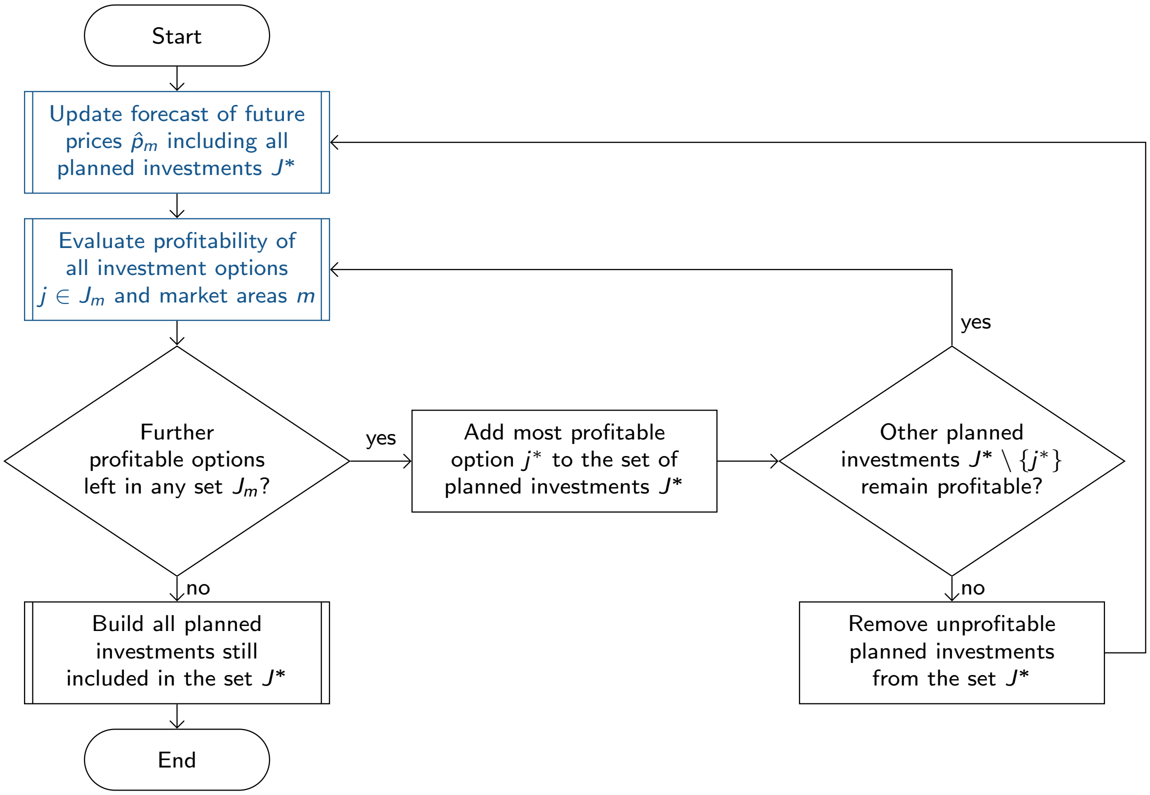


Figure 1: Simplified overview of the capacity expansion planning algorithm developed by Fraunholz et al. (2019). Starting with an initial model-endogenous long-term price forecast, the profitability of all investment candidates is evaluated. Potential investments are then gradually added to and removed from the – initially empty – set of planned investments until a Nash-equilibrium has been found. In order to extend the previous deterministic approach to a stochastic one, the subprograms highlighted in blue need to be modified.

to the capacity expansion planning problem, a Nash-equilibrium is determined in an iterative process. The algorithm terminates as soon as all planned investments are expected to be profitable, while at the same time none of the investors is able to increase their profit by carrying out additional or fewer investments. This situation satisfies the definition of a Nash-equilibrium, as there exists no incentive for any investor to unilaterally deviate from the determined equilibrium.

In a first step, a model-endogenous forecast of the future electricity prices $\hat{p}_{m,y,h}$ in all market areas m is carried out for multiple future years y and all hours of the year h. In the previous model versions, the price forecasts are determined by assuming a single weather year that realizes repeatedly throughout the investment horizon. Methodologically, the price forecast is implemented as a time-coupled linear optimization problem with the objective to minimize the total cost of electricity generation across all market areas. The forecast further assumes myopic foresight regarding the development of the future electricity demand and renewable feed-in as well as construction and decommissioning of conventional power plants.

Based on the expected hourly electricity prices, yearly contribution margins and finally net present values are computed for all investment options j available to the agents. In order to account for the technology specific investment horizons, the net present values are converted to annuities (Konstantin and Konstantin, 2018). These annuities are used as a metric to evaluate the profitability of a potential investment. Across all market areas, the most profitable investment option j^* is then chosen and added to the set of planned investments $\boldsymbol{J^*}$. If other previously planned investments now become unprofitable, they are gradually removed from the set of planned investments. The whole process is carried out in multiple iterations with the price forecast being updated numerous times in order to account for the price effect of the currently planned investments. Finally, the algorithm terminates when no more profitable investment options remain in any of the market areas. In this Nash-equilibrium situation, all planned investments in set $\boldsymbol{J^*}$ are carried out. As the investments are evaluated against the forecasted prices without taking into account the impact of one investment on the profitability of the other portfolio elements of the investors, the obtained equilibrium also corresponds to a competitive equilibrium.

While the described algorithm assumes an EOM design, several European countries have recently implemented CRMs (Bublitz et al., 2019). Since these mechanisms have a substantial impact on the capacity expansion planning, centralized capacity auctions can optionally be activated in each market area. For this purpose, the methodology developed by Renz et al. (2014) is used. At the end of each simulation year, descending clock auctions are carried out in order to contract a specific amount of secured generation, and storage capacity. Subsequently, the previously described usual capacity expansion planning procedure is run while taking into account the investment decisions resulting from the centralized capacity auctions.

The previous version of the capacity expansion planning algorithm can be characterized as a deterministic approach with myopic foresight. However, in reality, investors carry out their capacity expansion planning under uncertainty and consider their individual risk preferences. In order to account for these essential and previously neglected aspects, we modify and extend some parts of the previous algorithm (highlighted in blue in Fig. 1). Firstly, we construct multiple scenarios for the price forecast instead of relying on a single and deterministic one (Section 3.2). This allows us to compute an empirical distribution function of the profitability metric rather than using a single expected profitability value. Secondly, we construct a new decision rule for the profitability evaluation, which takes into account the uncertainty and adequately considers the risk aversion of the investors (Section 3.3).

3.2 Modeling of Long-Term Uncertainties

The uncertainties influencing investment decisions in competitive power markets are multifaceted and include the installed capacities and generation volumes of renewables, the load level and patterns, policy changes, commodity prices, and emission regulations, to name just a few. Scott et al. (2021) suggest a holistic consideration of all relevant uncertainties in order to depict their interactions and joint impact on the investment decisions. However, such a consideration can result in inadequate computational efforts and hardly interpretable results, especially if the modeling framework is comparably complex. Thus, as shown in the literature review of Anwar et al. (2022), a small set of uncertainties is often considered in isolation.

In our case study, we exemplary focus on fluctuations in solar and wind power generation as well as electricity demand patterns by considering different weather years. According to the literature review by Sadeghi et al. (2017), those are the most commonly assessed uncertainties in capacity expansion planning. Moreover, these aspects gain in importance given their influence on the realized short-term electricity prices (Lago et al., 2018). Finally, the influence of these drivers will also increase further due to both, the rising share of volatile electricity generation and new electrical applications, e.g., in the transport and heating sector.

Importantly, choosing weather years as uncertainty source also comes along with a crucial methodological benefit. Since the realization of a weather year is independent from previous realizations, we avoid path dependencies in the scenario tree (see below) and can construct thousands of scenarios with limited computational effort[2]. Apart from the unacceptable computational burden, our developed approach would in principle also allow us to consider further uncertainties like market design changes, capacity expansion of renewables, development of the annual electricity demand or commodity prices. Alternatively, the role of these uncertainties can at least be

[2]For example, if we consider n different weather years over a time horizon of 10 years, we can construct n^{10} sequences of weather years (i.e, scenarios), while the computational effort only increases by a factor of n compared to the case of a single weather year. In contrast, if we were to consider n carbon price pathways, the computational effort would also increase by a factor of n, while we would only obtain n different scenarios.

