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Multi-Commodity Real Options Analysis of Power Plant Investments: Discounting Endogenous Risk Structures

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Abstract

The value of power generation technologies can be derived from the investment cost, the plant's expected lifetime, and the discounted cash-flows, the latter of which typically are a combination of several underlyings, such as the price of fuel, electricity, and CO_2. To determine this value, most studies assume predefined, uniform, and constant discount rates, irrespective of the fact that the specific risk strongly varies with the technology concerned and also over time. In order to endogenize the technology-specific risk, we develop a new model that explicitly accounts for the (likewise technology-specific) combination of the underlyings. More specifically, we use a multivariate binomial tree real options approach for analyzing the value of different power plants (gas-fired and coal-fired, with and without carbon capture and storage (CCS); hydro; wind; photovoltaics) and for taking into account technical change. We further investigate the influence of alternative CO_2 policies on the plants' values, modeling the CO_2 price in three different ways and for three different carbon price levels (5, 25, 45€/t_{CO_2}): (1) as a stochastic process (Geometric Brownian Motion), reflecting the price development in the Emissions Trading Scheme of the European Union (EU ETS); (2) as a (constrained) stochastic process with a price floor, and (3) as a deterministic carbon tax. From the model application, using data from German exchange-based markets and a much-cited pilot study on future energy strategies and scenarios in Germany, we find a strong preference for hard-coal power plants in the low CO_2 price scenario (P_{2015} = €5) and a low value of waiting, irrespective of the CO_2 price policy assumed. In the case of the moderate CO_2 price scenario (P_{2015} = €25), the value of waiting is much higher for the CO_2 permits with a price floor and the CO_2 tax policy, leading to a dominance of the CCS power plants. In contrast, for the simulated EU ETS market, the conventional fossil fuel-fired power plants dominate the other technologies. In the high CO_2 price scenario (P_{2015} = €45), the value of waiting only delays the investment decision in the case of the floored CO_2 permit prices. For the two other policies, the model predicts an immediate investment in CCS power plants once the CCS technology becomes commercially available in 2020.

Key words: Real options, CAPM, multivariate binomial tree, carbon tax, energy technology choice, endogenous discount rate

1 Introduction

Increasing volatility of prices, technical change, and regulatory uncertainty all render investments in power generation assets more and more risky, calling for stochastic model approaches to support investment decisions. Therefore, the literature on stochastic models and their application to the energy sector has flourished in recent years. Reinelt and Keith (2007), for instance, investigate the cost of regulatory uncertainty in carbon capture retrofit investments, based on a two-dimensional model (volatile natural gas price, uncertain carbon regulations) for different coal-fired power plants using Bellman's Principle of Optimality (Bellman, 1957). However, such a separated comparison of alternative investment options is insufficient and remains silent about both the optimal timing of investment and the optimal technology mix.

Real options (RO) models (Black and Scholes, 1973; Dixit and Pindyck, 1994) are attractive in this respect and also account for the value of waiting (McDonald and Siegel, 1986). Therefore, it is not very surprising that in recent years RO models have been increasingly applied also in the energy literature, even though most applications have only dealt with a single stochastic variable at a time. However, multi-dimensional RO models (see McDonald and Siegel, 1986; Boyle et al., 1989) that account for several stochastic processes are still rare and usually neither account for multiple technology choices nor for risk-adjusted discounting caused by the correlation of the underlying assets concerned. In Siddiqui and Fleten (2010), a two-dimensional RO problem is solved in order to address the question of how a staged R&D program could be optimally implemented under uncertain electricity prices and operating cost. In Fleten and Näsäkkälä (2010), a similar approach is applied, modeling the spark spread and the electricity price stochastically. Whereas for the two-dimensional problem the option value can be determined analytically, for higher-dimensional problems only an expression for the threshold value can be found (Rohlfs and Madlener, 2011). In order to overcome this problem, Gahungu and Smeers (2009) suggest a Monte Carlo approach, allowing at least for a numerical approximation of the option value. Abadie et al. (2010, 2011) apply a three-dimensional RO model based on a binomial lattice in order to determine the optimal timing of abandonment of a coal-fired power plant in the European Union. A general approach to model the managerial flexibility inherent in multiple real options with multiple sources of risk is addressed in Kienzle and Andersson (2009). In their model application, two combined heat and power (CHP) plants are compared with each other, using a three-asset Monte Carlo simulation.

In this paper, we also model the situation of an investor facing the choice between different power plant technologies and having the additional flexibility to postpone the investment decision. Because all technological options considered generate electricity (or eventually additional heat or process steam), the future returns gained from such investments are determined by a few basic underlyings, such as the fuel, electricity, and carbon prices. Thereby, the economic risk of these prospective returns depends on the uncertainty of the single underlyings as well as on their combination, which is technology-specific. Therefore, we aim in our study to endogenize the risk treatment, e.g. by applying an endogenous discount rate. This endogenous risk treatment is afflicted with two main obstacles.

First, under the assumption of time-constant parameters (e.g. growth rate and volatility) for the stochastic processes of the underlyings, the risk of the prospective returns becomes time-dependent when constant ratios between input and output quantities are prescribed. This results in a time-dependency of the optimal technology. In order to perform the desired dynamic optimization of the investment strategy, the RO approach, which incorporates the value of waiting, is well suited for the problem at hand. Nevertheless, multi-asset option models in general assume that, once the investment has been made, the share of the different underlyings (assets) remains constant over time, leading to a time-invariant solution. This implies that neither the growth rate nor the volatility of the portfolio of underlyings must vary over time. However, due to the different performance of the underlyings, in reality, the portfolio would have to be readjusted over time, as the share of the well-performing assets in the portfolio increases, while the share of the others decreases. In the case of energy conversion (e.g. electricity generation) plants, the choice of the applied technology defines the input and output quantities as well as the ratio between them for the entire lifetime of the plant. With such a constant ratio between the input and output quantities, however, the influence of the resulting incoming and outgoing cash flows (e.g. for fuel, electricity, and CO_2 permits) on the prospective returns is directly coupled to the ratio between the asset prices. Due to unequal growth rates predicted for the prospective prices of the assets, a strong time-dependence in the ratio between the various input and output cash flows can be expected.

Second, a further main obstacle in the decision-making process is the evaluation of uncertain cash flows gained at different times. Due to the strong correlation of subsequent returns, a separate valuation of the resulting cash flows remains inaccurate. This problem can be illustrated by the following example. Let us suppose an uncertain cash flow in the first period that takes a value of either 100 or 200 (both, for simplicity, with the same probability). Due to the associated uncertainty, a risk premium would be required, reducing the expected utility below the utility of the average cash flow of 150. In the next period, the same cash flow may be gained but, due to the correlation between the two periods, the cash flow would be 100 if the cash flow of the previous period was 200, and vice versa. A segregated treatment of this period would again require a risk premium. However, if the cash flows of both periods are evaluated jointly, the associated risk vanishes. This example illustrates that discounting methods that combine risk- and time-discounting cannot be applied when cash flows with strong correlations between different periods are considered. Therefore, in our study, a segregated risk- and time- discounting method is applied.

The original contribution of this paper is threefold:

(1) From a modeling perspective, we present an RO-based approach, which allows for determining the optimal technology as well as the optimal time to invest for the case that the investor commits himself with the installed plant to a fixed ratio between inputs and outputs. This approach, because of its mathematical complexity, loses analytical tractability and requires a mixed binomial lattice and Monte Carlo approach with a segregated time- and risk-discounting. This discounting strategy allows to account for the technology-specific economic risk.

(2) From the investor's perspective, the application of the proposed model gives in-

sights into an optimized decision process when multiple technological options exist and replications for the underlying assets cannot be performed. Specifically, we evaluate the option value of investing in different types of power plants (gas-fired and coal-fired, with and without carbon capture and storage (CCS); hydro; onshore and offshore wind; photovoltaics), also taking into account the impact of technical change, which manifests itself by decreasing investment and operation and maintenance (O&M) cost as well as energy efficiency gains.

(3) From a political perspective, the model provides new insights into the effect of various CO_2 permit auctioning strategies. Thereby, regulatory uncertainty concerning climate change policies is addressed by modeling the CO_2 price in three different ways: (a) as an unconstrained stochastic process, (b) as a constrained stochastic process with a floor price, and (c) as a deterministic carbon tax. We show how a CO_2 price floor in the auctioning process affects the investment decision. Surprisingly, we find an unexpected extension of the delay time, which, however, can be explained by the elimination of price paths having a negative effect on the value of waiting.

