Price dynamics in the European Union Emissions Trading System and evaluation of its ability to boost emission-related investment decisions

Maria Flora [*]   Tiziano Vargiolu [†]

Abstract

The price of permits in the European Union Emissions Trading System (EU ETS) has historically been highly sensitive and prone to jumps. We consider different stochastic processes to model the price of permits, and show that the Variance Gamma (VG) model provides the best fit for the price distribution, among a selection of infinite activity processes. Using this result as a starting point, we assess the effects of the EU ETS in delivering low-carbon investments at the firm level, by modeling a price taker electricity producer subject to the EU ETS jurisdiction. We compute, via Least Squares Monte Carlo, the value of the real option the greenhouse gas emitter has, consisting in the opportunity to switch from its current high-carbon technology to a cleaner one. We use a VG specification for carbon prices, and a mean-reverting (Brennan-Schwartz) process for the price of fuel. Moreover, we further analyze the investment decision problem, in case of a CO_2 price stabilization mechanism in the form of a price floor, by explicitly computing the expected value of the investment project by means of Fourier methods. Our results show that the introduction of the price stabilization mechanism significantly affects the timing of the investment decision, and supports emission-related investments.

[*]Università degli Studi di Verona - Department of Economics - via Cantarane, 24 - 37129 Verona, Italy - maria.flora@univr.it - *corresponding author*

[†]Università degli Studi di Padova - Department of Mathematics - Via Trieste, 63 - 35121 Padova, Italy - vargiolu@math.unipd.it

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1 Introduction

In the past decades, it has become increasingly clear that a development model heavily based on fossil fuels is hardly sustainable on the long term. This is why the recent international environmental agreements (UNFCCC, Kyoto Protocol) have urged countries to adopt emission reduction measures and to invest in alternative energy projects. One of the policy tools of newest implementation, aimed at reducing greenhouse gas (GHG) emissions, is emission trading. Such a tool is aimed at internalizing the negative externalities generated through the production processes, by making the polluting private firms buy a number of emission allowances, corresponding to the tons of GHG they emit in the atmosphere.

Emission trading systems (ETS) are usually cap-and-trade schemes, in which the regulator sets the maximum amount of CO_2 and other polluting gases that can be emitted in the system, and then firms buy and trade the emission permits on the base of their needs. Each emission permit (or emission allowance) grants its owner the right to emit one ton of GHG.

The aim of this paper is to give a quantitative view on the evolution of the European Union Emissions Trading System (EU ETS) carbon market, and to analyze the emission reduction problem from the point of view of an electricity producer running a fossil fuel-fired power plant. The carbon-intensive electricity producer is confronted with the choice of either submitting to the ETS jurisdiction, or changing the production model, by switching production to low carbon sources of energy.

We take into account the uncertainty involving future European Union Allowance (EUA) prices and the irreversible costs connected to a new renewable power plant investment, and we consider the opportunity of switching production method as a real option. Computing the price of such a real option gives a measure of how convenient it is for the GHG emitter to shut down the fossil fuel-fired power plant and to invest in a renewable energy project. In this paper, we focus on an oil-fired power plant, and we choose photovoltaic (PV) energy as the alternative source of energy considered.

A proper valuation of the real option relies on a correct modeling choice of the EUA price dynamics. In the pertinent modeling literature, the appropriate stochastic modeling of the carbon price is still an open question (see Lukas and Welling (2014) and references therein), and the common approach is that of assuming that the carbon price follows a geometric Brownian motion (GBM). This paper aims at taking an additional step towards filling this gap. We consider different infinite activity stochastic processes, and determine which one is more suitable for replicating the carbon price behavior. Moreover, we model oil prices using a Brennan-Schwarz (BS) model. Our final result confirms qualitatively the findings of Brauneis et al. (2013), which had a research question similar to ours, but we find out that the choice of the driving processes for carbon and fuel prices heavily affects the shape of the expected optimal switching time.

Section 2 places this paper in the relevant literature on the subject. Section 3 presents the model and the methodology. As mentioned, pricing a real option requires consistently defining the price dynamics of the underlying assets, and this is why the first part of Section 3 is devoted to analyzing the EUA spot prices, in order to define a stochastic process able to consistently replicate their trend over time, while the subsequent parts are devoted to modeling oil price, PV energy cost and the real option payoff. Section 4 presents the results and conducts a sensitivity analysis, both with respect to parameters as with respect to the stochastic processes used to model prices. Section 5 concludes.

2 Relevant Literature

Since the European Union carbon market was established in 2005, the uncertainty related to the magnitude of compliance costs and to the impact of this type of climate policy on the power sector has motivated some research on this field. Some of the early contributions can be traced back to Barreto and Kypreos (2004) (see also Kunsch et al. (2004)), Laurikka and Koljonen (2006) and Szolgayova et al. (2008).

As time went by, the magnitude of the downward risk in the EU ETS started to motivate some research aimed at discussing the effects of bounding carbon prices by means of a regulatory minimum price for EU allowances. The theoretical studies by Weber and Neuhoff (2010), Grüll and Taschini (2011) and Wood and Jotzo (2011) act in this sense, analyzing the possibility of enhancing the incentives provided by the EU ETS, by introducing a CO_2 price floor. Franco et al. (2015) study the British electricity market reform and support the carbon floor policy as well, even if they advise to also simultaneously implement a feed-in tariff and a capacity mechanism for improved effectiveness. The carbon floor has been actually adopted in the UK and has evidenced its positive contribution in changing the energy mix. In fact, it led to the a 76% drop in coal consumption for electricity generation in 2016, compared to 2013 – when the carbon price floor was introduced (World Bank, 2017). Such a political intervention has been also envisaged for other emission trading schemes. For instance, Weng et al. (2018) suggest to introduce it in the new Chinese ETS, which has been officially announced on December 2017, and will become fully operational by 2020.

Most similar to our work are those of Abadie et al. (2011) and Brauneis et al. (2013), who also analyze the possibility of a carbon price floor, in a real options-based approach framework, to assess the effects on the firm-level investment decisions. Both compute the value of the option to abandon a fossil-fueled power plant, as a function of carbon prices. The former employs a binomial lattice model where the prices of coal and electricity follow a mean-reverting Brennan Schwartz model and the CO_2 permit price follows a geometric Brownian motion (GBM). The latter, instead, uses the least-squares Monte Carlo approach to solve the optimization problem of decision making in case of an electricity producer who has the option to replace the existing coal-fired power plant with a "cleaner" nuclear one, when both energy and CO_2 prices follow a GBM. Brauneis et al. (2013), moreover, compute the floor price required to trigger investment in the new low-carbon plant, and propose a number of different designs for the floor price.

In this paper, we study a problem similar to that of Brauneis et al. (2013), introducing a different stochastic process, both for fuel and carbon prices, in place of the GBMs originally used, and improving the way of how the option value is computed. For the fuel price, we choose a Brennan-Schwartz model, in analogy with Abadie et al. (2011), as energy commodity prices typically exhibit mean-reversion in their price levels. Conversely, carbon is a special asset that may resemble energy commodities in some aspects but differentiates itself in others. In fact, its price somewhat depends on an exogenous political decision, which caps the total supply of the product. This aspect reflects in the price process, featuring extreme events such as jumps and spikes, as well as heavy tails and leptokurtic behavior in the distribution. The majority of the papers on the ETS subject have used, for ease of modeling, GBM processes to describe the EUA price behavior (cfr. Szolgayova et al. (2008), Yang et al. (2008), Abadie et al. (2011), Brauneis et al. (2013), Lukas and Welling (2014), Compernolle et al. (2017), among others). Instead, we provide empirical evidence that the carbon log-returns are not normally distributed, and propose a different specification for the allowances price, based on geometric Lévy processes more general than the GBM. We base our analysis on historical data of EUA spot prices, and we deem that the most well-suited process to model carbon prices is a Variance Gamma (VG) process, which, to our knowledge, has never been used for this purpose.