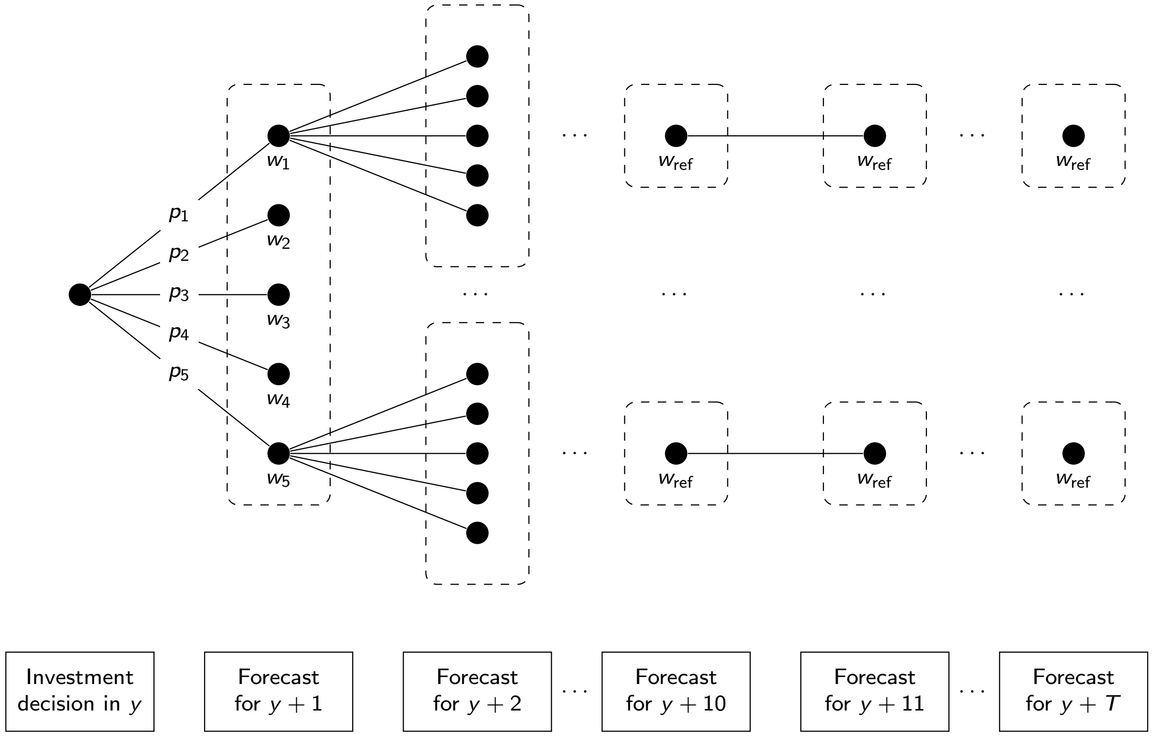


Figure 2: Developed scenario tree to consider the uncertainty induced by weather years in the capacity expansion planning. The figure shows possible sequences of weather years that could materialize over the lifetime of a potential investment.

considered via additional simulation runs – an approach that we choose for the electricity market design configuration in the modeled countries.

In order to take into account the uncertainty introduced by different weather years, we develop a scenario tree for each simulation year y and consider that different sequences of weathers years w_i could occur in the subsequent years (Fig. 2). The tree spans over the whole lifetime T of an investment option. However, in order to reduce the computational complexity, we only depict a full-factorial combination of all weather years in the scenario set until $y+10$ and use a representative – in our case the most probable – weather year w_{ref} thereafter (for a similar approach see Petitet et al., 2016). Please note that since the probability of a given weather year can by approximately derived from historical data (see below), we are also able to assign an individual probability to each scenario path. This might not be easily feasible for uncertainty sources other than weather years.

For each scenario path, a price forecast and profitability assessment of the investment options is carried out as described in Sections 3.1 and 3.3. In order to do so, time series for the electricity demand and renewable feed-in as well as the probability of occurrence p_i needs to be determined for each weather year w_i. For this purpose, we use five different weather years (2015–2019) and derive their respective probability of occurrence using a k-means clustering of the historical weather years 1980–2014. For details on the data sources and processing, please refer to Appendix A.1. While the investors carry out their capacity expansion planning under uncertainty regarding the sequence of weather years that will be realized, we use the probabilities of each weather year to construct a distinct sequence of weather years that is used for the day-ahead market simulation (see also Appendix A.1).

3.3 Decision Making of the Agents under Uncertainty

Based on the constructed scenario tree and the probability p_s for each scenario s to realize, we can now compute the profitability $\pi_{m,j,s}$ of each investment option $j \in \boldsymbol{J_m}$ and for all market areas $m \in \boldsymbol{M}$. The empirical distribution function and the *empirical cumulative distribution function* (ECDF) of the profitability of a specific investment option can then be used to derive various decision calculi, which allow for a consideration of both, expected profitability and risk exposure.

To start with, we define the expected profitability $\mathbb{E}$ as the expected value of the profitability distribution in Eq. (1).

$$\mathbb{E}\left(\pi_{m,j,s}\right) = \sum_{s} p_s \cdot \pi_{m,j,s} \quad \forall m \in \boldsymbol{M}, j \in \boldsymbol{J_m} \tag{1}$$

In order to include risk aversion when taking decisions under uncertainty, it is typically quantified by means of risk measures. Based on the empirical distribution function, risk measures can be defined in various ways: by descriptive statistics of the distribution (e.g., the variance), by the probability to fall below defined threshold values (e.g., the shortfall probability), or by figures based on quantiles of the distribution (Conejo et al., 2010).

Prominently, the *value at risk* (VaR_α) defined in Eq. (2) – with $P(s|*)$ as the cumulative probability of all scenarios s for which condition $*$ is satisfied – provides information on the $(1-\alpha)$-quantile of a distribution. However, this risk measure neglects information about potential fat tails and fails to meet the conditions of coherent risk measures[3]. Therefore, based on the VaR_α, the *conditional value at risk* (CVaR_α) defined in Eq. (3) depicts the expected value of the ECDF if the value falls below the VaR_α. The CVaR_α is a coherent and state-of-the-art risk measure that is deployed in many studies dealing with decisions under uncertainty in the electricity market context (e.g., Morales et al., 2010; Laur et al., 2018; Wozabal and Rameseder, 2020; Kraft et al., 2021; Möbius et al., 2021; Russo et al., 2021).

$$\mathrm{VaR}_\alpha\left(\pi_{m,j,s}\right) = \max\left\{\eta : P\left(s|\pi_{m,j,s} < \eta\right) \leq 1-\alpha\right\} \quad \forall \alpha \in (0,1), m \in \boldsymbol{M}, j \in \boldsymbol{J_m} \tag{2}$$

[3]Coherent risk measures satisfy the conditions of monotonicity, sub-additivity, homogeneity, and translational invariance.

$$\mathrm{CVaR}_\alpha\left(\pi_{m,j,s}\right) = \mathbb{E}\Big(\pi_{m,j,s}|\pi_{m,j,s} \leq \mathrm{VaR}_\alpha\left(\pi_{m,j,s}\right)\Big) \quad \forall \alpha \in (0,1), m \in \boldsymbol{M}, j \in \boldsymbol{J_m} \tag{3}$$

To combine the objectives of profitability and risk management, the mentioned papers model a linear combination of the expected value $\mathbb{E}$ and the CVaR_α – typically with $\alpha = 95\,\%$, i.e., considering the $5\,\%$ worst cases for the risk measure. We follow this approach and define the profitability metric $\pi^*_{m,j}$ as a linear combination with weights λ and $(1-\lambda)$ as shown in Eq. (4). Here, λ indicates the investor's risk aversion and can take values between 0 (risk-neutral) and 1 (highly risk-averse).

$$\pi^*_{m,j} = (1-\lambda)\cdot\mathbb{E}\left(\pi_{m,j,s}\right)+\lambda\cdot\mathrm{CVaR}_\alpha\left(\pi_{m,j,s}\right) \quad \forall \alpha \in (0,1), \lambda \in [0,1], m \in \boldsymbol{M}, j \in \boldsymbol{J_m} \tag{4}$$

In the simulation, the agents use the described calculus to evaluate competing investment options and eventually derive investment decisions (see Section 3.1). An investment option j in market area m is considered profitable if $\pi^*_{m,j} > 0$ holds. Further, when comparing two investment options, option 1 is considered more profitable than option 2, if $\pi^*_{m,1} > \pi^*_{m,2}$ holds. Given the ECDF of competing investment options in a market area m, the risk aversion of an investor can thus be decisive in determining whether and which investment option is realized.