The remainder of this paper is organized as follows: In Section 2 the RO model with the segregated discounting is described. Section 3 summarizes the economic and technical data used for the model application. Section 4 presents the results obtained, and the impact of varying the CO_2 price. Section 5 concludes and presents some political implications.

2 The model

The present study aims at determining the optimal technology to invest, as well as the optimal time to invest, for the case that an electric utility has the choice of building a new power generation unit. The concept of the model is presented in Fig. 1. The core of this model is a multi-dimensional real options approach (more precisely: an option to wait, see McDonald and Siegel, 1986), where the value of all technological options is based on multiple underlying assets (fuel price, electricity price, CO_2 price), following correlated stochastic processes.

In order to allow for a more realistic approach and thus a more complicated modeling (e.g. technological innovation, floored prices), we make use of the multi-dimensional lattice method (for the one-dimensional case introduced by Cox, Ross, and Rubinstein, 1979, hereafter CRR, and explained in subsection 2.2). Starting with a known state at $t = 0$

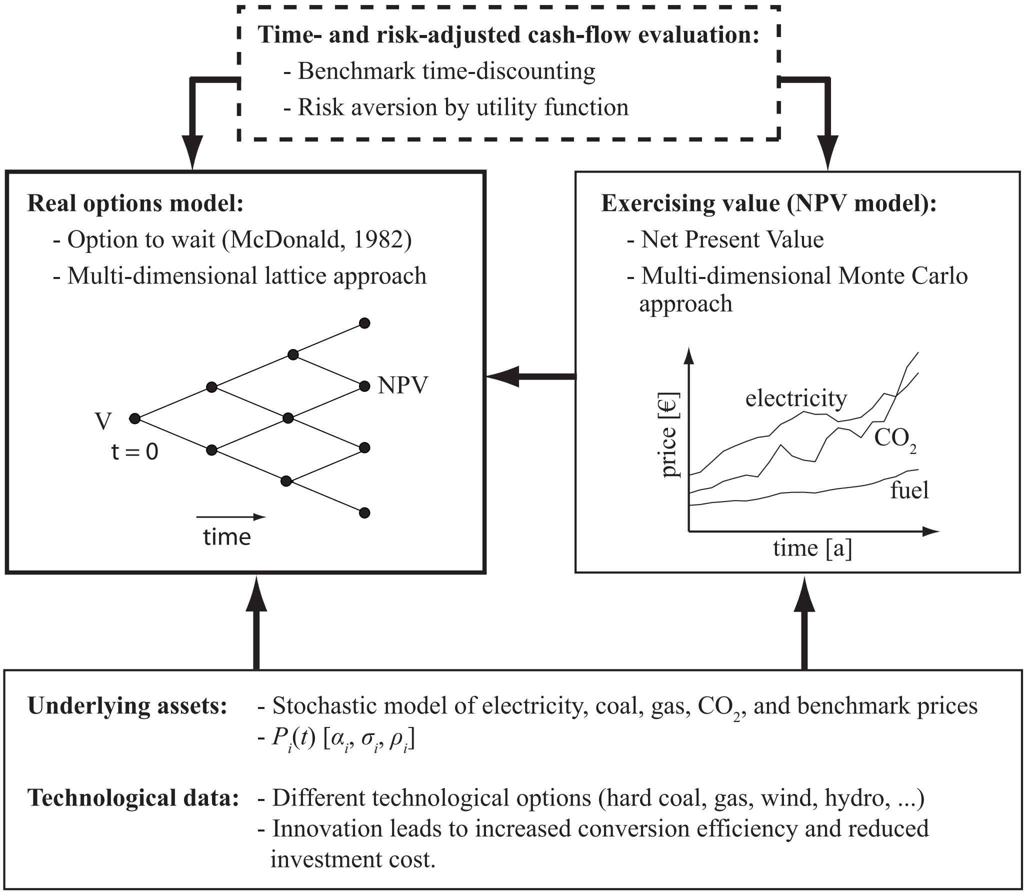


Figure 1: Schematic model description

with the deterministic prices $P_i(t = 0)$, the multi-dimensional tree is constructed, thereby accounting for the different growth rates, volatilities and correlations between all underlying assets. Rolling up the decision tree, the investor is given the opportunity to invest in one of the various power plants or to delay the investment decision by one period, depending on the exercising value and the value of waiting. Formally, this yields an option value, $V(t)$, of the form

$$V(t) = \max(NPV_i, V(t+1)_{\text{discounted}}, 0). \tag{1}$$

The exercising value of the option is given by the NPV of the best-performing power plant. This exercising value of all technologies at each node is calculated using the same stochastic processes of the underlying assets by way of the Monte Carlo simulation technique (see subsection 2.3). The time- and risk-adjusted cash flow evaluation, grounded on benchmark time-discounting and an approach for risk-discounting based on a utility function, builds the bridge between the two models.

2.1 Stochastic price path modeling

In this study, m stochastic price processes are used to model the various price paths and the path of the benchmark asset. We assume that all those paths can be described by simple Geometric Brownian Motions, with constant growth rates α_i and volatilities σ_i, yielding

$$\frac{dP_i(t)}{P_i(t)} = \alpha_i dt + \sigma_i dZ_i, \tag{2}$$

where dZ_i are increments of correlated Gauss-Wiener processes, so that $E[dZ_i dZ_j] = \rho_{ij}dt,\ i \neq j$, and ρ_{ij} denotes the correlation between process i and process j.

2.2 Construction of the n-dimensional lattice

For the development of the multi-dimensional lattice, we apply the commonly used method of logarithmic prices (see Abadie and Chamorro, 2008; Abadie et al., 2011) but in contrast to these references, we remain in a risky world. Hence we start with a logarithmic transformation of the price variables, such that

$$x_i(t) \equiv \ln P_i(t). \tag{3}$$

Applying Itô's Lemma for the dynamic processes, it follows from Eq. (2) that

$$dx_i(t) = \nu_i dt + \sigma_i dZ_i(t). \tag{4}$$

For a discrete time step, Δt, the first momentum of Eq. (4) is given by

$$E[\Delta x_i] = \alpha_i \Delta t \tag{5}$$

and the second momentum by

$$E\left[\Delta x_i^2\right] = \sigma_i^2 \Delta t + \alpha_i^2 (\Delta t)^2. \tag{6}$$

For the correlation of two processes, the following condition must hold:

$$E[(\Delta x_i - \alpha_i)(\Delta x_j - \alpha_j)] = \rho_{ij}\sigma_i\sigma_j\Delta t. \tag{7}$$

From Eqs. (5)-(7) two conditions for each asset ($2m$) and one correlation for each asset combination $[m(m-1)/2]$ result. The number of nodes from the multi-dimensional lattice approach is given by 2^m, leading to the same number of unknown probabilities. Additionally, the values of Δx_i are unknown. Overall, we have $(2^m + m)$ unknowns and $(m^2 + 3m)/2$ equations plus the trivial assumption that the sum of all probabilities equals unity ($\sum p_i = 1$).

To construct the nodes of the lattice, different options exist. One possible and common way is to impose the discrete increments (Δx_i) and to calculate the corresponding probabilities. For a one-dimensional lattice, this method goes back to the CRR model (Cox et al., 1979). This procedure can also be applied for the case of multi-dimensional lattices (for the two-dimensional case, see Boyle et al., 1989). However, the method may lead to negative probabilities when a high correlation between assets exists. In order to overcome this inconvenience, various approaches have been proposed in the literature. Gamba and Trigeorgis (2007), for instance, use a log-transformed binomial lattice approach, but still face the (reduced) problem of negative probabilities. To overcome this imprecision, we first analyze their cause in the lattice approximation. To illustrate this, Fig. 2 depicts iso-probability contours for two correlated assets with various correlation coefficients. If the nodes of the binomial tree form an orthogonal grid, as in the CRR model (upper three