We use this finding in a real option framework, to evaluate the real option value of replacing a polluting power plant with a renewable one, under the EU ETS jurisdiction. The underlying asset of the real option moves accordingly to both a Brennan-Schwartz and a VG process, as it depends on both fuel and carbon prices. On the other hand, the exercise price of the option (*i.e.*, the renewable plant investment cost) depends on the levelized cost of electricity (LCOE) of the selected renewable technology. We base our analysis on Biondi and Moretto (2015) and Fraunhofer ISE (2015), who find that the LCOE of a PV plant is well modeled as a decreasing exponential in a horizon (1976–2010) of more than 30 years (Biondi and Moretto (2015)), and expected to follow a similar trend up to 2050 (Fraunhofer ISE (2015)). By using the ingredients above, we are able to compute the option payoff, both in a base scenario and in a regulatory intervention one, using closed formulas whenever possible, fact that effectively lowers the computational burden.

3 Methodology

We consider a price-taker and risk-neutral power generating firm, that operates a "dirty" electricity generation technology in Italy.[1] Being subject to the EU ETS jurisdiction, the firm has either to buy the necessary EUAs to run its business, or it can decide to switch production model towards more sustainable energy sources, in order to avoid the compliance costs. In either case, we require the firm to always have exactly one power plant under operation, with a similar electricity output: this also has the side effect that the agent's switching decision does not affect market prices. As previously

[1] Choosing a specific geographic region where to base our project is just a tool for consistently defining the technical characteristics and output of the new plant, powered by renewable sources. Nevertheless, our model can be used for different geographical locations.

mentioned, we focus on an oil-fired power plant, and choose PV technology as a case study. In order to reduce the dimensionality of the problem, we suppose that the two alternative plants, the "clean" and the "dirty" one, produce roughly the same amount of electricity per year, with the same assumed revenue in terms of electricity sold[2]. In this way, when evaluating the real option, we get rid of the electricity price variable[3]. The technical characteristics of the firm at $t = 0$ are reported in Table 1.[4]

3.1 Price modeling

In what follows, we model the three relevant variables, i.e. the carbon and oil spot prices and the levelized cost of PV-generated electricity, with three different specifications. As concerns EUA and WTI crude oil prices, which are the two state variables that we assume to be stochastic, their correlation is assumed to be equal to zero, after Chevallier (2012), who finds the time-varying correlation between these two variables to be in the range $[-0.05; 0.05]$.

3.1.1 Carbon price

EU carbon prices have followed a particular path over time. We are currently in the third carbon trading phase, but the price behavior is still marked by high volatility and uncertainty. As Grüll and Kiesel (2012) show, the high price sensitivity of permits and their proneness to jumps are structural features of the EU ETS in its present configuration. For these reasons, a simple GBM model does not seem appropriate to describe carbon prices. We perform a data analysis to verify this conjecture, using daily spot prices of EUAs traded on the European Energy Exchange (EEX). The sample period

[2]Here we must emphasize that oil plants deliver base power, while PV typically has a high peak on mid-day, i.e. when the electricity price is higher. However, this also depends on the solar radiation level reaching the ground, i.e. on the cloudiness during a given day. Therefore, the profit from selling electricity has to be adapted to this. Luckily, the synthetic indicator that we use in the paper (LCOE) allows to average out all these differences and gives, as a result, the average cost of electricity along the entire life of a power plant.

[3]Although other options are in principle possible, as dismissing the old polluting plant or substituting it with a newer one with the same technology, Brauneis et al. (2013) found out that these two choices are almost never optimal: for this reason, we exclude them from the beginning, with the effect of reducing the number of state variables.

[4]We refer the reader to Appendix A.1 for the computation of some of the values in the table.

Table 1: Technical characteristics of the oil-fired power plant.

Variable	Unit	Value
Capacity	MW	10
Residual lifetime	years	25
Capacity factor*	rate	80%
Efficiency¶	rate	40%
Electricity produced	kWh/year	$7.01 \cdot 10^7$
Fuel consumption	tons/year	$1.48 \cdot 10^4$
CO_2 emission factor	tons/kWh	$2.64 \cdot 10^{-4}$
CO_2 emissions per year	tons/year	46,200
Operating & maintenance costs	million EUR/year	0.5
Decommissioning costs	million EUR	1

* The capacity factor is the ratio of a power station actual generation to its maximum potential generation. This value represents the theoretical capacity factor of an oil-fired power station in good condition. In Italy there are some examples of fuel oil plants which have been running in full swing over the recent years: the Livorno Marzocco power plant, Tuscany, operating since 1965, in 2007 had a capacity factor of 79% (see http://enipedia.tudelft.nl/wiki/Livorno_Powerplant).

¶ The efficiency of a power station is a percentage measure given by the ratio between the electricity produced and the heat energy needed in order to produce it. According to IEA (2008), the average efficiency of oil-fired electricity production in Italy, over the 2001-2005 period, was 41%. For ease of calculation, 40% is taken as a proxy.

stretches from 01/01/2015 to 01/06/2017, *i.e.* 574 observations. The chi-squared goodness of fit test of a Gaussian distribution on log-returns gives an extremely low p-value ($7.76 \cdot 10^{-10}$) and the null hypothesis of normality is rejected at the 1% significance level. This is mainly due to the pronounced leptokurtic behavior of the log-return distribution, which causes the high peakedness about the mean and lack of shoulders.

These characteristics suggest to use more general stochastic processes to model this variable. In particular, we focus on infinite activity Lévy processes rather than on jump-diffusion ones, as it has been argued that these processes lead to a more realistic description of the price dynamics at various time scales (see Cont and Tankov (2004) Chapter 4.1.1 and references therein). Among the most popular choices of such processes, we compare the Variance Gamma (VG), the Normal Inverse Gaussian (NIG) and the Generalized Hyperbolic (GH) processes. Figure 1 shows the comparison between

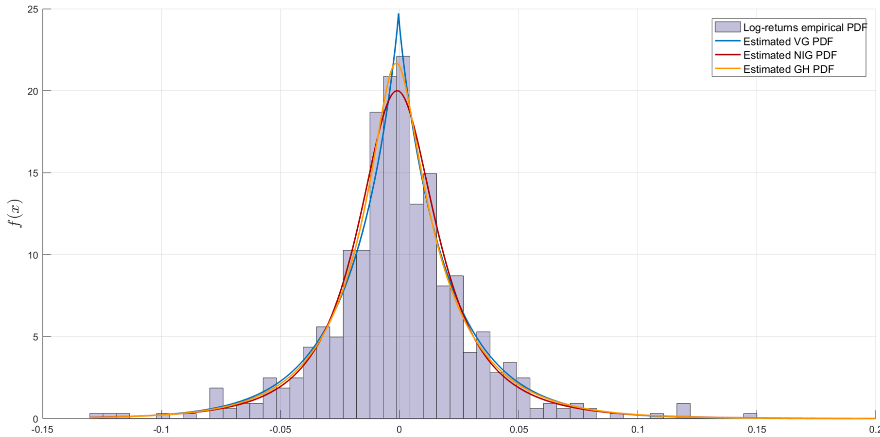


Figure 1: Variance-Gamma, Normal Inverse Gaussian and Generalized Hyperbolic fits on EUA spot prices, listed at the European Energy Exchange (EEX).

the empirical probability density function (PDF) and the PDFs of the three selected processes. The three processes all provide a close fit to the historical price distribution.