The agent-based simulation, with the help of the introduced decision calculus, stands out as it enables us to diversify the risk aversion for each agent, investment option, and market area. In particular, different risk attitudes could be implemented for different technologies or market areas to assess the development of the electricity system. However, to ensure comparability of the results and due to a lack of reliable data for parametrization, we do not apply such a diversification in our case study, but rather evaluate simulations for fixed $\alpha = 95\,\%$ and varying $\lambda \in \{0.0, 0.5, 1.0\}$ in terms of investment behavior, electricity prices, and resource adequacy.

4 Data and Assumptions

In the following, we provide an overview of the data and assumptions used in our simulation study. Section 4.1 focuses on the general model input data. In Section 4.2, we then define the different market design configurations and risk attitudes that are analyzed.

4.1 Overview of the Required Model Input Data

As previously mentioned, substantial amounts of input data need to be prepared to run the detailed bottom-up simulation model PowerACE. Table 2 provides an overview of the main model inputs and the respective data sources. The investment options comprise combined cycle gas turbines (CCGT), open cycle gas turbines (OCGT) as well as lithium-ion and redox-flow batteries for all market areas, whereas investments in nuclear and coal-fired power plants are only eligible in selected countries – following the respective real-world regulations at the time of writing. In contrast to conventional power plants and utility-scale storage units, the development of the renewable generation capacities is not determined endogenously, but follows exogenously defined expansion pathways. Some details on the input data are provided in Appendix A.

Table 2: Overview of the input data used in all simulations carried out with PowerACE.

Input data type	Resolution	Sources and comments
Conventional power plants	unit level	S&P Global Platts (2015), and own assumptions (cf. Appendix A.2)
Fuel prices	yearly	ENTSOG and ENTSO-E (2020); IEA (2020)
Carbon prices	yearly	de Vita et al. (2016), scaled to reach 150 EUR/t_{CO_2} in 2050
Investment options	yearly	Louwen et al. (2018); Schröder et al. (2013), and own assumptions (cf. Appendix A.3)
Transmission capacities	yearly	ENTSOG and ENTSO-E (2020)
Electricity demand	hourly, market area	historical time series from ENTSO-E (2021), yearly volumes from ENTSOG and ENTSO-E (2020); Eurostat (2021), and own assumptions (cf. Appendix A.1)
Renewable feed-in	hourly, market area	historical time series from ENTSO-E (2021), installed capacities from ENTSOG and ENTSO-E (2020); Eurostat (2021); IRENA (2021), and own assumptions (cf. Appendix A.1)

4.2 Definition of Market Design Configurations and Risk Attitudes

Since the electricity market design has a strong impact on the distribution of risk among investors and society, we run simulations with two different market design configurations. In doing so, we model ten interconnected European market areas, which represent a significant portion of the European electricity market. The traditional electricity market design in Europe is an EOM, in which upfront investment costs are only recovered through operation margins in the energy market. Therefore, as shown in Fig. 3a, we first consider a European EOM design. However, several countries have implemented CRMs over the past few years. These mechanisms typically aim to reduce the risks for new investments by offering capacity providers supplementary income on top of the earnings from selling electricity on the market.

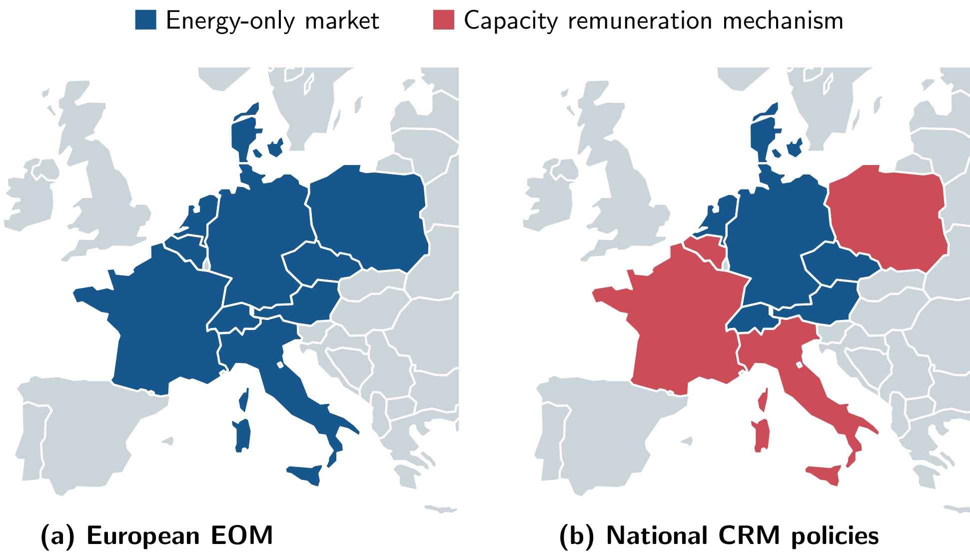


Figure 3: Regional scope of PowerACE and assumed electricity market designs. In configuration (a), all countries rely on an EOM, while configuration (b) reflects the current real-world setting with CRMs implemented in some of the countries. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

However, in case of asymmetrical – i.e., uncoordinated national – implementations, CRMs may come along with both positive and negative cross-border effects. We therefore compare the EOM setting to a configuration with national CRM policies corresponding to the current real-world setting (Fig. 3b).

For both of these market design configurations, we analyze the impact of different risk perceptions and attitudes by varying the parameter λ in Eq. (4). As previously mentioned, we refrain from defining individual risk aversions for each agent, investment option, and market area to ensure comparability of the results and due to a lack of reliable data for parametrization. Instead, we first run benchmark simulations with both market designs and where all investors are assumed to behave risk neutral ($\lambda = 0.0$). This parametrization implies that investors base their decisions solely on the expected profitability across all considered scenarios. We then compare the results to those of a setting with a high degree of risk aversion by assuming $\lambda = 1.0$ and $\alpha = 0.95$ for all investors. Thus, the investors only consider the CVaR, while the expected profitability across all scenarios is not taken into account. Additional results for a moderate risk aversion ($\lambda = 0.5$ and $\alpha = 0.95$ – i.e., both the expected profitability and the CVaR are considered with equal weight) are included in Appendix B.

5 Results and Discussion

The subsequent sections present and discuss the results of our simulation study. We first focus on the installed conventional generation and storage capacities that emerge from the capacity expansion planning (Section 5.1). Next, we show the impact of these investment decisions on wholesale electricity prices (Section 5.2), and resource adequacy (Section 5.3). Please note that all results are evaluated in aggregated form, but separately for the countries using CRMs (group A) and those relying on EOMs (group B) in the national CRM policies. This allows us to isolate the effects of market designs and the investors' risk aversion.

