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Investment dynamics in the energy sector under carbon price uncertainty and risk aversion

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ABSTRACT

Decarbonizing the electricity system in order to contribute to climate change mitigation is a key policy goal. Yet, uncertain political and economic conditions (e.g., electricity prices) create uncertainty for energy companies. The dynamics of carbon price developments and aversion to uncertainty may have decisive impacts on companies' investment decisions and thus environmental and distributional outcomes. In this paper, we incorporate a dynamic portfolio approach in a simulation model of investments in the electricity sector to explore and disentangle the impacts of both uncertainty and risk aversion on companies' investment decisions. We find that policy uncertainty and risk aversion tend to delay the transition to a low-carbon energy system, with higher levels of either factor causing even further delays. However, the mechanism for the delay depends on how risk aversion is modeled, e.g. whether companies are averse to losses, or variances or if they use a higher discount rate in uncertain situations. Employing the loss-averse approach, the company prefers technology with a low likelihood of negative returns for the portfolio; meanwhile, the mean-variance approach indicates an aversion to both positive and negative deviations in returns. With a high discount rate, investors favor less capital-intensive technologies. To account for the impact of risk aversion in policy framework we, therefore, need more empirical work on understanding these behavioral traits of energy companies.

1. Introduction

Under the United Nations Framework Convention on Climate Change, governments around the world have set targets to transit to a low-carbon energy system [44]. The transition requires a large number of investments in low-carbon technologies and energy infrastructure. However, companies in the energy sector often face an array of uncertainties of different degrees, such as future energy demand and electricity prices, the capital cost of technologies, fuel prices, intermittence of variable renewable energy, other companies' investment decisions, climate policies, geopolitics, etc. These uncertainties may cause investments to be risky to different extents.

Investments in the energy infrastructure are often capital-intensive and feature a high degree of irreversibility [11], and investments made today may affect a country's energy landscape and its environmental performance for decades to come [16,45]. In the energy system modeling literature, different techniques have been used to model investment decisions under uncertainty and risks. Much of the literature falls into the category of real options modeling. This approach focuses on how uncertainties evolve over time and takes into account the irreversibility of the investment, the uncertain future cash flows, and the timing of the investment [11,14,18]. Using the real option approach, previous studies, see for example [5,17–19,35,36,39–41,50,51] have found that uncertainties in climate policy would defer investments in low-carbon technologies and this may make the transition more costly. The value of waiting for more information that defers the investments in the real option-based analysis is a risk neutral mechanism and thus does not allow for examining how the interplay of uncertainty and risk aversion affects investment decisions.

To incorporate companies' concerns about uncertainty and risk, different approaches have been used in energy system models and various decision-making frameworks. For instance, expected utility theory is one of the approaches that has been applied. A standard assumption in economic models is that consumers maximize a concave utility function. Applying expected utility theory, model studies show that risk averse companies would make different investment decisions

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compared to a risk-neutral company, therefore some have suggested alternative policy designs for providing adequate system capacity [38] and for allocating emission permits [13]. Anwar et al. [1] found that an investor's profitability is not only affected by his/her own risk averseness, but also by the risk preferences of his/her competitors. Szolgayová et al. [42] find that assuming that firms are risk-averse, they will not only value flexibility, but also risk reductions from diversification over the different (carbon mitigation) options including investment in abatement innovation.

Another approach, derived from the expected utility approach, is the mean-variance approach or the modern portfolio theory. The underlying mechanism is that for a given level of expected return (the mean), an asset portfolio would be created that minimizes risk (measured by variance or standard deviation), or for a given level of risk, an asset portfolio would be created that maximizes expected return [12,33]. Studies have shown that the mean-variance approach can suggest ways to develop diversified power-generating portfolios with minimized risk, see examples such as Awerbuch and Berger [2] and this review paper [10].

Rather than being averse to variances, companies can also be averse to the probability or size of potential losses. In that case, measures of risk that capture the tail information of the distribution of the return are needed. The Value-at-Risk (VaR) approach was first used in the late 1980s by major financial firms to measure the risks of their trading portfolios, and now it is a widely used metric for losses applied to investment portfolios [28,31]. It is also used in regulatory requirements of banking supervision. β-VaR represents the maximum potential loss (denote by α) for a portfolio, with the probability of not exceeding this loss being equal to β. In other words, it denotes the β-th quantile of the loss distribution, ensuring that the portfolio loss will not surpass α with a β probability. The Conditional Value-at-Risk (CVaR), is defined as the conditional expectation of losses above the threshold α (at a pre-specified probability β) and is a coherent risk measure when losses are not distributed normally [8]. CVaR is often used in studying investments in the energy system, for instance [7,15,25,32,34,47]. Bruno et al. [7] found that the higher the risk aversion, the more forward contracts are signed (to reduce cash flow uncertainty). Ji et al. [25] found that risk aversion leads to higher electricity system investment costs and higher operational costs. Maier et al. [32] studied renewable investments in Brazil and found that higher risk aversion leads to lower system capacity. Munoz et al. [34] investigated the effects of risk aversion on transmission and generation investments in the US and found that risk aversion has a limited effect on overall levels of transmission and generation investments. However, with a high renewables target and high fuel price, higher levels of risk aversion lead, in their analysis, to more investment in wind and solar.

The risk-adjusted discount rate is another approach for incorporating risks in energy investment decisions, see e.g. [3,6,24,27,49]. When evaluating an investment option that will generate cash flows over many years into the future, the company needs to choose a discount rate to calculate the Net Present Value (NPV) of future revenues and costs. The greater the (perceived) risk the higher the discount rate used by a company, which means that a larger (expected) return is required by the company [30].

In the literature, some studies apply adjustments to the discount rate, e.g. risk premia derived from frameworks such as the Capital Assed Pricing Model (CAPM) [37,43], while some other studies used rule-of-thumb approaches that generally raise the discount rate as uncertain situations arise [29]. Jensen and Meibom [24] found that a higher discount rate results in a delay of investment in a combined cycle gas plant in the Nordic power system. Barazza and Strachan [3] and Yang et al. [48], using agent-based models, show that companies with lower discount rates are more willing to invest, but Yang et al. [49] have also shown that companies who use low discount rates can have a higher risk of going bankrupt because their higher willingness to invest implies a higher exposure to risk.

Building on the existing literature, this study seeks to further explore the impact of both uncertainty and risk aversion on companies' investment decisions and the low-carbon transition of the electricity system. The novelty of this study is three-fold.

First, while existing dynamic investment modeling approaches like real options are typically risk neutral, and static portfolio approaches fail to capture transitional dynamics under uncertainty, in this study, we incorporate a dynamic portfolio approach in a simulation model and capture both the investment uncertainty and the aversion against risk among the companies. The uncertainty that we investigate in this study is about the future carbon price. This uncertainty will have an impact on future electricity prices, thus the expected profits of different technologies and have consequences on how the company chooses to invest.

Second, there are different approaches to modeling how investors react to risk in the energy system. As discussed above, some studies assume that investors are concerned about deviations from average returns, while some other studies assume that investors are more worried about the values that are at risk in the tail of the return distribution, yet other studies assume investors focus on the level of expected return using adjusted discount rates. However, previous studies have not addressed if and how these different approaches would affect results in an energy system simulation model.

In addition, another contribution of this study is that the electricity price, the electricity production, and the development of the production mix are endogenously determined in this model. Consequently, the covariance between the carbon price and the electricity price is endogenously captured and varies as the electricity system changes. Hence, our modeling approach will show how investment decisions affect both the emissions and the market outcomes.

Hence, this study advances existing literature on investment decision-making under uncertainty and risk aversion in the electricity system by offering a comprehensive representation of the system. In contrast to other papers that typically focus on a single risk aversion modeling approach or do not provide a comprehensive analysis, we evaluate three risk aversion modeling approaches and their impact on electricity prices and investment profitability and the implications they have for the evolution of the electricity system. By analyzing and comparing these approaches within a single paper, we facilitate a deeper understanding of their traits and their system impacts.

The remaining part of the paper is organized as follows. In Section 2, we present the model structure and the case design. In Section 3, we present and discuss the model results regarding the system capacity mix, the electricity price, and the CO_2 emissions. Lastly, in Section 4, we conclude this paper and discuss possible implications.

2. Method

2.1. Overall model description[1]

The model is built on Jonson et al. [26] and Yang et al. [49]. It stimulates the power company's investment decisions in new power plants as well as the supply and demand dynamics in the electricity market.

The electricity system is initialized with coal and gas power plants, with installed capacities of 64 GW and 2 GW, respectively. This initial capacity corresponds to a stationary state solution for the electricity system with a carbon tax set to zero in the base case, given the fuel and technology cost parameters as well as the base case discount rate (6%

[1] A full model description can be found online at https://github.com/happiABM/uncertainty_and_risk_aversion. The model code is also uploaded there. The model is programmed in Python 3.9.

per year) chosen for this paper. The initial plants have different remaining lifetimes and will be retired over time. All the initial plants belong to one representative company, which will also make all the new investments.[2]

Each year, plants that reach the end of their lifetime are removed one by one, while the power company evaluates all possible new investment options and chooses to invest in the one(s) with the highest profitability (the profitability evaluation is described in the following section). There are five types of technologies the company can choose to invest in coal-fired, gas combined cycles (GCC),[3] nuclear, wind, and solar PV plants.

A stylized carbon price scenario is implemented, i.e., the carbon price that actually materializes in the model. The price stays at 0 for the first 10 years, and then increases gradually by 2 euro/ton CO_2 per year until it reaches 100 euro/ton CO_2, and thereafter it stays constant.[4]

The company only knows historical (carbon and electricity) prices. Due to the uncertainty in future carbon prices, the power company estimates the profitability of investing in each technology by making a probabilistic forecast of future carbon prices (see Section 2.2) and how the carbon price will affect the company's estimation of the future electricity prices and each technology's load factor.