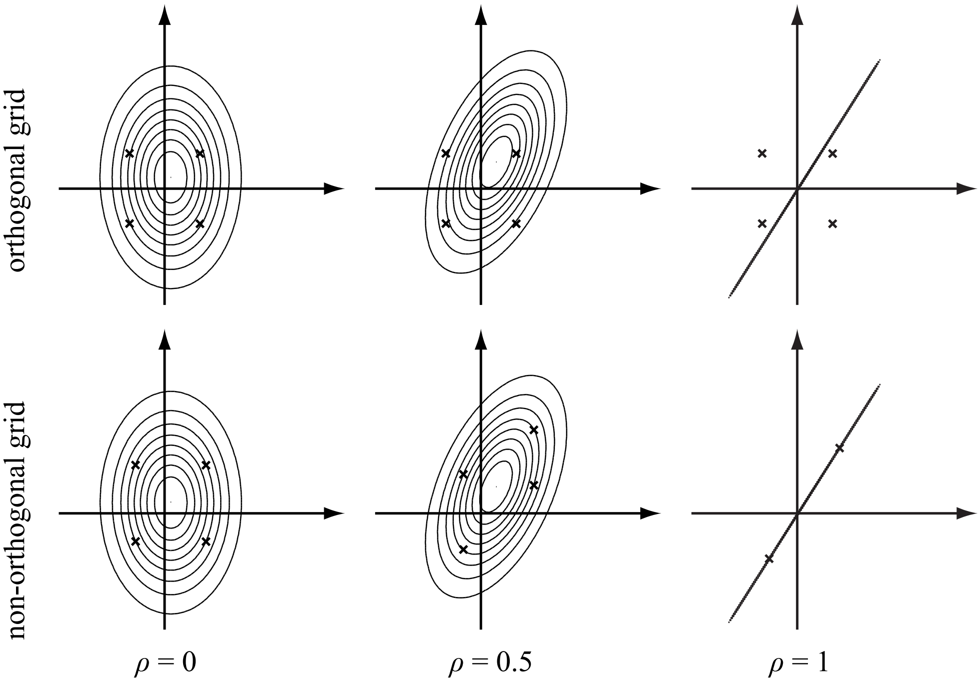


Figure 2: Orthogonal vs. non-orthogonal grid in the case of different correlation coefficients

graphs), the discretization of the probability distribution becomes imprecise for higher correlation coefficients. For perfectly correlated assets ($\rho = 1$), e.g., when the probability distribution becomes quasi one-dimensional (with a new axis orientation), a rectangular discretization definitely fails to reproduce the desired distribution. Therefore, we apply a method proposed by Rubinstein (1994), constructing a non-rectangular tree for m different assets. In this method, the discrete increments (Δx_i) are rotated and translated in a way such that their orientation matches with the one of the correlated, non-centered distribution.

To practically determine the nodes of the non-rectangular tree, we first transform the yearly variances and the growth rates to the desired width of the time step Δt according to $\sigma_{i,\Delta t} = \sigma_{i,1}\sqrt{\Delta t}$ and $\alpha_{i,\Delta t} = \mu_{i,1} \cdot t$. Thereafter, we construct the covariance matrix $\boldsymbol{Cov(X_i, X_j)}$ with given variances and correlation coefficients. As this is a symmetrical positive-definite matrix, Cholesky decomposition can be applied, yielding a lower-triangular matrix $\boldsymbol{L_{ij}}$. Multiplying a vector containing all node directions (with the length of unity in each direction) by this lower-triangular matrix and adding the corresponding growth rate to each node, we receive a matrix that contains again the vectors of all node directions, but this time adjusted in such a way that all nodes are afflicted with an equal probability of $1/2^m$.

2.3 Evaluating the node-specific option value

In options theory, the evaluation of the option value begins at the end branches of the binomial tree when exercising the option (roll-up). In the case of real options, the exercising value at the specific node is commonly given by the NPV of the investment. As we do not retain the classical NPV approach (where time and risk are coupled), and instead make use of benchmark time-discounting, combined with utility functions for an enhanced treatment of risk structures, the utility value and not the NPV is used for the evaluation. With multiple investment options available, the technology with the highest utility is chosen. If all utilities are negative at the strike date, the option will expire with a value of zero (no investment). For the preceding nodes, the additional option of postponing the investment decision arises, creating a value of waiting. The value of waiting is the utility of the time-discounted NPV of the 2^m subsequent nodes. Note that the utility of the time-discounted NPV does not confirm with the option value of the subsequent nodes, as the utility cannot directly be time-discounted. Therefore, the option value can formally be written as

$$V(t) = \max \left\{ U[NPV(i,t)], U\left[\frac{1}{2^m} \sum_{i=1}^{2^m} \left(\beta U^{-1}(V(t+1)) \right) \right], 0 \right\}, \tag{8}$$

where $V(t)$ represents the option value at the current node. For time-discounting, the deflator β is introduced, which results from an additional stochastic process (also correlated to the basic underlying assets), representing the evolution of the market value of a well-diversified portfolio (see subsection 2.5 for details).

2.4 Computing the node-specific exercising value

At each node in time t_d (d indicates the time of decision-making), the expected returns of all available investment opportunities have to be estimated, based on the actual prices at the specific node. As all prices are assumed to follow stochastic processes, the resulting exercising value is stochastically distributed, displaying the riskiness (or risk structure) of the proposed investment. In order to account for the flexibility to abandon the operation of the power plant in cases where the cost of the input quantities exceeds the revenues of the outputs, we limit the total loss of each period to the O&M cost, $C_{\mathrm{O\&M}}$. Formally, this yields

$$\begin{aligned} NPV(j,t_d) &= \int\limits_{t_d}^{t_d+LT(j)} \beta(t^*)CF(t^*)dt^*, 0 - I(j,t_d) \\ &= \int\limits_{t_d}^{t_d+LT(j)} \beta(t^*)\sum_i \left\{\max[c_i(j,t_d)P_i(t^*), C_{\mathrm{O\&M}}]\right\} dt^* - I(j,t_d), \end{aligned} \tag{9}$$

where $P_i(t^*)$ is the price of the commodity i, which again follows a Geometric Brownian Motion and factor $c_i(j,t_d)$ denotes the weighting of the price, dependent on the specific power plant j and on the date when the power plant is built, t_d (thus allowing for technical change). For example, the weighting factors of a conventional power plant built at $t_d = 2015$ are $c_{\mathrm{el}} = 2.5 \cdot 10^6\,\mathrm{MWh}/\mathrm{a}$, $c_{\mathrm{coal}} = -6.3 \cdot 10^5\,\mathrm{t_{coal}}/\mathrm{a}$, $c_{\mathrm{CO_2}} = -1.6 \cdot 10^6\,\mathrm{t_{CO2}}/\mathrm{a}$, $c_{\mathrm{gas}} = 0\,\mathrm{m^3}/\mathrm{a}$, and $c_{\mathrm{O\&M}} = -1.3 \cdot 10^7$ (negative values imply that the corresponding commodity price causes costs instead of revenues). The variable $I(j,t_d)$ denotes the investment cost of the power plant j at time t_d. Integrating the instantaneous cash flows over lifetime $LT(i)$ additionally allows to account for technology-dependent plant lifetimes. Due to the temporal distribution of the cash flows, an adequate time-discounting is required, for which the deflator β is again used. Further information regarding the discounting is provided in subsection 2.5 below.

Due to the lack of an analytical tractability of Eq. (9), the Monte Carlo Simulation technique is used to determine the distribution of the NPV, evaluating the cash flow at time t by the prevailing prices of the respective simulation path.

2.5 Time- and risk-discounting

In the presented NPV approach for the exercising value as well as in the real options approach itself, the cash flows and option values have to be discounted in order to account for their temporal character and their uncertainty. This implies that cash flows gained at different times have to be somehow combined. By doing so, it is assumed that an investor generally prefers earlier cash flows, which can then either be used for consumption or be reinvested. Additionally, the risk adjustment should account for the fact that the economic risk varies with the applied technology due to the different combinations of the underlying assets. Therefore, the risk evaluation constitutes one of the main obstacles in this study. The desired method of discounting has to fulfill the following requirements:

1. Reflecting the project or power plant's specific risk structure;
2. Consistency between the NPV and the RO approach;
3. From the RO approach: The discounting must be higher than the average growth rate, as otherwise the investment is always made at t_{end};

Standard asset pricing models, such as for example the CAPM (see Sharpe, 1964; Lintner, 1965), perform a segregated treatment of the cash flows of different periods. Following the Fisher separation theorem, this discounting procedure is well-suited for investors able to diversify their capital. However, although electric utilities try to optimize their power plant portfolio in terms of risk and return, they usually remain in the field of their core competence in order to make profits. Therefore, we build the discounting method upon a different basic principle. Specifically, we assume that the shareholders of the electric utility in general request an equal or better performance of the proposed project than they could achieve by investing in another benchmark project or share. By accounting for the correlation between the benchmark share and the project, a discount factor β (deflator) can be constructed according to

$$\beta = \frac{P_M(\tau)}{P_M(t)}, \tag{10}$$

where $P_M(\tau)$ denotes the price of the market-based benchmark share at the reference point in time and $P_M(t)$ is the respective price at the actual time. In our model application, we exemplarily focus on an investment decision in the European area, which is why we use the German stock market index DAX as the benchmark asset. As the average growth rate of the investment surpasses in many cases the stock market growth, the third requirement does not hold, leading to a maximum (infinite) delay of the investment decision. Therefore, we further request an additional rate of return r, expanding the deflator to

$$\beta = \frac{P_M(\tau)}{P_M(t)} \cdot \frac{1}{(1+r)^{t-\tau}}. \tag{11}$$

Note that this extension of the deflator must be interpreted as a time preference of the investor and not as a risk premium.