However, Table 2 indicates that, among the three, the VG process is the most indicated to describe the price dynamics, as it displays the highest p-value in Pearson's chi-squared goodness-of-fit test (which thus fails to reject the null hypothesis of VG distribution with a high probability), and the lowest value of the Bayesian Information Criterion (BIC). It must be noted, however, that the other two infinite activity candidates, the NIG and the GH, appear to be almost equally good, with closely equivalent BIC values. The three of them are all markedly superior to the GBM, whose BIC value is remarkably higher.

The bottom panels of Figure 2 show that, in particular, the VG process graphically fits the data on spot carbon prices better than the GBM, both for the cumulative density function (CDF, bottom left panel) and for the probability density function (PDF, bottom right panel). The carbon parameters of the VG model, estimated via maximum likelihood estimation (MLE), are reported in Table 3.

	χ^2 GoF p-value	BIC
GBM	$7.76 \cdot 10^{-10}$	-2362.68
VG	0.44	-2454.34
NIG	0.25	-2453.90
GH	0.36	-2449.55

Table 2: The table shows the p-value of Pearson's chi-squared goodness-of-fit test (χ^2 GoF) and the value of the Bayesian Information Criterion (BIC) for each model considered. The results of the chi-squared test show that the null hypothesis is rejected only for the GBM case. The BIC test shows that the VG model is the one providing the best fit.

Parameter	Estimated value
$\hat{\mu}$	$-5.09 \cdot 10^{-4}$
$\hat{\sigma_P}$	0.030
$\hat{\theta_P}$	$-3.59 \cdot 10^{-9}$
$\hat{\alpha}$	0.935

Table 3: Estimated daily parameters for carbon spot data fitted via maximum likelihood estimation (MLE) using a VG model.

3.1.2 Oil price

In commodity markets, a widely accepted assumption is that of mean reverting spot prices (see for example Lutz (2010)). Thus, in analogy with Abadie et al. (2011) who use it for coal and gas prices, we choose a Brennan-Schwartz (BS) process (see Brennan and Schwartz (1980)) for the WTI crude oil spot price D_t:

$$\mathrm{d}D_t = k(\theta_D - D_t)\,\mathrm{d}t + \sigma_D D_t\,\mathrm{d}W_t \tag{3.1}$$

where k is the speed of reversion toward the mean, θ_D is the long run mean price level, σ_D is the volatility of the process and $\mathrm{d}W(t)$ is the increment of a Wiener process. We estimate the parameters using daily WTI crude oil spot prices from 01/01/2000 to 01/01/2017, available on the U.S. Energy Information Administration website. The estimated oil parameters are reported in Table 4.

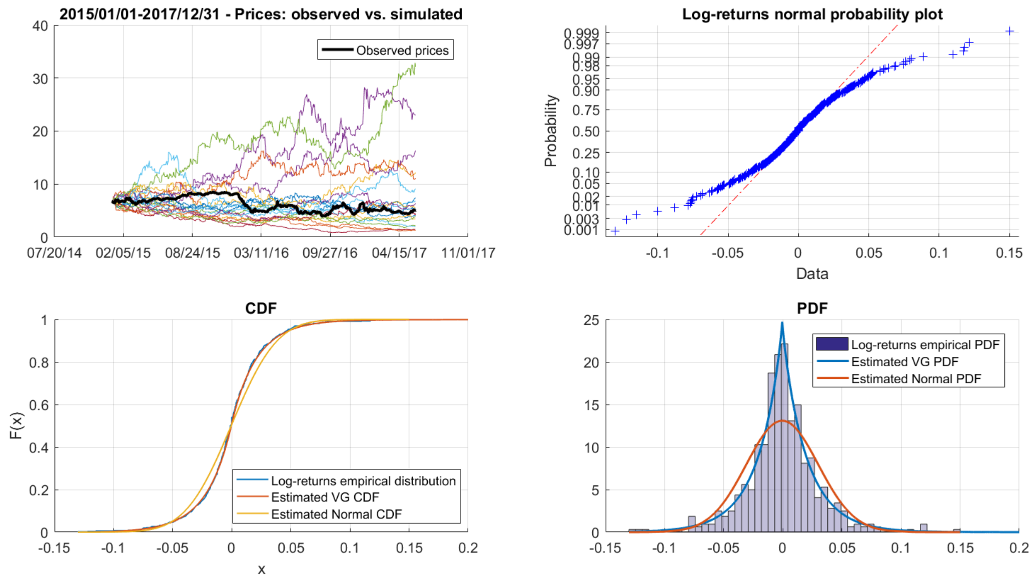


Figure 2: Variance-Gamma vs. Normal fit on EUA spot prices. The left top panel shows observed EUA prices (solid black line) compared with those simulated using a VG process. The right top panel displays the normal probability plot of EUA log-returns. The data points form a curve that markedly deviates from the straight line, which indicates that data are not normally distributed. The bottom panels show the empirical CDF and PDF against the estimated VG and normal ones.

3.1.3 The LCOE of PV technology

Once defined the total electricity output produced in the entire lifetime of the solar plant, the investment required to build it is expressed by its LCOE. Taking into account the benefits given by the so-called "learning curves" over time, the LCOE is modeled as a decreasing exponential, as seen in Biondi and Moretto (2015):

$$\mathrm{LCOE}(t) = \mathrm{LCOE}(0)\, \mathrm{e}^{\alpha_C t}\,, \tag{3.2}$$

where $\alpha_C < 0$ is the product between the negative learning curve coefficient and the average growth rate of the PV industry.

In our case, the LCOE depends on a number of factors, including the price of PV modules, the capacity factor of the plant, and the installation, maintenance, insurance and decommissioning costs. Due to the uncertainty related to government incentives, we did not include them in our analysis.

Parameter	Estimated value
$\hat{k}$	0.0014
$\hat{\theta}_D$	445.64
$\hat{\sigma}_D$	0.025

Table 4: Estimated daily parameters for WTI crude oil spot data fitted via MLE using a BS model.

To estimate the current LCOE and the LCOE parameter α_C in (3.2), we first need to estimate the magnitude of the costs outlined above and to compute the learning curve coefficient and the average growth rate of the PV industry, as α_C is the product of the two.

The learning curve coefficent. According to Fraunhofer ISE (2015), the learning rate LR of PV industry ranges between 0.19 and 0.23. We take the average 0.21 as a proxy. The economic meaning of such a value is that, each time the cumulated capacity doubles, the unitary cost decreases by 21%. The learning curve coefficient is then $\frac{\log(1-LR)}{\log 2} = -0.34$.