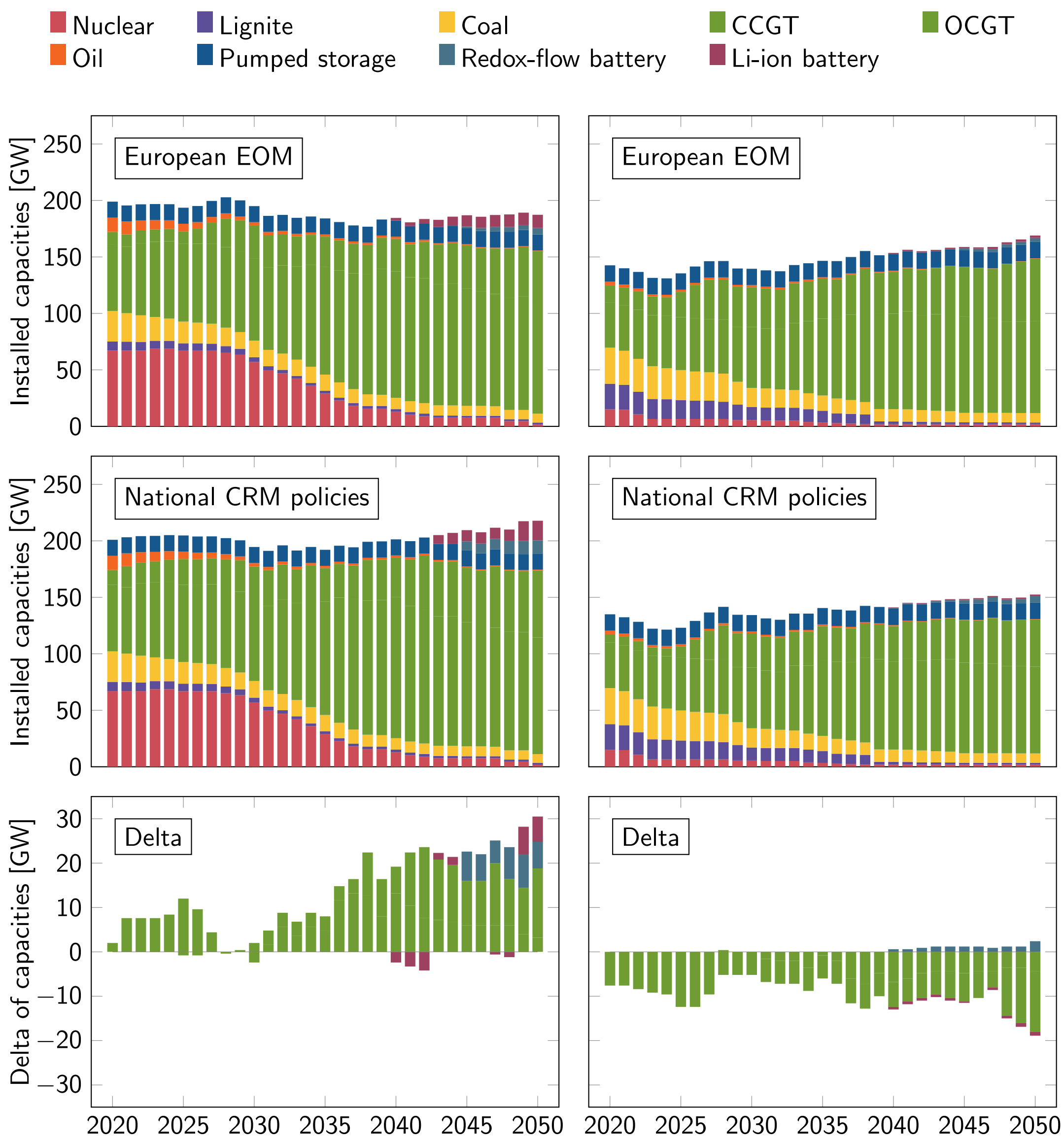
5.1 Conventional Generation and Storage Capacities

The future technology mix emerges from (1) the model-endogenous expansion planning for conventional power plants and storage units, (2) exogenous decommissioning of conventional power plants based on their technical lifetime, and (3) exogenous pathways for the expansion of renewables. Since the exogenous assumptions are not affected by market design and risk attitudes, we concentrate on the results of the endogenous capacity expansion in the following.

Fig. 4 illustrates the development of installed conventional power plant capacities and utility-scale storage units for both market design configurations assuming risk-neutral investors. Overall, substantial requirements for firm capacity remain despite the assumed strong expansion of renewables up to 2050. Moreover, a significant fuel switch from nuclear and coal to gas-fired power plants can be observed, which is mostly driven by the exogenous carbon price path (cf. Table 2).

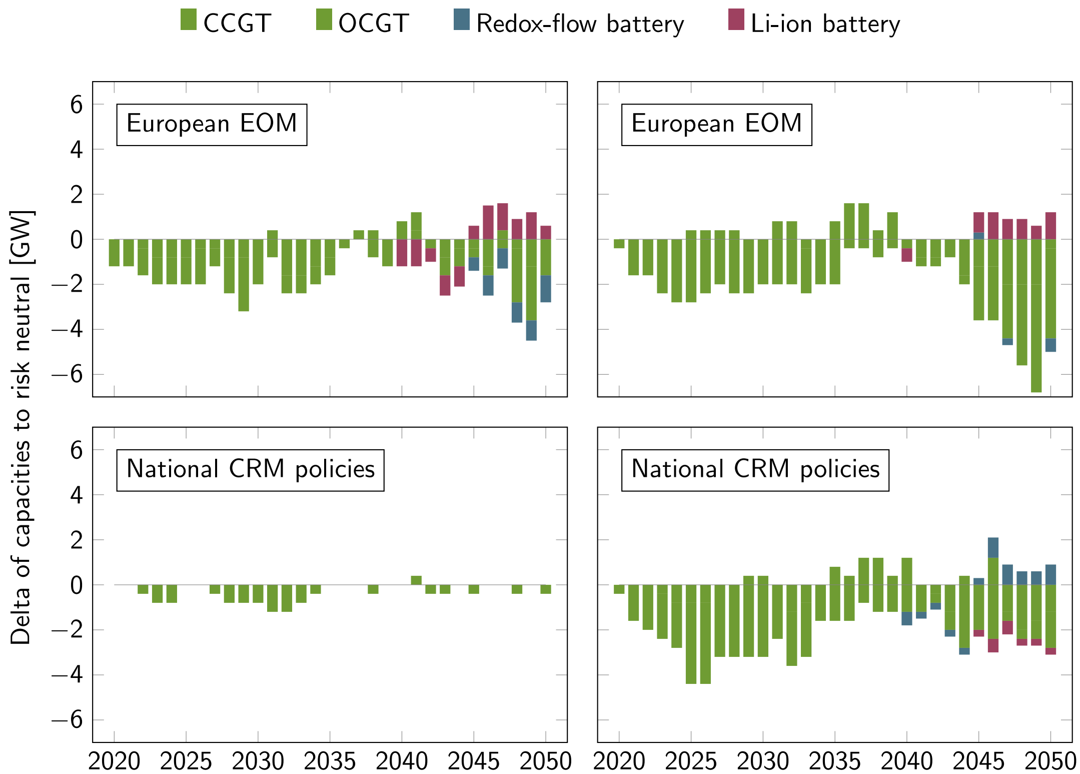
In the configuration with national CRM policies, the introduction of CRMs in the countries of group A fosters substantial investments in dispatchable capacity in these countries. This is particularly relevant towards the end of the simulation period, where the high share of renewables reduces the expected operating hours of conventional power plants, rendering such investments unprofitable in an EOM design. Contrary to country group A, significantly fewer investments are realized in the countries of group B, which continue to rely on an EOM in the configuration with national CRM policies. These results stand in line with previous research that has shown the distorting market impact of asymmetrical CRM implementations (Bucksteeg et al., 2019; Fraunholz et al., 2021a).

Let us now move on to the impact of an increased investors' risk aversion. In Fig. 5, we compare the deltas of installed capacities in the settings with highly risk-averse investors to the respective risk-neutral settings (Fig. 4). Under a European EOM design, a higher risk aversion of the investors leads to fewer investments and thus reduced amounts of installed capacities in both country groups. Again, the effects are most pronounced towards the end of the simulation period. This follows intuition given the increasing shares of renewables that also make the expected profitability of investments more dependent on the respective sequence of weather years. Consequently, investments are exposed to higher risk towards 2050 and might not be carried out anymore in the case of highly risk-averse investors.



