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Summary
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September 2011

Abstract

Uncertainty about long-term climate policy is a major driving force in the evolution of the carbon market price. Since this price enters the investment decision process of regulated firms, this uncertainty increases the cost of capital for investors and might deter investments into new technologies at the company level. We apply a real options-based approach to assess the impact of climate change policy in the form of a constant or growing price floor on investment decisions of a single firm in a competitive environment. This firm has the opportunity to switch from a high-carbon "dirty" technology to a low-carbon "clean" technology. Using Monte Carlo simulation and dynamic programming techniques for real market data, we determine the optimal CO_2 price floor level and growth rate in order to induce investments into the low-carbon technology. We show these findings to be robust to a large variety of input parameter settings.

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1. Introduction

In the context of reducing long-term carbon price uncertainty stemming from ambiguous climate change policy, some contributions in the academic literature have suggested several forms of regulatory price management, mainly in the form of a price cap or safety valve[1] (Pizer (2002); Jacoby and Ellerman (2004); Szolgayová, Fuss, and Obersteiner (2008)).[2] If realized abatement costs turn out to be higher than expected (i.e. the emission cap is too low) the price cap serves as a ceiling on the carbon price and emitters can buy additional permits at the specified price[3]. McKibbin and Wilcoxen (2002), Helm (2008), Burtraw, Palmer, and Kahn (2010), Fell and Morgenstern (2009), and Philibert extend this discussion by analyzing a "symmetric safety valve", also referred to as a price collar. This approach not only insures emitters against higher than expected costs, but also sets a minimum carbon price, thereby bounding compliance costs downward. Experience from the EU ETS, the world's largest multi-national carbon trading scheme, provides evidence for the thought that an overestimation of abatement costs might be a more realistic scenario than an underestimation. Therefore, a price floor might be a more critical design element within a fixed price range than a cap.

A price floor reduces uncertainty over future profitability by guaranteeing a minimum rate of return to an investor or firm pondering an investment decision. This argument is particularly important in the energy sector, which is characterized by capital-intensive low-carbon technologies and long-lived power plants. In this sense a minimum carbon price creates incentives to invest in new technologies over and above those already induced by the (unmanaged) market price. Abatement will still take place if the costs of CO_2-reductions are lower than the price of allowances, since profit-maximizing firms will implement the emissions reductions and sell the surplus allowances. A second argument in favor of the implementation of a price floor is the possibility that it would limit the volatility of carbon market prices (Grüll and Taschini (2011)). In times of growing volatility in fuel prices this fact would favor renewable energy.

[1] The idea of combining price (tax) and quantity (allowances) instruments, usually referred to as a hybrid system, was initially suggested by (Roberts and Spence (1976)).
[2] Alternative ways to reduce climate policy uncertainties are mentioned in (Lambie (2010)).
[3] (Murray, Newell, and Pizer (2008)) extend the concept of a price ceiling with an unlimited volume of extra permits by the idea of an allowance reserve that caps this volume.

An intensive academic discussion about such a downside insurance in carbon markets started only recently with the work of Wood and Jotzo (2011). This is surprising given that the concept of a price floor has already found its way into legislation in the United Kingdom and Australia (HM Treasury and HM Revenue & Customs (2010); Australian Government (2011)). In the case of the UK the floor is one of several measures for encouraging low-carbon energy investments (Department of Energy & Climate Change (2011)). Commencing on 1 April 2013 at around 15.70 GBP/ton CO_2, following a straight line to 30 GBP/ton in 2020 and targeting 70 GBP/ton in 2030, the UK price floor is designed to top up the carbon price of the EU ETS – which the UK is a member of – to a national target level. Since other countries under the EU ETS do not have a similar price floor, this measure will increase abatement costs in the UK relative to other EU countries. UK legislators justify this higher burden by arguing that regulatory uncertainty about future carbon prices may undermine long-term price signals and incentives and that the carbon price from the EU ETS might not be strong and stable enough to stimulate sufficient investments in low-carbon technologies.[4] The Commission implicitly agrees to this diagnosis when stating that, in order to boost low-carbon technologies, "[…] appropriate measures need to be considered, including revisiting the agreed linear reduction of the ETS cap" (European Commission (2011)). In this sense an additional goal evolves from a cap-and-trade system: it could be used to promote technological innovation to a greater extent than automatically induced by the long-term price signals from the market.

Taking this logic as our starting point, we contribute to this debate about price management in the form of a floor price in the carbon market. Setting aside organizational questions concerning the implementation of the floor (for these we refer to Wood and Jotzo (2011)) we focus on how investment decisions in the electric power sector are affected by the introduction of a permit price floor. We employ a real options model of an individual electricity producer who currently operates a "dirty" power generation technology, which we define as a technology that has considerably higher CO_2 emissions per production unit than alternative technologies. This implies that the firm has comparatively large compliance costs. The company furthermore faces an investment decision which would permit it to switch to a "clean" generation technology, i.e. a technology with low emissions per production unit. By simulating sets of cashflow paths as functions of technology specific cost

[4] (Grubb and Neuhoff (2006)) argue that uncertainty concerning expected permit prices is a major reason for firms to delay investment under the EU ETS.

related to construction, fuel and carbon emissions, we show that a regulatory intervention in the form of a price management mechanism in the CO_2-market influences the optimal timing of the investment decision of this company. In particular, we demonstrate that the introduction of a price floor can lead to an earlier adoption of low-carbon technologies. In this case, the CO_2-market acts as an instrument for technology policy.

The methodology we apply is similar to that in several contributions dealing with investment decisions in the power sector under different dimensions of uncertainties. Comparable studies, among others, are Laurikka and Koljonen (2006), Fuss et al. (2008), Szolgayová, Fuss, and Obersteiner (2008), Yang et al. (2008), Fuss et al. (2009), Fuss and Szolgayová (2010), Chen and Tseng (2011), Kettunen, Bunn, and Blyth (2011) and Zhu and Fan (2011). However, none of the aforementioned contributions evaluate the influence of a carbon price floor on the investment decision in general and the timing of the technology switch specifically. The only study employing, at least in passing, a price floor in a quantitative model is Abadie, Chamorro, and González-Eguino (2011). In contrast to their work, we do not only perform a detailed analysis of a constant floor price level but investigate different designs of the floor. In particular, we perform an in-depth investigation of a price floor mechanism with linearly increasing minimum prices. In addition, we endogenously compute the floor price necessary to trigger abandonment of the “dirty” technology at an earlier time. Finally, we perform a number of robustness checks using a large variety of different input parameter settings. These tests qualitatively substantiate our main finding of the existence of a trigger minimum price design.

In what follows, chapter 2 presents the model we use to analyze the influence of a price floor on a firm’s optimal investment decision. Chapter 3 contains results from Monte Carlo simulations and backward dynamic programming as well as robustness checks. Chapter 4 concludes.

2. The model

We model a single power generating firm which is a price taker in all markets and supplies electricity inelastically. The firm has to comply with an emissions trading system by obtaining emissions permits covering its production needs. We assume it to buy and redeem the necessary carbon certificates at the end of each period. This ensures that the company never holds any surplus certificates which it would wish to sell back to the market.

2.1. Structure of the decision problem

The firm currently operates a “dirty” technology (D) power plant with a remaining life of L^{D^*}. This technology is characterized by high emissions per production unit, causing the firm to face high costs of compliance with the emissions trading system.[5] The company has to make a decision about replacing the currently operating power plant before the end of its economic life. In particular, the firm can choose one of three courses of action at the beginning of each period, modeled in discrete time: (i) discontinuing business, (ii) replacing the existing power plant with a new power plant using the same technology D, or (iii) replacing the existing power plant with a new power plant using a “clean” technology (C), which is characterized by low emissions per production unit.[6]

If the firm chooses option (i), we assume that the disinvestment is associated with costs (disassembly of the power plant, termination of contracts, etc.) and revenues (sale of the old power plant and/or the land it is built on) which sum to zero, with cash flows of zero in every period thereafter.[7] If it chooses options (ii) or (iii), it faces a technology dependent investment cost of Inv^{θ}, where $\theta \epsilon \{C, D\}$. The investment cost is distributed uniformly over the construction time of l^{θ}. During the construction time, the current plant is assumed to continue operating, yielding cash flows of CF_t^D every period. After construction is finished, the old power plant is closed down with net revenues and costs of zero and the new power plant starts yielding cash flows of CF_t^{θ} for every period of its life of L^{θ}.[8] Note that, while decisions are always made at the beginning of a period, cash flows are assumed to accrue at its end.

Except for the case where the firm decides to (irreversibly) discontinue business, we require it to have exactly one power plant under operation at all times, i.e. there may be no gap between the end of the life of the current power plant and the end of the construction time of a new power plant, and the old and a new power plant may not be operated simul-

[5] The exact parameters for our numerical analysis will be provided in section 3.

[6] (Fuss and Szolgayová (2010)) conduct a similar analysis investigating the decision to switch from a coal-fired power plant to a wind farm. However, they focus on the role of uncertainty associated with the technological progress of green technologies and do not account for a carbon price floor.

[7] Note that we regard the replacement decision for this one power plant in isolation and disregard any effects it might have on other activities of the firm.