Following Jonson et al. [26], we use 64 times slices to represent wind and solar variability as well as variability in electricity demand over the year, and the variability parameter represents a country's weather conditions and electricity demand like Germany (the parameter value is provided in Table S1 in the Supplementary material). The electricity demand is iso-elastic [26] and is assumed constant over years [22].

We run the simulation for 100 years in total. As the old plants get retired and new investment decisions are made on an annual basis, the system capacity mix evolves.

2.2. Modeling decision-making under carbon price uncertainty and risk aversion

2.2.1. Estimation of future carbon prices

The company faces uncertainties when making investment decisions. The main uncertainty investigated in this study is rooted in the stringency of future climate policy.

In our model, we address this uncertainty by assuming that the future carbon price and its distribution are not known by the investors. To account for the uncertainty, the investor is assumed to have a subjective probability distribution of future carbon prices. This approach aligns with the Knightian concept of uncertainty, as it emphasizes the lack of knowledge about the true probability distribution of the carbon price, but where the investor uses a subjective probability distribution for guiding its investment decisions.

This uncertainty will have an impact on the expected profits of different technologies and have consequences on what the power company chooses to invest in. As investments made today will affect the whole system's capacity mix for several decades, there is also uncertainty about the future level of installed capacity in the system and, since electricity prices are endogenous, this generates uncertainty about future electricity prices as well.

We simulate the company's expectations about future carbon prices in the following way. The company knows the historical carbon prices and uses the past five year's average price as a reference to infer future prices. The company's expectation for the future carbon price is assumed to be a discrete uniform distribution:

$$\left[\overline{p}_{future}^{CO2}\right] = \overline{p}_{past}^{CO2} \times [\omega - 3\Delta_{CO_2}, \omega - 2\Delta_{CO_2}, \omega - \Delta_{CO_2}, \omega, \omega + \Delta_{CO_2}, \omega + 2\Delta_{CO_2}, \omega - 3\Delta_{CO_2}] \quad (1)$$

- $\overline{p}_{future}^{CO2}$ = a set of possible future carbon prices that the company expects. Each value stands for a future price level on average, not for a particular year.
- $\overline{p}_{past}^{CO2}$ = the prevailing carbon price. In this study, the power company uses the past five-year average price.
- ω = the average/median value of the discrete uniform distribution.
- Δ_{CO_2} = the step spread in the carbon price.

In the base case, we use average/median $\omega = 1.5$, i.e. the company assumes that the future carbon price will be on average 50% higher than the average price of the past five years. When assessing investment options, the future carbon prices in the distribution are assumed to be constant over the whole lifetime of the power plant. Further, a spread $\Delta_{CO_2} = 0.25$ is used, i.e. the $[\overline{p}_{future}^{CO2}] = \overline{p}_{past}^{CO2} \times [0.75, 1.0, 1.25, 1.5, 1.75, 2.0, 2.25]$.

The future carbon price equals the past five year's average price multiplied [0.75, 1.0,1.25, 1.5, 1.75, 2.0, 2.25]. This means that the company expects the price level would range from as low as 75% of and up to more than twice as high as the past five year's average price.

Given the difficulty of parameterizing the uncertainty in the carbon price and how companies perceive the uncertainty, we analyze different assumptions on Δ_{CO_2} in the sensitivity analysis. We keep the average/median value unchanged ($\omega = 1.5$), and test for different spreads of the Δ_{CO_2} values in the set [0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.35, 0.4, 0.45, 0.5]. The result is presented in Section 3.3.

2.2.2. Evaluation of investment options

Taking into account the system condition and the carbon price uncertainty, the company makes a forecast simulation of the future electricity market and calculates the *profitability index* for investment in each possible technology *T*. The *profitability index* is defined in the following five steps.

First, for a given carbon price in the price set $[\overline{p}_{future}^{CO2}]$, e.g. the i^{th} point in the set, the company calculates a net present value of its portfolio profit over the lifetime of technology *T*, if an investment was made in technology *T*,

$$\pi_T(i) = \sum_{t=1}^{L} \frac{R_{t,T}(i) - C_{t,T}(i)}{(1+\mu)^t} - I_T \quad (2)$$

- $\pi_T(i)$ is the net present value of the portfolio profit when investing in technology T and the carbon price is the i^{th} point in the price set $[\overline{p}_{future}^{CO2}]$.
- $R_{t,T}(i)$ and $C_{t,T}(i)$ respectively are the portfolio revenue and total operating cost in year t for the company if an investment was made in technology T and the carbon price is the i^{th} point in the price set $[\overline{p}_{future}^{CO2}]$.
- I_T is the capital cost of technology T.
- μ = the discount rate. We use 6%/year in the base case.

[2] We also have tested the model for 10 homogenous companies. The result was almost identical to the analysis of one representative company, so we choose to use one company to save computational time.

[3] The gas-fired plant can be fuelled by either natural gas or biogas, depending on which has the lower operating cost when the carbon price is also taken into account.

[4] As countries continue to implement stricter emission reduction targets to combat climate change, the number of available allowances for emitting greenhouse gases becomes more limited. This diminishing supply drives up the carbon price over time. This trend is evident in the European Union Emissions Trading System (EU ETS), where, following the implementation of Phase III in 2013, carbon prices have experienced consistent growth. As of March 2023, the price has reached 90 euros per ton of CO2. The carbon price could also be implemented through carbon taxes. It is also evident from integrated assessment models that the carbon prices need to increase if we are to meet the climate targets in the Paris Agreement [46].

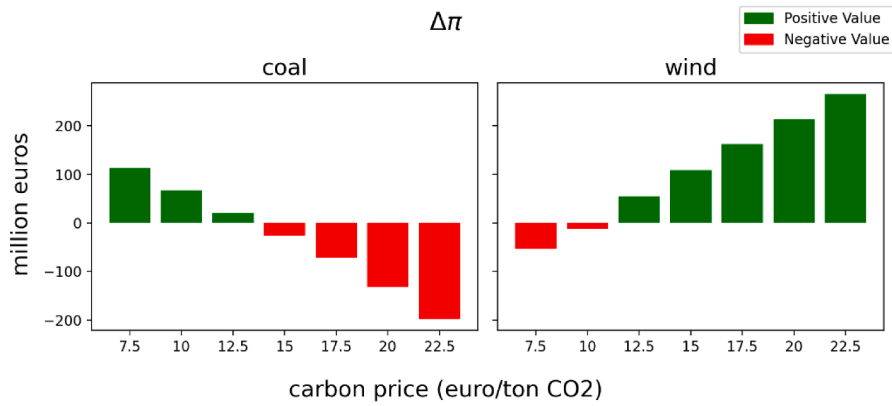

Fig. 1. An illustration of the expected change in profit (Δπ) under different carbon prices for investing in a coal power plant (left panel) versus investing in a wind power plant (right panel). If a company is loss averse using the VaR approach, it will consider how many cases the change in profits will be positive (green) versus negative (red). The number of positive cases must exceed the company's threshold λ.

- L is the lifetime of plant T. (The value is provided in Table S3 in the Supplementary material.)

Secondly, for the same carbon price level that is used in the first step, the company also calculates a net present value of its portfolio profit $\pi_0(i)$ over the lifetime of technology T, if no investment would be made,

$$\pi_0(i) = \sum_{t=1}^{L} \frac{R_{t,0}(i) - C_{t,0}(i)}{(1+\mu)^t} \tag{3}$$

- $\pi_0(i)$ is the net present value of the portfolio profit if *no* investment was made and the carbon price is the i^{th} point in the price set $[\overline{p}^{CO2}_{future}]$.
- $R_{t,0}(i)$ and $C_{t,0}(i)$ respectively are the company's portfolio revenue and total operating cost in year t if no investment was made and the carbon price is the i^{th} point in the price set $[\overline{p}^{CO2}_{future}]$.

In the third step, the company calculates the change in the profit of investing in technology T, if the carbon price is the i^{th} point in the price set $[\overline{p}^{CO2}_{future}]$,

$$\Delta\pi_T(i) = \pi_T(i) - \pi_0(i) \tag{4}$$

For every carbon price in the set $[\overline{p}^{CO2}_{future}]$, the company repeats the calculation of steps one to three above Eqs. (2)–(4), and then in the fourth step, the company calculates the expected increase in the portfolio profitability E_T of investing in technology T,

$$E_T = \frac{1}{n}\sum_{i=1}^{n} \Delta\pi_T(i) \tag{5}$$

- $n =$ number of points in the set $[\overline{p}^{CO2}_{future}]$. ($n = 7$ in the base case analysis).

Note that the expected increase in profitability is defined as the *change* in overall portfolio profit for the company if an investment in technology T was made. This is different from the profit of investing in the technology per se.

We also make the following assumptions when estimating the company's expected profitability:

- The forecast is based on uncertain, but constant carbon prices over the lifetime of technology T, while the actual carbon price in the model that will be materialized in the future increases over time.
- When making an investment assessment, the company assumes that all the plants existing in the current system will remain in the system over the lifetime of the technology that is being assessed.
- In the forecast simulation, the investment in the plant is based on the assumption of price-taking behavior, i.e., the investment is small so that the electricity price is not affected by the investment.

In the fifth and last step, the company calculates the *profitability index* for investing in technology T, which is the expected profitability E_T multiplied by the Capital Recovery Factor (CRF) and divided by the capital cost of this technology T,

$$profitability\ index_T = E_T \times \frac{CRF}{I_T} \tag{6}$$

$$CRF = \frac{\mu}{1-(1+\mu)^{-L}} \tag{7}$$

The company evaluates the *profitability index* for each of the five technologies (coal-fired, gas combined cycle, nuclear, wind, and solar PV) and then makes the investment decision. If the company is risk neutral, it would choose the technology T with the highest positive profitability index. However, if the company is risk averse, then the selection criteria will be adjusted by the risk measures as described below.