The time-discounting method described above is applied to evaluate the exercising value by way of the Monte Carlo simulation technique. This leads, for each simulated path, to an expected value and thus to a distribution displaying the associated risk structure of the project. To reduce this distribution to a single, risk-adjusted expected value, as is needed in the real options approach, a risk-adequate evaluation of this distribution is required. Following the basic theory, risk aversion can be explained by concave utility functions (von von Neumann and Morgenstern, 1944), which transform the nominal cash flows into utility values. Due to the concave shape, the marginal gain of utility decreases with increasing nominal value. The nominal value of the average utility is, therefore, always less than the average nominal value itself (as shown in Fig. 3). Due to the fact that also negative exercising values may occur, the utility function has to be defined for positive and for negative values. One possible and adequate shape for the utility function is given by a

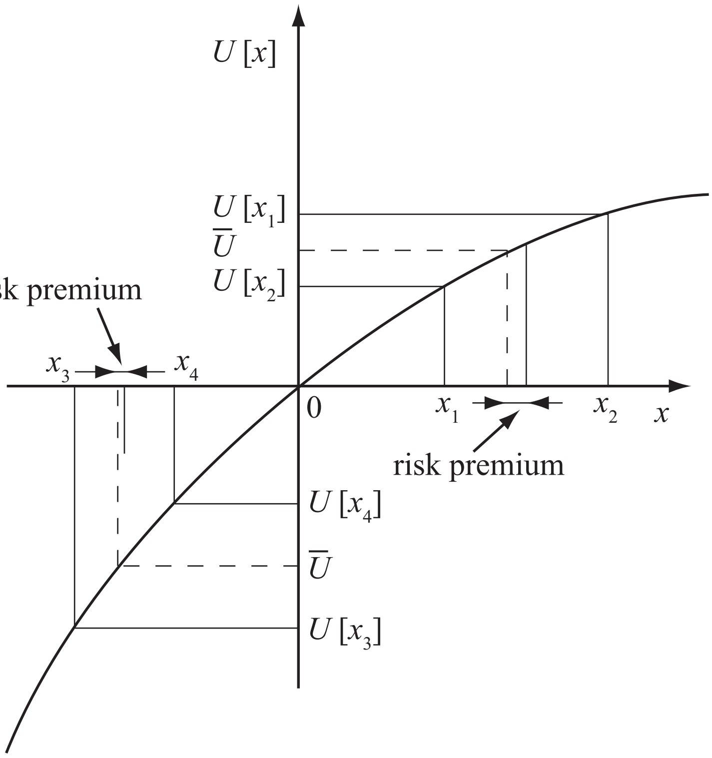


Figure 3: Discounting by means of a utility function

quadratic function, according to

$$U(x) = a \cdot (x + c) - b \cdot (x + c)^2. \tag{12}$$

In this case, the constants a, b, and c have to be adjusted to express the investor's attitude towards risk. The constant b represents the risk aversion of the investor and the constant c shifts the utility function, allowing for the evaluation of negative values. Note that while the marginal utility decreases with increasing nominal value, the marginal negative utility increases for higher losses, also indicating risk-averse behavior. This implies that the investor would prefer a certain loss of, say, 75 units compared to an uncertain loss of either 50 or 100 units. Note that this assumption is contrary to the S-shaped utility function from prospect theory (see Kahneman and Tversky, 1979), predicting in the negative branch a risk-loving investor (convex shape) as well as a saturation for gains and losses. However, in our analysis we decided to rule out negative saturation, assuming that the maximal loss of the proposed investment does not exceed the funds of the investor.

In the RO model, the option to wait includes the discounted option value of the subsequent time step, $(t+1)$. Keeping a consistent separation between time- and risk-discounting, the average utility at time t, $\overline{U[x(t)]}$, is given by the utility of the discounted values of the underlyings at time $(t+1)$, i.e.

$$\overline{U[x(t)]} = \overline{U[\beta \cdot x(t+1)]}. \tag{13}$$

Note that this equation implies the discounting of the expected values with the deflator β before applying the utility function and before averaging. The direct application of this equation requires that all expected values obtained from the Monte Carlo simulation of $(t+1)$ have to be stored, leading to high computational cost. A solution to this problem is to factor out the deflator β, leading to

$$\overline{U[x(t)]} = \beta^* \cdot \overline{U[x(t+1)]}, \tag{14}$$

where $\overline{U[x(t+1)]}$ is the only variable known from the previous time step and β^* a modified deflator. Unfortunately, the sum of the linear and the quadratic part in Eq. (12) does not allow for such a direct separation approach. Therefore, it is necessary to store the average linear value $\overline{x}$ as well as the average quadratic value $\overline{x^2}$, which can be discounted separately according to

$$\begin{aligned} \overline{x(t)} &= \beta \cdot \overline{x(t+1)}, \\ \overline{x^2(t)} &= \beta^2 \cdot \overline{x^2(t+1)}. \end{aligned} \tag{15}$$

2.6 Numerical simulation

All simulations in this section were performed with the same temporal discretization. For the real options model, only a limited number of time steps $(N = 7)$ with a step size of

$\Delta t_{RO} = 5\,\mathrm{a}$ has been used (starting from 2015 and ending at 2050). Due to the strongly increasing computational effort with the number of steps, seven steps were found to be still feasible for simulations of five-dimensional options pricing. The step size for evaluating the exercising value at each node by the Monte Carlo NPV approach is $\Delta t_{NPV} = 1\,\mathrm{a}$. Because of the large number of resulting nodes (32,768 at the last time step[1], the number of price paths in the Monte Carlo simulation has been limited to $n = 100$ for all time steps except the first and the second ones, where $n = 10,000$ and $n = 1000$, respectively. The computation time needed is up to 25 minutes in a non-parallelized simulation on a quad core computer (2.4 GHz) for the case that all nine technological options (see Table 2) are taken into account. In order to evaluate the accuracy of the results, the complete simulation has been performed ten times. Therefore, the mean, minimum, and maximum option values are presented for each parameter variation in turn. For the time-discounting, a markup of 4% on the return of the benchmark asset has been assumed for all technologies considered.

3 Data

3.1 Economic data

The economic and market boundary conditions are, on the one hand, very important and, on the other hand, at the same time highly controversial. Because of the power plant's long life-span, long-run projections for the underlying assets are necessary. As we consider the latest investment decision in 2050 (with the technological data provided in subsection 3.2) and a maximal lifetime of 30 years (hydro power), price projections until 2080 are required.

In this study, the parameter set used is built upon two different sources: On the one hand, historical price data provided by the European Energy Exchange (EEX) for electricity, coal, and natural gas as well as the EU ETS emission allowances and, on the other

[1]Note that the 32,768 nodes at the end of the tree represent 34 billion (!) possible price paths.