(a) Country group A **(b) Country group B**

Figure 4: Aggregated conventional power plant and utility-scale storage capacities in (a) country group A and (b) country group B with risk-neutral investors. The bottom parts of the figure show the deltas of installed capacities between the national CRM policies and the European EOM design. *Abbreviations:* CCGT—combined cycle gas turbine, CRM—capacity remuneration mechanism, EOM—energy-only market, OCGT—open cycle gas turbine.



(a) Country group A **(b) Country group B**

Figure 5: Aggregated conventional power plant and utility-scale storage capacities in (a) country group A and (b) country group B with highly risk-averse investors. The figure shows the deltas of installed capacities as compared to the respective risk-neutral setting depicted in Fig. 4. *Abbreviations:* CCGT—combined cycle gas turbine, CRM—capacity remuneration mechanism, EOM—energy-only market, OCGT—open cycle gas turbine.

In the period between 2035 and 2040, we can also observe that postponed investments are overcompensated, since the expected capacity deficits – which would induce scarcities – trigger new investments. Temporarily, this effect even leads to slightly higher amounts of installed capacity compared to the case with risk-neutral investors. Overall, the effects of risk aversion are rather small with risk-averse decision making by investors leading to less than 3 % fewer installed capacities compared to the case with risk-neutral investors. Importantly, this finding stands well in line with the theory of peak load pricing in an EOM which states that a certain amount of scarcity situations is required to refinance all cost of the generation capacities – particularly those of the most expensive unit in the merit order. However, such scarcity situations can already occur if only one power plant unit less than required to cover the demand is being built. The resulting scarcity prices would then positively affect the economics of all generation and storage units in the market (Cramton and Ockenfels, 2012). Thus, even when assuming highly risk-averse investors, the total installed capacities are only slightly reduced as compared to the setting with risk-neutral investors. Moreover, cross-border electricity exchange dampens the impact of fluctuations in renewable feed-in and demand caused by different weather years.

In the case of national CRM policies, we find substantial differences between countries with CRMs (group A) and countries with EOMs (group B). Since the introduction of CRMs implies that minimum capacity targets for the respective countries are met, even high risk aversion of the investors only has a marginal impact on the installed generation capacities. Contrary, in country group B, the effects of high risk aversion remain comparably strong and are – particularly in the first half of the simulation period – even more pronounced than in the European EOM configuration. These results confirm again that an asymmetrical implementation of CRMs does not only affect the countries implementing these mechanisms, but also other interconnected market areas that remain with an EOM.

5.2 Wholesale Electricity Prices

The amount of dispatchable capacity in each market area has an immediate impact on the wholesale electricity prices. Against this background, Fig. 6 depicts the simulated development of the volume-weighted average electricity prices in country groups A and B for both market designs assuming risk-neutral investors.

In all settings, we observe strong price fluctuations even between subsequent simulation years. These are mostly driven by the exogenously defined sequence of weather years (see Appendix A.1), which affects the patterns of both, renewable electricity generation and electricity demand. For both market design configurations, country group A starts from a lower price level compared to country group B. This relation changes through the course of the simulation due to the exogenously defined higher renewable shares in country group B towards 2050.

Yet, the most relevant finding when comparing the settings with risk-neutral investors is the impact of the market design on the mean prices in the two country groups (bottom part of Fig. 6). Whereas the national CRM policies lead to a reduction of prices in the countries with CRMs (group A), the countries with EOMs (group B) are affected by negative cross-border effects of these abroad market design changes and face an increase of electricity prices. These findings are directly related to the previously described impact of the market design on the expansion of firm generation and storage capacities.

In addition to the role of market design, Fig. 7 illustrates the development of the electricity prices assuming highly risk-averse investors compared – ceteris paribus –

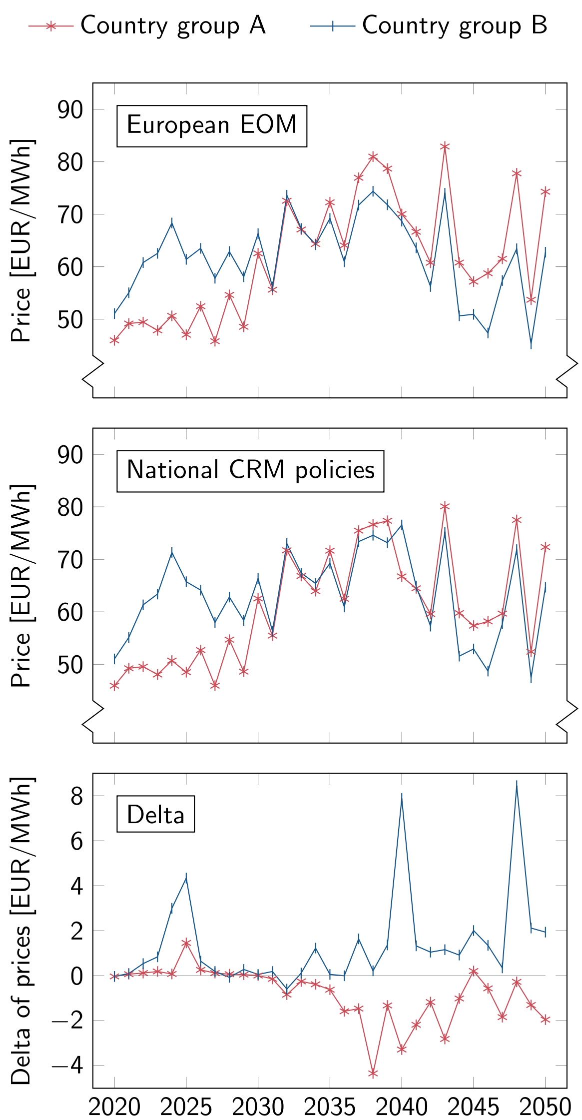


Figure 6: Volume-weighted day-ahead electricity prices in country group A and country group B with risk-neutral investors. The bottom part of the figure shows the delta of prices between the national CRM policies and the European EOM design. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

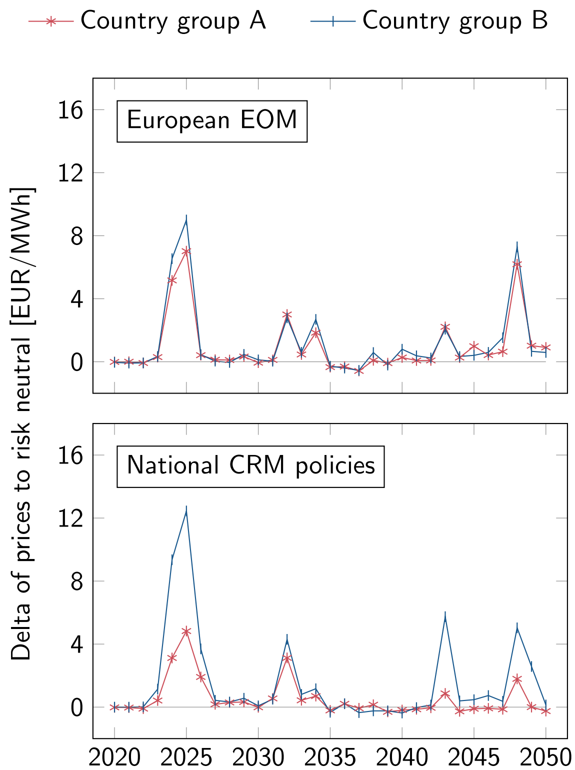


Figure 7: Volume-weighted day-ahead electricity prices in country group A and country group B with highly risk-averse investors. The figure shows the deltas of prices as compared to the respective risk-neutral setting depicted in Fig. 6. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

with risk-neutral investors. In the European EOM configuration (top part of Fig. 7), the higher degree of risk aversion leads to a slight increase in electricity prices which follows a similar pattern in both country groups. Again, these developments are a direct outcome of the lower amounts of firm generation and storage capacities as compared to the cases with risk-neutral investors.

The picture changes when looking at the national CRM policies (bottom part of Fig. 7). Clearly, the higher risk aversion plays a less pronounced role in country group A due to the introduction of CRMs that assure certain firm capacity targets.

In contrast, the changes in market design have negative cross-border effects and render investments in country group B even more risky than in the European EOM setting. Consequently, the higher degree of the investors' risk aversion results in a stronger price increase as compared to country group A and also as compared to the European EOM configuration.