2.2.3. Modeling risk aversion

As discussed in Section 1, we implement and compare three different approaches to representing risk aversion: (1) the VaR approach, (2) the mean-variance approach, and (3) the discount rate approach.

In this study, for the VaR and mean-variance approaches, the assessment of a new investment is evaluated against how they affect the portfolio risk for the company, while for the discount rate approach, we assume that the company applies the same risk premia (a higher discount rate) for all the technologies, even though they may have different risk characteristics.

(1) VaR approach

When using the VaR approach the company not only evaluates the expected profitability E_T, but also evaluates the probability that an investment may result in losses – the company is concerned about the tails of the distribution.

In this study, we calculate the number of cases with positive profits (out of a total of seven cases of different carbon prices) and the number must be larger than a threshold number λ for the company to consider investing. This implies that in the β-VaR notation, we use $\alpha = 0$, and the varying λ corresponds to the β value.

A higher λ value, i.e. the higher the required probability that the investment generates positive profits, means a higher aversion to losses.

For instance, if the company has a loss aversion level of 4 ($\lambda = 4$), in the case illustrated in Fig. 1, the company will not invest in coal power plants, since the expected profits from investing in a coal power plant are only positive in three out of a total of seven cases which is lower than the company's required threshold λ. While for wind, since wind only has two negative cases, and five positive cases which are larger than the company's λ threshold, the wind will be considered as an investment option.

(2) The mean-variance approach

The mean-variance analysis takes into account not only the expected profit but also the variance of the profits it. Based on Eqs (2–6), the variance-adjusted expected profit $E_T^{'}$ and the *profitability index* of technology T becomes,

$$\pi_T^{'}(i) = \frac{1}{n}\sum_{i=1}^{n}\pi_T(i) - \gamma \cdot var(\pi_T(i)) \tag{8}$$

$$\pi_0^{'}(i) = \frac{1}{n}\sum_{i=1}^{n}\pi_0(i) - \gamma \cdot var(\pi_0(i)) \tag{9}$$

$$E_T^{'} = \pi_T^{'}(i) - \pi_0^{'}(i) \tag{10}$$

$$profitability\ index\ _T = E_T^{'} \times \frac{CRF}{I_T} \tag{11}$$

- $var(\pi_T(i)) = \frac{1}{n}\sum_{i=1}^{n}(\pi_T(i) - \overline{\pi_T})^2$ is the variance of $\pi_T(i)$. $\overline{\pi_T}$ is given by $\frac{1}{n}\sum_{i=1}^{n}\pi_T(i)$.
- $var(\pi_0(i)) = \frac{1}{n}\sum_{i=1}^{n}(\pi_0(i) - \overline{\pi_0})^2$ is the variance of $\pi_0(i)$. $\overline{\pi_0}$ is given by $\frac{1}{n}\sum_{i=1}^{n}\pi_0(i)$.

Here γ is the risk aversion parameter in the mean-variance approach. The larger the value, the more averse is the company to the variance.

(3) The discount rate approach

When evaluating an investment option that generates cash flows over many years, it is important for the company to select an appropriate discount rate to calculate the Net Present Value (NPV) of future revenues and costs. The discount rate is chosen based on the perceived risk associated with the investment, with a higher perceived risk resulting in a higher discount rate used by the company. This means that a higher expected return is required by the company to compensate for the additional risk. The theoretical justification behind using a higher discount rate when a single project is uncertain is weak, but it is commonly used by practitioners [9]. Therefore, the risk-adjusted discount rate approach used in this study can be interpreted as a rule-of-thumb approach.

In this study, the discount rate is used in Eqs. (2), (3), and (7) above. we employ a single discount rate to discount the revenues for the company's entire portfolio. This approach does not differentiate between discount rates among various technologies. By using a single discount rate, we aim to provide a simplified analysis while acknowledging that this assumption may not fully capture the nuances in risks associated with each technology.

2.3. Analysis design

We design the analysis as follows:

First, we run the model with a risk neutral company. Secondly, we compare the risk neutral case with cases when the company is risk averse using the VaR approach, the mean-variance approach and the risk-adjusted discount rate approach, respectively. Lastly, we run the model with different levels of carbon price uncertainty.

Table 1
Values of risk aversion and uncertainty parameters used for each case.

Parameters Cases	VaR parameter λ	Mean-variance parameter γ	Discount rate parameter μ	carbon price uncertainty Δ_{CO_2}
Risk neutral case	$\lambda = 0$	$\gamma = 0$	$\mu =$ 6%/year	0.25
VaR approach	$\lambda = [0, 3, 5, 6, 7]$	$\gamma = 0$	$\mu =$ 6%/year	0.25
Mean-variance approach	$\lambda = 0$	$\gamma = [0,\ 0.5, 0.8,\ 1.0,\ 1.3] \cdot 10^{-11}/€$	$\mu =$ 6%/year	0.25
Discount rate approach	$\lambda = 0$	$\gamma = 0$	$\mu = [6\%, 7\%, 8\%, 9\%]$/year	0.25
Different levels of carbon price uncertainty	$\lambda = [3, 5, 7]$	$\gamma = 0$	$\mu = 6\%$/year	$\Delta_{CO_2} = [0.1,\ 0.15,\ 0.2,\ 0.25,\ 0.3,\ 0.35,\ 0.4,\ 0.45,\ 0.5]$

For the risk neutral case, both the VaR parameter (λ) and the mean-variance parameter (γ) are set to 0, and the discount rate (μ) is set at 6%/year (assumed to be the risk-free discount rate in this study) i.e. $\lambda = 0$, $\gamma = 0$, $\mu = 6\%$year.

For the VaR approach, we vary the VaR parameter (λ), while keeping the mean-variance parameter and the discount rate parameter the same as the risk neutral case ($\gamma = 0$ and $\mu = 6\%$/year). We test 5 different λ values to compare different levels of risk aversion.

- $\lambda = 0$, ($\beta = 0\%$).
- $\lambda = 3$, at least three out of seven cases ($\beta = 43\%$) of different carbon prices must be positive for considering the investment.
- $\lambda = 5$, at least five out of seven cases ($\beta = 71\%$) must be positive profits.
- $\lambda = 6$, at least six out of seven cases ($\beta = 85\%$) must be positive profits.
- $\lambda = 7$, seven out of seven cases ($\beta = 100\%$) must be positive profits.

For the mean-variance approach, we keep the VaR parameter and the discount rate parameter the same as the risk neutral case ($\lambda = 0$ and $\mu = 6\%$/year), while varying the mean-variance parameter (γ), and we test five γ values:

- $\gamma = 0$.
- $\gamma = 0.5 \cdot 10^{-11}/€$.
- $\gamma = 0.8 \cdot 10^{-11}/€$.
- $\gamma = 1 \cdot 10^{-11}/€$.
- $\gamma = 1.3 \cdot 10^{-11}/€$.

These γ values are determined through trial and error, so that the impact on the system evaluation of changing γ is clearly illustrated.

For the discount rate approach, we vary the discount rate parameter μ, while keeping both the VaR parameter and the mean-variance parameter to zero ($\lambda = 0$ and $\gamma = 0$). We test five μ values for the discount rate approach.

- $\mu = 6\%$/year.
- $\mu = 7\%$/year.
- $\mu = 8\%$/year.
- $\mu = 9\%$/year.
- $\mu = 10\%$/year.

Lastly, we also test how different levels of uncertainty in carbon price

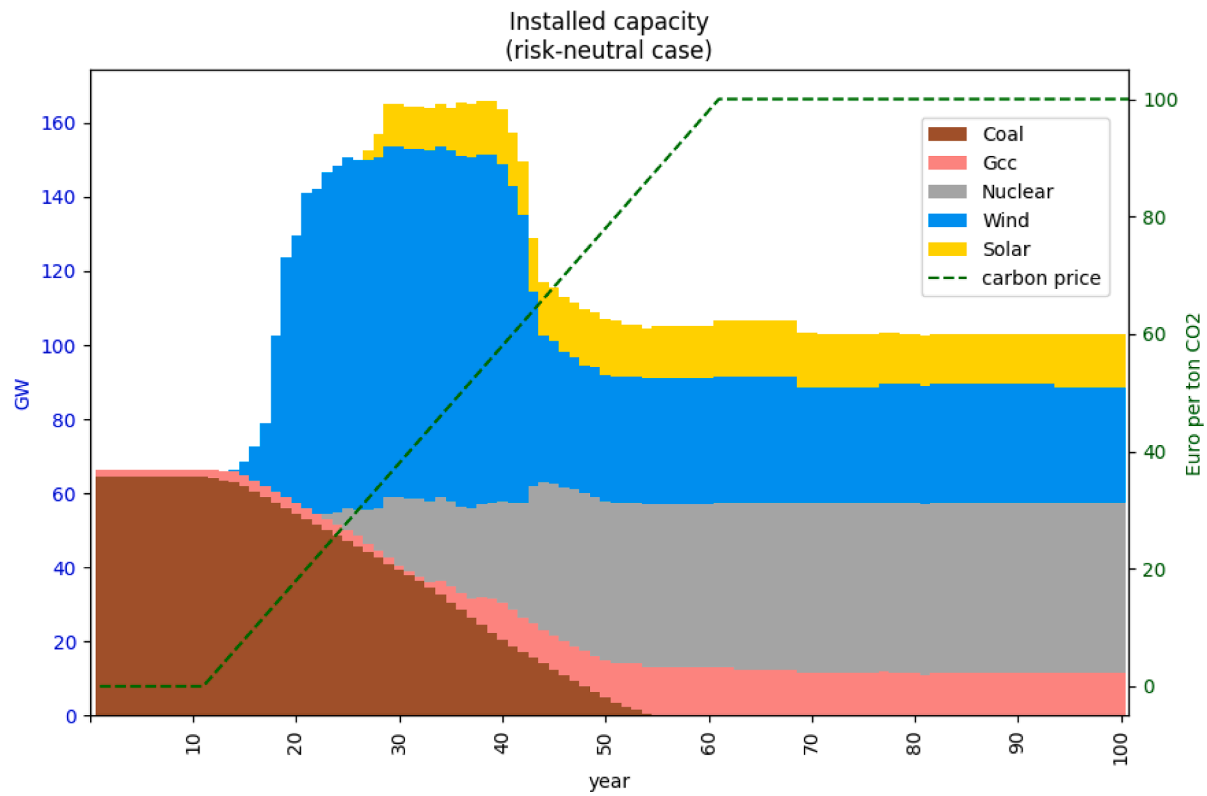

Fig. 2. The development of system installed capacity over 100 years in the risk neutral case($\lambda = 0$, $\gamma = 0$, $\mu = 6\%$year). The dashed line is the actual carbon price that is materialized in the model.

