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# « Uncertainty about long term climate targets: A real option approach to investment appraisal »

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# Uncertainty about long term climate targets: A real option approach to investment appraisal

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## Abstract

This article analyses how investors cope with carbon price uncertainty on the long run. More precisely, we assume that climate targets are not well established, so decision makers do not know if climate policy will be highly or moderately restrictive. It means that the long run carbon price drift is uncertain. However, there is a progressive resolution of this uncertainty. A real option analysis is conducted, in the case of a Carbon Capture and Storage (CCS) project appraisal. We show that this additional uncertainty decreases investment probability, but does not lead to a lag of investment, as generally assumed in real option literature.

Keywords: Carbon Capture and Storage (CCS), climate policy, regulatory uncertainty

## Résumé

Cet article analyse comment les investisseurs font face à l'incertitude sur le prix du carbone à long terme. Plus précisément, les objectifs climatiques de long terme ne sont pas clairement fixés, si bien que les décideurs privés ne peuvent savoir si la politique climatique sera moyennement ou très contraignante. Cependant, nous supposons que cette incertitude devrait se résorber progressivement. Une analyse par option réelle est menée dans le cas de l'évaluation d'un projet de Capture et Stockage du Carbone (CSC). Nous montrons que l'incertitude additionnelle réduit la probabilité d'investissement, mais ne produit pas de report de l'investissement, alors que ce résultat est généralement admis dans la littérature sur les options réelles.

Mots-clés:Capture et Stockage du Carbone (CSC) ; Politique climatique ; Incertitude de régulation

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## 1 - Introduction

Climate change may affect firms' profitability by local abrupt changes such as droughts, floods or sea level rise. But the main effects today are generally indirect for firms and are linked tothe binding obligation to limit Greenhouse Gas Emissions (GHG). Firms have different kinds of strategy to comply with climate policy. For instance, they can reduce their own emissions or use compensatory approaches such as emissions trading. However, climate targets on the long run are uncertain. Firms have to cope with regulatory uncertainty, which is an individual's perceived inability to predict the future state of the regulatory environment (Hoffman *et al*, 2008).

Regulatory uncertainty has several aspects. A first aspect is about climate targets on the long run. A second one concerns economic incentives (taxes, emissions trading and standards) and their implementation process (for instance rules about new entrants, fraud risks). There is also an uncertainty about interaction between the new climate regulation and other regulations. In this article, we will focus on the regulatory uncertainty about long-term goals. Indeed, this is a sensitive topic for decision makers in energy sector, because they have to plan their investments on decades and to incur high sunk costs. This uncertainty is generally considered as a discrete process, because political negotiations can completely transform the design of the regulation in a very short time (Engau and Hoffman, 2009). This discontinuous resolution of regulatory uncertainty provides incentives for firms to adopt a postponing strategy(Fuss *et al*, 2008; Yang *et al*, 2008). As a result, it could lead to a 'lock-in' effect, keeping carbon intensive technologies in place longer.

Nevertheless, policy makers have to cope with a continuous information flow about climate change, such as information on climate sensitivity, technology availability and efficiency, social adaptation and so on.  As a consequence, their beliefs about the right target evolve progressively, following a policy learning process. For instance, the choice of a value for carbon concentration in the atmosphere is still discussed. A few years ago, most models were focus on a 550ppm target but nowadays, a 450ppm target is consideredmore and more as desirable (IPCC, 2007).

Such disparities lead inevitably to different climate policies, more or less restrictive and so to different carbon price trends.

To our knowledge, no article has been published about this progressive resolution of uncertainty, whereas the learning process is predominant and influences policy negotiationson the long run. We propose a framework for analyzing the behavior of private decision makers under a long term regulatory uncertainty, which means that investors do not currently know if the climate target is going to be moderately or highly restrictive. In our modeling, it leads to an uncertainty about the carbon price drift (low or high) on the long run.

In this article, we will follow a real option approach because it is accurate to project appraisal, in a context of high uncertainty, irreversibility of the investment and flexibility of the decision (Cortazar*et al*, 2008). A real option is indeed the right but not the obligation to undertake a business investment opportunity. Some important theoretical considerations on this issue can be found in Dixit and Pindyck (1994).

Our empirical results are based on a case study, namely the implementation of a CCS (Carbon Capture and Storage) chain on a firm producing bioethanol from sugar beets. It means that the carbon stream coming from the firm (here the fermentation step) is dehydrated, compressed and then transported by pipelines to be stored in the subsurface (here a salin aquifer). CCS is a promising technology that could help to reach low concentration targets, notably when combined with biomass production (IEA, 2009). Moreover, the profitability of this project is very sensitive to carbon price drifts (Laude *et al*, 2011).