Growth rate of the PV industry. According to Fraunhofer ISE (2015), in a pessimistic scenario the 2015-2050 compound annual growth rate will be 5%, in the intermediate scenario it will be 7.5%, while, in the optimistic one, the growth rate will be 10%. We take 7.5% as a proxy. The LCOE parameter α_C is thus equal to -0.0255.

The current cost of PV technology. Since the plant will be built in Italy, we assume an average full load hours value of 1250 kWh/kW, which corresponds to a 14.3% capacity factor. As for the cost estimates, Fraunhofer ISE (2015) provides an estimate of the costs of a 1 MW PV utility in Germany, related to 2014. We use them to compute the LCOE relative to year 2014, and then update it to year 2017 with the exponential relationship in (3.2). The LCOE relative to 2014, resulting from these assumptions, is equal to 0.087 €/kWh. Thus, according to (3.2), the LCOE for 2017 is 0.081 €/kWh.

3.2 The real option payoff - A closed-form solution

At the beginning of each period, until the end of its economic life, the company can choose to replace the existing power plant with another one, based on PV technology, with no carbon emissions. Given the fact that this decision (1) can be taken at any moment in time prior to the end of the economic life of the oil-fired power plant, (2) is irreversible in that it implies high sunk costs (decommissioning of the existing plant and construction of the PV one), and (3) is affected by the uncertainty related to some key variables, such as the price of CO_2 and that of fuels, it can be modeled as a real option.

In case the firm decides to invest in the alternative energy plant, it will have to pay for the decommissioning of the oil-fired plant, whose cost is reported in Table 1. Given the negligible construction time of PV plants, we assume the switching decision to have immediate effect. We further assume the PV plant to have an economic lifetime of 25 years (average economic lifetime of PV plants according to IEA (2014a)).

The real option, thus, has a strike price K equal to the sunk costs the firm incurs once it decides to invest:

$$K(t) = c + Q \cdot \mathrm{LCOE}(t)\,,$$

where c represents the decommissioning cost of the high-carbon plant, and Q is the total electricity produced over the PV plant lifetime. On the other hand, exercising the option grants Φ, which represents the conditional expected value, under a suitable risk-neutral probability $\mathbb{Q}$, of the savings the company obtains by investing in the clean technology plant, discounted with a risk-free factor r, and summed up from the moment when the investment takes place, t, until the end of the model horizon, T. This payoff depends on whether the CO_2 permits are priced on a baseline scenario, where the market price simply follows the VG process seen previously, or on a regulatory intervention scenario, where there is a price floor on CO_2 permits.

3.2.1 Baseline scenario

Given the price dynamics in the previous section, the payoff of exercising the option is

$$\begin{aligned}\Phi(D_t, P_t, t) = \mathbf{E}^{\mathbb{Q}} \Bigg[\int_t^T B D_s \, \mathrm{e}^{-r(s-t)} \, \mathrm{d}s \; + \int_t^T X P_s \, \mathrm{e}^{-r(s-t)} \, \mathrm{d}s \, + \\ + \int_t^T Op \; \mathrm{e}^{-r(s-t)} \, \mathrm{d}s \; \Bigg| \; \mathcal{F}_t \Bigg] + K(T) \, \frac{T_{pv} - (T-t)}{T_{pv}} \, \mathrm{e}^{-r(T-t)} \end{aligned} \tag{3.3}$$

where D is the oil spot price, P is the carbon spot price, which are multiplied respectively by the fuel consumption coefficient of the oil-fired plant B, and by its yearly CO_2 emissions X, while Op represents the operating and maintenance costs of the high-carbon technology plant. The model horizon is set to coincide with the residual economic lifetime of the fossil fuel-powered plant (25 years). If the end of the model horizon does not also coincide with the end of the economic lifetime of the low-carbon plant (T_{pv}), in $t = T$, the existing plant is sold for its book value, and an additional positive cash flow is given.

With the dynamics seen above, it is very simple to provide the solution to (3.3) in closed form (we refer the reader to Appendix A.2 for the detailed procedure):

$$\begin{aligned}\Phi(D_t, P_t, t) =& B \left[\frac{1 - \mathrm{e}^{-(T-t)(r+k)}}{r+k} (D_t - \theta_D) + \frac{\theta_D}{r} \left(1 - \mathrm{e}^{-r(T-t)}\right) \right] \\ &+ X \, P_t \; (T-t) + \frac{Op}{r} \left(1 - \mathrm{e}^{-r(T-t)}\right) \\ &+ K(T) \, \frac{T_{pv} - (T-t)}{T_{pv}} \, \mathrm{e}^{-r(T-t)} \, . \end{aligned} \tag{3.4}$$

3.2.2 Regulatory intervention scenario

If we include a price stabilization mechanism in the model, we need to reconsider the total payoff of the producer in Equation (3.3). In presence of a floor F on EUA prices, we need to substitute $\max(P_s \, , F)$ in place of P_s in Equation (3.3). It can be noticed that

$$\max(P_s \, , F) = P_s + (F - P_s)^+ \; . \tag{3.5}$$

Then, the new benefits equation Φ_F becomes

$$\Phi_F(D_t, P_t, t) = \Phi(D_t, P_t, t) + \mathrm{Fl}(P_t, t) \tag{3.6}$$

where

$$\mathrm{Fl}(P_t, t) := X \int_t^T \mathrm{e}^{-r(s-t)}\, \mathbf{E}^{\mathbb{Q}}\left[(F - P_s)^+ \middle| \mathcal{F}_t \right] \mathrm{d}s\,.$$

In fact, bounding carbon prices downwards with a floor F is equivalent to having a put option with F as strike price, and the solution to (3.6) is again the solution to (3.3), plus the integral on $[t, T]$ of the price of such a put option.

To compute the value of this additional term, we employ Fourier techniques. Fourier methods give the price of the put option as an integral formula involving the characteristic function of the underlying process. This, combined with the time integral, returns a semi-explicit formula for the payoff. The formula for the put option price (see Theorem 15.9 in Pascucci (2011)) is

$$\mathrm{Price}(P_t, F, T) = \frac{\mathrm{e}^{-r(T-t)} P_t^{\gamma} F^{1-\gamma}}{\pi} \int_0^{\infty} \mathrm{e}^{-iu \log \frac{P_t}{F}} \frac{\phi_{X_T}(-(u + i\gamma))}{(iu - \gamma)(iu - \gamma + 1)}\, \mathrm{d}u\,, \tag{3.7}$$

where $\phi_{X_T}(u)$ is the characteristic function, under $\mathbb{Q}$, of the underlying log-price process X. This formula returns the price of a put for all $\gamma < 0$ such that $\mathbf{E}^{\mathbb{Q}}[P_T^{\gamma}]$ is finite (thus for all $\gamma \in (-45, 0)$ with our parameters).