[8] We model the dirty technology D as being static, meaning that a new dirty power plant’s cash flows follow the same stochastic process as the current dirty power plant’s.

taneously. Since the object of our analysis is the replacement decision for the currently operating plant, we can thus set

$$T = L^{D^*} - \max_{\theta}\left[l^{\theta}\right] \tag{1}$$

and refer to $[1, T]$ as the investment decision horizon. This is the time interval over which the firm has the opportunity to freely choose between all three options. If it waited longer than T, it could no longer choose freely between technologies D and C if it wanted to meet the requirement to have a plant under operation at all times. We require the company's decision to be irreversible for the model horizon. In other words, if the company decides to build a new plant of technology θ, it will then operate this plant (and this technology) until after the end of the model horizon $H < T + \min_{\theta}\left[L^{\theta}\right]$. If the firm decides to discontinue this line of its business, it will never re-enter it.

Our question concerning the introduction of a price floor in the carbon market is threefold: firstly, we are interested in whether the dirty plant is replaced or not. If this is the case, we secondly investigate which technology is chosen. Thirdly, we want to determine at which point in time t^* – if ever– the "dirty" plant is optimally replaced by the "clean" one.

2.2. Stochastic price processes

We assume the CO_2 price to follow a Geometric Brownian Motion (GBM) as in Szolgayová, Fuss, and Obersteiner (2008) und Yang et al. (2008).[9] The CO_2 price P is therefore modeled as having two components – an expected drift and a random walk:

$$dP = \mu_P P dt + \sigma_P P dz \tag{2}$$

[9] Note that we choose GBM processes for the ease of modeling and because the specific form of stochastic process is not the focus of our analysis. It is however quite possible to introduce other stochastic processes into the model. As will become clear later on, the use of processes generating non-normally distributed outcomes requires adjusted techniques for assessing the timing of the investment decision. Specifically, we currently use ordinary least squares regression to estimate expected values. This simple and robust approach would have to be modified by employing more advanced regression techniques. With regard to the type of process specifications to use, we consider models including regime switches and jumps in the price paths to be particularly promising candidates for future work. They have attained increased relevance in light of the recent discussion about the use of nuclear power and alternative technologies, as well as the large impact of environmental policy decisions, both of which carry the potential to instantly and strongly affect the circumstances on carbon markets.

where μ_P is the drift rate, σ_P denotes the standard deviation, and dz is a standard Wiener process. We use the same underlying process, albeit with different parameters, to model the price our firm receives for selling electricity, PE, and to model its technology specific variable costs (operating, maintenance and fuel costs), VC^{θ}. Each realization of these processes is discretized, departs from a fixed value at time $t = 0$, and is being simulated for the entire model horizon H. We assume the individual processes to be uncorrelated in the larger part of the subsequent analysis, but report results obtained with correlated processes in section 3.4.

2.3. Dynamic programming

Our derivation of the optimal decision in this context is loosely based on the approach of Longstaff and Schwartz (2001), which brings together backward oriented dynamic programming techniques and forward oriented simulation techniques, and is thus a versatile procedure which allows for handling multivariate state variables (see Gamba and Fusari (2009)). The key insight of Longstaff and Schwartz (2001) was that the conditional value (expectation) of future payments can be estimated from the cross-sectional information in the simulation by using a least squares approach.[10]

Consider Figure 1 showing the time structure of the model. At the beginning of every period in the interval $[1, T]$, the firm can choose to either continue producing using its current power plant, to irreversibly switch to the technology C by building a new power plant, or to discontinue business altogether.

[10] The instrument modeled by (Longstaff and Schwartz (2001)), an American Call option, has the characteristics that (i) the underlying does not pay any dividends, and (ii) there are only two alternative courses of action at each node - to exercise or not to exercise. In our example, the investments generate cash flows in every period and we face the three-fold decision problem of continuing production with the current technology, investing in the new technology, or exiting the business altogether.

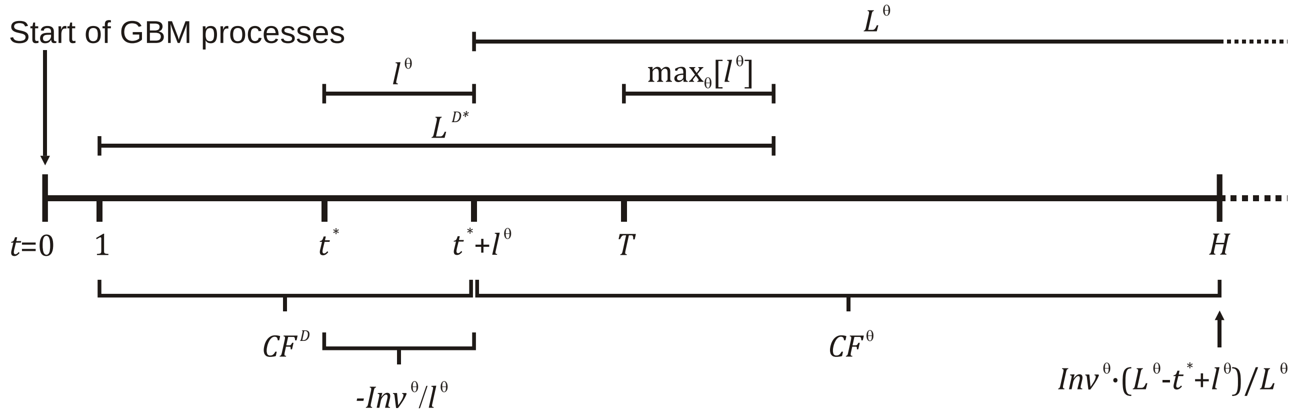

Figure 1: Model time structure

Our optimization procedure starts with a Monte Carlo simulation, which is used to generate paths for the relevant state variables. Based on these simulated paths, the dynamic programming algorithm compares the expected outcome of investing in a new technology C plant with delaying the investment for one more period, and with the possibility of exiting the business immediately. Note that, in our solution algorithm, we do not allow for reinvestment in technology D at any time $t < T$. Given a positive discount rate, such a strategy would always be suboptimal. A new plant of technology D generates the same cash flows as the existing plant, yet requires payment of the investment cost. For this reason, if an optimal solution entails reinvesting in technology D, this decision can only be made at $t = L^{D^*} - l^D$. We therefore do not consider premature reinvestment in D in our numerical solution algorithm.

The optimal exercise decision at any point in time is obtained as the maximum of the immediate investment value, the expected value from delaying the decision, and zero in case of disinvestment. Since the expected continuation value depends on future outcomes, the procedure must work backwards from the latest ($t = T$) to the earliest possible investment time ($t = 1$) (Cortazar, Gravet, and Urzua (2008)). Following this procedure we obtain, for each path, the optimal decision. This can be to discontinue business at any time $t \epsilon [1, T]$, to reinvest in technology D at time $t = L^{D^*} - l^D$, or to invest in the clean technology at any time $t \epsilon [1, T]$.

Operationally, the procedures of the dynamic programming approach differ between time $t = T$ and any $t < T$. The following sections provide the algorithm we follow to solve the dynamic programming problem.

2.3.1. Determination of the decision at $t = T$

We start by calculating the net present value of a plant investment at $t = T$ for each simulated path:

$$NPV_{t,i}^{\theta} = \overbrace{\sum_{n=t+1}^{t+l^{\theta}} r(t,n) \cdot CF_{n,i}^{D}}^{(a)} - \overbrace{\sum_{n=t+1}^{t+l^{\theta}} r(t,n) \cdot \frac{Inv^{\theta}}{l^{\theta}}}^{(b)} + \overbrace{\sum_{n=t+l^{\theta}+1}^{H} r(t,n) \cdot CF_{n,i}^{\theta}}^{(c)} + \overbrace{+\, r(t,H) \cdot \frac{L^{\theta} - (H - T - l^{\theta})}{L^{\theta}} \cdot Inv^{\theta}}^{(d)} \tag{3}$$

where $i \epsilon [1, \ldots, I]$ is the index of the specific simulated path under consideration, and $r(t,n)$ denotes the discount factor applied at time t to cash flows occurring at time n. Furthermore, the cash flow $CF_{t,i}^{\theta}$ is defined as:

$$CF_{t,i}^{\theta} = \left(R_{t,i} - VC_{t,i}^{\theta} - CC_{t,i}^{\theta} - \frac{Inv^{\theta}}{L^{\theta}} \right) \cdot (1 - \tau) + \frac{Inv^{\theta}}{L^{\theta}}$$

where $R_{t,i}$ is the revenue (calculated as the electricity output in MWh times the price for electricity $PE_{t,i}$) at time t on the simulated path i, $VC_{t,i}^{\theta}$ are the variable costs (calculated as the electricity output in MWh times the technology dependent variable cost factor) for each of the two technologies, $CC_{t,i}^{\theta}$ are the carbon costs (calculated as the CO_2 output in tons times the price of carbon certificates $P_{t,i}$), Inv^{θ}/L^{θ} is the depreciation for the power plant, and τ is the corporate tax rate.