This paper is organized as follows. Next section sets up our modeling of regulatory uncertainty. Section 3 presents calibration and scenarios used. Section 4 describes and discusses our results, and then section 5 summarized our main findings.

## 2 – Model

This section presents first how carbon price is modeled if the decision maker knows the carbon drift on the long term (no regulatory uncertainty). Then,we briefly explain the real option algorithm. Lastly, we consider the case of an uncertain carbon drift (long run regulatory uncertainty).

## 2.1 – The decision maker knows the carbon drift

The two most common stochastic movements to mimic price commodity are the geometric Brownian motion (GBM) and the mean-reverting process (MR). We choose here to model carbon price as a mean-reversion process along a deterministic trend, likein Hervé-Mignucci (2010). These two movements capture indeedsome different aspects of carbon price behavior. On one hand, a long-term geometric drift is useful to show that prices rise under an increasing environmental constraint. On the other hand, other mandatory emission markets, like the American $SO_2$ market,display mean-reversion features on the long term. Moreover, carbon price also depends on the marginal cost of available technologies and tends to be aligned with it (Blyth *et al*, 2009).

Our model is based on Lucia and Schwartz (2002). This logarithmic model with one factor is written:

$$\ln(P_t) = f_t + X_t$$

$$dX_t = -\kappa X_t dt + \sigma dz$$

With $P_t$ the carbon price, $\sigma$ the carbon pricevolatility, $\kappa$the mean reversion speed and$f_t$a determinist function that describes the long term drift. This system becomes:

$$dP_t = \kappa(a_t - \ln(P_t)P_t dt + \sigma P_t dz \quad (1)$$

With:

$$a_t = \frac{1}{\kappa}\left(\frac{\sigma^2}{2} + \frac{df}{dt}\right) + f_t$$

$a_t$ is the drift of the carbon price. Here, the function $f_t$is:

$$f_t = \ln(P_0) + \alpha t$$

With $P_0$ the initial carbon price and α the carbon drift. We now can state:

$$dP_t = \underbrace{\left(\frac{\sigma^2}{2} + \alpha\right) P_t dt}_{\textcircled{1}} + \underbrace{\kappa[(\ln(P_0) + \alpha t) - \ln(P_t)]P_t dt}_{\textcircled{2}} + \underbrace{\sigma P_t dz}_{\textcircled{3}} \quad (2)$$

1) is the drift carbon price, 2) characterizes the mean-reversion process and 3) the diffusion process.

## 2.2 Algorithm

As mentioned above, the firm produces bioethanol, but the profitability of the bioethanol process is not addressed. Implementation of a CCS chain does not change the production process, so we focus only on CCS project profitability. If the CCS chain is implemented, the annual cash-flow process can be described as:

$$CF_t = q_t^c . P_t^c - q_t^g . P_t^g - O\&M_t,$$

Where$q^c$ is the amount of carbon avoided; $P^c$ is the carbon price; $q^g$ is the natural gas consumption; $P^g$ is the natural gas price; and O&M are the operation and maintenance costs.

If we denote the initial investment by $I_0$ and T the maturity date, then the profit function is given by:

$$\Pi_T = CF_T - I_0, \Pi_t = RPV_t - I_0, \qquad t = T-1, \ldots, 1.$$

Where $RPV_t$ (the running present value) is defined recursively by:

$$RPV_T = CF_T, \qquad RPV_t = CF_t + \frac{RPV_{t+1}}{1+r}, \qquad t = T-1, \ldots, 1,$$

In our real option model, the investor chooses to invest or wait at every time step. To obtain the price of our real option, we use the following optimal stopping problem:

$$\sup_{\tau \in [1,T]} \mathrm{E}[e^{-r\tau\Delta t} \Pi_\tau | P_t] \quad (1),$$

Where$[1, \mathcal{T}]$ denotes the set of all stopping times with values in {1,…, T}. In the following, we focus on Monte Carlo methods for solving task (1).It is well known that (1) can be solved with the Dynamic Programming Principle (DPP) in terms of the value process $V_t$:

$$\begin{cases} V_T = CF_T - K_T \\ V_t = max\{RPV_t - K_t, e^{-r\Delta t}\mathbb{E}[V_{t+1}|P_t]\}, \qquad l = L-1, \dots, s. \end{cases}$$

The system is solved thanks to a Least Square Method (Longstaff and Schwartz, 2001;Jonen, 2009), adapted to real options. The key idea is to realize Monte Carlo simulations. Then the continuation value is estimated through a regression based on the set of simulated path.