Table 1: Economic data used

Parameter	$P_{i,0}$ [€]	α_i	σ_i	$\rho_{i,\text{el}}$	$\rho_{i,\text{coal}}$	$\rho_{i,\text{gas}}$	ρ_{i,CO_2}	$\rho_{i,\text{M}}$
P^a_{el}	60	4.00%	4.00%	1.000	0.608	0.702	0.518	0.140
P^b_{coal}	69	4.18%	7.09%	0.608	1.000	0.603	0.250	0.260
P^c_{gas}	5.5	4.03%	6.70%	0.702	0.603	1.000	0.273	0.150
$P^d_{CO_2}$	20	4.14%	7.07%	0.518	0.250	0.273	1.000	0.201
P^e_{M}	1	2.00%	2.00%	0.140	0.260	0.150	0.201	1.000

Notes: [a]base-load futures traded at the EEX (F1BY, July 1, 2002 - February 2, 2012); [b]coal futures traded at the EEX (FT4Y, May 2, 2006 - January 5, 2012); [c]natural gas futures traded at the EEX (G0BY, July 2, 2007 - January 5, 2012); [d]EUA price (F2PE & F2EA, October 4, 2005 - January 5, 2012) at the EEX. [e]German equity index (DAX, March 2, 1992 - January 5, 2012).

hand, the German stock market index DAX for representing the benchmark asset, have been used to determine the correlation coefficients between the assets. For the other two important parameters, the growth rate α_i and the volatility σ_i, in a first go we applied the maximum likelihood method (Hogg and Craig, 1978; Hull, 2008) to the previously mentioned data. Expectedly, the parameters estimated from the historical data of the last eight to ten years lead to implausible results if applied over a projection period of 70 years. Mainly, this is due to the large difference in growth rates and also the high volatilities. Therefore, we calculated the missing quantities from the data provided in the German "Pilot Study 2010" ("Leitstudie 2010" Nitsch et al., 2010). In their study, three different scenarios (high, moderate, and low) with price projections for electricity, coal, gas, and emission allowances, have been proposed. For the growth rate, we used the price development of the moderate scenario. Note that the prices given in Nitsch et al. (2010) are in real terms, based on the year 2007. In our model, nominal prices are used, discounted by a benchmark asset. Therefore, the applied growth rates are increased by the growth rate of the benchmark asset ($\alpha_\text{M} = 2\%$). For the volatility, we assume that the variance of the stochastic processes equals the variance found in the three different scenarios at $t = 2050$. The values estimated are, compared to previous studies (e.g. Rohlfs and Madlener, 2011), very low. Therefore, the proposed model application aims at investigating long-run price uncertainties rather than short-run fluctuations. This assumption is in our opinion justifiable through the long construction lead times of the power plants, rendering short-run price

Table 2: Power plant data

Name, **abbr.**, O&M cost, lifetime		Unit	2015	2020	2030	2040	2050
Photovoltaics, **PV**,	sp. production	$^{kWh}/_{kW_p,a}$	912	916	925	935	946
1% Investment/a, 20 a	sp. invest. cost	€/kW_p	1903	1203	994	937	903
Onshore wind, **ONW**,	av. utilization	h/a	2100	2200	2350	2450	2550
4% Investment/a, 18 a	sp. invest. cost	€/kW_p	1180	1030	980	940	900
Offshore wind, **OFFW**,	av. utilization	h/a	3500	3700	3800	3850	3900
5.5% Investment/a, 18 a	sp. invest. cost	€/kW_p	2625	2100	1800	1500	1300
Hydro, **HYDRO**,	av. utilization	h/a	5494	5516	5541	5566	5593
5.5% Investment/a, 30 a	sp. invest. cost	€/kW_p	2838	2961	3182	3323	3497
Hard coal, **HC**,	efficiency	–	47	50	51	51	51
2% Investment/a, 25 a	av. utilization	h/a	5000	5000	5000	5000	5000
	sp. invest. cost	€/kW_p	1300	1300	1300	1300	1300
	CO_2 emissions	kg/MWh_{el}	656	620	609	609	609
Hard coal Integrated	efficiency	–	–	52	54	54	54
Gasification Combined Cycle,	av. utilization	h/a	–	5000	5000	5000	5000
HC-IGCC	sp. invest. cost	€/kW_p	–	1500	1500	1500	1500
2% Investment/a, 25 a	CO_2 emissions	kg/MWh_{el}	–	598	577	577	577
Hard coal Integrated	efficiency	–	–	43	45	45	45
Gasification Combined Cycle	av. utilization	h/a	–	5000	5000	5000	5000
with CCS, **HC-IGCC-CCS**	sp. invest. cost	€/kW_p	–	2200	2200	2200	2200
2% Investment/a, 25 a	CO_2 emissions	kg/MWh_{el}	–	107	102	102	102
Combined gas and steam	efficiency,	–	59	60	62	62	62
COGAS,	av. utilization	h/a	5000	5000	5000	5000	5000
2% Investment/a, 25 a	sp. invest. cost	€/kW_p	700	700	700	700	700
	CO_2 emissions	kg/MWh_{el}	336	330	320	320	320
Combined gas and steam	efficiency	–	–	50	52	52	52
with CCS, **COGAS-CCS**	av. utilization	h/a	–	5000	5000	5000	5000
2% Investment/a, 25 a	sp. invest. cost	€/kW_p	–	1100	1100	1100	1100
	CO_2 emissions	kg/MWh_{el}	–	59	57	57	57

Notes: Source: Nitsch et al. (2010)

variations rather unimportant for "strategic" investment decisions.

3.2 Specifications of the available technologies

The technological data used are taken from the German "Pilot Study 2010" ("Leitstudie 2010", Nitsch et al., 2010), which provides projections for the required specifications till 2050. Table 2 summarizes the data used. In order to allow for a comparison of the different technologies, we decided to base our analysis on the investment in a power plant with an electricity generation capacity of 500 MW_{el}. Fuel consumption (if any) is calculated by the given net efficiency and the specific energy contents of the fuel (30 $^{MJ}/_{t}$ for hard coal and 8 $^{MJ}/_{m^3}$ for natural gas). The cost for transporting and storing CO_2 (additionally occurring for the CCS technologies with an absorption rate of 90%) is assumed to be 4 $^{€}/_{t_{CO2}}$ (see McCoy, 2008). For the escalation of the transporting and storing cost of CO_2, the market development has been assumed.

4 Results

This section presents results from applying the previously described model, examining the option value as well as the optimal time to invest for the case that all available technologies are treated separately and for the case that the various technologies compete. While subsection 4.1 focuses on investment decisions for the baseline scenario, as described in section 3, subsection 4.2 investigates the influence of a different CO_2 permits price policy, e.g. the influence of a price floor, a deterministic carbon tax, and a variation of the initial CO_2 price level.

4.1 Baseline scenario with investment options treated individually and combined

In the baseline scenario, the economic and technological data presented in Tables 1 and 2 are used. These data mainly agree with those presented in the German "Pilot Study 2010" ("Leitstudie 2010", Nitsch et al., 2010).

Individual option values: The option value for the case that each technology is evaluated separately is shown in Table 3. Additionally to the mean value of the ten simulations performed, the minimum and the maximum are given, showing that a sufficient number of price paths has been simulated in the Monte Carlo simulations.