As Madan et al. (1998) show, the characteristic function for the VG process is

$$\varphi_{X_T}(u) = \mathbf{E}\left[\mathrm{e}^{iuX_T}\right] = \mathrm{e}^{i\mu T u} \left(1 - i\theta_P \frac{u}{\alpha} + \frac{1}{2}\sigma_P^2 \frac{u^2}{\alpha} \right)^{-T\alpha}. \tag{3.8}$$

As shown in Appendix A.2, as a necessary condition for (3.8) to be under the EMM $\mathbb{Q}$, we need to have

$$\mu = r + \alpha \log\left(1 - \frac{\theta_P + \frac{1}{2}\sigma_P^2}{\alpha} \right). \tag{3.9}$$

Looking back at (3.6), and using (3.7) along with (3.8), we get that the value of the additional term in the payoff is:

$$\mathrm{Fl}(P_t,t) = X \int_t^T \frac{\mathrm{e}^{-r(s-t)} P_t^{\gamma} F^{1-\gamma}}{\pi} \cdot$$
$$\cdot \int_0^{+\infty} \frac{\mathrm{e}^{-iu\log\frac{P_t}{F} + \mu(s-t)(\gamma - iu)} \left(1 + i\theta_P \frac{u+i\gamma}{\alpha} + \frac{1}{2}\sigma_P^2 \frac{(u+i\gamma)^2}{\alpha}\right)^{-(s-t)\alpha}}{(iu-\gamma)(iu-\gamma+1)} \,\mathrm{d}u\ \mathrm{d}s =$$
$$= X\frac{P_t^{\gamma}F^{1-\gamma}}{\pi} \int_0^{+\infty} \frac{\mathrm{e}^{-iu\log\frac{P_t}{F}}}{(iu-\gamma)(iu-\gamma+1)} \left[\frac{\mathrm{e}^{(T-t)\,m(u)} - 1}{m(u)}\right] \mathrm{d}u\,, \tag{3.10}$$

where

$$m(u) = -r - i\mu(u+i\gamma) - \alpha \log\left(1 + i\theta_P \frac{u+i\gamma}{\alpha} + \frac{1}{2}\sigma_P^2 \frac{(u+i\gamma)^2}{\alpha}\right),$$

with μ satisfying (3.9).

Choice of the damping parameter
Even if, theoretically, Equation (3.7) is valid for any suitable γ (here, $\gamma \in (-45, 0)$), many authors have noticed that the integrand in the pricing formula may be oscillatory or highly peaked, depending on the choice of γ.

As a criterion for the selection of the damping parameter, we plot the integrand in (3.7) as a function of the different variables, and examine the graphs in order to detect oscillatory behaviors. For example, as Figure 3 shows, the more the maturity increases, the smaller γ needs to be. According to our graphical results, with the estimated VG parameters, an optimal choice for γ lies in the interval $[-1, 0)$. Specifically, we choose $\gamma = -0.8$.

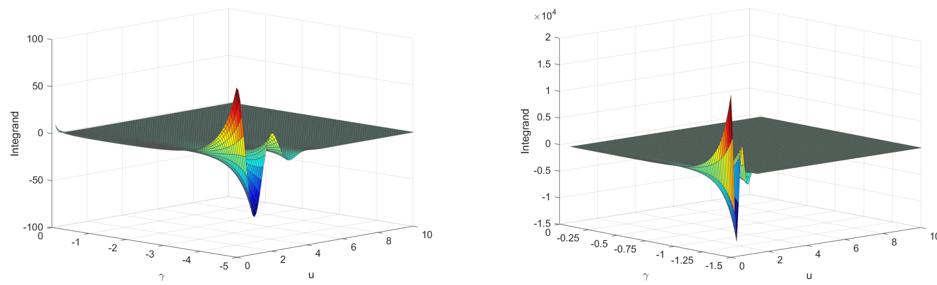
3.3 The investment decision problem

If the firm exercises the option, it has to pay the strike price $K(t)$ in exchange for $\Phi(D_t, P_t, t)$. The real option R to defer the investment is thus an American call option on the value of the project:

$$R(P_t, D_t, t) = \max_{\tau} \mathbf{E}\left[\mathrm{e}^{-r(\tau-t)}\left(\Phi(D_\tau, P_\tau, \tau) - K(\tau)\right)\right],$$

where the maximum is taken over all stopping times τ with $t < \tau < T$.

The classical method of dealing with real options is to solve a partial integral differential equation (PIDE) subject to two key boundary conditions,



(a) T = 2, $\gamma \in [-5, 0]$ **(b)** T = 20, $\gamma \in [-1.5, 0]$

Figure 3: Integrand for the VG model with the estimated parameters.

the value-matching and the smooth-pasting ones. In many practical cases (in particular in multidimensional cases like ours), however, it is not possible to do so, and instead of finding a closed-form solution, numerical methods are employed. As a computational method, the traditional choice is that of recombining binomial trees. However, binomial trees are well suited to approximate models where all the state variables are diffusions (see Edoli et al. (2016) for a general treatment and Abadie et al. (2011) for an implementation with Brennan-Schwartz processes). Instead, when some state variables present the possibility of jumps, binomial models are not suitable anymore: in principle, they can be generalized to more complex multinomial models, but at the price of needing a potentially infinite number of nodes to capture all the moments of the jump process (for the special case of the VG process, see Cantarutti and Guerra (2018)). For this reason, we implement a Least Squares Monte Carlo (LSMC) simulation, which is much more flexible and is able to reproduce a VG process with its exact distribution.

Once the payoff given by exercising the option is computed at each point in time, an efficient exercise rule is to assess the convenience of investing in the project, as opposed to deferring the investment at every point in time when the decision has to be made. The value given by deferring the investment decision to the following period is the so-called *continuation value*. As outlined in Longstaff and Schwartz (2001), this can be computed by means of a least-squares Monte Carlo simulation. We follow Brauneis et al. (2013), and assume a quadratic relationship between the value of continuing, $CV_{t,i}$, and the value our relevant simulated variables assume at each time the investment decision has to be made.

$$CV_{t,i} = \alpha_t + \beta_1 D_{t,i} + \beta_2 P_{t,i} + \beta_3 (D_{t,i})^2 + \beta_4 (P_{t,i})^2 + \varepsilon_{t,i} \, , \tag{3.11}$$

where i indicates the different Monte Carlo simulated paths and $t \in [0, T]$. Through the least-squares analysis, we determine the regression coefficients providing the best fit. Using these estimated coefficients and working backwards, at each point in time the payoff given by exercising the option is compared to the continuation value.

4 Results

This section discusses the results obtained using our model. In what follows, we use an initial market price for oil of 54.00 \$ per barrel (365.73 €/ton), and an initial carbon price of 5.05 €/ton of CO_2. We use a risk-free annual interest rate r equal to 2.5%. All other parameters are as stated in the previous sections. The results are shown in terms of expected value of the option (computed as the average of the values on all simulated paths) and of cumulative investment probability, defined as the sum of the number of paths in which the investment takes place before a certain year, over the total number of simulated paths. We run our model on MATLAB, with 10,000 simulated paths.

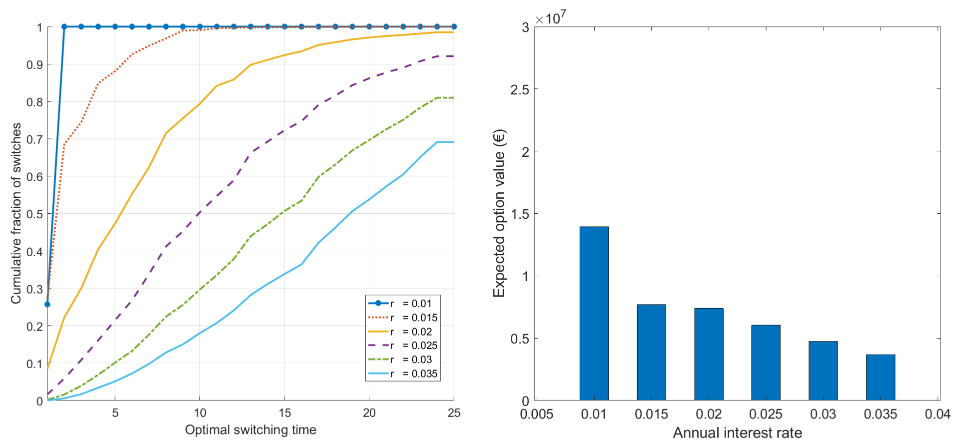
4.1 Baseline scenario

Using the parameters stated above, and assuming no policy interventions in the carbon market, the probability to invest in the clean energy project before 10 years reaches 50%. Before the end of the model horizon, the optimal strategy consists in replacing the oil-fired power plant in 92% of the cases (Fig. 4a, dashed purple line).