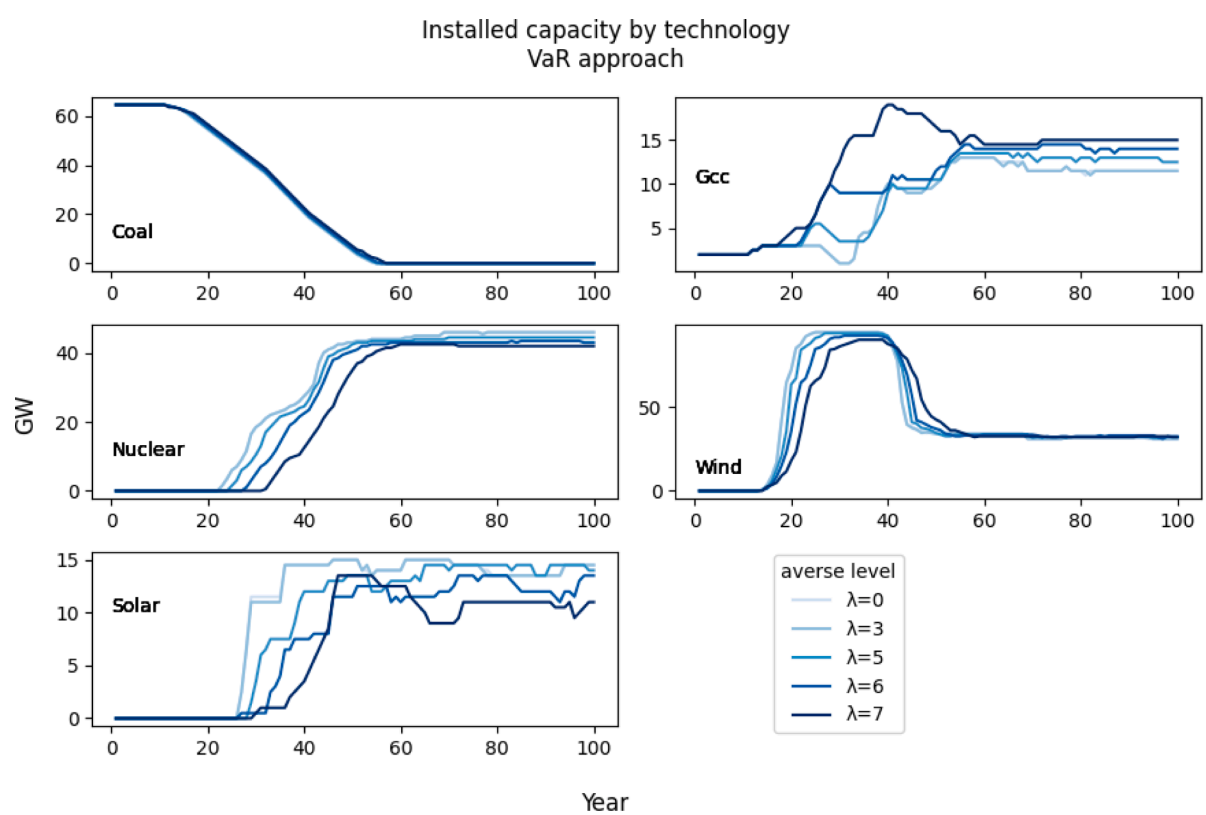

Fig. 3. The system installed capacity in cases with different aversion levels to losses ($\lambda>=0$,$\gamma = 0$,$\mu = 6\%$year). It shows that when the company is more averse to losses (a higher λ value), there is a further delay in investments in low-carbon technologies, while more investments are in GCC. (Note that the scale is different for each panel. The line of $\lambda = 0$ is not very visible in this plot as it overlaps with the line of $\lambda = 3$.).

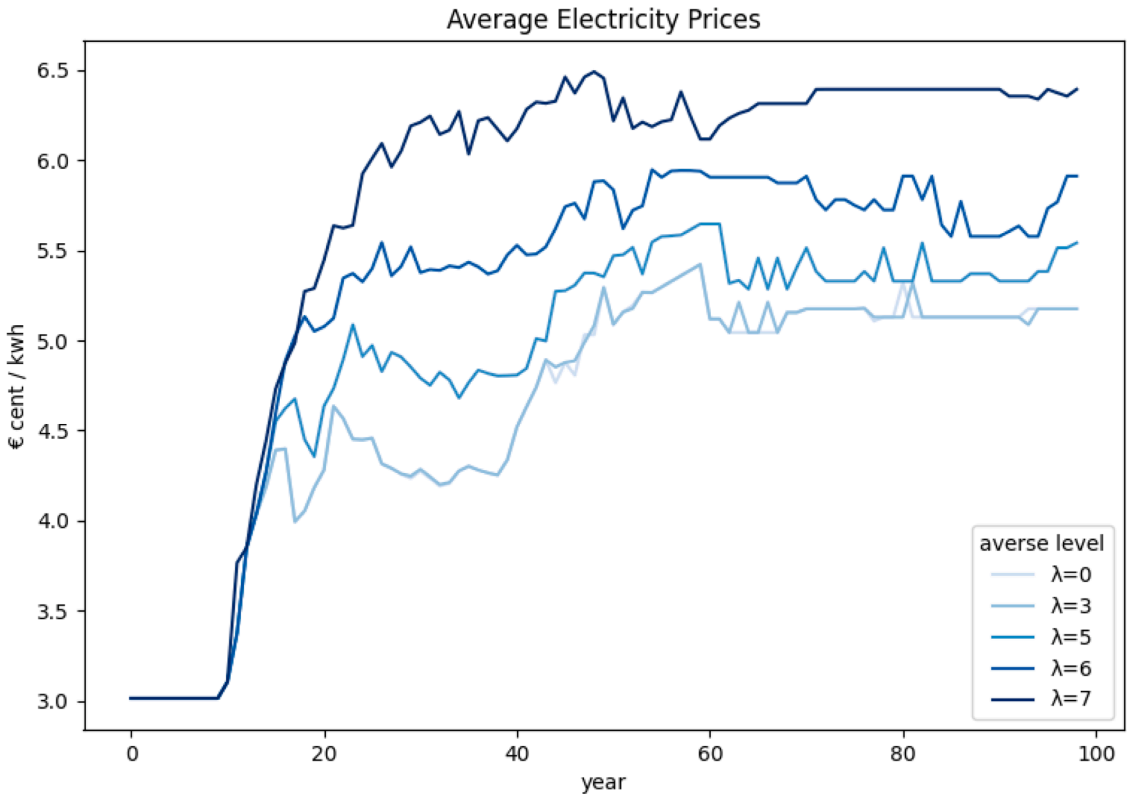

Fig. 4. Average electricity price in cases with different aversion levels to losses (λ>=0, $\gamma = 0$, $\mu = 6\%$year). The more averse to losses (a higher λ value), the higher the electricity price. (The line of $\lambda = 0$ is not very visible as it overlaps with the line $\lambda = 3$.) The higher electricity price associated with higher λ is due to lower investments and hence lower installed capacity as a result of the higher degree of risk aversion.

(together with risk aversion to losses) affect the results, in which we vary the carbon price uncertainty level (ΔCO_2) and the VaR parameter (λ), while keeping the mean-variance parameter (γ) at 0 and the discount rate parameter (μ) at 6%/year.

The design of each case and its key parameters are summarized in Table 1.

3. Results and discussion

We present the results for different cases in terms of the system capacity mix, electricity prices, and CO_2 emissions.

3.1. Impact of different levels of risk aversion using VaR

We first present the installed capacity in the risk neutral case ($\lambda = 0$, $\gamma = 0$, $\mu = 6\%$year), and then compare it with risk aversion cases with an increased aversion to losses using the VaR approach. In this section, risk aversion is implemented by using the VaR approach ($\lambda > 0$, $\gamma = 0$, $\mu = 6\%$ year), and in the next Section 3.2, we will compare the VaR approach with the other two approaches for modeling risk aversion.

Fig. 2 shows that in a risk-neutral case, the growing carbon price causes the system to gradually transition from a fossil-based system to a low-carbon system. In the beginning, the system relies heavily on coal with some natural gas, and afterward, the carbon price starts to rise and the old plants are reaching the end of their life, the system becomes gradually dominated by wind, solar, nuclear, and gas combined cycles (GCC) which initially are run on natural gas and then after some fifty years switch to biogas. It is worth highlighting that after an initial expansion, the capacity of wind energy begins to decline around year 30, coinciding with the expansion of nuclear capacity. As discussed in one of our previous studies (Yang et al. [49], this can be attributed to the variation in electricity prices throughout the year. Since wind is a variable renewable technology, its revenue per kWh of electricity generated may differ from that of nuclear energy, depending on the specific time slices during which production occurs. When the installed capacity of wind energy reaches sufficiently high levels, the wind eventually starts to receive lower revenues per kWh than nuclear energy, leading to a halt of investments in wind and eventually to a decline in its capacity. This observation underscores the importance of considering the dynamic interplay between electricity prices and the revenue generation potential of various energy technologies.