In order to maintain comparability, irrespective of the specific time at which the clean investment is realized, we consistently evaluate all investment programs over our model horizon of H periods. Equation (3) rests on the simplifying assumption that the plant will be sold for its remaining book value at the end of this time.[11] The net present value from equation (3) thus is the sum of four terms: (a) the cash flows from the (existing) technology D plant during the construction time of the new (D or C) plant; (b) the discounted (negative) investment outlay for the new plant, distributed linearly over the construction time; (c) the discounted sum of the cash flows from the plant over the time interval from the end of its

[11] Note that in section 3 we choose H to be sufficiently long that alternative treatments of the residual plant value have a negligible impact on the optimal decision.

construction until the end of the model horizon H; and (d) the discounted revenue from selling the plant for its book value at $t = H$.

Because present values coming from simulated cash flow paths themselves are uncertain, we need to form an expectation of these values. We achieve this by regressing the net present values obtained under (3) on a linear combination of a set of basis functions of the simulated state variables at time $t = T$, using a simple least-squares specification (Gamba and Fusari (2009) and Longstaff and Schwartz (2001)):

$$\begin{aligned}
&NPV_{t,i}^{\theta} = c_t^{\theta} + \\
&+\beta_{R,t}^{\theta} \cdot R_{t,i} + \beta_{VC,t}^{\theta} \cdot VC_{t,i}^{\theta} + \beta_{CC,t}^{\theta} \cdot P_{t,i} + \\
&+\beta_{R^2,t}^{\theta} \cdot \left(R_{t,i}\right)^2 + \beta_{VC^2,t}^{\theta} \cdot \left(VC_{t,i}^{\theta}\right)^2 + \beta_{CC^2,t}^{\theta} \cdot \left(P_{t,i}\right)^2 + \\
&+\varepsilon_{t,i}^{\theta}
\end{aligned} \tag{4}$$

where c_t^{θ} is a constant, the $\beta_{\cdot,t}^{\theta}$ are regression coefficients, $P_{t,i}$ is the carbon price at time t on the simulated path i, and $\varepsilon_{t,i}^{\theta}$ is a white random error term.

We then use the regression parameters we obtain to calculate the estimated net present value for each simulated path at time $t = T$:

$$\begin{aligned}
&\mathrm{E}_t\left[NPV_{t,i}^{\theta} \middle| R_{t,i}, VC_{t,i}^{\theta}, P_{t,i}\right] = \hat{c}_t^{\theta} + \\
&+\hat{\beta}_{R,t}^{\theta} \cdot R_{t,i} + \hat{\beta}_{VC,t}^{\theta} \cdot VC_{t,i}^{\theta} + \hat{\beta}_{CC,t}^{\theta} \cdot P_{t,i} + \\
&+\hat{\beta}_{R^2,t}^{\theta} \cdot \left(R_{t,i}\right)^2 + \hat{\beta}_{VC^2,t}^{\theta} \cdot \left(VC_{t,i}^{\theta}\right)^2 + \hat{\beta}_{CC^2,t}^{\theta} \cdot \left(P_{t,i}\right)^2
\end{aligned} \tag{5}$$

where $\mathrm{E}_t[\cdot]$ is the expectation operator, applied at time t.

In the next step, we decide between exiting the business, reinvesting in technology D, and investing in technology C. We thus obtain the following expected net present value conditional on optimal investment behavior:

$$\begin{aligned}
&\mathrm{E}_t\left[NPV_{t,i}^{opt} \middle| R_{t,i}, VC_{t,i}^{D}, VC_{t,i}^{C}, P_{t,i}\right] \\
&\qquad = \max\left[0, \mathrm{E}_t\left[NPV_{t,i}^{D} \middle| R_{t,i}, VC_{t,i}^{D}, P_{t,i}\right], \mathrm{E}_t\left[NPV_{t,i}^{C} \middle| R_{t,i}, VC_{t,i}^{C}, P_{t,i}\right]\right]
\end{aligned} \tag{6}$$

2.3.2. Determination of the decision at $t < T$

The conditional expected net present value obtained in the previous section forms the basis for the analysis at $t = T - 1$. Here we distinguish between the treatment of the case where (i) we invest in the clean technology and (ii) we continue production using the dirty technology.

In case (i), we again calculate each path's net present value of investing in the clean technology using equation (3). We then use these to estimate the regression according to equation (4) and calculate the vector of I expected net present values when investing in the clean technology using equation (5).

For case (ii) we use the values obtained from equation (6) for $t = T$, add the cash flow for period $t = T - 1$, which accrues at the end of the period, and estimate the following regression for $t = T - 1$:

$$\begin{aligned}
&\mathrm{E}_{t+1}\left[NPV_{t+1,i}^{opt} \middle| R_{t,i}, VC_{t,i}^{\theta}, P_{t,i}\right] + CF_{t+1,i}^{\theta} = c_t^{opt} + \\
&+\beta_{R,t}^{opt} \cdot R_{t,i} + \beta_{VC^D,t}^{opt} \cdot VC_{t,i}^{D} + \beta_{VC^C,t}^{opt} \cdot VC_{t,i}^{C} + \beta_{CC,t}^{opt} \cdot P_{t,i} + \\
&+\beta_{R^2,t}^{opt} \cdot \left(R_{t,i}\right)^2 + \beta_{(VC^D)^2,t}^{opt} \cdot \left(VC_{t,i}^{D}\right)^2 + \beta_{(VC^C)^2,t}^{opt} \cdot \left(VC_{t,i}^{C}\right)^2 + \beta_{CC^2,t}^{opt} \cdot \left(P_{t,i}\right)^2 + \\
&+\varepsilon_{t,i}^{D}
\end{aligned} \tag{7}$$

We then calculate the estimated net present value for each simulated path at time $t = T - 1$ using equation (5) with the coefficient estimates obtained from equation (7) to obtain the expected net present values $\mathrm{E}_t\left[NPV_{t,i}^{\theta} \middle| R_{t,i}, VC_{t,i}^{\theta}, P_{t,i}\right]$. Finally, we obtain the expected net present value conditional on optimal investment behavior at $t = T - 1$ by applying equation (6). The arguments of the maximum function in (6) now are the expected net present values from cases (i) and (ii), and zero.

By repeating the steps undertaken for $t = T - 1$ for all other times $t \epsilon [T-2, T-3, \ldots, 1]$, we derive the net present value conditional on optimal investment behavior for the entire investment decision horizon. The result along each simulation path is then the time of the (temporally) first case where the decision is other than to continue operating the dirty technology plant. In other words, starting at time $t = 1$ and progressing forward through time, we record for each path the earliest point in time where the optimal decision is to either invest into technology C or to exit the business altogether.

3. Numerical Results

This section presents results from example calculations using our methodology. While the procedures can be applied to any decision regarding the timing of the switch to a low-emissions technology, for our numerical examples we compare a coal fired “dirty” plant to a hydro powered “clean” plant. The following parameters characterizing the investment decision are geared to real market data, with the revenues and costs associated with the clean and dirty technologies being taken from findings of the European Commission’s Strategic Energy Review (EC Energy Review 2008). Specifically, we assume that a power company currently operates a technology D plant with an installed capacity of 1MW, $Inv^D = 1.265$ mio EUR (1265 EUR/kW), and $L^{D^*} = 14$ years. The construction time in the case of reinvestment in technology D is $l^D = 3$ years and the new plant has a life of $L^D = 40$. The technology C plant is characterized by $L^C = 50$ years and $l^C = 4$ years. Following equation (1) this implies that $T = 10$ and that the existing plant needs to be replaced at a yet to be determined optimal time $t \in \{0, 1, \dots, 10\}$. We also consider a reinvestment in the currently operated technology D which implies a lead time of 3 years. However, since this decision is, if ever, taken only at $t = 11$ (3 years prior to the end of the existing coal plant’s economic life) and thus lies outside our analysis’ time interval of interest, we do not explicitly report detailed results on that aspect.[12]

Assuming an average load capacity of 85%, a coal plant’s annual output is 1 MW · 8760 h · 0.85 = 7446 MWh. Due to a lower annual load ratio of 50%, a hydro plant with the same output requires an installed capacity of 1.7 MW at a cost of 1800 EUR/kW. Hence, the alternative requires an investment of $Inv^C = 3.06$ mio EUR. We furthermore assume initial unit costs of 0.0164 EUR/kWh for the coal plant and 0.0074 EUR/kWh for the hydro plant. CO_2 emissions are set to 820 g/kWh and 6 g/kWh, respectively. Irrespective of the type of operated plant, we use an initial market price for power of 0.08 EUR/kWh in our analysis. The discount rate is chosen to be $r = 5\%$. Finally, we assume linear depreciation and a corporate tax rate of 50%.

[12] Note that we do not report detailed results for the case where the firm decides to reinvest in technology D. This decision is, if ever, only taken at $t = L^{D^*} - l^D = 11$, after a decision at $t = T = 10$ not to invest in a new technology C plant. This case is of limited interest to our analysis since we focus on the question of whether and when investment in C takes place.