5.3 Resource Adequacy

Apart from the electricity prices, the amount of firm generation and storage capacities also plays a major role for the ability of the electricity system to meet the demand at all times, often referred to as *resource adequacy*. A comprehensive analysis of the resource adequacy requires a Monte Carlo simulation with several combinations of weather years and power plant outages. Since the focus of this article is on capacity expansion planning, such an analysis is out of our scope. Instead, our simulation of the day-ahead markets relies on a deterministic sequence of weather years and constant power plant availability throughout the course of a year. Nevertheless, we can draw some conclusions regarding resource adequacy by comparing the *energy not served* (ENS) volumes arising from scarcity situations for the different market design configurations and risk attitudes of the investors. Fig. 8 displays the cumulative ENS volumes for both market designs and country groups up to the year 2050.

In the European EOM setting (top part of Fig. 8) we can observe that despite the rather small impact of risk aversion on the capacity expansion planning (see Section 5.1), the cumulative ENS volumes increase strongly when assuming highly risk-averse rather than risk-neutral investors. This stands in line with the findings presented for the wholesale electricity prices and is true in both, country group A

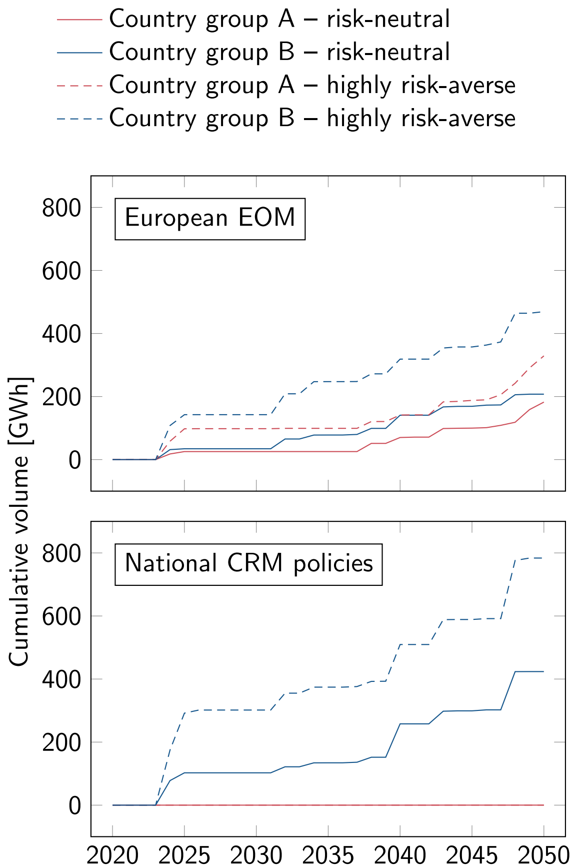


Figure 8: Energy not served volumes in country group A and country group B with risk-neutral versus highly risk-averse investors. The figure shows the cumulative volumes from 2020 up to the respective simulation year. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

(with an increase of the cumulative volumes from roughly 200 to 350 GWh) and country group B (increase from roughly 200 to 450 GWh).

When looking at the national CRM policies (bottom part of Fig. 8), we observe substantial differences between the two country groups. In the countries with CRMs (group A), scarcity situations do not occur at all, since the implemented CRMs – by definition of the capacity requirement – guarantee sufficient amounts of firm generation and storage capacity to be installed. Consequently, the higher degree of the investors' risk aversion also does not affect the ENS volumes. This stands in strong contrast to the countries with EOMs (group B). Here, the cumulative ENS volumes are already twice as high (roughly 400 vs. 200 GWh) under the national CRM policies with risk-neutral investors as compared to the respective European EOM setting. Assuming investors with a high degree of risk aversion leads to a further strong increase in the cumulative ENS volumes to roughly 800 GWh. In conclusion, both the degree of the investors' risk aversion and the market design – either directly or through negative cross-border effects – have a strong impact on the frequency and severity of scarcity situations. This finding is again strongly related to the capacity expansion planning in the different settings and underlines the benefits that our novel approach offers.

6 Conclusion and Policy Implications

In this article, we developed a novel approach to consider risk aversion and market design in capacity expansion planning. For this purpose, we extended the agent-based simulation model PowerACE by constructing model-endogenous scenario trees and implementing a new decision metric that comprises the expected profitability and the corresponding CVaR of a potential investment. As an exemplary source of uncertainty, we considered the impact of different weather years on the feed-in of renewables and electricity demand. The enhanced model was then applied in a multi-country case study of the European electricity market. We carried out simulations with different degrees of investors' risk aversion as well as two market designs, namely a European EOM and asymmetrical CRM implementations.

For the case of risk-neutral investors, we find substantially higher investment incentives in the countries using CRMs, while the remaining countries relying on EOMs are confronted with negative cross-border effects. As a direct consequence of the model-endogenous capacity expansions, wholesale electricity prices decrease slightly in the countries with CRMs and the levels of resource adequacy increase. Rather obviously, the opposite is true for the countries without CRMs.

Assuming risk-averse investors proves to affect the capacity expansion planning by slightly reducing investments. Interestingly, we find the impact of risk aversion to be substantially higher in an EOM compared to a CRM. This finding stands in line with previous results from the literature. However, our simulations also illustrate that while CRMs dampen the impact of risk aversion in the countries using these mechanisms, neighboring countries without CRMs are affected by negative cross-border effects and risk aversion becomes even more relevant there than in the case of a European EOM. This is reflected by higher wholesale electricity prices as well as a lower level of resource adequacy in these countries.

Based on our findings, we strongly recommend that policymakers and regulators consider the impact of risk aversion when evaluating different market design options. While an EOM and a CRM may lead to similar outcomes under rather strong theoretical assumptions, this may no longer be the case when considering the characteristics of real-world electricity markets with risk-averse actors. Moreover, particularly in the European setting, it is crucial to account for cross-border effects of a market design. Consequently, decisions on national market designs should always consider the design of the interconnected market areas.

While we have concentrated on a single source of uncertainty in this article, we would like to delve further into potential cross-impacts of different uncertainties in future work. In particular, regulatory uncertainties such as carbon pricing or bidding zone reconfigurations seem worthwhile to investigate, although the related path dependencies bring along new methodological challenges. Moreover, we have so far focused on the supply side of the electricity system and made simplifying assumptions regarding the development of the total electricity demand and the respective flexibility potential. While this is unlikely to change the general relations of our results, the magnitude of the found effects might indeed be affected. Analyzing this aspect in more detail could be another interesting direction for future research. Finally, it may also be promising to analyze the risk attitudes of real-world investors in order to better parametrize our model. For this purpose, laboratory experiments with experienced professionals from the energy sector could be carried out.

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A Input Data

A.1 Time Series for Fluctuating Renewable Feed-In and Electricity Demand

As a data basis for the hourly profiles, we use the feed-in and demand data of the years 2015–2019 from the ENTSO-E Transparency Platform (ENTSO-E, 2021), which are processed and supplemented to fill data gaps. Since the total amount of electricity generation per year and technology as well as the total electricity demand of individual countries from ENTSO-E (2021) greatly differ from other established sources, the hourly profiles are scaled to the yearly volumes provided by Eurostat (2021). The capacity factors for each renewable technology are then derived from the linearly interpolated capacities stated in IRENA (2021). Accordingly, at the end of data preparation process, hourly time series of the electricity demand and the capacity factors per renewable technology are available for each of the modeled countries and each weather year in the range 2015–2019.

Apart from the described data, our modeling approach also requires information on the probabilities of occurrence for each weather year. These are defined by comparing the German feed-in profiles for solar and wind from 2015 to 2019 with those generated for the period 1990–2014 by Pfenninger and Staffell (2016) and Staffell and Pfenninger (2016). More specifically, we use a k-means clustering based on the hours that the capacity factor of one technology lies with in a predefined interval. Hence, the clustering maps the weather years 1990–2014 to the years 2015–2019. As a result, we obtain the probabilities of occurrence for each year between 2015 and 2019 that are shown in Table 3. Moreover, the table shows how the historical weather years were mapped to the years 2015–2019.