When the company is averse to losses, we see delays both in the phase-out of fossil technologies and in the expansion of the low-carbon technologies (compared to the risk neutral case).

Fig. 3 shows that with an increasing level of risk aversion (to losses), there is a small increase in coal investments and a clear increase in GCC investments. In contrast, for low-carbon technologies, we see that the more averse to losses, the further the adoption of nuclear is delayed, and the slower will be the expansion of wind and solar technologies.

The results can be interpreted as follows. During the initial 10 years of the simulation, when the carbon price is zero, the company deduces that the carbon price will remain at zero based on the available observational data. Consequently, the company estimates that investing in low-carbon technologies would not be profitable. Then as the observed carbon price grows gradually, the expected profitability of the low-carbon technology starts to grow as well. In the risk neutral case, the company only checks if the expected profitability is positive, and then chooses the technology with the highest expected profitability. However, when the company is averse to losses, it also takes into account the probability that the technology causes a reduction in portfolio profits for different expected carbon prices, and that possibility must satisfy the company's criteria for the investment to be considered.

For the risk neutral company, given that the investment in low-carbon technology takes place, the chance of losses is compensated by

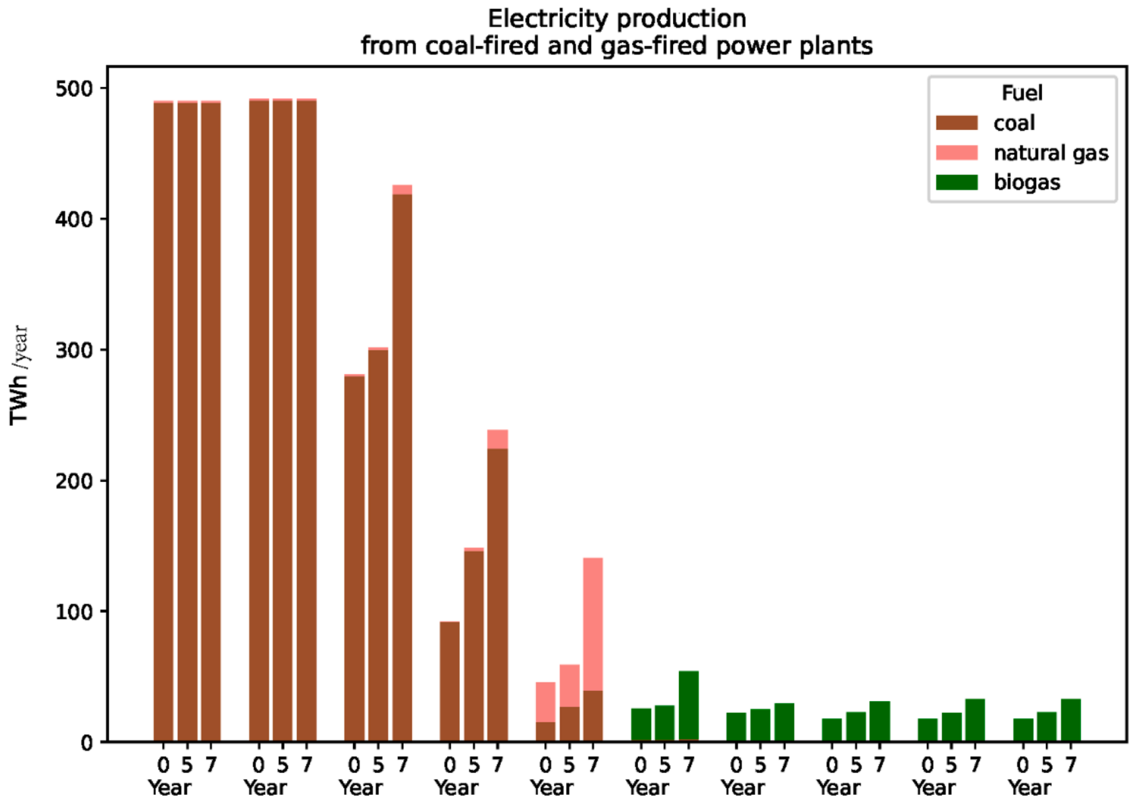

Fig. 5. Annual electricity production from coal-fired and gas-fired power plants in cases with different levels of risk aversion.The greater the aversion to losses (a higher λ value), the higher the reliance on coal and gas becomes. Consequently, this leads to increased CO2 emissions.

the positive profits that may take place if the carbon price is on the high end of the set of plausible future carbon prices $\overline{p}^{CO2}_{future}$, while in the case that the company is averse to losses, the chance(s) of negative profits may determine the decision. An investment option can have positive expected profits, but the probability of losses may be too high for the company to consider investing. In addition, the company considers that a lower carbon price than the expected price can materialize, i.e. when the carbon price is in the lower range of the set of $\overline{p}^{CO2}_{future}$, the investment may in such cases turn out to be unprofitable for low-carbon technologies. The probability of generating negative profits by investing in low-carbon technologies decreases as the observed carbon price continues to grow, while the opposite holds for coal power. Therefore, we observe that the more risk averse the company is, the later it starts to invest in nuclear and solar.

The reason for the slower expansion of wind technology is that compared to a risk neutral company, a company that is averse to losses would require a higher electricity price. As more wind installations would bring down the average electricity price, we see that the more risk averse the company is, the slower the expansion of wind.

The reason for more investments in gas-fired plants and also slightly more in coal-fired in the case of higher aversion to losses is that initially the system is dominated by coal-fired and some gas-fired power plants. This implies that the electricity price is set by the running cost of coal or gas most of the time slices. Consequently, there will be a large covariance between the assumed carbon prices and the estimated electricity prices when evaluating the different possible investments. This causes the variability in profits to be smaller for coal and gas investments than the CO_2-neutral technologies, causing the CO_2-neutral technologies to be riskier in the beginning. As the carbon price grows over time, more and more CO_2-neutral technologies have been installed in the system while old coal plants get retired, the system becomes less and less dominated by fossil fuel technologies, consequently, the covariance between the assumed carbon prices and the estimated electricity price decreases over time. In addition, with the gas combined cycle, the company also has the option to use either natural gas or biogas leading to additional flexibility to choose the type of fuel depending on the carbon price.

We also observe in Fig. 3 that when the company is averse to losses, the total installed capacity is overall lower, especially for nuclear, solar and wind before year 40.[5] This also means that the overall electricity output will be lower and that the average electricity price is higher when the company is more risk-averse (Fig. 4). Fewer investments are being made because of the aversion to losses. Since the overall production capacity drops, due to fewer investments overall, and there is also a higher reliance on technologies with high running costs (especially with higher carbon prices) (Fig. 5), the average electricity prices will be larger, which in turn incentivizes investments in all technologies.

Fig. 4 shows that the electricity prices rise during years 10 – 50, and this is primarily linked to the increasing carbon price. As discussed in our previous paper [49], when the carbon price rises, it raises the fuel costs for coal and natural gas, which in turn increases the electricity price during hours when coal or natural gas determines the electricity price. After approximately year 50, all coal power plants are decommissioned, and biogas replaces natural gas around the same time. Consequently, the electricity price no longer increases with the carbon price. However, the electricity price remains higher than at the beginning of the modeling period, since the costs of the technologies that replaced coal are higher than that of coal plants. It is important to acknowledge that technological advancements may play a vital role in lowering electricity production costs, but given the scope of this study, we did not incorporate such mechanisms in this paper.

Furthermore, as more fossil-fuel technologies are used for electricity

[5] We use an iso-elastic demand function in this model, therefore, the electricity demand is still met.