Completing our basic parameter setting, we arbitrarily assume the revenues and the unit costs to have drift and diffusion rates of 1%, respectively, with one exception. The unit cost process of the coal plant is modeled as having a diffusion rate of $\sigma_{VC^D} = 5\%$ because of more volatile coal prices included in the total cost. The price process of CO_2 emission allowances is assumed to have a drift rate of $\mu_P = 8\%$ and a diffusion rate of $\sigma_P = 30\%$, which on the one hand reflects consent price forecasts (e.g. a price of 30 EUR per ton CO_2 in 2020) and on the other hand historical CO_2 return volatility. The price processes start with the following initial values:

Parameter	*Value*
$R_{0,i}$	7446000 kWh · 0.0800 EUR/kWh = 595680 EUR
$VC_{0,i}^{D}$	7446000 kWh · 0.0164 EUR/kWh = 122114 EUR
$VC_{0,i}^{C}$	7446000 kWh · 0.0074 EUR/kWh = 55100 EUR
P_0	15 EUR/ton
$CC_{0,i}^{D}$	0.82 ton/MWh · 7446 MWh · 15 EUR = 91586 EUR
$CC_{0,i}^{C}$	0.006 ton/MWh · 7446 MWh · 15 EUR = 670 EUR

Table 1: Initial values for the simulation

We set our total model horizon H to be 40 years. Since we model our parameters to roughly correspond to the situation in the EU in 2010, this corresponds to a horizon until 2050, which is the latest date for which useful emission quantity forecasts are available (See European Commission (2011)). We then run 10000 simulations for all stochastic components and derive an optimal point in time t^* for replacing technology D with C by applying the algorithm as described in section 2.3.

3.1. An illustrative example

For the ease of understanding of our methodology, we present a brief numerical example in this section. We simulate ten cash flow paths with a total of 40 cash flows each, with all parameters taken from above. Figure 2 plots the ten cash flow time series for technology D and C plants:

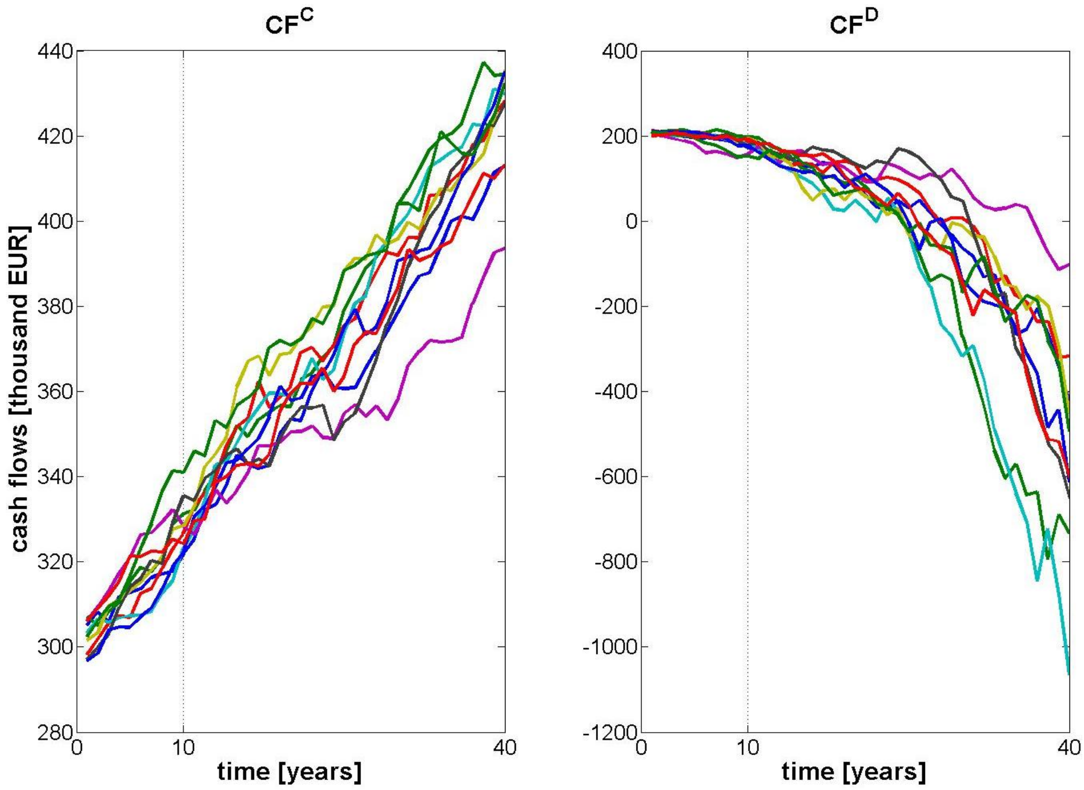

Figure 2: Example price paths. Deviating from the baseline parameter setting, these cash flow paths use a diffusion rate of 10% for the CO_2 price process, eliminating extreme price paths due to high volatility and making the plot easier to read.

Due to our use of a fairly high CO_2 allowance price drift rate of $\mu_P = 8\%$, the cash flows coming from operating technology D turn negative very quickly, whereas those from C are less exposed to high carbon prices and thus exhibit a positive slope, resulting in positive *NPVs*. Since no "dirty" cash flow path exhibits an *NPV* greater than the corresponding "clean" one, all subsequent calculations for time $t = 10$ are restricted to the technology C cash flows. The individual "clean" *NPVs* and the expected *NPV*s from the regression approach, respectively, are:

$NPV_{10,i}^C$	2718	2639	3285	2266	2129	2444	2598	2508	2961	1907
$\mathrm{E}_{10}\left[NPV_{10,i}^C \middle| R_{10,i}, VC_{10,i}^C, P_{10,i}\right]$	2748	2882	2887	2479	2120	2411	2490	2612	2972	1854

Table 2: Expected net present values and net present values from an immediate investment in the clean technology at $t = 10$ (thousand EUR).

The parameter estimates from the quadratic regression as outlined in section 2.3 yield $\hat{c}_{10}^C = -10746$, $\hat{\beta}_{R,10}^C = 237$, $\hat{\beta}_{VC,10}^C = -2152$, $\hat{\beta}_{CC,10}^C = -55$, $\hat{\beta}_{R^2,10}^C = -0.4$, $\hat{\beta}_{VC^2,10}^C = 18$, $\hat{\beta}_{CC^2,10}^C = 0.1$. Due to the very low number of simulation paths, the signs of these estimates partly appear counterintuitive (in particular the estimate $\hat{\beta}^{C}_{CC,9}$, derived from the data in Table 3). However, with our standard number of 10000 state variable paths, the parameter of the linear revenue term exhibits a positive, and all linear cost related variables negative signs. The signs of the quadratic term parameters are more difficult to interpret, yet this is of limited importance since these terms are included only as controls.

Since all expected *NPV*s are positive, at $t = 10$ investment in C is undertaken in all simulation runs. So far our methodology thus suggests $t = 10$ as the optimal switching time in every path. Working backwards in time, at $t = 9$ we again first calculate the net present values for all cash flow time series and subsequently estimate the "clean" *NPV*s based on the level of the state variables at $t = 9$. The results from applying the regression approach can be seen in Table 3.

$NPV^{C}_{9,i}$	2751	2677	3288	2309	2136	2505	2665	2550	3004	1953
$\mathrm{E}_9\left[NPV^{C}_{9,i} \middle| R_{9,i}, VC^{C}_{9,i}, P_{9,i}\right]$	2887	2913	2934	2485	2207	2493	2586	2504	2960	1868

Table 3: Expected net present values and net present values from an immediate investment in the clean technology at $t = 9$ (thousand EUR).

The corresponding estimated regression parameters are: $\hat{c}^{C}_{9} = -46130$, $\hat{\beta}^{C}_{R,9} = 149$, $\hat{\beta}^{C}_{VC,9} = -18$, $\hat{\beta}^{C}_{CC,9} = 119$, $\hat{\beta}^{C}_{R^2,9} = -0.1$, $\hat{\beta}^{C}_{VC^2,9} = 0.2$, $\hat{\beta}^{C}_{CC^2,9} = 1$.

At this stage, standard discounted cash flow analysis would yield a recommendation for immediate investment since all expected *NPV*s are positive. However, it may be a superior strategy to delay the investment to the point in time which has so far been identified to be optimal, namely $t = 10$. The corresponding expected *NPV*s of the next period's optimal decision are therefore the expected *NPV*s presented in Table 4.

The decision between an immediate investment and a deferment now requires a reference value, which can be obtained from equation (7). For each path, we then again use all available state variables as independent variables and the expected *NPV* stemming from the following period's optimal behavior plus the cash flow from technology D for the current period as the dependent variable. Note that contrary to the regression at $t = 10$, at all earlier points in time we use both the D and C cost values, since there is also the possibility of a further deferment in the period after the next. This implies possible dependencies of next period's expected optimal *NPV* on the current cost level of the existing (D) plant. The regression at $t = 9$ yields the following parameter estimates: $\hat{c}^{opt}_{9} = -39839$, $\hat{\beta}^{opt}_{R,9} =$

396, $\hat{\beta}^{Copt}_{VC^D,9} = -60$, $\hat{\beta}^{opt}_{VC^C,9} = -2769$, $\hat{\beta}^{opt}_{CC,9} = -43$, $\hat{\beta}^{opt}_{R^2,9} = -0.3$, $\hat{\beta}^{opt}_{(VC^D)^2,9} = 0.2$, $\hat{\beta}^{opt}_{(VC^C)^2,9} = 23$, $\hat{\beta}^{opt}_{CC^2,9} = 0.2$. They in turn resulting in the following expected optimal *NPV*s at $t = 9$:

$\mathrm{E}_9\left[NPV^{opt}_{9,i} \middle| R_{9,i}, VC^{opt}_{9,i}, P_{9,i}\right]$	2808	2956	2927	2543	2131	2429	2545	2631	3023	1882

Table 4: Expected continuation values at $t = 9$ (thousand EUR).