## 2.3 – The decision maker doesn't know the carbon drift

We assume now that the decision maker does not know the carbon drift. More precisely, the carbon drift can be either high or low, reflecting a very strict or a moderate political constraint. Actually, there is only one true carbon trend, but the investor is currently unable to forecast which one. However, the two drifts are more and more distant overtime, since there is more information about climate change and its social consequences.

In our framework, the separation between the two deterministic curves is progressive, so no price jump is needed. We still use the same carbon price movement, described by equation (2). At the beginning ($t_0$), the initial carbon price is the same for every simulation, but subsequently, it evolves following (2). At date t, if the carbon price is closer to the high deterministic drift than to the low, the price trajectory is going to converge to the highest curve at date t+1, with the carbon drift $\alpha_{up}$. On the contrary, if the carbon price is closer to the low deterministic drift, the carbon drift becomes $\alpha_{down}$.

Figure 1 gives an illustration of the way a carbon price trajectory is capture by the deterministic carbon drifts. Even if it is difficult to determine which drift the carbon path follows on the first years (the blue curve), it seems captured by the highest deterministic curve (in green). But this path comes down the intermediate curve (in red), because of the yearly volatility. Finally, the carbon path converges on the lowest drift in this sample (in black).

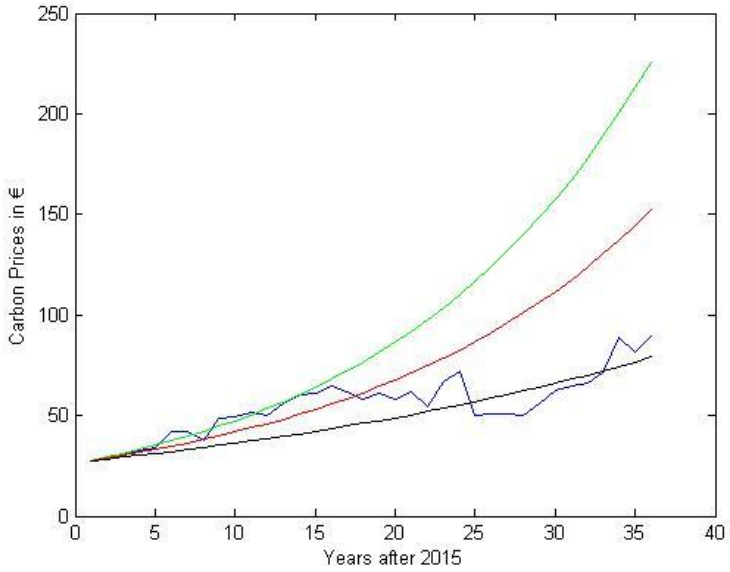

**Figure 1: Example of a carbon price path under the bifurcation scenario.**

## 3 – Calibration and Scenarios

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The firm is assumed to produce 1.2Mhl/yr of ethanol. The CCS chain is added on the fermentation step, so 93,000 tons $CO_{2eq}$ by year could be avoided. The stream is assumed to be sufficiently pure to avoid a capture step, so only dehydration and compression steps are required. The project may start between 2015 and the 2050. It ends in any case in 2050 because ethanol installations are too old and must be replaced. The initial investment costs 49.10M€ and O&M costs 1.50M€ every year.

Carbon price modeling cannot be based on historical data because the carbon market is a young market. The EU ETS (European Union Emission Trading Scheme) has been launched in 2005, but the first phase (achieved in 2007) is generally seen as a trial phase and the economic crisis has affected the second one. Moreover, this market depends highly on political will and new information about climate change. Then, experts opinions are of the most interest to build scenarios.

The low carbon drift has been established at $\alpha_c=3\%$ and the high carbon drift at $\alpha_c=6\%$. The first drift is more accurate for a 550ppm long term target and the second could be considered for a 450ppm target. The highest price profile is the most consistent with the Quinet report prices, designed for French targets (Quinet*et al*, 2009). We add in section 4.1 an intermediate scenario with $\alpha_c=4.5\%$, assumed to be the 'best guess'. These three values are in line with the current assumption of most modelers (Aldy, 2010). The carbon price in 2015 is up to 27€/t$CO_2$, according to the World Energy Outlook (IEA, 2008). The mean-reversion speed $\kappa$is assumed to be 0.2 like in Laurrika and Koljonen (2006). We chose also a relatively low carbon price volatility of 10%, because we only take into account the long term volatility and not the intra-annual volatility (Yang and Blyth, 2008). Regarding the real option modeling, the discount rate is set at 4%. 100,000 simulations have been launched for each experiment.