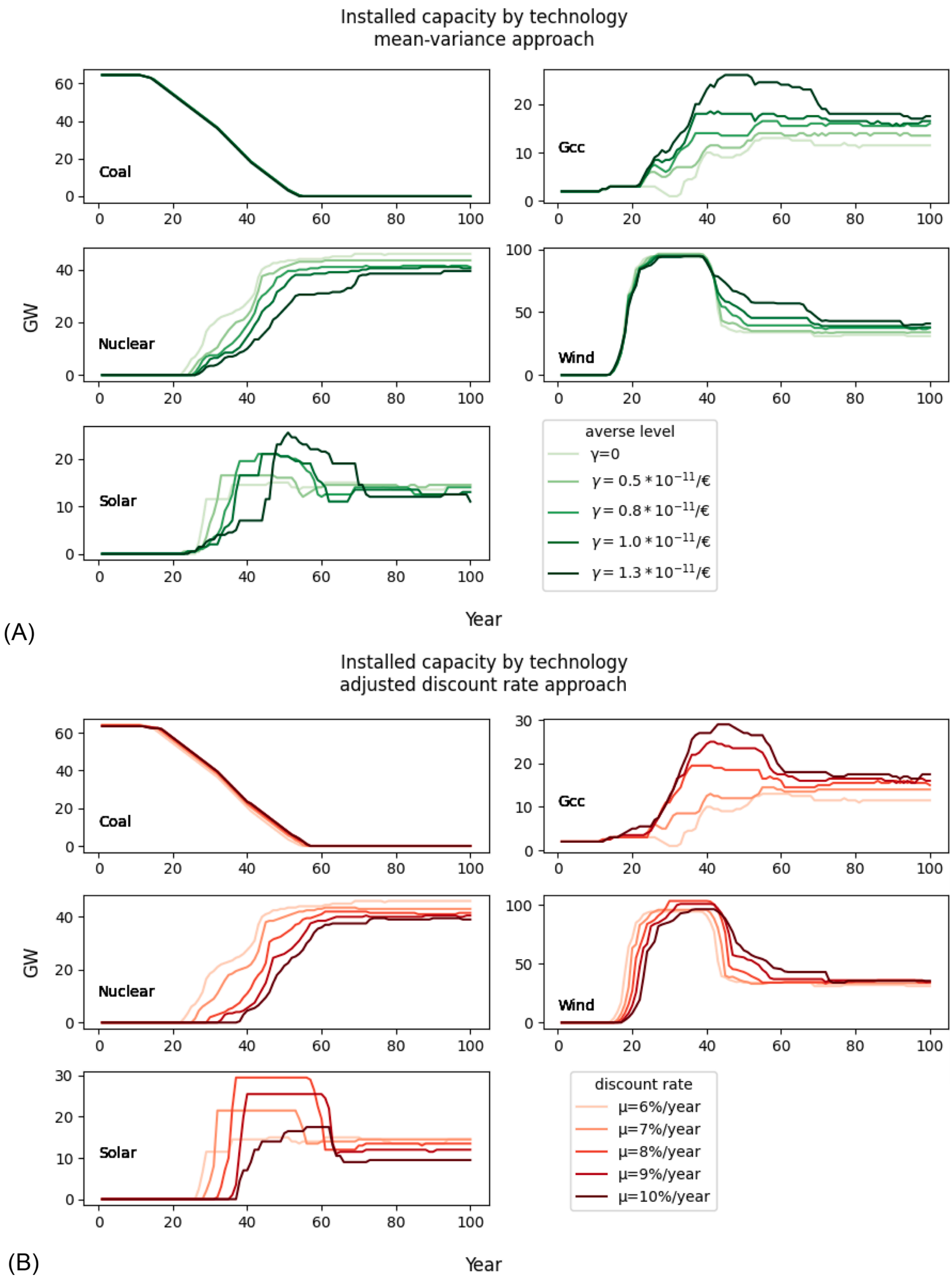

Fig. 6. System installed capacity of each technology over time for different risk aversion approaches. (A) the mean-variance approach; (B) the adjusted discount approach. Similar to the VaR approach, we observe a delay in investments in low-carbon technologies while more investments are in GCC. (Note that the scale is different for each panel).

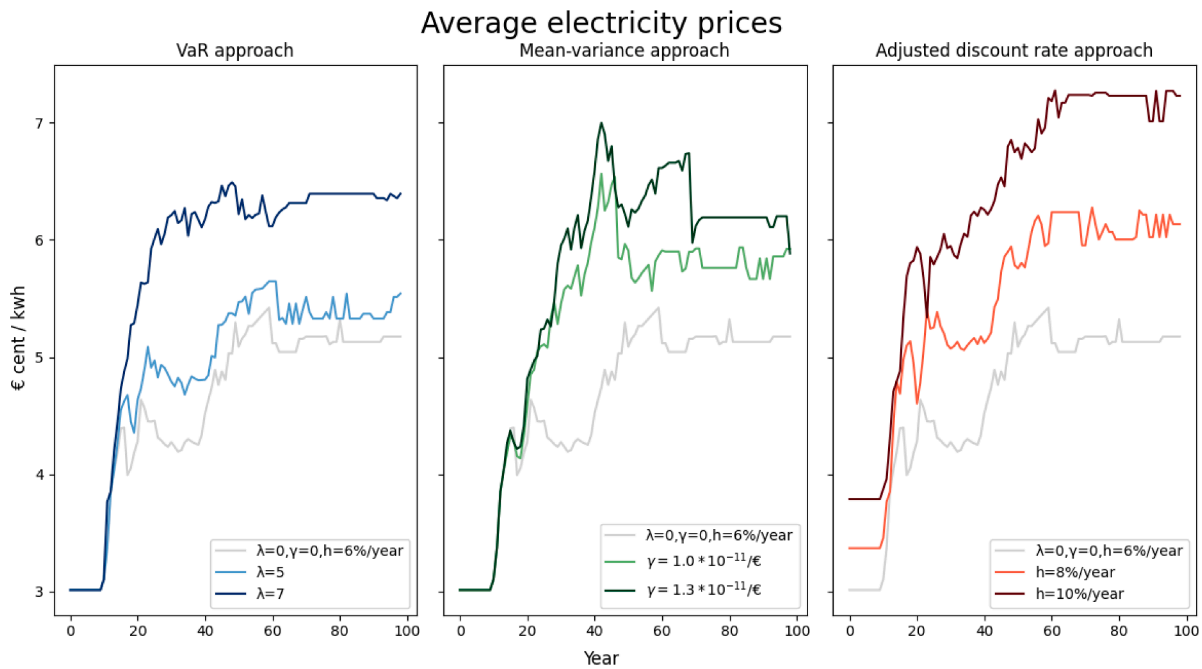

Fig. 7. Average electricity price for cases using different risk aversion approaches. All three approaches tend to generate higher electricity prices when a higher risk aversion level is assumed.

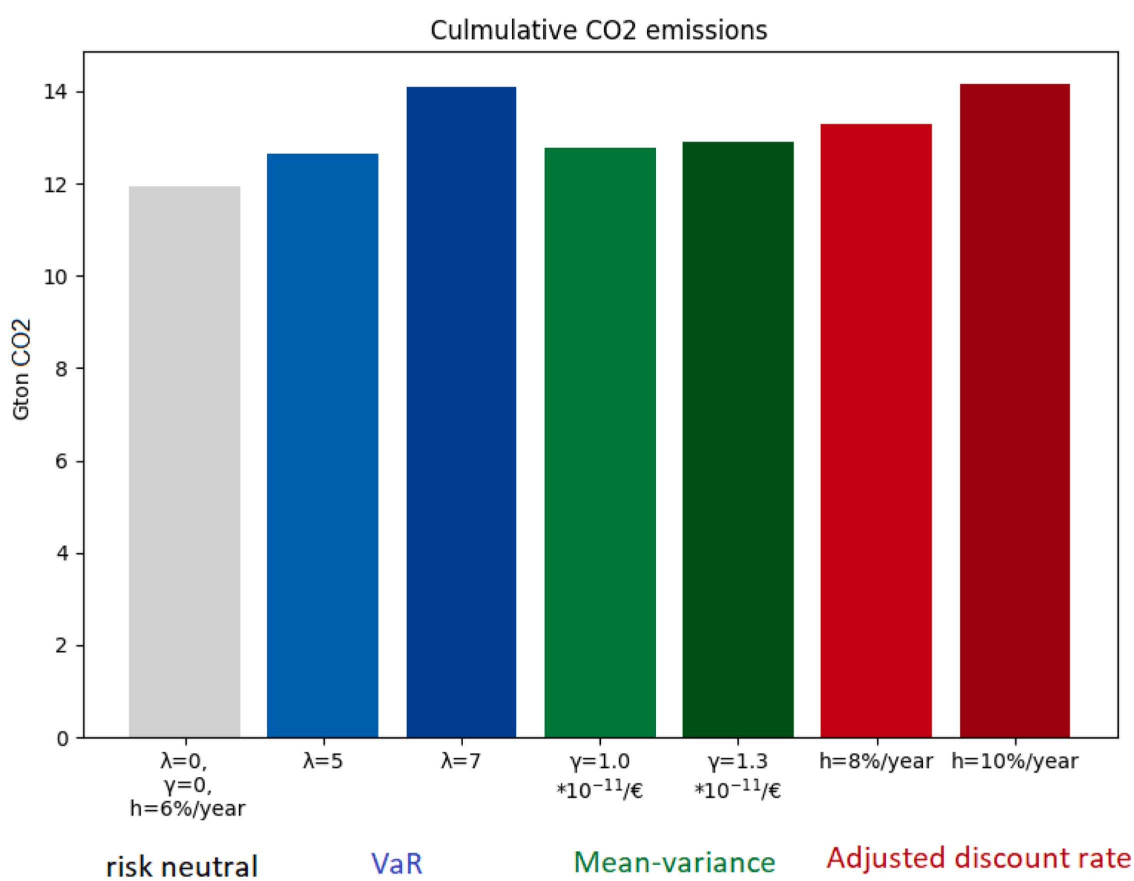

Fig. 8. Cumulative CO_2 emissions for cases using different risk aversion approaches. All three approaches tend to generate larger CO_2 emissions when a higher risk aversion level is assumed.

production in cases where the company is more averse to losses, there are higher CO_2 emissions due to the increased usage of coal plants. As shown in Fig.5, in the initial years, when the carbon price is low, electricity production is primarily dominated by coal-fired power plants, with a small contribution from gas power plants. As the carbon price rises over time, the operating costs for both coal and natural gas also

Table 2
A summary of the outcomes for technology investments, cumulative emissions, and electricity prices when employing three distinct risk aversion strategies. Detailed information on cumulative investments can be found in the supplementary material, specifically within section S3.2.

Result Cases	Low-carbon technology investment	Fossil technology investment	Cum. emissions	Electricity price
Risk neutral	Reference	Reference	Reference	Reference
VaR approach	(1) Delay expansion of nuclear and wind. (2) lower cumulative investments in nuclear, wind and solar	more cumulative investments in GCC and slightly more in coal	increases with the aversion level	increases with the aversion level
Mean-variance approach	(1) delayed expansion of nuclear and solar (2) lower cumulative investments in nuclear, more in wind and solar	more cumulative investments in GCC	increases with the aversion level	increases with the aversion level
Discount rate approach	(1) delayed investments in wind, nuclear and solar. (2) lower cumulative investments in nuclear, and slightly more in wind	more cumulative investments in GCC and coal	increases with the aversion level	increases with the aversion level

increase. However, since coal has a higher emission intensity than natural gas, its running costs escalate more rapidly, resulting in a decline in electricity production from coal power plants over time. (In contrast, production from zero-carbon emission technologies experiences a steady increase). Around year 40, coal and gas switch places in the merit order as the carbon price becomes sufficiently high. Gas power plants transition from using natural gas to biogas as their fuel source around year 50. This shift occurs because biogas becomes more cost-effective than natural gas when the carbon price is factored in. Therefore, no emissions from the gas-fired plant thereafter. For a comprehensive depiction of the production profile across all technologies, please refer to Figure S1 in the supplementary material.