This result, however, is quite sensitive to the choice of the discount rate r, as shown in Fig. 4. If r is higher than the one assumed in our model, the investment probability shifts downward and the expected option value declines. On the contrary, the lower the discount rate, the higher the probability of switching production method, with $r = 1\%$ suggesting almost immediate investment.

As a second sensitivity test, we look at the impact that different long term mean prices for oil θ_D have on the optimal timing of the investment.

We thus run our model with a set of different θ_D, corresponding to a reduction or increase of 3%, 6% or 9% with respect to the initial θ_D estimate. Figure 5 shows that having higher long term mean values for oil prices results in earlier investment for a given probability value, and this is contextual to an increase in the expected option value. An increase in θ_D of 9% with respect to our estimate leads to a probability of 100% that it is optimal to exercise the option before the end of the model horizon. On the other hand, a decrease of 9% in the same initial value results in a decrease by 20% in the corresponding probability.



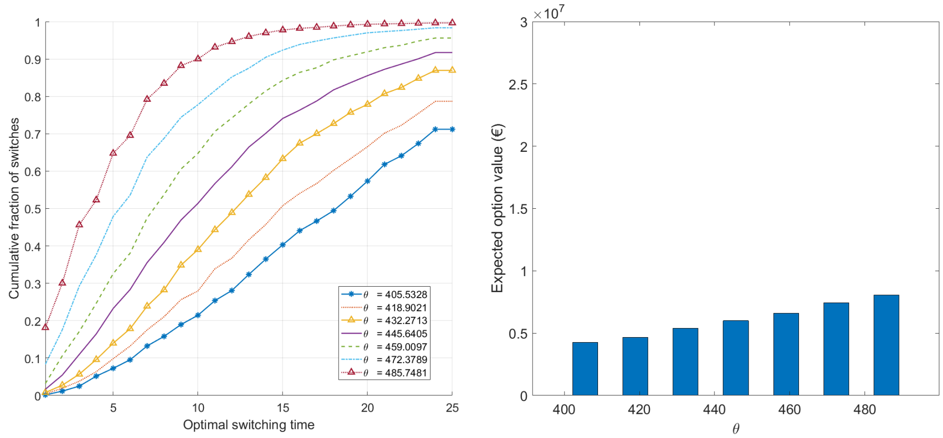
(a) Cumulative investment probability

(b) Expected option value

Figure 4: Sensitivity analysis of the results using different annual risk-free interest rates r.

4.2 Regulatory intervention scenario

The impact of introducing a minimum price for EU emission allowances is shown in Fig. 6. In Fig. 6a and 6b, we show the results on the investment probability and on the expected option value, respectively, of having a carbon floor price equal to {10, 20, 30, 40} €/ ton of CO_2. As the floor gets higher, the number of simulation runs in which it is convenient to invest in the clean energy project increases for each point in time, and the option to replace the "dirty" technology with a "clean" one appreciates in value. Specifically, with a floor of 10 €, the probability that exercising the real option before 10 years



(a) Cumulative investment probability **(b)** Expected option value

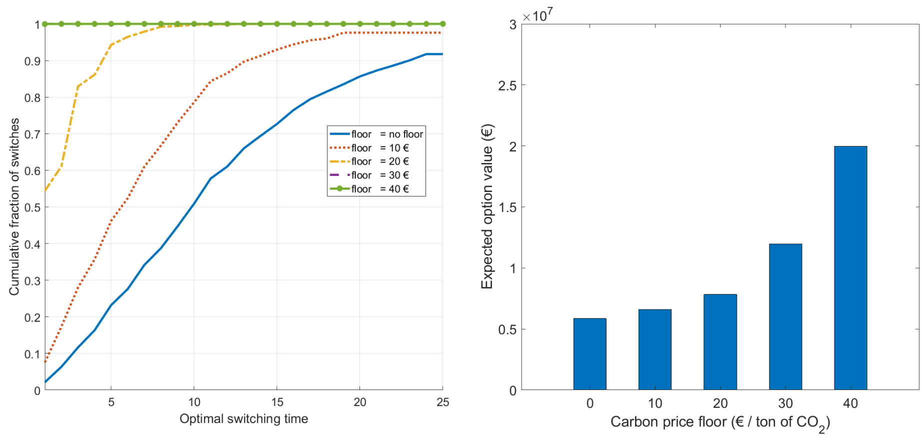
Figure 5: Sensitivity analysis of the results using different long term means θ_D for oil.

is optimal shifts from about 50% to almost 80%. With a floor as high as 20 €/ton (in line with the current market price as of February 2019), in about 55% of the cases it is optimal to invest immediately in the project, and the probability rises to 100% if the floor is 30 €/ton. Finally, we run again our model using two different risk-free interest rates r, and the results, reported in Fig. 7, confirm the positive effect of a floor on carbon prices.

4.3 Further considerations

As previously mentioned in Section 2, this paper investigates a similar problem to that of Brauneis et al. (2013). Our results corroborate the core finding in their paper, namely that a carbon floor is beneficial for low-carbon investments, as it increases the probability than it is optimal to invest. However, the result in Figures 6 and 7 qualitatively differs from those obtained in the aforementioned work: the higher the floor, the higher, but also the steeper, the cumulative investment probability curve. This discrepancy could be due either to the difference in the models (different types of firm considered, different switching options, different number and nature of the stochastic variables considered), or to the different modeling choices of the stochastic variables, or to both these changes.

As previously mentioned, both the fuel and carbon prices in Brauneis et



(a) Cumulative investment probability **(b)** Expected option value

Figure 6: Investment probability evolution over the years (6b) and expected option value (6b) with different carbon floor prices, $r = 2.5\%$.

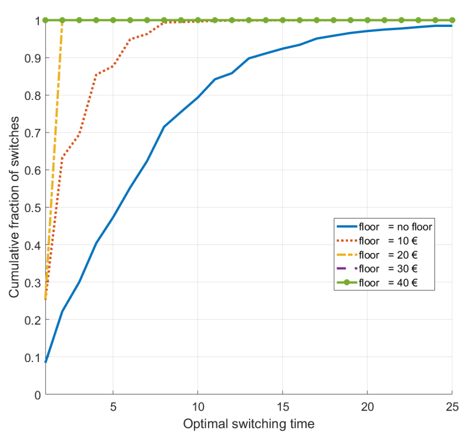
al. (2013) follow a GBM. To understand whether this choice acts as a source of divergence in the results, we first analyze an intermediate alternative model where the carbon price follows a GBM (as in Brauneis et al. (2013)) instead of a VG process (as in the previous section), while the fuel price is still represented by a BS process.