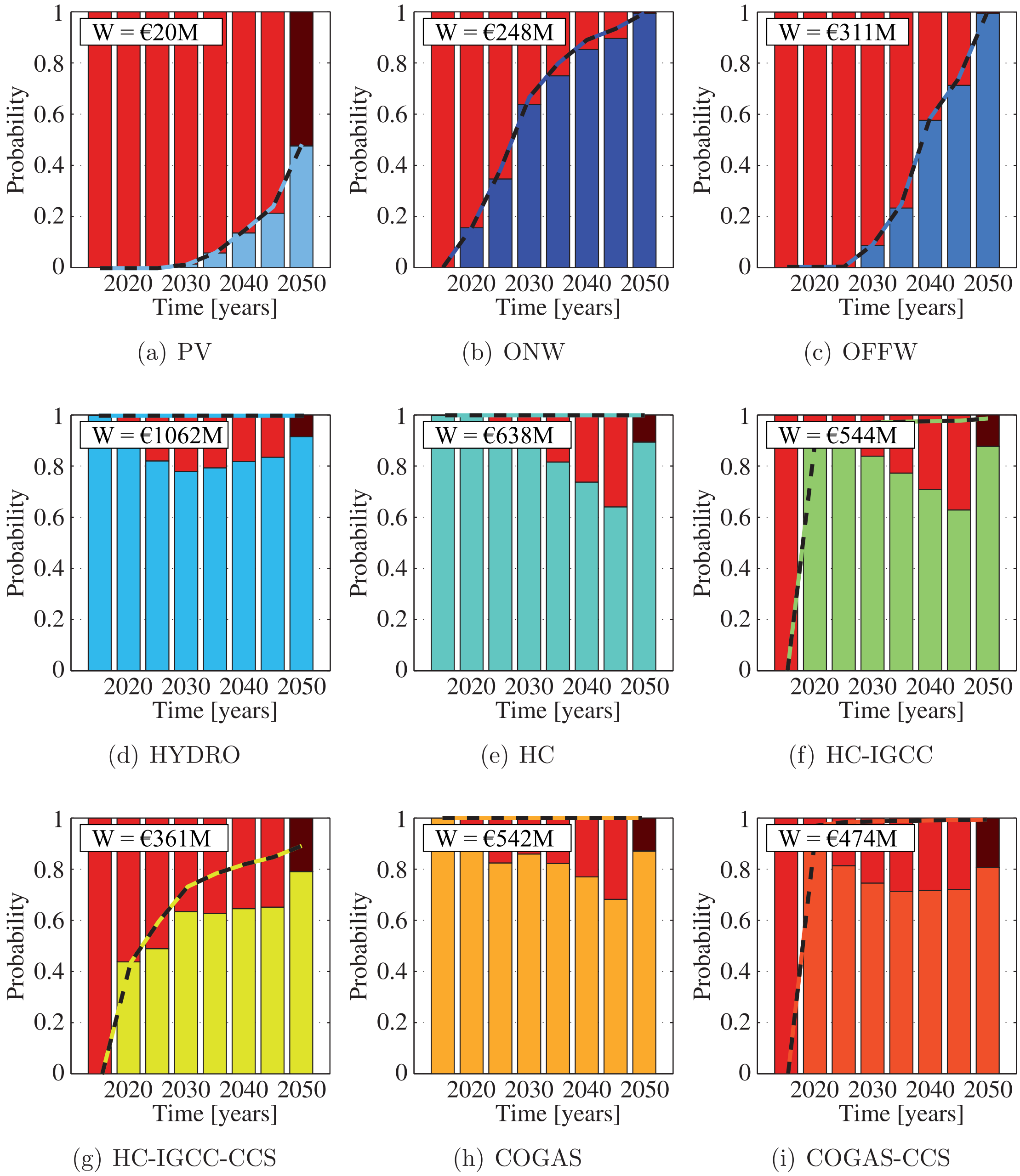
Next to the plain values, plots depicting the probability distribution of the investment decision are presented (see Fig. 4), thereby giving more insights into the decision process.

In general, those figures contain two different pieces of information: First, the eight bars, each representing one time step, illustrate the distribution of the decisions made at the specific time steps resulting from the various states of the world accounted for. Practically, the bars are determined by the sum of the probabilities of each investment decision at each node of the considered time step. For the photovoltaics power plant, for example, we find a probability to end in a state of the world that is preferable to invest for $t = 2050$ of about 44 percent. While the last node only allows the option to expire ("no investment") if the state of the world is not supporting a profitable investment, the preceding nodes may suggest to wait. The second information given in those plots is the cumulative probability of an investment in the specific power plant. Due to the fact that positive investment decisions in preceding time steps preclude an investment at a later time (only one investment is possible), only nodes which follow a decision path of "waiting" may result in an investment. Therefore, the cumulative probability can provide some insights regarding the overall probability of having invested in the specific power plant. This probability is estimated by a second Monte Carlo simulation that is based on the previously identified decision tree.

The option value of the PV power plant of €19.8 million is the lowest one obtained. The model suggests to wait at least until $t = 2030$, before the first time a positive investment decision is proposed. Even until 2050, the probability to invest stays below 45 percent. For the onshore and offshore wind power plants, the option value is much larger (€248 million and €311 million, respectively). Although the optimal time to invest is earlier and the overall probability to invest higher for the onshore wind park (ONW) compared to

Table 3: Option value for the case of a segregated treatment of all technologies

		Option value [million €]					Option value [million €]		
No.	Power plant	Mean	Min	Max	No.	Power plant	Mean	Min	Max
1	PV	19.8	19.8	19.9	6	HC-IGCC	543.4	541.8	545.0
2	Onshore wind	248.5	247.7	249.1	7	HC-IGCC-CCS	359.8	358.0	361.0
3	Offshore wind	310.9	310.6	311.3	8	COGAS	544.8	543.2	547.0
4	Hydro	1066.2	1061.5	1072.0	9	COGAS-CCS	473.7	472.9	475.2
5	HC	636.7	633.0	639.4					



(a) PV (b) ONW (c) OFFW

(d) HYDRO (e) HC (f) HC-IGCC

(g) HC-IGCC-CCS (h) COGAS (i) COGAS-CCS

Figure 4: Distribution of the investment decision at the eight calculated nodes for the baseline case (bars) and cumulative probability to invest (dashed lines).

the offshore wind park (OFFW), the option value is higher. Note that the prediction of a longer waiting time for the offshore wind power plant is mainly caused by the strong reduction of the specific cost of investment and the increasing average utilization rather than by the increase in the electricity price. This shows that the option value is not only influenced by the assumed stochastic price paths but also by the technological innovation. Interestingly, the cumulative probability of the offshore wind park is practically linearly increasing, while the growth of the probability for the onshore wind park shows a saturation, asymptotically reaching the value of 100 percent. The highest option value as well as an immediate investment is proposed for the hydro power plant (HYDRO), caused by the high ratio between average utilization and specific investment costs as well as due to the long lifetime. Note that the decision process of all four technological options is only influenced by two stochastic parameters, viz. the electricity price and the benchmark asset (here: DAX) used for the stochastic discounting.

The option value of the five fossil-fired power plants is generally higher than the one of the renewable energies (excluding the hydro power plant). For the HC and the COGAS power plant, an immediate investment in 2015 is suggested. As the HG-IGCC and the COGAS-CCS technologies are assumed to be available only from 2020 onwards, a probability of zero in 2015 and a very high probability in 2020 are proposed.

Compared to the increasing probability to invest found for the renewable technologies, the HC and the HC-IGCC power plant show a clearly decreasing probability over time for the investment decision and an increase in the probability of waiting. However, at the latest possible point in time to invest, a jump of the probability occurs. The HC-IGCC-CCS technology is the only one for which a longer delay is predicted. Note that although the instantaneous probability increases only slightly over time, a stronger increase in the cumulative probability is found. At first sight, this behavior seems absurd. Why should the cumulative probability rise while the instantaneous one does not? An explanation for this behavior can be found in the multi-dimensionality of the problem. The threshold value, which constitutes the border between the regimes of “investing” and “waiting”, defines a complex surface in this multi-dimensional space. Therefore, the various price paths can penetrate the region of “investing” from multiple directions. If the regime of “waiting” is largely increased in one dimension (e.g. due to an increase in the CO_2 permit price), a penetration into the regime of “investing” by price paths can still occur from other directions (e.g. due to reducing fuel or increasing electricity prices), thus increasing the cumulative probability to invest.

Overall, the model predicts high chances for investments into all fossil-fired power plants, except for the HC-IGCC-CCS plant in the case where each technology is treated separately. However, as a separate treatment of the technologies is rather academic (in reality, the investor is normally faced with the opportunity to choose between different alternative technologies), the next paragraph will provide insights into more realistic investment decisions, i.e. such where the various technologies actually compete with each other.

Combinations of various technologies: For the case that the investor is facing the additional option to choose between various technologies and the option to delay the investment decision, the simulation as well as the simulation results becomes more realistic (and thus more valuable but, unfortunately also more complicated). In first simulations, a dominant behavior of the hydro power plant is found. Because of the fact that the investment in new hydro power plant capacity is strongly limited by the few possible locations remaining in Germany, we excluded this technology from the following analysis.

Table 4 summarizes the average, minimum, and maximum option values for three different sets of technologies.