The expected continuation values are greater than the expected payoffs from an immediate investment in paths $i \in \{2,4,8,9,10\}$, which makes it the optimal decision at $t = 9$ in these paths to defer the investment in C. Moreover these results cause the vector of updated expected optimal *NPV*s at $t = 9$ to equal $\mathrm{E}_9\left[NPV^{opt}_{9,i}\right]$ for these paths, and to equal the discounted values of $\mathrm{E}_{10}\left[NPV^{opt}_{10,i}\right]$ for the remaining paths. Hence, for the next step of our methodology at $t = 8$, this information is used to determine $\mathrm{E}_8\left[NPV^{opt}_{8,i}\right]$.

Continuing like this until $t = 1$ yields a vector of optimal switching times t^*_i for all simulated price paths. This allows us to draw a simulation-based inference regarding the optimal time at which technology C should be realized.

3.2. Results without a CO_2 emission price floor

We start the analysis proper by determining the optimal time t^* for the replacement of technology D with C in the case where the price of CO_2 emission allowances is not regulated. Table 5 shows the results from 10000 simulations without a CO_2 price floor.

t^*	1	2	3	4	5	6	7	8	9	10
#switches	0	43	297	447	465	476	452	562	807	**6451**

Table 5: Number of simulation runs (out of 10000) with optimal replacement at time t^*. The optimal strategy results in technology D being replaced by C in all paths.

In the overwhelming majority of paths we find the optimal strategy to consist of investing in a C plant at $t = 10$. In the case of no CO_2 price regulation, simulations thus essentially suggest the end of the investment decision horizon as the optimal time to switch from technology D to C.[13]

3.3. Results with a CO_2 emission price floor

In this section we examine the effect on the distribution of optimal replacement times of introducing a minimum price P^{min} for CO_2 emission allowances, set by regulatory institutions. As noted in section 2.2, the price floor is implemented by having the CO_2 price follow a GBM. However, if the market price trajectory falls below P^{min}, the price used for the cost calculations is instead set to P^{min} until the GBM appreciates again to a price higher than P^{min}. Setting P^{min} equal to 30 EUR/ton yields the data depicted in Table 6. It displays, for each point in time $t \in \{1, \dots, 10\}$, the number of simulations yielding this time as the optimal investment date.

t^*	1	2	3	4	5	6	7	8	9	10
#switches	3	170	435	864	646	598	714	876	932	**4762**

Table 6: Number of simulation runs (out of 10000) with optimal replacement at time t^* when $P^{min} = 30$ EUR/ton. Again Technology D is replaced by C in all paths.

Increasing P^{min} from 30 to 40 and 45 EUR/ton respectively, changes the distribution of the optimal time of exercise as follows:

P^{min}	t^*	1	2	3	4	5	6	7	8	9	10
40	*#switches*	516	1419	1053	805	655	503	518	520	795	**3216**
45	*#switches*	**7074**	754	356	193	160	76	131	128	183	945

Table 7: Number of simulation runs (out of 10000) with optimal replacement at time t^* when $P^{min} = 40/45$ EUR/ton. Technology D is replaced by C in all paths.

We interpret these results as evidence of a very sensitive relation between P^{min} and t^*. Apparently, t^* does not shift smoothly from the future to earlier points in time as P^{min} increases. Instead, there seems to be a critical level of P^{min} at which t^* shifts quickly from the latest to the earliest possible investment date. In our setup, we find the level of P^{min} which shifts the majority of paths' t_i^* from $t_i^* = 10$ to $t_i^* = 1$ to be around 42.50 EUR/ton.

[13] Increasing the carbon price by means of a higher drift rate in formula (2) leads to earlier optimal switching times. This result corroborates the findings of (Szolgayová, Fuss, and Obersteiner (2008)).

Obviously, the methodology chosen is characterized by a pronounced binary pattern in t^*. This is due to the regression approach used in the estimation of the present values of the uncertain future cash flow time series. It removes the greatest part of the variation in the price paths by basing decisions on expected values.

Figure 3 plots the distribution of optimal switching times t^* over different values of P^{min}. As long as $P^{min} < 40$ EUR/ton our simulations indicate the optimal switching time to be dominated by $t^* = 10$. When P^{min} increases further, the optimal switching time quickly shifts from $t^* = 10$ to $t^* = 1$. Also, all other possible investment decision dates ($t = 2, t = 3, \ldots, t = 9$) are of minor importance. This graphically substantiates the proposition of a binary pattern within the investment decision. The intersection of the $t^* = 1$ and $t^* = 10$ trajectories can be found around $P^{min} = 42.50$. This floor price level can be interpreted as the geometric solution to the question of the critical P^{min} which triggers t^* to shift from 10 to 1.

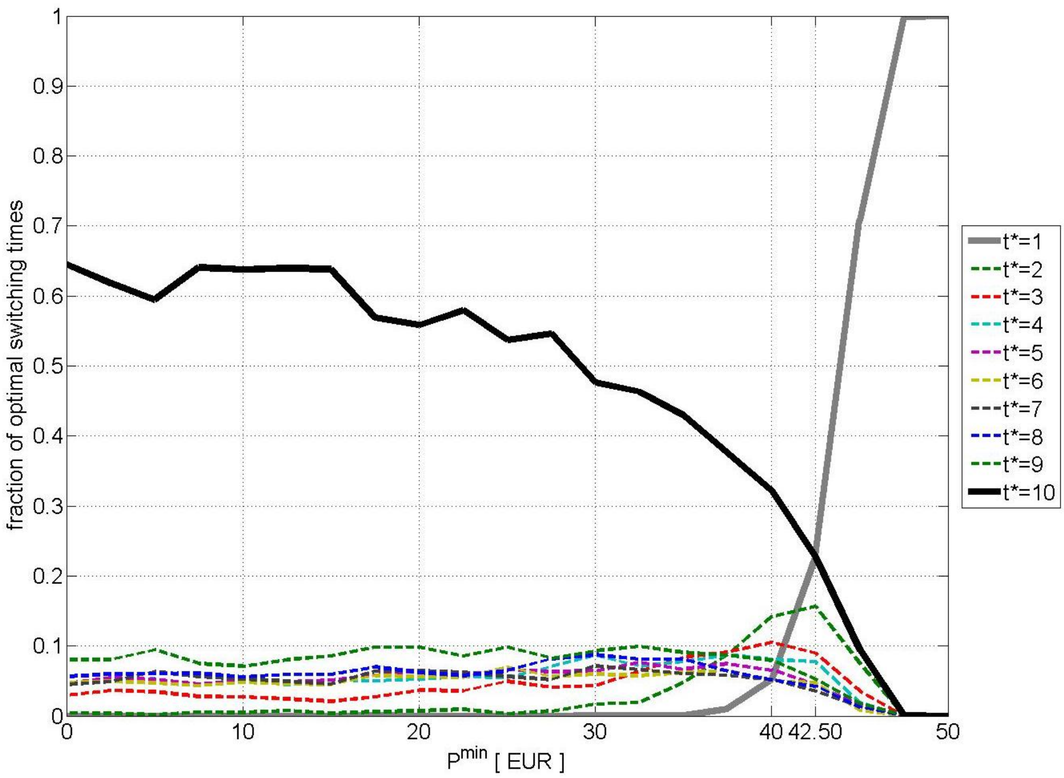

Figure 3: Distribution of optimal switching time t^* over different minimum prices for CO_2

In reality it seems unlikely that any regulator will be able to directly implement a minimum price of triple the current market price. For this reason we analyze the effects of a different price floor mechanism. In this second approach, we set the starting floor price P_0^{min} to a value close to the current market price and increase it by an increment M in every period thereafter.[14] If the initial minimum price P_0^{min} is for example set to 15 and the increment is chosen to be $M = 1$, the next period's minimum CO_2 prices will be 16, then 17,and so on. Contrary to a fixed level of $P_t^{min} = P^{min}$ this approach does not result in a distribution of optimal switching times peaking at $t^* = 1$ or $t^* = 10$, but rather concentrates the optimal switching decision to a time in the interior of $[1, \dots, 10]$ (especially when the diffusion rate μ_P of the CO_2 price process is low). The modal outcome of t^* depends on the choice of M. Table 8 shows results from simulation runs where $P_0^{min} = 15$ and all other parameters are set according to our basic scenario:

M	t^*	1	2	3	4	5	6	7	8	9	10
1	*#switches*	0	102	465	648	666	600	722	747	1088	**4962**
2	*#switches*	4	296	716	834	849	864	758	868	1159	**3652**
2.5	*#switches*	2	387	912	1160	1209	954	896	740	971	**2769**
3	*#switches*	2	533	1462	**1779**	1500	1239	955	610	443	1477
4	*#switches*	88	2116	**3757**	2887	1105	19	17	0	8	3
5	*#switches*	1042	**5960**	2893	105	0	0	0	0	0	0
6	*#switches*	**7742**	2252	6	0	0	0	0	0	0	0
7	*#switches*	**9977**	23	0	0	0	0	0	0	0	0

Table 8: Number of simulation runs (out of 10000) with optimal replacement at time t^* when $P_0^{min} = 15$ EUR/ton and an increment of $M \in \{1, 2, 2.5, 3, 4, 5, 6, 7\}$. The higher the increment, the earlier the replacement investment comes to be realized. Our results indicate the requirement of $M \gtrsim 3$ EUR per year for the mode of optimal switching times to occur earlier than at $t = 10$.