3.2. Compare different approaches for modeling risk aversion

In this section, we compare the model outcome when using various risk aversion approaches. Additionally, we explore the underlying mechanisms behind each of these methods to provide a clearer understanding of their distinctions.

3.2.1. Comparing the system outcomes

Fig. 6A and B show the development of the system installed capacity for different levels of risk aversion when using the mean-variance approach (Fig. 6A) and discount rate approach (Fig. 6B). Together with Fig. 3, we observe that the three approaches share many similarities. In particular, when the company is more risk averse, investments in low-carbon technologies are delayed, while investments in gas power plants are higher. In addition, for all approaches, the more risk averse the company, the higher the electricity price (Fig. 7), and the higher cumulative CO_2 emissions will be (Fig. 8). The results are summarized in Table 2.

3.2.2. Comparing the underlying mechanisms

The underlying mechanisms behind the three approaches are different. Using the VaR approach means that the company favors technology that has a low probability of negative returns for the portfolio, whereas using the mean-variance approach means the company is averse to both positive and negative deviations in the returns, i.e. a high risk aversion parameter would favor the technology that has a low return variance for the portfolio. For the discount rate approach, a high

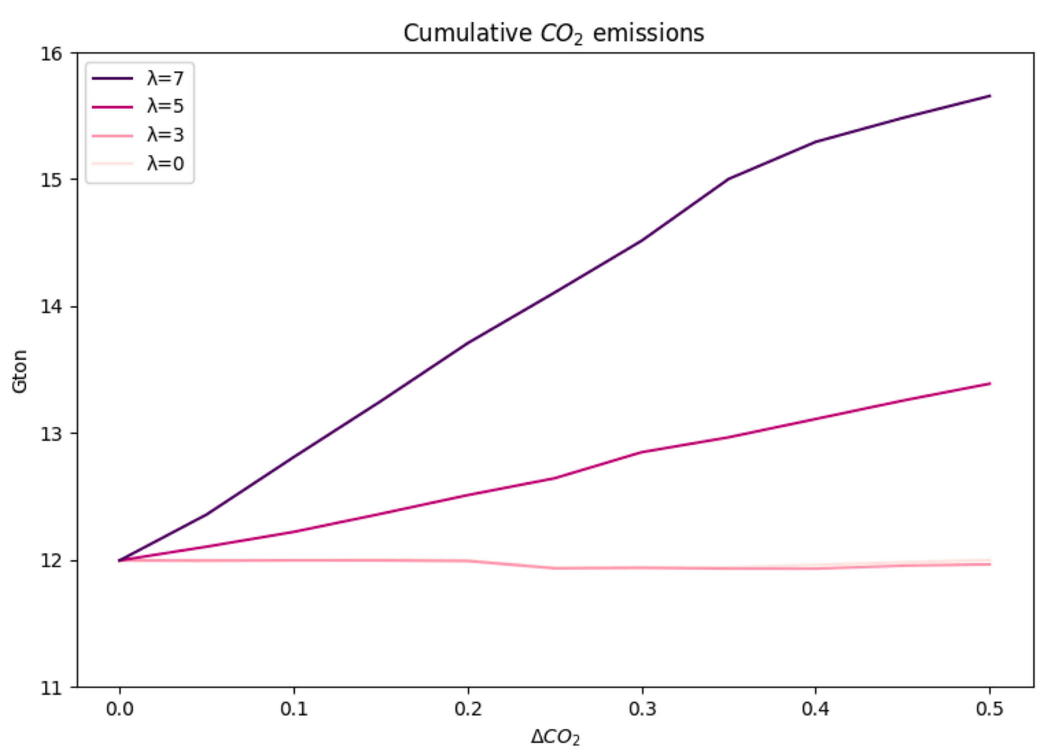

Fig. 9. Cumulative CO_2 emissions over the whole simulation period (100 years). The level of carbon price uncertainty is represented by ΔCO_2, the higher ΔCO_2, the higher the uncertainty. Each line represents a different averse level to losses, and the higher the λ, the higher the risk aversion. Cumulative CO_2 emissions increase as the carbon price uncertainty or risk aversion increases. (Note that the line of $\lambda = 0$ is not visible in this plot as it overlaps with the line of $\lambda = 3$.).

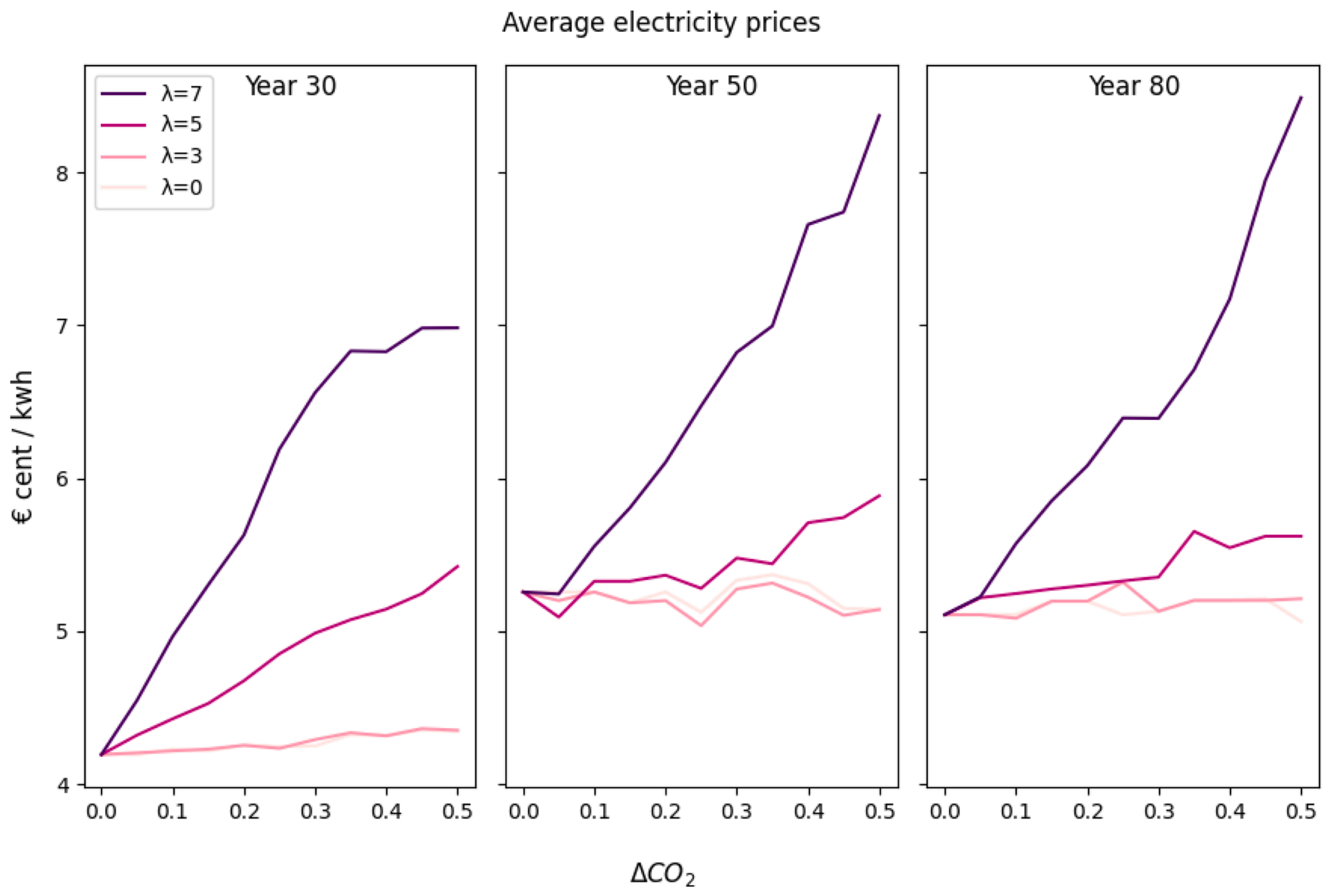

Fig. 10. Electricity price for different levels of carbon price uncertainty at years 30, 50, and 80. The level of carbon price uncertainty is represented by ΔCO_2. The higher ΔCO_2, the higher the uncertainty. Each line represents a different level of aversion to losses. The higher the λ value, the more averse the company is to losses. It can be seen that the electricity price rises as the uncertainty or the aversion level raises. (Note that the line of λ=0 is sometimes not visible as it overlaps with the line of $\lambda = 3$.).

discount rate means that the investor prefers less capital-intensive technologies, whereas a low discount rate tends to favor capital-intensive technologies [20,49].

Take the delayed expansion of nuclear technology for example. In the VaR approach: the reason for the delay is that in the beginning when the expected carbon price is low, the probability of having negative returns is high, so the probability of negative returns decreases with increasing carbon prices, and hence, the more aversion against losses, the longer the company waits to invest. In the mean-variance approach, however, it is because the expected profit of nuclear has a relatively large variance compared to other technologies: the more the company is averse to variance, the more it would disfavor nuclear investments. In the discount rate approach, it is because low-carbon technologies such as nuclear and wind plants have high capital costs that cause delays and a lower level of investments when the discount rate increases.