4.3.1 The effect of the VG process in carbon prices

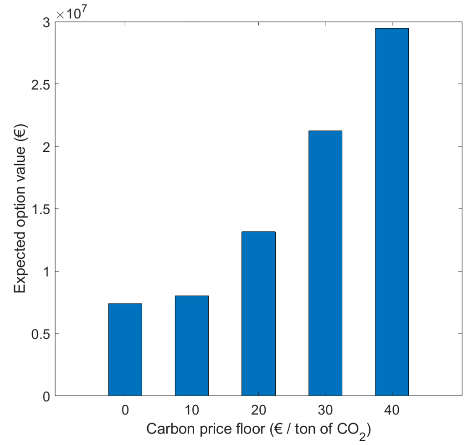
Figure 8 shows the corresponding investment probabilities and expected option values. The carbon floor affects the timing of the green investment by inducing a "left-up" shift on the probability curves, quite similar to our original model. For this reason, we can conclude that the effect of substituting a VG process for carbon prices to the original GBM, while better representing the descriptive statistics of carbon prices' time series, does not significantly affect the decision process.

4.3.2 The effect of the BS process in fuel prices

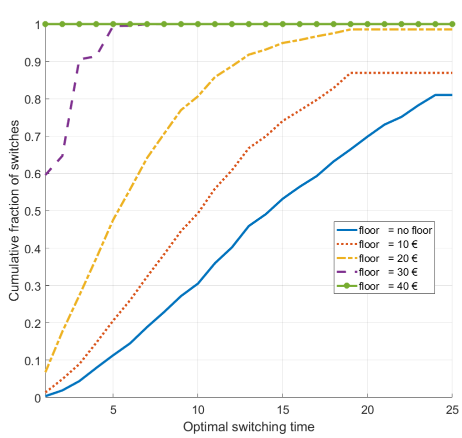
We then consider a model that implements the original modeling choice of Brauneis et al. (2013), i.e. two GBMs for fuel and carbon prices. The effect of this modeling choice on the cumulative switching probability, in the presence



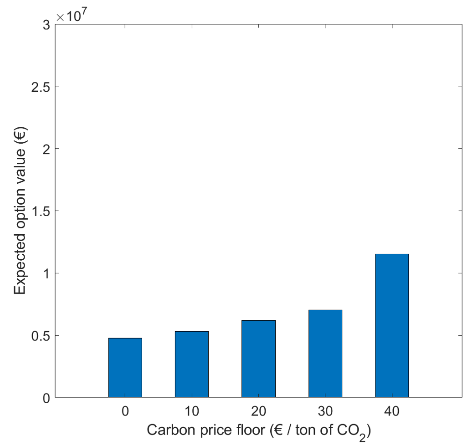
(a) Cumulative switches, $r = 2\%$



(b) Expected option value, $r = 2\%$



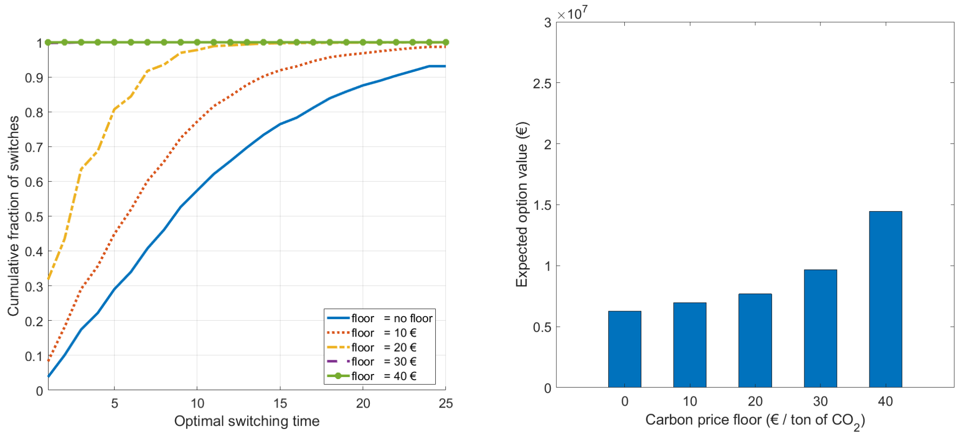
(c) Cumulative switches, $r = 3\%$



(d) Expected option value, $r = 3\%$

Figure 7: Sensitivity analysis of the results with a floor, using different annual risk-free interest rates r.

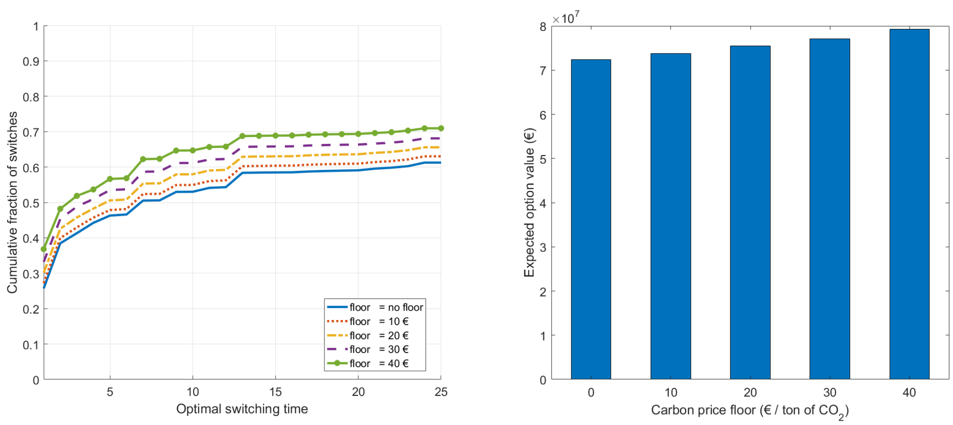
of various carbon floor levels, is reported in Figure 9. The consequence of the increasing floor levels is now qualitatively similar to that of Brauneis et al. (2013): there is a parallel upward shift in the cumulative probability curve as the floor gets higher, and each curve has roughly the same slope. The interesting fact is that the expected value of the real option is comparatively higher in the GBM+GBM case (Figure 9b) than in the VG+BS case (Figure 6b), even though the optimal timing of the investment is postponed. It can



(a) Cumulative investment probability

(b) Expected option value

Figure 8: Sensitivity of the results to the choice of the carbon price dynamics. This figure shows the results in presence of a carbon floor price, when the carbon price follows a GBM rather than a VG. $r = 2.5\%$.



(a) Cumulative investment probability

(b) Expected option value

Figure 9: Sensitivity of the results to the choice of the carbon and oil price dynamics. This figure shows the results in presence of a carbon floor price, when both the carbon and oil prices follow a GBM. $r = 2.5\%$.

be conjectured that the reason for this behavior lies in the fact that, when the price of oil is modeled as a GBM, its volatility and drift make the option value grow larger as time goes by. This increases the convenience to wait rather than to invest immediately, anticipating further future growth of the payoff.

These results indicates the importance of the modeling choices of the relevant stochastic variables in the model, and their different impact on the final outcome. By using models more sophisticated and realistic than the standard ones used in the literature for fuel and carbon prices, the optimal investment timing is anticipated with respect to GBM-based models.