## 4 – Results

### 4.1 The decision maker knows the carbon drift

Three carbon price drifts are tested separately: $\alpha_c=3\%$, $\alpha_c=4.5\%$ and$\alpha_c=6\%$. A carbon drift increase has a positive effect on investment, see Table 1. The probability of investment between 2015 and 2050 is almost zero in the lowest scenario, but it is close to 99% in the highest scenario.At a moderate carbon drift of 4.5%, the probability of investment is around three-quarters. Moreover, the optimal date of investment appears earlier. The waiting period is reduced of nine years between the highest and the lowest scenario.

It means also that the decision maker has delayed its choice by eight years in the most favorable scenario. The option value for $\alpha_c=3\%$ is extremely low, which is consistent with its low probability of investment. On the contrary, the option value exceed 36M€ if $\alpha_c=6\%$, because the project profitability is almost sure.

| Carbonprice drift | 3% | 4.50% | 6% |
|---|---|---|---|
| **Option Value (M€)** | 0.01 | 6.61 | 36.23 |
| **Optimal Date** | 2032 | 2024 | 2023 |
| **Probability of investment** | 0.57% | 74.94% | 99.28% |

**Table 1 : Option values, optimal dates and probabilities of investment, with carbon drifts known**

Investment profiles for the three carbon price drifts (low, moderate and high) are drawn on Figure 2. The yearly investment rate is so small for the lowest scenario that related investment profile cannot be distinguished. At $\alpha_c$=4.5%, we notice that the maximum of investment is around 8% of the simulations. The optimal date is not very clear at first sight, since the yearly investment is almost the same in 2023 and 2024. On the contrary, with the highest carbon price drift, the investment peak is isolated and closed to 30% of the simulations.

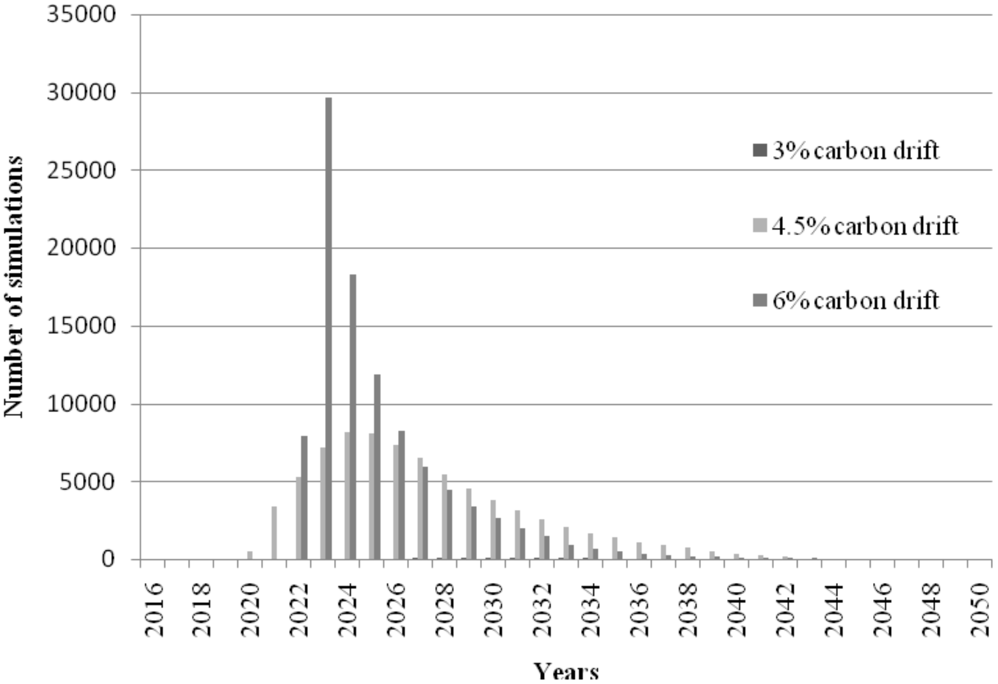

**Figure 2 : Investment profile for carbon drifts of 3%, 4.5% and 6%.**

## 4.2 – The decision maker does not know the carbon drift

In this new set of simulations, the signal on the real carbon price drift is blurred because of carbon price volatility.