The different underlying mechanisms for each approach indicates a need for more empirical research to understand the underlying preferences and risk attitudes of real-world investors and companies for more realistic modeling assumption and for providing more accurate policy insights.

3.3. Impact of different levels of uncertainty

This section discusses how different levels of uncertainty in the carbon price, together with risk aversion, would affect the investment decision and the transition to a low-carbon electricity system (see Eq. (1) for how uncertainty is modeled and see Table 1 for the case design.)

Fig. 9 displays the system's cumulative CO_2 emissions for different levels of carbon price uncertainty under different levels of aversion against losses. The result shows that if the company is risk neutral, or exhibits a relatively low level of aversion against loss ($\lambda = 3$), cumulative emissions stay at almost the same level as the carbon price uncertainty increases, but if the company has a relatively high level of aversion against losses ($\lambda = 5$ and $\lambda = 7$), the cumulative CO_2 increase along with the uncertainty level of the carbon price.

The increase in CO_2 emissions here is caused by the delayed adoption of low-carbon technologies, which leads to higher usage of fossil power plants for electricity production. With a higher uncertainty level (a higher ΔCO_2 value), the uncertainty range of the carbon price in $\overline{p}^{CO2}_{future}$ will be larger. This leads to a higher probability that a low-carbon technology would be not profitable, and fewer investment decisions are taken overall. Further, as discussed above, initially when the system is dominated by coal and gas, these technologies are in most time slices on the production margin causing a high degree of covariance between the carbon price and the electricity price. This implies that the variability of the returns (including the probability of a loss) in these technologies is smaller than for nuclear, solar and wind.

Moreover, Fig. 10 shows that when a company is highly averse to losses (λ=5 and λ=7), a higher uncertainty in the carbon price would lead to higher electricity prices, consequently, the electricity price could be mitigated by reducing the perceived uncertainty level in the carbon price among the investors (lower ΔCO_2 value). The higher electricity price is due to an overall lower amount of investments in nuclear, solar and wind, but more investments in gas-fired capacity (Fig. 11), which has a relatively high running cost, and a larger load factor of existing coal plants, which also have a high running cost when the carbon price

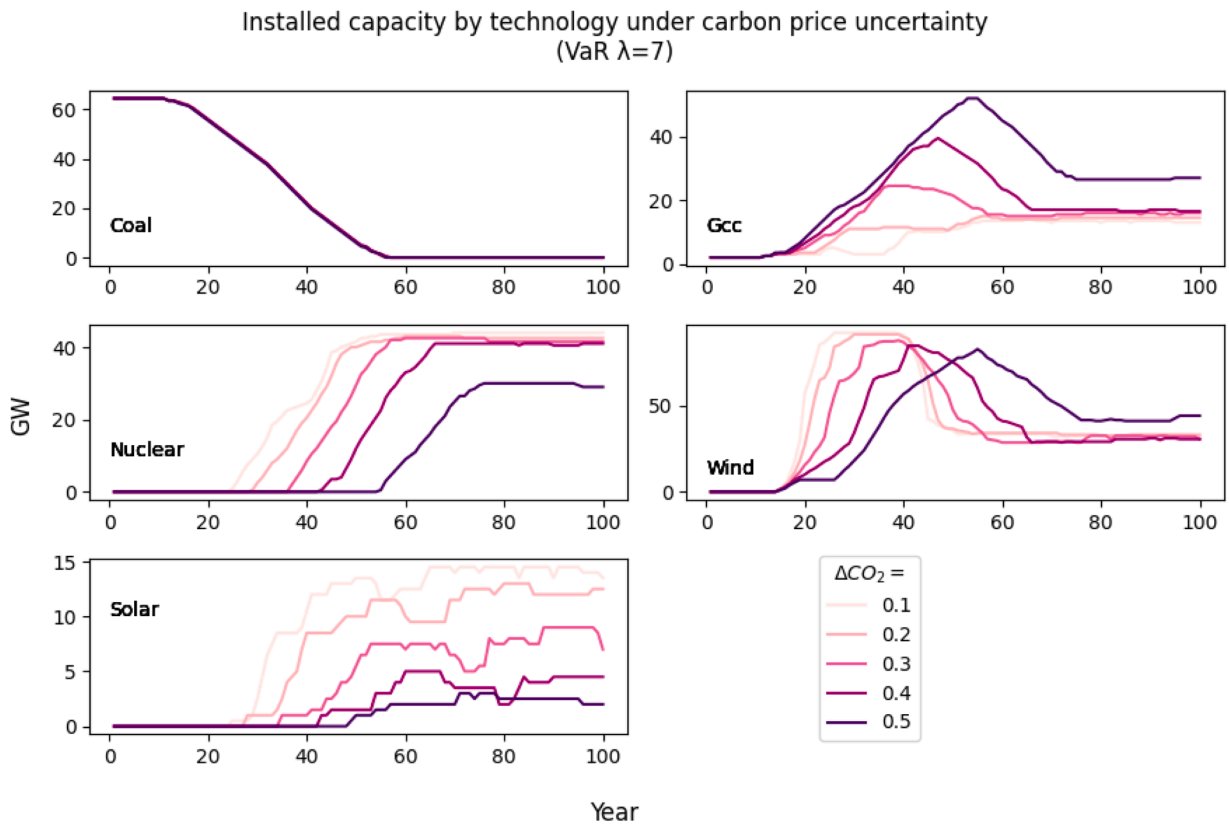

Fig. 11. Installed capacity of each technology for different levels of carbon price uncertainty. When the uncertainty level is higher (a higher ΔCO_2), we observe a further delay in investments in low-carbon technologies and more investments in GCC. (Note that the scale is different for each panel. The risk aversion parameters in this plot are set as $\lambda = 7, \gamma = 0, \mu = 6\%$/year).

grows. This relates to the covariance of the carbon and electricity prices as discussed above.

4. Conclusion

Timely investments in low-carbon technology are crucial for the low-carbon transition of the electricity system. In this study, we model companies' investment decisions in new power plants under climate policy (specifically, carbon price) uncertainty and risk aversion. We explicitly model companies' expectations about future carbon prices and analyze how the perceived uncertainty in the prices combined with different levels of risk aversion affects companies' investment decisions, and in turn, how these investments affect the low-carbon transition of the electricity system.

Additionally, by reviewing the literature on the energy system study, we found that different methods have been used to model risk aversion, but there is a lack of an explicit comparison of how these different approaches affect investment decisions and the response of the overall system. In this study, we compare three different approaches to modeling risk aversion, where we distinguish the aversion against losses (the Value-at-Risk approach), aversion against fluctuations in average returns (the mean-variance approach), and the risk-adjusted discount rate approach.

Three main conclusions can be drawn from this study.

First, we find that uncertainty in the carbon price together with risk aversion will delay the transition to a carbon-free electricity system. As the uncertainty surrounding carbon prices increases, or as an investor becomes more risk-averse, the delay in transitioning to low-emission electricity production grows, resulting in higher cumulative CO_2 emissions from electricity generation. This implies that to avoid delays and low levels of investments in low-carbon technologies, it is helpful if policymakers can provide credible policy commitments that could lower investors' perceived risk. In addition, a high level of carbon price uncertainty and risk aversion would also lead to an overall lower investment level, which leads to a higher electricity price for the consumer. As increases in energy prices have a significant distributional impact, and are especially adverse for low-income households [4], there may be a need for policymakers to take measures to reduce the impact if they are induced by uncertainty in policy frameworks.

As emphasized by the IEA [21], establishing robust, consistent, and long-term policy signals for CO_2 emission reduction is crucial. Governmental plans, roadmaps, and targets play a vital role in determining the trajectory and speed of the transition. These should be supported by mandatory CO_2 reduction policies that grow increasingly stringent over time, including mechanisms like emissions trading schemes, carbon taxes, or transferable CO_2 performance standards. In addition to policy certainty, other risk mitigation instruments can be employed to reduce investors' risk aversion when investing in renewable energy. As noted by IRENA [23], governments and development banks may implement risk mitigation tools, including guarantees (e.g., loan guarantees and off-taker guarantees), insurance products, and partnerships among investors, local financial institutions, and national governments. These measures aim to reduce investors' exposure to risks such as political, policy, credit, and currency fluctuations. This paper does not aim to provide a definitive policy recommendation but rather to list a range of policy options that could be further explored in future research.

Second, from a methodological modeling perspective, this study shows that the timing and amount of the investment differ between risk neutral and risk averse companies. This implies that when modeling investment decisions, it is important to take into account companies' risk aversion behavior. This also calls for more empirical research to better understand the investor's attitude towards uncertainty and risks. Specifically, this research should focus on examining how investors react to deviations from average returns and losses occurring in the tail end of the return distribution.

Finally, by implementing three different approaches – the VaR approach, the mean-variance approach, and the discount rate approach – to model how investors behave when facing risk, we find that in general, these three approaches give similar results, which is that risk aversion tend to delay the transition. Nonetheless, the reason for the delays and the specific mechanisms dictating preferences for technology investments differ across the three approaches. Using the VaR approach means the investor focuses on the tail of the profit distribution, whereas the mean-variance approach means the investor is averse to the spread of the returns, and using the risk-adjusted discount rate approach means that the investor becomes averse to capital-intensive technologies. The implication is that when modeling risk aversion, modelers should understand the behavior and decision criteria of companies in order to choose the method that suits the research question best. Only in this way, modeling results can then be productively transferred to the policymaking sphere.

Data availability

A full model description can be found online at https://github.com/happiABM/uncertainty_and_risk_aversion. The model code and data are also in the same repository. The model is programmed in Python 3.9.

CRediT authorship contribution statement

Jinxi Yang: Conceptualization, Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Sabine Fuss:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Supervision. **Daniel J.A. Johansson:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Funding acquisition. **Christian Azar:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.egycc.2023.100110.

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