The first set includes solely the new renewable energy technologies, namely photovoltaics, onshore, and offshore wind. The option value of this combination of €311 million is equal to the value of the single technology "offshore wind". Comparing Fig. 4(c) and Fig. 5(a) shows that the offshore wind technology is dominant. Although higher prob-

Table 4: Relative option value for combinations of various technologies

		Option value [million €]		
Nos.	Power plant	Mean	Min	Max
1-3	Renewables except hydro	**310.9**	310.6	311.2
5-9	Conventionals	**641.1**	638.3	642.9
1-3,4-9	All except hydro	**642.0**	638.9	644.3

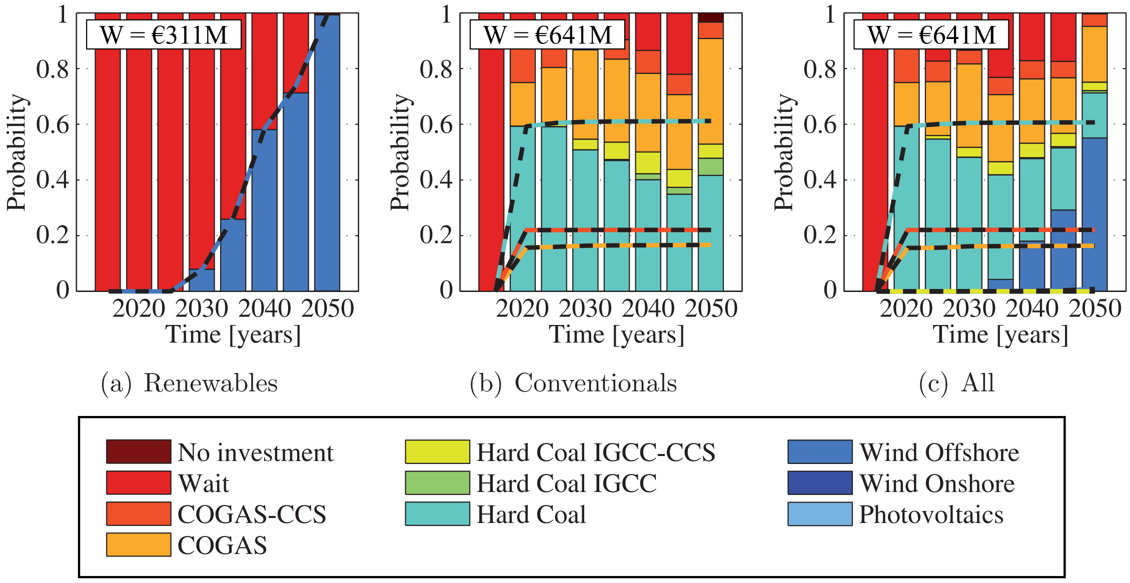


Figure 5: Distribution of the investment decision at the seven calculated nodes for a non-volatile CO_2 price.

abilities of earlier investment in onshore wind technology were predicted in the previous subsection, those investments are delayed by the offshore wind technology and its high value of waiting.

The second set includes all fossil-fired power plants (hard coal- and gas-fired) and their CCS options. The option value of €641 million is only about three million euros above the value of the HC power plant, although its probability decreased to around 60 percent. In contrast to the HC power plant, a delay of the investment decision in the first time step is proposed. Nevertheless, the probability to invest at $t = 2020$ is more than 90 percent, including a probability of nearly 20 percent for the COGAS-CCS option. Only in a very few price constellations is the present value of the HC-IGCC-CCS or the COGAS-CCS power plant the highest.

The last set includes all technological options, renewable energy, and fossil-fired power plants. The option value as well as the distribution of the investment decision in the first time steps does not differ from the previous set. Therefore, the additional consideration of the renewable energy technologies in this case has no influence. However, the distribution of the best performing power plant at the latest time step (2050) is strongly determined by the offshore wind power plant, although the first increase in the probability of adoption is as late as in 2035. Compared to Fig. 5(b), the probability of the CCS options is further reduced.

The probability of no investment in 2050 is reduced to less than five percent, indicating that only a few price constellations exist where no technology has a positive present value. A high probability of no investment would have shown that unrealistically low prices for electricity have been assumed. Nevertheless, a substitution of the fossil-fired power plants by the three renewable energy technologies considered here can be found from 2035 onwards. With a probability of more than 50 percent, the renewable energy technologies strongly dominate the hard coal and both CCS technologies, but have no impact on the investment decision today, following the nodes of a positive investment decision.

4.2 Influence of different CO_2 price levels and policies

The proposed model does not only support decision-makers from industry to find optimal strategies in terms of the technological choice and the waiting time, but it also yields new insights into the effect of various CO_2 trading schemes. This can help politicians in their decision towards an optimized CO_2 emission mitigation policy. In the following, we present the influence of three different initial prices for CO_2 permits in 2015 (€5, €25, €45) as well as the influence of a price floor. For the variations of the initial CO_2 permit price, an additional adaptation of the electricity price is necessary. Due to the large share of coal-fired power plants in the German energy mix (in 2010: 43%), we assume an electricity price elasticity of $0.64\,{}^{€_{\mathrm{el}}}/_{€_{\mathrm{CO_2}}}$[2].

The academic debate on price floors is still in its infancy, though the concept of price floors has already found its way into policy and legislative proposals (Wood and Jotzo, 2011). One of the novel aspects is an annually increasing reserve price when permits are auctioned. Such schemes have been proposed for various emission trading systems

[2] Quotient of the input and output factors of a hard coal power plant (c_{el}, $c_{\mathrm{CO_2}}$), as presented in subsection 2.4.

Table 5: Option value for combined technologies

			Volatile price			Flooring			CO_2 tax		
P_{CO_2}	Nos.	Power plant	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
€5	5-9	Conventionals	**662**	657	667	**458**	455	460	**459**	454	463
	1-3,5-9	All (excl. hydro)	**662**	659	665	**459**	456	464	**460**	455	465
€25	5-9	Conventionals	**641**	638	643	**393**	391.9	395	**405**	404	407
	1-3,5-9	All (excl. hydro)	**642**	639	644	**417**	416	418	**427**	425	428
€45	5-9	Conventionals	**1036**	1033	1038	**722**	720	724	**1038**	1036	1041
	1-3,5-9	All (excl. hydro)	**1037**	1034	1041	**735**	734	736	**1039**	1037	1040

in the US (e.g. for California), Australia, or the UK (Brunner et al., 2009). However, the European Commission mentioned that "a floor price may unduly interfere with the market" (Gardner, 2009). Wood and Jotzo (2011) state that such arguments seem to overlook the fact that permit markets are entirely caused by governmental regulations and that a different design will just result in a different market outcome. They find that price floors in emission trading systems can reduce excessive price volatility and provide better management of cost uncertainty in the event of lower than expected abatement costs, which in turn improves the predictability of returns and increases the expected returns for low-emission investments. Nevertheless, such a minimum reserve price for auctioned permits could only yield the desired effect in an international permit trading scheme if the share of auctioning is large.

In the simulation results presented, the CO_2 price floor is realized by way of introducing a deterministic lower border, defined by

$$P_{\mathrm{CO_2,border}} = P_{\mathrm{CO_2}}(t = 2015) \cdot \exp(\alpha_{\mathrm{CO_2}} t). \tag{16}$$

With the given lower border, the price of the emissions is the maximum of the stochastic price and the deterministic price border or, formally, $\max(P_{\mathrm{CO_2,stochastic}}, P_{\mathrm{CO_2,border}})$.

The option values found for the six different sets are summarized in Table 5. Comparing the different initial prices for CO_2 permits, a clear increase in the option value was found for $P_{\mathrm{CO_2}} =$ €45, whereas the option values for $P_{\mathrm{CO_2}} =$ €5 and €25 are nearly equal. It should be kept in mind, however, that the electricity price was varied accordingly to the