Figure 4 presents the fraction of optimal switching times for different P_0^{min} when M is set to 3 EUR/ton. If a minimum price for CO_2 is combined with a constant annual increase of this minimum price, optimal switching times are – over large parts of the parameter space – again dominated by two points in time, namely $t^* = 1$ and $t^* = 10$. However, when P_0^{min} falls in the interval between 20 and 33 EUR/ton, other points in time can be observed to

[14] Note that this is a generalization of our approach in that our previous analysis is a special case where $P_0^{min} = P^{min}$ and $M = 0$.

exhibit peaks and thus constitute the predominant times at which the clean plant should be built.

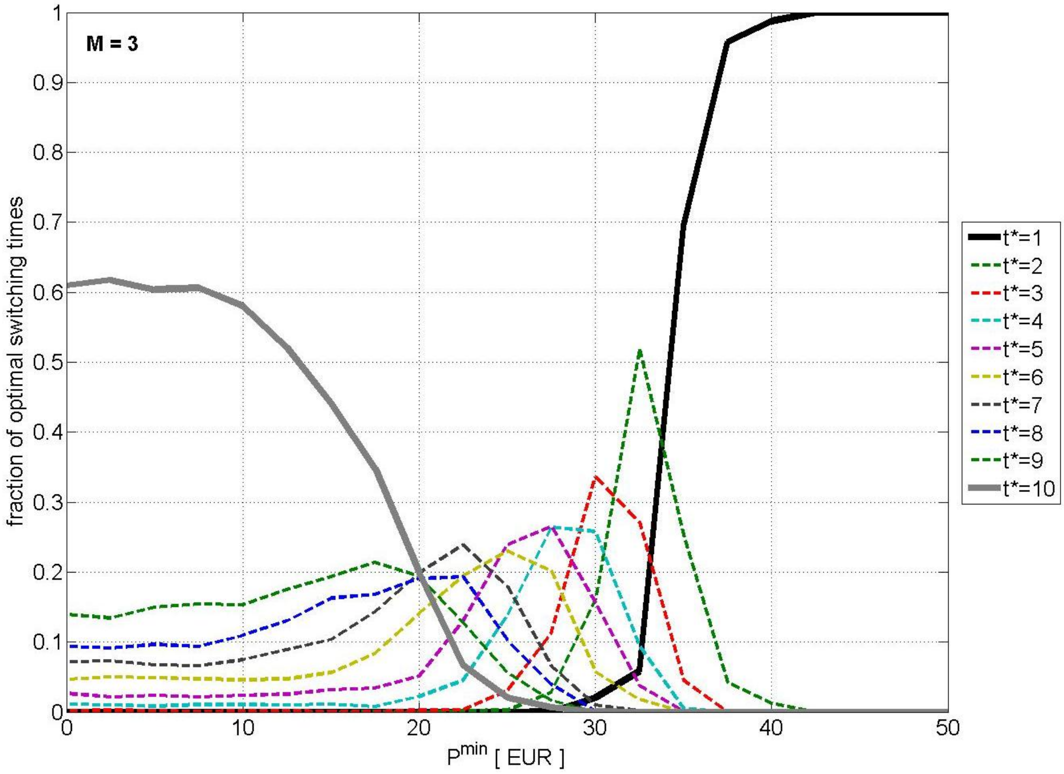

Figure 4: Fraction of optimal switching times t^* with respect to different P_0^{min} when $M = 3$.

3.4. Discussion and Robustness Checks

As pointed out in the preceding section, the choice of input parameters is crucial for the results regarding the optimal switching time t^*. Since some of our parameter settings result in very different optimal switching times for only slightly modified parameters we now assess the robustness of our results by running simulations with a large set of parameter setting variations. Our main interest lies in the effects of changes in

- the initial minimum CO_2 price P_0^{min}
- the chosen increment M
- the drift rate μ_P, and
- the diffusion rate σ_P of the CO_2 price process, as well as
- the discount rate r.

More precisely, we jointly vary our parameters over the following values: $P_0^{min} \in \{0,2.5,5,\ldots,50\}$, $M \in \{0,1,\ldots,5\}$, $\mu_P \in \{0,0.02,\ldots,0.1\}$, $\sigma_P \in \{0.1,0.2,\ldots,0.5\}$ and $r \in \{0.03,0.04,\ldots,0.07\}$, yielding a total of 21 · 6 · 6 · 5 · 5 = 18900 combinations of different input parameter choices and requiring the simulation of 3×10^{10} individual values. All other parameters are held constant, because they only concern revenues and technology related costs and lifetimes and are thus considered to be relatively reliable. The following figures plot results from the majority of the 18900 parameter settings. In the interest of clarity we only report the decision time which maximizes the fraction of our 10000 paths in which the switch to technology C occurs at this time (mode). This is done graphically in Figures 5 through 7. White areas indicate that t^* predominantly equals 10, whereas black areas label cases where the modal outcome is $t^* = 1$. Other optimal points in time are shaded gray. We do this separately for three different discount rates, namely $r \in \{0.03,0.05,0.07\}$, drift rates (rows of the plot matrix), and diffusion rates (columns of the plot matrix). This yields 30 subplots per figure. In each subplot, the abscissa shows the different increments $M \in \{0,1,\ldots,5\}$ and the ordinate labels the different initial minimum CO_2 prices, $P_0^{min} \in \{0,2.5,5,\ldots,50\}$.

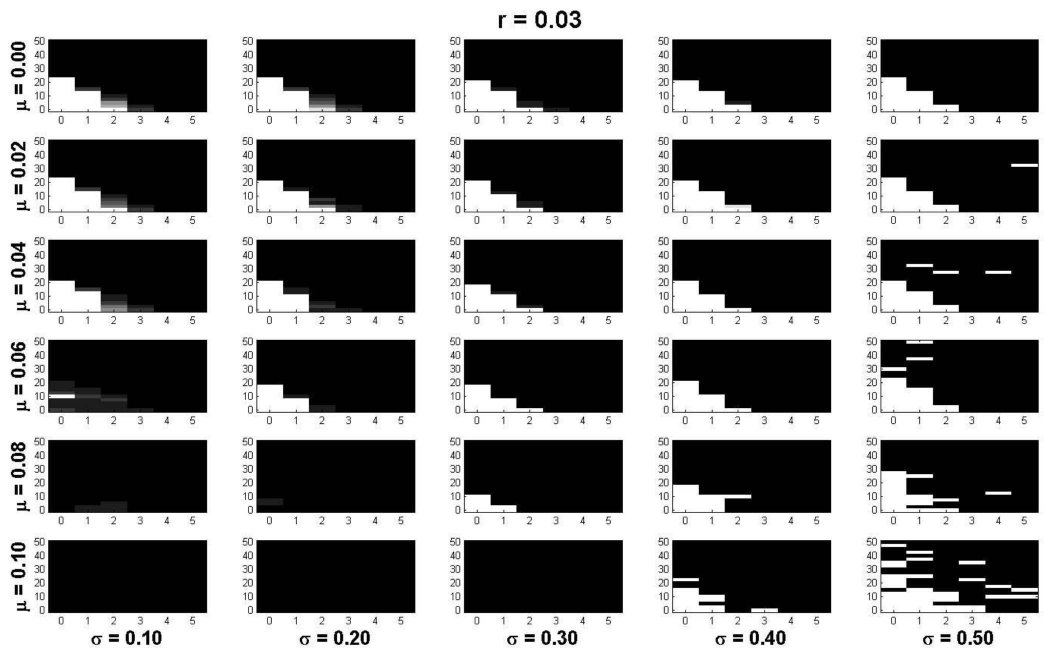

Figure 5: Most frequently chosen times for switching from technology D to C when $r = 3\%$. Black indicates that the modal outcome from 10000 simulation runs is $t = 1$ and white indicates it to be $t = 10$.