5 Conclusions

In this paper, we depart from the usual assumption of GBM used in the literature for the carbon spot price, and provide empirical evidence that infinite activity Lévy processes, and VG processes in particular, are able to consistently replicate the carbon log-returns empirical distribution. We then use this result to evaluate the impact of the EU ETS on renewable energy investments in the power generation sector. We consider two different scenarios: a baseline scenario (the EU ETS market in its current configuration), and a regulatory intervention one, where a floor price on carbon allowances is applied.

Our results show that a minimum CO_2 price of 30 €/ton of CO_2 would trigger immediate investment in the clean energy plant, and this result is quite robust to changes in the risk-free interest rate. On the other hand, without regulatory interventions, only in 50% of the simulated paths the optimal decision consists in exercising the option before 10 years. We also find out that these results are heavily affected by the choice that one does in modelling carbon and fuel prices.

Thus, according to the results of our model, a pure carbon trading system has a limited impact on renewable energy investments, and a policy intervention in the EU ETS seems advisable. Through a floor price, one of the goals of the EU ETS, namely boosting low-carbon investments in the power generation sector, could be achieved. Such a price management mechanism has already been implemented in the UK, as well as in other emission trading programs, the northeastern US Regional Greenhouse Gas Initiative (RGGI), the California emission trading program and the Québec one. The floor, in these programs, has been successful in enhancing environmental outcomes (see World Bank (2017), Narassimhan et al. (2018), Borghesi and Montini (2016)). This work confirms the positive impact of such a policy intervention, even with models more sophisticated and realistic than the standard ones used in literature.

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A Appendix

A.1 Technical characteristics of the oil-fired power plant

Given the capacity and the capacity factor values reported in Table 1 (10 MW and 80%, respectively), the yearly electricity output is computed:

$$\text{Electricity output} = 10,000\,\text{kW} \cdot 0.8 \cdot 365 \cdot 24\text{h} = 7.01 \cdot 10^7\,\text{kWh/year}.$$

The corresponding amount of energy needed to produce such an output is retrieved by simply dividing the electricity output by the efficiency rate of the plant (40%, as reported in Table 1), which results in $1.75{\cdot}10^8$ kWh/year. Given that the calorific value of crude oil is 42.5 MJ/kg, or 11,800 kWh/ton, the fuel consumption of the oil-fired plant is computed:

$$\text{Fuel consumption} = \frac{1.75 \cdot 10^8\,\text{kWh/year}}{11,800\,\text{kWh/ton}} = 1.48 \cdot 10^4\,\text{tons/year}.$$

As stated by the Intergovernmental Panel on Climate Change, the default CO_2 emission factor for crude oil is 73,300 kg/TJ IPCC (2006), or $2.64 \cdot 10^{-4}$ tons/kWh (since $1\,\text{kWh} = 3.6\,\text{MJ}$). The yearly carbon emissions are thus given by

$$CO_2\text{ emissions} = 1.75{\cdot}10^8\,\text{kWh/year} \cdot 2.64{\cdot}10^{-4}\,\text{tons/kWh} = 46,200\,\text{tons/year}.$$

A.2 Solving the benefits equation

A.2.1 The oil spot price

The oil spot price follows a Brennan-Schwartz process, defined as

$$\mathrm{d}D_t = k(\theta_D - D_t)\,\mathrm{d}t + \sigma_D D_t\,\mathrm{d}W_t\,. \tag{A.1}$$

Given an initial time $t \in [0, T]$, a quantity of interest in computing the real option payoff is $y(s) := \mathbf{E}\left[D_s \,|\, \mathcal{F}_t\right]$, which can be easily inferred from the dynamics (A.1). In fact, this dynamics can be written in integral form as

$$D_s = D_t + \int_t^s k(\theta_D - D_u)\,\mathrm{d}u + \int_t^s \sigma_D D_u\,\mathrm{d}W_u$$

Computing the conditional expectation to both members, the stochastic integral cancels out, and the final result is

$$\mathbf{E}\left[D_s \,|\, \mathcal{F}_t\right] = D_t + \int_t^s k(\theta_D - \mathbf{E}\left[D_u \,|\, \mathcal{F}_t\right])\,\mathrm{d}u$$

By differentiating with respect to s, this yields the differential equation

$$y'(s) = k(\theta_D - y(s))$$

which, with the initial condition $y(t) = D_t$, has as unique solution

$$\mathbf{E}\left[D_s \,|\, \mathcal{F}_t\right] = y(s) = \theta_D + e^{-k(s-t)}(D_t - \theta_D) \tag{A.2}$$

A.2.2 Solving $\Phi(D_t, P_t, t)$

We can now use equation (A.2) to solve (3.3), the equation for Φ.

Let us begin by solving the first expected value block:

$$\begin{aligned}
\mathbf{E}\left[\int_t^T B D_s\,\mathrm{e}^{-r(s-t)}\,\mathrm{d}s \,\middle|\, \mathcal{F}_t\right] &= B\int_t^T \mathrm{e}^{-r(s-t)}\,\mathbf{E}\left[\,D_s|\mathcal{F}_t\,\right]\,\mathrm{d}s = \\
&= B\int_t^T \mathrm{e}^{-r(s-t)}(\theta_D + e^{-k(s-t)}(D_t-\theta_D))\,\mathrm{d}s = \\
&= B\left[\frac{1-\mathrm{e}^{-(T-t)(r+k)}}{r+k}(D_t - \theta_D) + \frac{\theta_D}{r}\left(1-\mathrm{e}^{-r(T-t)}\right)\right].
\end{aligned} \tag{A.3}$$

As for the second expected value block, we need to impose a restriction on the parameters, in order for the the discounted EUA price to be a martingale. Being P a geometric Lévy process, this is equivalent to $\mathbf{E}^{\mathbb{Q}}[\mathrm{e}^{-rt}P_t] = P_0$. From Equation (3.8), we know that

$$\mathbf{E}^{\mathbb{Q}}[P_t] = P_0\mathbf{E}^{\mathbb{Q}}[\mathrm{e}^{X_t}] = P_0\mathrm{e}^{\mu t}\left(1 - \frac{\theta_P}{\alpha} - \frac{1}{2}\frac{\sigma_P^2}{\alpha}\right)^{-\alpha t}$$

thus $(\mathrm{e}^{-rt}P_t)_t$ is a martingale if and only if

$$\mu = r + \alpha\log\left(1 - \frac{\theta + \frac{1}{2}\sigma^2}{\alpha}\right) , \tag{A.4}$$

and the second expected value block becomes

$$\mathbf{E}^{\mathbb{Q}}\left[\int_t^T XP_s\,\mathrm{e}^{-r(s-t)}\,\mathrm{d}s\middle|\,\mathcal{F}_t\right] = X\int_t^T \mathrm{e}^{rt}\,\mathrm{e}^{-rt}P_t\,\mathrm{d}s = X\,P_t\,(T-t)\;. \tag{A.5}$$

The solution to the third expected value block is trivial:

$$\mathbf{E}^{\mathbb{Q}}\left[\int_t^T Op\;\mathrm{e}^{-r(s-t)}\;\mathrm{d}s\middle|\,\mathcal{F}_t\right] = \frac{Op}{r}\left(1 - \mathrm{e}^{-r(T-t)}\right)\;. \tag{A.6}$$

Putting together equations (A.3), (A.5) and (A.6), we have the solution for (3.3), given in (3.4).

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