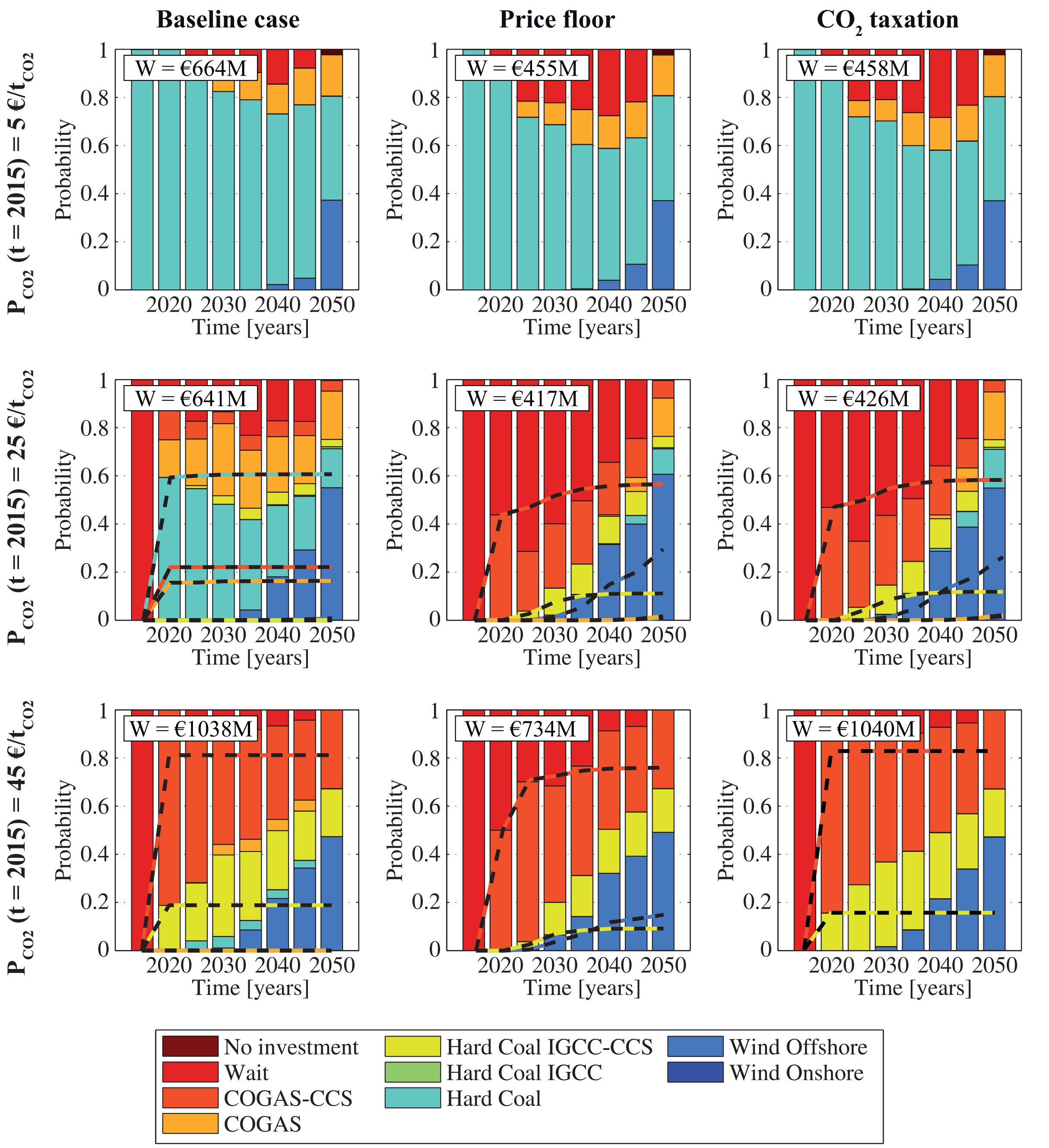


Figure 6: Distribution of the investment decision at the seven calculated nodes for a non-volatile CO_2 price.

changing cost of electricity generation of a hard coal power plant. Therefore, a higher permit price allows increasing option values in the case of switching to low carbon or renewable technologies. As can be seen from Fig. 6, a clear preference for COGAS-

CCS and HC-IGCC-CCS power plants exists at $P_{\mathrm{CO}_2} =$ €45. The slight increase in the option value from $P_{\mathrm{CO}_2} =$ €25 to $P_{\mathrm{CO}_2} =$ €5 comes along with a switch to the HC power plant. The renewable energy technologies are found to be less supported by both a higher and a lower price of CO_2 permits. For $P_{\mathrm{CO}_2} =$ €5, the wind offshore power plants are dismissed by the HC power plant; for $P_{\mathrm{CO}_2} =$ €45, by the CCS technologies. However, due to investment decisions in early stages, the cumulative probability of investments in renewable energy technologies remains zero.

The price flooring policy significantly decreases the option value in all cases due to the increased average cost of CO_2 permits. For $P_{\mathrm{CO}_2} =$ €5, the decision process is not significantly influenced by the change in policy, predicting an immediate investment in HC power plants. For the other two initial prices, a strong influence of flooring is found. Conventional technologies, such as hard coal and COGAS power plants, are nearly completely displaced and a strong preference of the COGAS-CCS technology is found. The inevitable period of waiting is caused by the fact that this technology is not available before the year 2020. Additionally, a share of 30 percent in the cumulative probability of offshore wind power plants for $P_{\mathrm{CO}_2} =$ €25 and 17 percent for $P_{\mathrm{CO}_2} =$ €45 is predicted. However, a strongly intensified probability of waiting is found for the medium and the higher CO_2 price scenarios. Note that this is a rather unexpected behavior, as the floored CO_2 permit price was initially introduced with the intention to reduce uncertainty and to promote faster investment decisions.

The policy of a carbon tax is investigated by using a deterministic carbon price.[3] For the low and the intermediate CO_2 price scenarios ($P_{\mathrm{CO}_2} =$ €5 and $P_{\mathrm{CO}_2} =$ €25) the results strongly agree with the ones obtained for the price flooring policy, both with regard to the option value as well as in the probability distribution. Compared to the baseline case, the option value is reduced by approximately 30 percent. This reduction is caused by the probability of a very low CO_2 price in the baseline scenario, which increases the value of the HC power plant. For the high CO_2 price scenario ($P_{\mathrm{CO}_2} =$ €45), the option value

[3] As we make use of the same model without removing the CO_2 price from the stochastic variables, we impose a very low volatility of the CO_2 price, e.g., $\sigma_{CO2} < 10^{-6}$.

corresponds to the one of the baseline case, which results from an investment in either a HC-IGCC-CCS or a COGAS-CCS power plant (in $t = 2020$). Due to the low CO_2 price paths, which are included in the baseline scenario, low probabilities for the HC and the COGAS power plants are predicted. As such price paths do not exist in the case of a carbon tax, the conventional fossil-fired power plants are completely displaced.

5 Conclusion and political implications

This paper introduces a new multi-dimensional, real options-based approach to evaluate real-world investments in the energy sector. Such investment decisions are characterized by the fact that the choice of the technology fixes the ratio between input and output quantities over the entire lifetime of the power plant. However, caused by the different developments of the relevant prices, the ratio between, for instance, the coal and the gas price changes over time. Therefore, the expected cash flows and their uncertainty varies over the project's lifetime and is strongly dependent on the technology applied. The presented real options approach accounts for this fixed ratio between inputs and outputs, thereby requesting a separation between time- and risk-discounting.

The proposed model is applied in order to examine the option value and the probability to invest in different technologies, such as photovoltaics, on- and offshore wind, hard coal-, and gas-fired power plants. Forecasts for future prices and the technological progress are adopted from a major case study ("Leitstudie 2010") on future energy strategies and scenarios in Germany. First investigations were conducted, where each power plant is evaluated individually, showing high potentials for immediate investments in conventional (hard coal- and gas-fired) power plants. Carbon dioxide capturing technologies are found to have lower chances, especially for the hard coal IGCC technology. However, CCS, in addition to combined gas and steam power plants, might become economically viable until 2020. For renewable energy technologies, the predicted option value is much lower than for the conventional power plants. Due to the expected improvements in onshore and offshore wind parks, a high value of waiting is predicted. In a second step, combined evaluations of the various technologies were performed. We find that renewable energy as well as CCS technologies is largely displaced by the conventional hard coal and combined-cycle gas and steam power plants, respectively.

In a further step, a variation of the initial ($t = 2015$) CO_2 permit price (€5, €20, €45) was performed and the influence of a price floor in the auctioning process of the permits and a CO_2 taxation was investigated. We are able to show that with a CO_2 permit price of €5 the conventional hard coal power plant is strongly preferred, whereas for a price of €45 the combined-cycle gas and steam power plant with CCS becomes the first choice. The CO_2 price flooring has a negative influence on the conventional power plants. However, a much higher value of waiting was predicted by the model, whereas investments in CCS technologies are further delayed. A CO_2 taxation has a similar influence as the flooring for the low and the intermediate CO_2 price scenarios. For the high initial CO_2 price of €45, the tax policy significantly reduces the value of waiting compared to the flooring policy.

Before conducting this study, we were convinced that a CO_2 price flooring reduces the risk for investments in CCS power plants and, therefore, increases the chances of this technology. Surprisingly, due to the elimination of the lower branch of the CO_2 permit price, a largely increased value of waiting was found, delaying the investment decision. These findings indicate that a CO_2 price flooring might not be the best opportunity to support investments in fossil-fired power plants with CCS technology in the upcoming years, which in our opinion is a very interesting result for policy-makers.

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