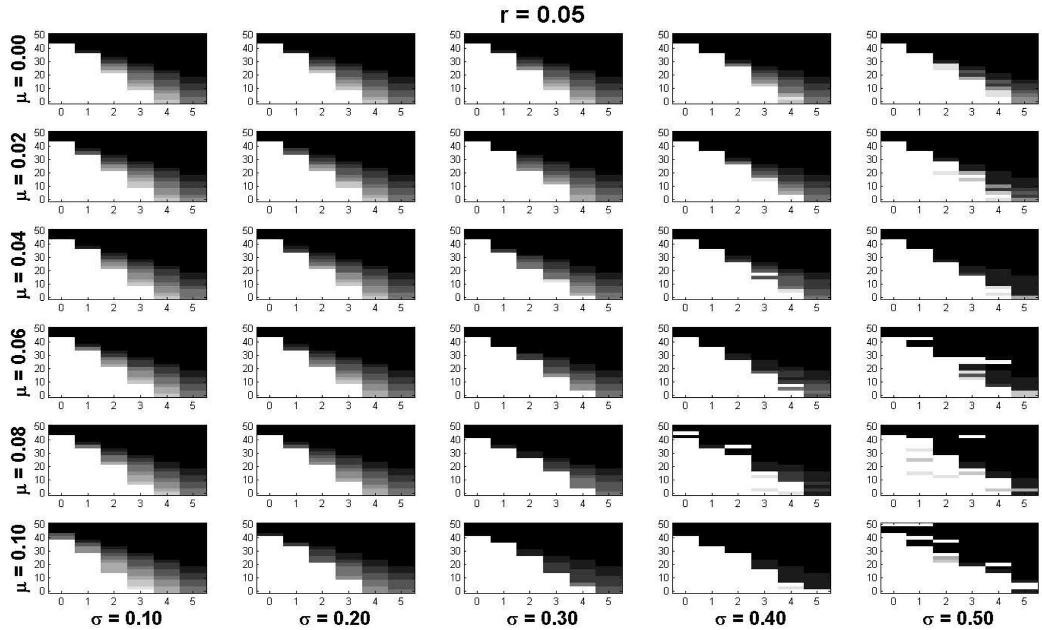

Figure 6: Most frequently chosen times for switching from technology D to C when $r = 5\%$. Black indicates that the modal outcome from 10000 simulation runs is $t = 1$ and white indicates it to be $t = 10$.

In the case of $r = 3\%$ (Figure 5), low drift rates and high diffusion rates yield later optimal switching times, while $t = 1$ is more often found to be the optimal time to switch from technology D to C if the drift rate is high and the diffusion rate of the CO_2 price process is low. As Figures 6 and 7 show, t^* shifts to later points in time with increases in the discount rate. If we increase the latter to 0.07, almost all parameter settings result in a deferment of the investment into technology C to the end of the investment decision horizon at $t = 10$ (with the exception of those cases where P_0^{min} and M are relatively high).

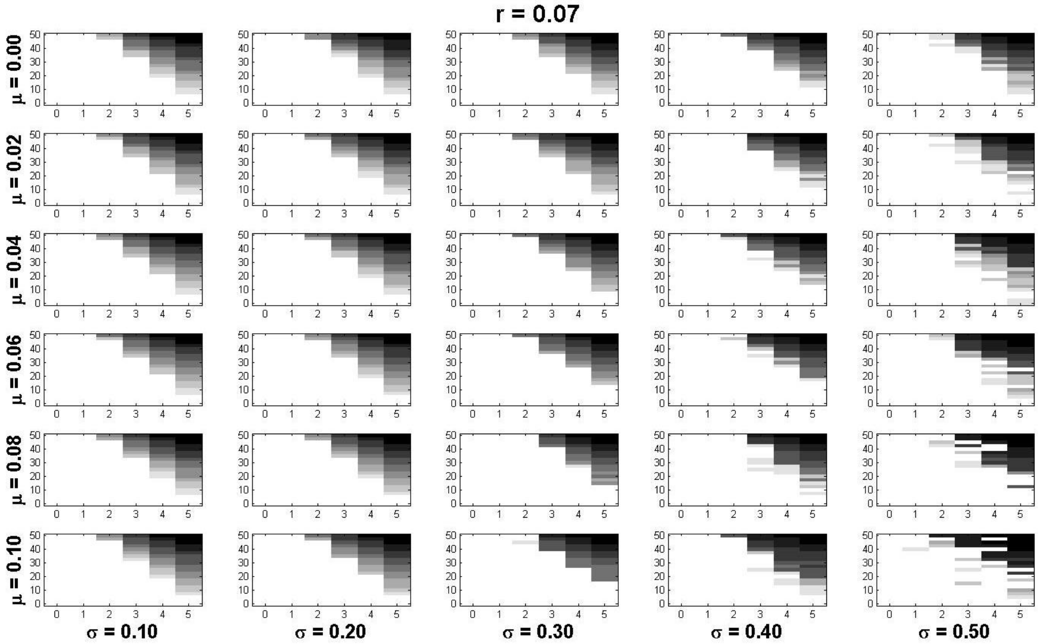

Figure 7: Most frequently chosen times for switching from technology D to C when $r = 7\%$. Black indicates that the modal outcome from 10000 simulation runs is $t = 1$ and white indicates it to be $t = 10$.

Taken together, we find a clear pattern in these plots. For each combination of the discount, the drift and the diffusion rates there exists a pair of P_0^{min} and M which moves the optimal time for replacing technology D with C from $t = 10$ to $t = 1$. This provides a clear argument for CO_2 price policy in the form of a price floor.

We also briefly assess the effects of different levels of input parameters employing a ceteris paribus analysis. The following figures depict the distribution of t^* for 10000 simulation runs, varying one of the input parameters of interest and keeping all other parameters constant. By default, we set $P_0^{min} = 30$ EUR/ton, $M = 0$, $\mu_P = 8\%$, $\sigma_P = 30\%$ and $r = 5\%$. We vary the latter four separately to reveal the effects different levels of these parameters have on the investment decision.

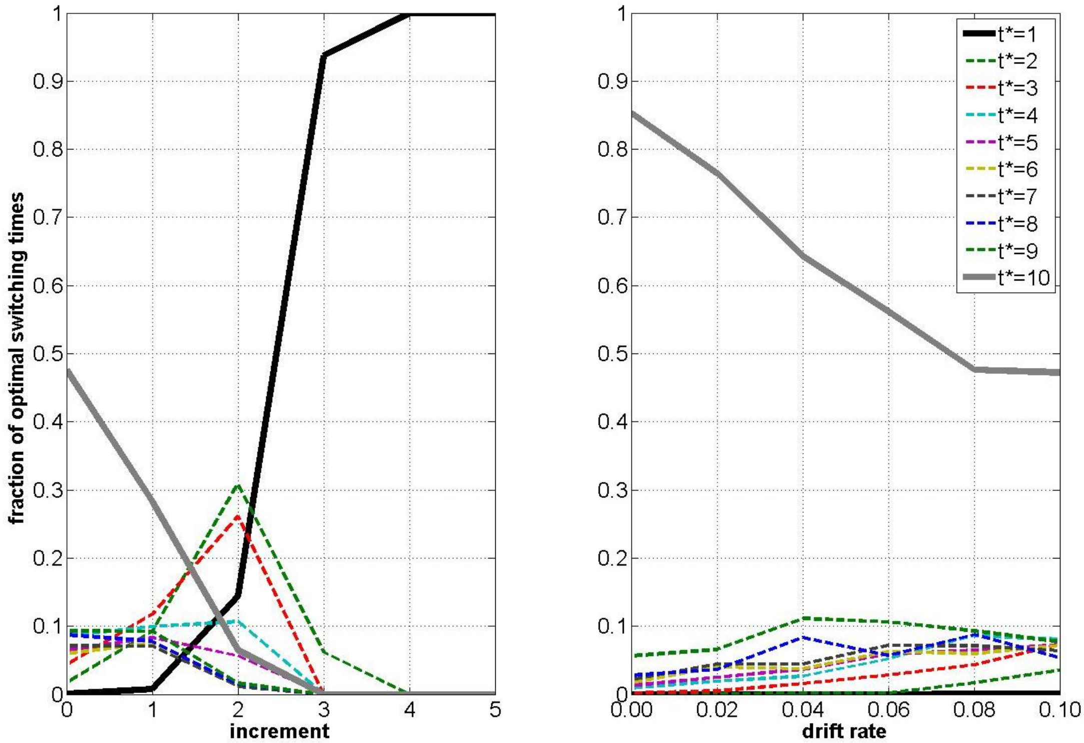

Figure 8: The left hand plot depicts effects of different levels of the increment M, the right hand plot sketches the impact of different drift rates μ_P of the CO_2 price process. P_0^{min} is set to 30 EUR/ton.

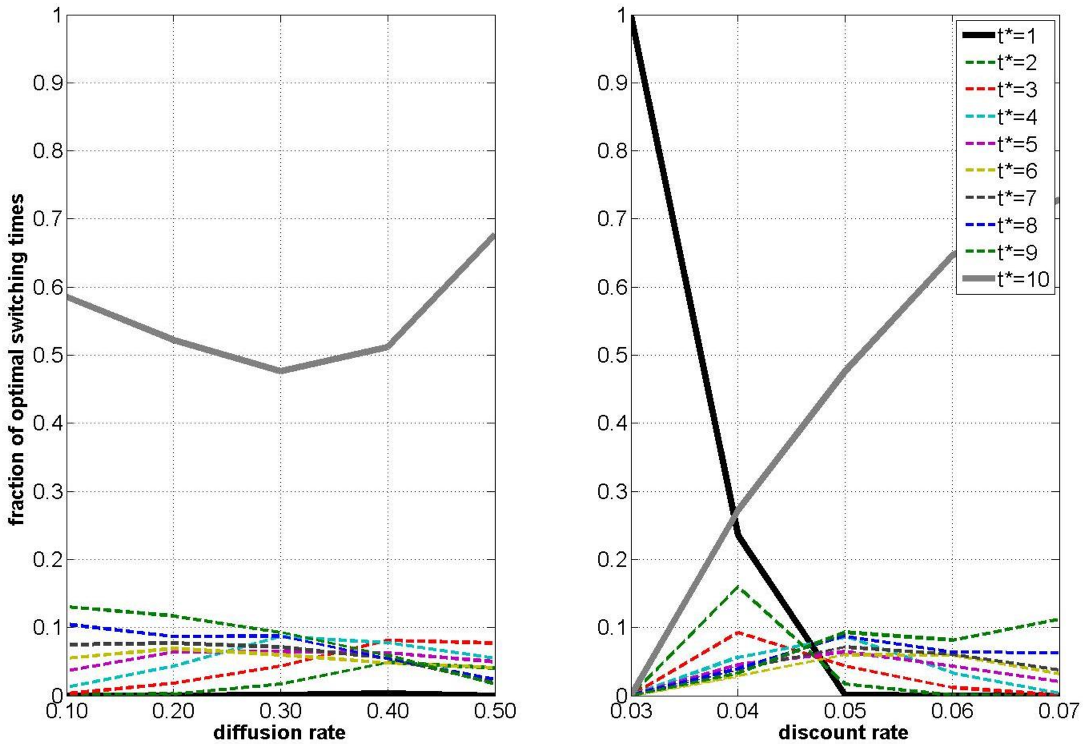

Figure 9: The left hand plot shows the effect of different diffusion rates σ_P on the optimal switching time. On the right, effects of different discount rates r on the investment timing problem are shown. Again, P_0^{min} equals 30 EUR/ton.