Table 3: Determined probabilities of occurrence for the modeled weather years as derived from the k-means clustering.

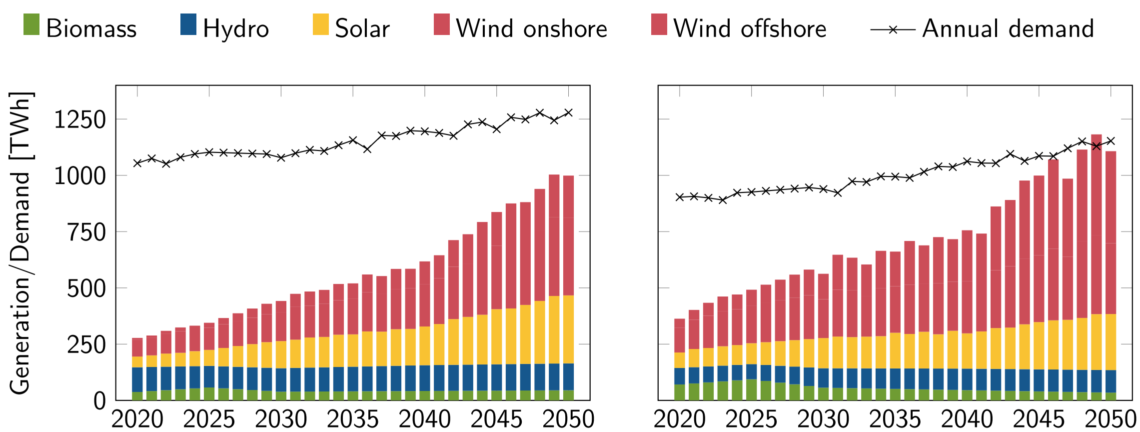
Weather year	Probability	Assigned historical weather years
2015	17.5 %	1981, 1990, 1994, 1995, 2000, 2002
2016	20.0 %	1982, 1987, 1996, 1997, 2003, 2010, 2013
2017	37.5 %	1980, 1983, 1986, 1988, 1989, 1992, 1993, 1998, 1999, 2004, 2007, 2008, 2011, 2012
2018	15.0 %	1985, 1991, 2001, 2006, 2014
2019	10.0 %	1984, 2005, 2009

For each of the modeled scenarios, the solar and wind power feed-in is then determined by multiplying the capacity factors of the time series – which depend on the respective weather year – with the installed capacities according to the assumed expansion pathways from the current Ten-Year Network Development Plan (TYNDP – ENTSOG and ENTSO-E, 2020). The TYNDP also provides information on the development of the total yearly electricity demand. The weather years do not only affect the renewable generation profiles, but also the electricity demand patterns, leading to slightly varying total demand quantities. Thus, the hourly demand profiles are scaled with respect to the quantities of the TYNDP, such that the average of the five years 2015–2019 equals the total demand quantity of the TYNDP. Since the data from the TYNDP only covers the period up to 2040, we use an own extrapolation for the remaining simulation years up to 2050.

While the investors carry out their capacity expansion planning under uncertainty regarding the sequence of weather years that will be realized, we use the probabilities of each weather year to construct a distinct sequence of weather years that is used for the day-ahead market simulation (Table 4). For this sequence of weather years, Fig. 9 shows the total yearly electricity demand and renewable feed-in by technology.

Table 4: Sequence of weather years applied for the day-ahead market simulation. In order to construct this randomized sequence, the probabilities for each weather year as shown in Table 3 are used.

Simulation year	Weather year
2020	2016
2021	2018
2022	2015
2023	2019
2024	2017
2025	2017
2026	2017
2027	2017
2028	2017
2029	2017
2030	2016
2031	2019
2032	2017
2033	2016
2034	2017
2035	2018
2036	2015
2037	2018
2038	2017
2039	2018
2040	2017
2041	2016
2042	2015
2043	2017
2044	2019
2045	2015
2046	2019
2047	2016
2048	2017
2049	2015
2050	2016



(a) Country group A **(b) Country group B**

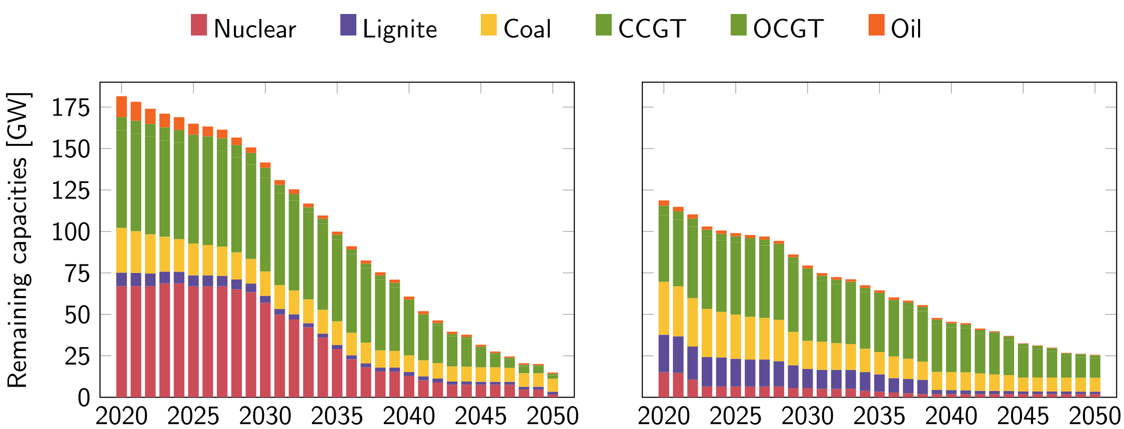
Figure 9: Assumed renewable electricity generation and electricity demand in (a) country group A and (b) country group B using the sequence of weather years defined in Table 4. *Source:* own illustration based on data from ENTSO-E (2021); ENTSOG and ENTSO-E (2020); Eurostat (2021); IRENA (2021), and own calculations/assumptions.

A.2 Conventional Power Plant Fleets

Contrary to the model endogenous expansion planning, decommissioning of existing power plants is exogenously defined based on the respective age and technical lifetime of the generation units, which remain unchanged for all simulations. Fig. 10 shows the remaining capacities until 2050 without additional investments on a technology aggregated level.

A.3 Investment Options

An overview of the techno-economic characteristics of the different investment options modeled in PowerACE is provided in Tables 5 and 6.



(a) Country group A **(b) Country group B**

Figure 10: Assumed conventional power plant capacities in (a) country group A and (b) country group B without additional new investments. *Source:* own illustration based on data from S&P Global Platts (2015), and own assumptions. *Abbreviations:* CCGT—combined cycle gas turbine, OCGT—open cycle gas turbine.

Table 5: Conventional power plant investment options modeled in PowerACE with their respective techno-economic characteristics. *Source:* Schröder et al. (2013); Louwen et al. (2018), own assumptions.

Technology	Block size [MW_{el}]	CCS	Net efficiency[1] [%]	Lifetime [a]	Building time [a]	Specific investment (2015–2050)[1] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed [$\frac{EUR}{kW_{el}\,a}$]	O&M costs var.[2] [$\frac{EUR}{MWh_{el}}$]
Nuclear	1600	–	33–34	60	4	6000	42	12
Coal	600	no	45–48	40	4	1800	60	6
		yes	36–41			3143–2677		30
Lignite	800	no	43–47	40	4	1500	30	7
		yes	30–33			3840–3324		34
CCGT	400	no	60–62	30	4	800	20	5
		yes	49–52			1216–1078		18
OCGT	400	no	40–42	30	2	400	15	3

Abbreviations: CCGT—combined cycle gas turbine, CCS—carbon capture and storage, OCGT—open cycle gas turbine, O&M—operation and maintenance

[1] Resulting from technological learning, the net efficiency is assumed to increase over time. Since conventional power plants can generally be regarded as mature technologies, it is further assumed that only the specific investments of the CCS-technologies are declining.

[2] Including variable costs for carbon capture, transport and storage, where applicable.