The probability of investment is now of 47.5%. We have seen in section 4.1 that the highest carbon scenario clearly leads to investment and the lowest to give up the project in almost all simulations. It is then not surprising that the probability of investment drops now under 50%, following the bifurcating in price trajectories. This value is lower than the probability of investment in the case of the previous intermediate scenario (74.5%). Indeed, there are now less intermediate trajectories, since carbon paths are captured either by $\alpha_{up}$or by $\alpha_{down}$.

The optimal date of investment is 2022, which means seven years of waiting. It is earlier than in the case of $\alpha_{up} = 6\%$ and two years before the optimal date of the intermediate scenario. Despite the global increase of uncertainty, the decision maker tends to take his decision earlier, because of the lack of intermediate trajectories. The option value is 14.20M€, so greater than for α=4.5%. Even if the optimal date is sooner, the value of waiting is much bigger. The two deterministic trends are very close in the first years and so the decision maker has difficulties to distinguish from each other. But the option value is still below 36.23M€, because the probability of investment is lower than with$\alpha_{up} = 6\%$.

The yearly investment peak is very significant with more than 11% of simulations leading to investment in 2022. However, it is nearly half the peak of $\alpha_{up} = 6\%$.Around 70% of the simulations leading to investments are realized in four years (2021 to 2024), but there is no investment before 2020. The investment profile with bifurcation of price path has a similar shapein the investment profile with $\alpha_{up} = 6\%$, but the yearly investment probability is lower and closer by one year. It means that there is no delay of investment, but a shortfall of investment.

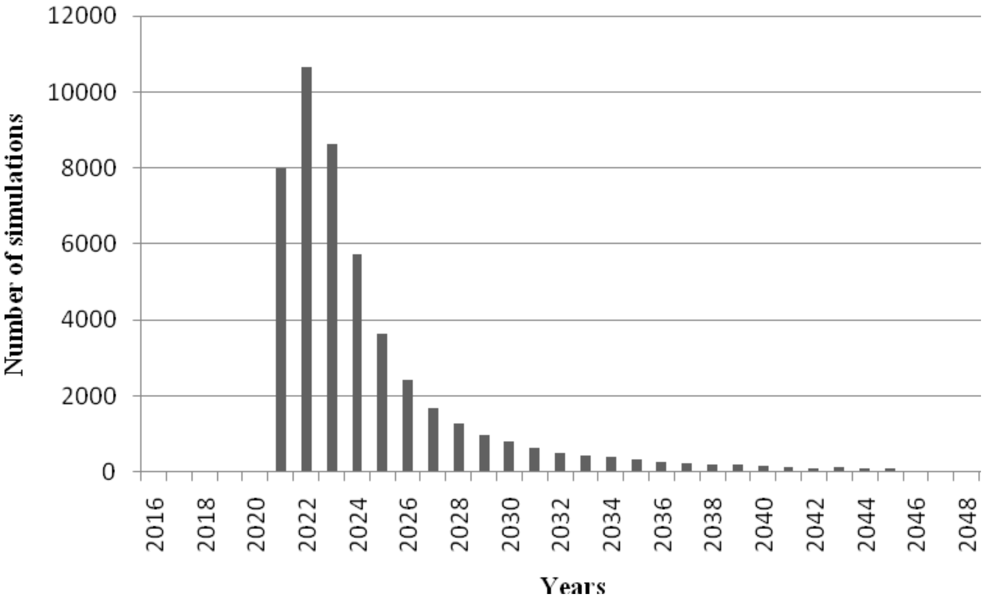

**Figure 3 : Investment profile for bifurcation of carbon drifts**

## 5 - Conclusion

We used a real option approach to study the impact of climate policy uncertainty on investment. This means that the decision maker does not know the carbon price drift for the long run. The case study is a carbon capture and storage (CCS) project, which could be delayed. We compared scenarios with known and unknown carbon price drift.

This article provides evidence that regulatory uncertainty does not necessarily mean that the decision maker intends to delay the project. He does not take more time before doing their choice, compared to a scenario without (or less) uncertainty. On the contrary, we have shown that the optimal date of decision could be earlier. These results are not common in real option literature. Generally, firms are assumed to adopt a postponing strategy to cope with regulatory uncertainty. However, we modeled a continuous resolution of uncertainty over time that reduces more the incentive to postpone investment than a discontinuous resolution in one abrupt step (for instance a carbon price jump).

The impact of regulatory uncertainty is yet negative, since the probability of investment decreases. Moreover, there is no period of investment revival in our results when the decision maker knows the real carbon trend. So, regulatory uncertainty about long term $CO_2$ targets does not postpone projects but discourages investmentpermanently. To trigger investment, it would be necessary to ensure the long run climate targets.

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