Note that, for the given parameter setting, the mode of the optimal switching time is $t^* = 10$ for any volatility of the CO_2 price process. Furthermore, the fraction of cases where $t^* = 10$ is the optimal switching time is highest for very low and very high diffusion rates. This is a departure from the findings for the other parameters, which exhibit a monotonously increasing or decreasing pattern for the fractions of optimal switching times $t^* = 1$ and $t^* = 10$. Since this "volatility smile" could also have been the result of a too low number of simulation runs, we replicated this effect with 100000 simulations, obtaining the same result. This pattern can be attributed to the fact that higher volatility of the CO_2 price implies a greater number of very high carbon price scenarios as well as very low price scenarios. A greater number of high CO_2 price paths do not affect the investment decision, since as soon as the CO_2 price exceeds a critical threshold, an early investment into technology C is optimal in any case. However, since lower prices also become more frequent, this benefits the dirty technology and results in the observed pattern of deferred switching times. Furthermore the discount rate plays a prominent role, since there is great variability in optimal switching times in a narrow bandwidth of discount rates. This shows that the investment timing decision to a large degree depends on the capital costs of the firm.

Another aspect of our setup that we check for robustness are the uncorrelated processes of state variables (revenues, unit costs using technologies D and C, CO_2 costs). We tackle this point by introducing a (largely) non-zero correlation matrix of the form:

$$\rho = \begin{bmatrix} 1 & 0.5 & 0.5 & 0.8 \\ 0.5 & 1 & 0.2 & 0.2 \\ 0.5 & 0.2 & 1 & 0 \\ 0.8 & 0.2 & 0 & 1 \end{bmatrix}$$

We assume that revenues are positively linked to costs, since any power producer will try to pass increased costs on to consumers. Nonetheless, the correlations are chosen with the main aim of capturing what possible effect the use of correlated state variables could have, without trying to exactly mirror real world correlation structures. We chart the effects we find as the difference in the fractions of optimal switching times between a simulation using uncorrelated state variables and one employing correlated state variables.

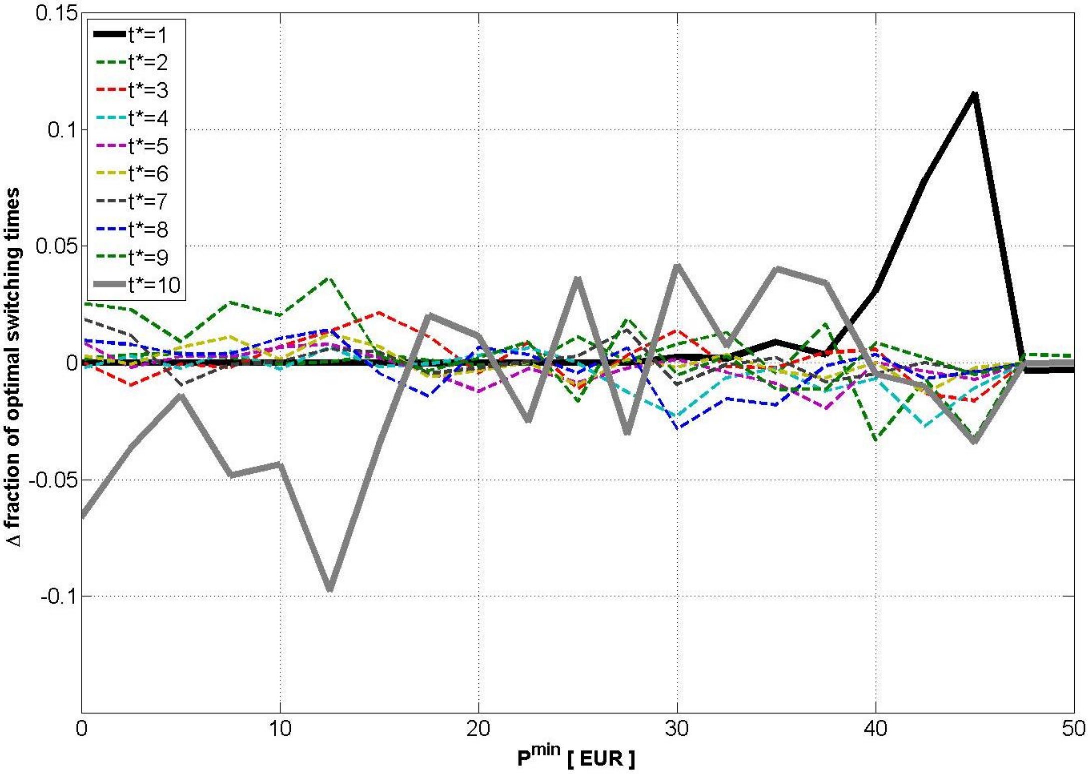

Figure 10: Differences in the fraction of optimal switching times. The plot shows changes from the uncorrelated setup when introducing correlation between the state variable processes.

Figure 10 shows that the optimal switching times from $t^* = 2$ to $t^* = 9$ are hardly affected by introducing correlation. At the same time, applying the correlation matrix ρ results in a smaller (greater) fraction of cases where $t^* = 10$ ($t^* = 1$) when P^{min} is low (high). The following table reports the exact number of simulations with correlated state variables leading to $t^* = \{1, \dots, 10\}$, and can be readily compared to tables 5 and 7 for the same results using uncorrelated state variable processes:

P^{min}	t^*	1	2	3	4	5	6	7	8	9	10
0	*#switches*	0	59	302	423	557	508	641	659	1062	**5789**
40	*#switches*	825	1089	1111	737	658	504	473	555	881	**3167**
45	*#switches*	**8233**	431	193	85	89	55	89	90	132	603

Table 9: Number of simulation runs (out of 10000) with optimal replacement at time t^* when $P^{min} = 0/40/45$ EUR/ton and the revenue, unit cost and CO_2 price processes are correlated according to ρ.

4. Conclusion

In this paper we evaluate the effects of downward limited stochastic CO_2-prices on the investment decision of a profit maximizing energy producer. We apply an approach derived from real-option valuation and demonstrate that a CO_2 price floor can be used to induce emitters to accelerate their investments in low-carbon technologies. Since the decarbonization of the power sector, which accounts for a substantial proportion of total greenhouse gas emissions, is a conditio sine qua non for achieving lower emission targets, we choose this industry for our analysis. The key argument lies in the fact that the decision to invest in low-carbon generation technologies immediately may be superior to continuing to operate a high-carbon technology, especially in high permit price regimes. This decision is taken by comparing the expected net present value of an immediate clean investment to that resulting from the deferment of an investment. Our results based on Monte Carlo simulations identify the appropriate level of a constant minimum CO_2-price in our setting – implying an immediate "clean" investment – to fluctuate between 40 and 45 Euros per ton. An alternative solution is to introduce a fixed initial minimum price with a growth rate regime, as it is currently being implemented in the UK (HM Treasury and HM Revenue & Customs (2010)). Simulations reveal that under this approach, the starting CO_2 price floor can be considerably lower, with its optimal level – unsurprisingly – depending on the growth rate.

However, our results turn out to be relatively sensitive with respect to the model inputs. We perform extensive robustness checks and find patterns in the distribution of optimal switching times which enable us to derive robust findings. In particular, some parameter settings balance the optimal investment timing somewhere in the interior of the investment decision horizon. We use this observation to clearly identify the impacts of changes in the CO_2 price floor, its growth rate, the drift and diffusion of the CO_2 price process and the discount rate.

Moreover, we demonstrate that the carbon market not only helps the regulator to meet emission targets in an allocationally efficient way, but can also be used as an instrument to stimulate the adoption of low-carbon technologies. Several political proposals (e.g. in Australia, the UK and US) in the recent past support this view of the carbon market. Meanwhile it has become apparent that a permit trading system will not suffice as the sole driver in reaching the target of a decarbonized economy. A mixture of policy instruments will instead be necessary to stabilize our climate. A carbon price floor is one such instrument, which is able to enhance the role of an emissions trading system in this process.

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