Table 6: Electricity storage investment options modeled in PowerACE with their respective techno-economic characteristics. *Source:* Louwen et al. (2018), own assumptions.

Technology	Block size [MW_{el}]	Storage capacity[1] [MWh_{el}]	Round-trip efficiency[2] [%]	Lifetime[2] [a]	Building time [a]	Specific investment (2015–2050)[2] [$\frac{EUR}{kW_{el}}$]	O&M costs fixed[2] [$\frac{EUR}{kW_{el}\,a}$]
Li-ion battery	300	1200	85–95	20–30	2	3149–572	63–11
		3000				7643–1388	153–28
RF battery	300	3000	75–85	20–30	2	4206–892	84–18

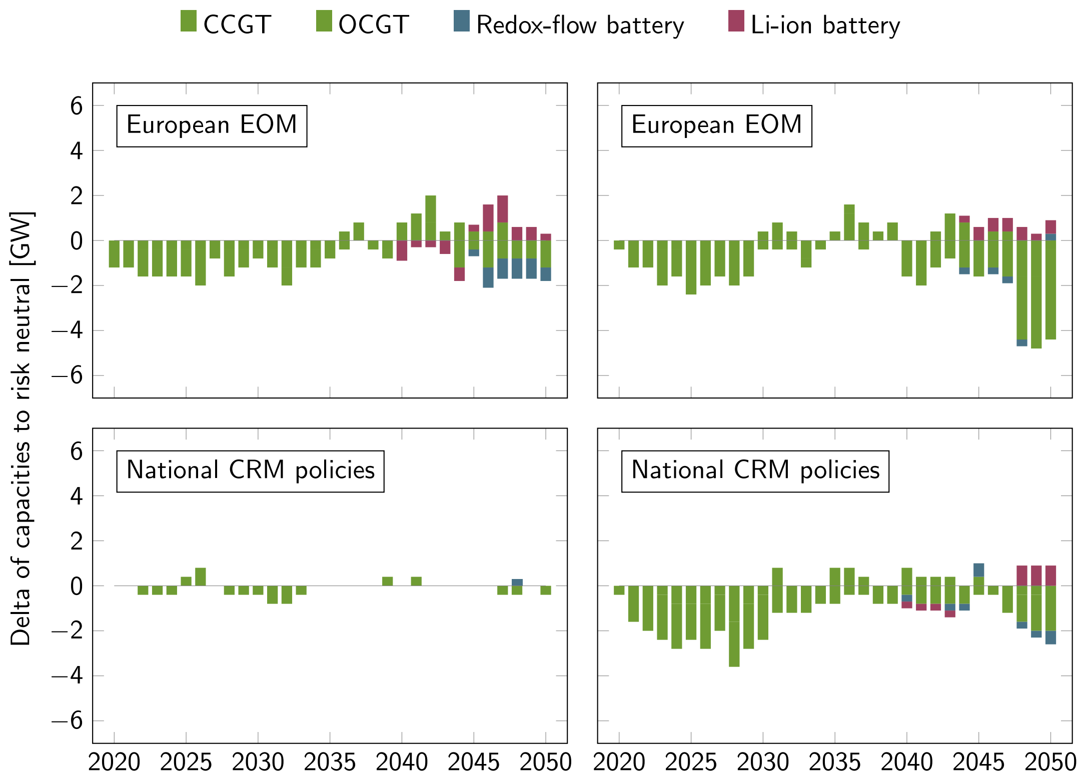
Abbreviations: O&M—operation and maintenance, RF battery—redox-flow battery

[1] For RF batteries, a substantial share of the investment expenses is related to the converter units. Consequently, for economic reasons, only higher storage capacities of 3000 MWh_{el} are eligible as investment options for this technology.

[2] Resulting from technological learning, round-trip efficiency and lifetime are assumed to increase over time for the emerging storage technologies. Analogously, specific investments and fixed costs for O&M are assumed to decline.

B Additional Results

Figs. 11–13 provide additional model results for the case of moderately risk-averse investors. Generally, these results lie in between those for risk-neutral and highly risk-averse investors presented in Section 5 of the main article.



(a) Country group A **(b) Country group B**

Figure 11: Aggregated conventional power plant and utility-scale storage capacities in (a) country group A and (b) country group B with moderately risk-averse investors. The figure shows the deltas of installed capacities as compared to the respective risk-neutral setting depicted in Fig. 4. *Abbreviations:* CCGT—combined cycle gas turbine, CRM—capacity remuneration mechanism, EOM—energy-only market, OCGT—open cycle gas turbine.

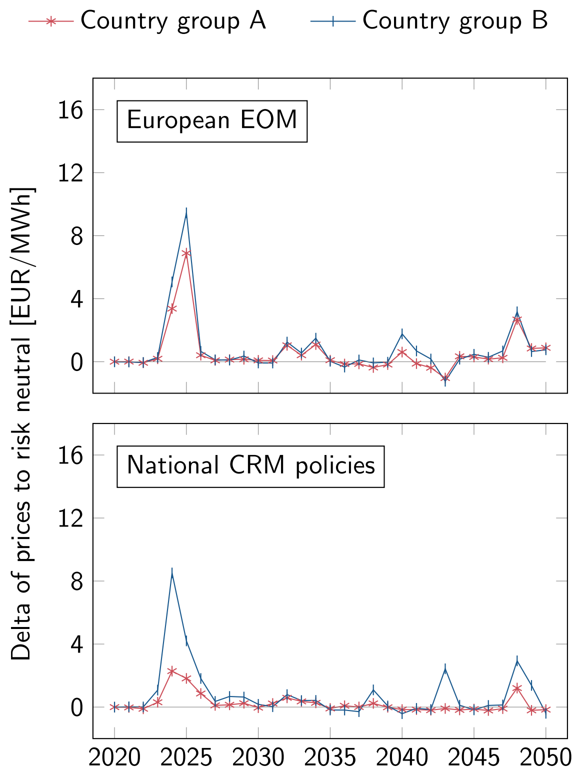


Figure 12: Volume-weighted day-ahead electricity prices in country group A and country group B with moderately risk-averse investors. The figure shows the deltas of prices as compared to the respective risk-neutral setting depicted in Fig. 6. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

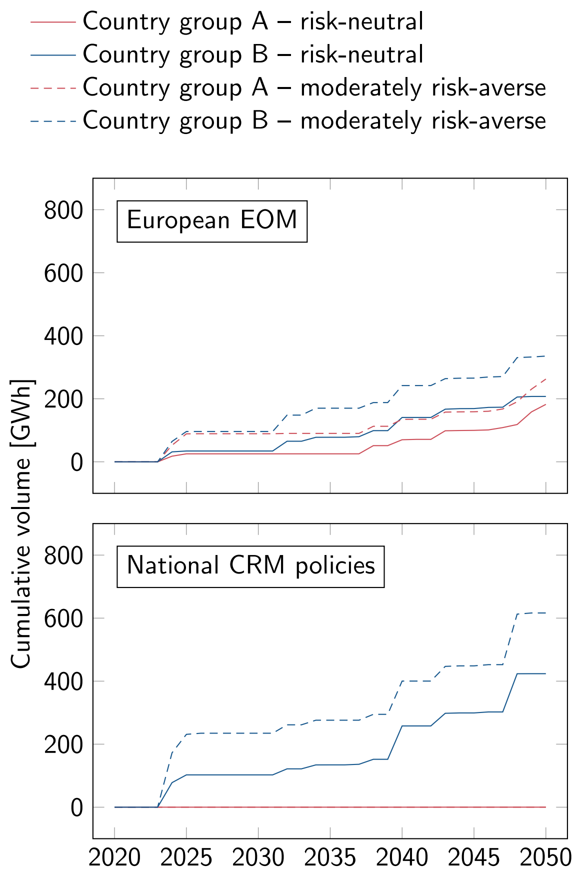


Figure 13: Energy not served volumes in country group A and country group B with risk-neutral versus moderately risk-averse investors. The figure shows the cumulative volumes from 2020 up to the respective simulation year. *Abbreviations:* CRM—capacity remuneration mechanism, EOM—energy-only market.

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