Biomass and CCS:
The influence of learning effect

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Abstract

Combining bioethanol production and Carbon Capture and Storage technologies (BECCS) provides a opportunity to create negative emissions while producing biofuels. However, high capture costs reduce the profitability. This article tackles carbon price uncertainty and technological uncertainty through a real option approach. We first compare the case of an early versus a delayed CCS deployment. An early technological progress may arise from aggressive R&D and pilot project programs, but the expected reduction in costs is still uncertain. We show thus that the amount of avoided emissions is higher and that investments are carry out sooner but after 2030. In a second set of experiments, we apply an additional aid which consists in rewarding sequestered emissions rather than avoided emissions. In other words, CO_2 emissions from the CCS implementation are not taken into account anymore. Investment level is then higher and the project may becomes attractive before 2030.

Keywords: Real options; Learning effect; Carbon capture and storage; Biomass.

JEL: Q54 ; Q55

1 - Introduction

Interest in carbon capture and storage (CCS) technologies has increased significantly in recent years, sparked by greenhouse gas (GHG) growing emissions combined with a continually increase in the demand for energy, see IPCC (2005), IEA (2010). However, CCS is entering in a critical innovation phase and the CCS stakeholders are now calling for an early deployment of large-scale demonstration projects to trigger CCS deployment, de Coninck (2009). More precisely, public funding tends to decline after a R&D successful phase; whereas private stakeholders consider that the technology is still too expensive and risky to be implemented in the short run. This is a classical trap in an innovation process, generally named the "valley of death", see Murphy and Edwards (2003).

One of the most challenging issues regards capture process itself. Indeed, it has been hardly tested at commercial scale, even if it constitutes the only way to prove the commercial feasibility of CCS. According to most experts, further research on capture components (membranes, sorbents and solvents) are needed, van Alphen (2010). However, the collaboration between industrial actors is slowed down by intellectual property issues since technological change is perceived as a competitive advantage. A solution could be to create public-private partnerships to reduce uncertainty and increase financial resources that are currently assumed too low to realize integrated commercial-scale CCS demonstration projects, e.g. combining capture, transport and storage. Implementing this kind of projects would allow a considerable improvement in global knowledge and know-how. Therefore, it is very likely to lead to a major reduction in costs. On the contrary, if these projects are delayed, the learning process will be spread over decades and the global CCS deployment as well.

In this study, we focus on a variant of the CCS technology portfolio, for which part of the stored CO_2 comes from biomass instead of fossil fuel. Combining CCS with biomass energies (BECCS) has the unique potential to create negative emissions and at the same time produce energy – see IPCC (2005) - such as electricity and heat (Rhodes, 2007 ; IEA, 2009) or biofuels (Möllersten *et al.*, 2003; Mathews, 2007; Lindfeldt and Westermark, 2008). Actually, the CO_2 withdrawn from the atmosphere by BECCS can even exceed the amount of CO_2 emitted during the production process. To reach this goal, it is necessary to sequester the emissions from the biomass conversion and to lower the emissions of the energy production part. According to Azar *et al.* (2006) or Read and Lermit (2005), BECCS chains can contribute to achieve very low emission targets (even below 450ppm). We focus here on biofuel production. More precisely, we consider the case of a bioethanol refinery which process sugar beets, retrofitted with CCS. A technical and geological description of this project can be found in Fabbri *et al.* (2010).

The aim of this article are the following: First, we wonder whether negative emissions technology is profitable and under which conditions. Second, we search to quantify the impact of short run versus long run learning effects on the optimal investment timing. Third, we investigate another way to subsidize CCS projects which is rewarding sequestered rather than avoided emissions and compare the impact on investor's behaviour.

Investment projects are often studied through discount cash flow (DCF) methods, but this approach is not relevant to CCS and BECCS implementation. First, DCF methods assume that future cash flow streams are highly predictable, which is unrealistic. BECCS is indeed subjected to a number of uncertainties i.e. carbon price, energy price and capital cost evolution. Second, capital-intensive technologies like CCS and BECCS induce a barrier to entry in the carbon market. Third, investors do not have a passive behavior, meaning that they can delay their final decision, waiting for better information or market conditions. Because of these three features (uncertainty, delay and sunk costs), a real option (RO) approach seems more convenient. The term 'real option' was coined by Myers (1977) analogous with financial options. It is the right, but not the obligation, to undertake a business investment opportunity. Some of the most important theoretical considerations can be found in the contributions of Dixit and Pindyck (1994) and Trigeorgis (1996).

To our knowledge, no other RO analysis of biofuel production combined with CCS has yet been achieved, whereas several papers studied CCS applied on electric plants, see Laurikka and Koljonen (2006), Abadie and Chamorro (2008), Heydari *et al.* (2010), and only one focuses on biomass electricity production with CCS (Szolgayová *et al.*, 2008). Following Murto (2007) and Fuss and Szolgayová (2009).

This paper is organized as follows: Section 2 gives further explanations about technological progress, learning effect and CCS; Section 3 describes the real option model, scenarios and calibration ; Section 4 presents and discusses the results. Finally, some conclusions are drawn in Section 5.

2 - Technological progress, CCS and BECCS

2.1 - Technological progress and learning curves

Different kinds of learning effects have been identified by notably Grübler and Messner (1998) and Junginger *et al.* (2006). We retain here the typology given in the detailed survey of Kahouli-Brahmi (2008):

- **Learning-by-doing:** It refers to the improvements during the production process. This effect is due to experience for instance in Operation and Maintenance, labor efficiency, changes in production and so on.
- **Learning-by-researching:** Research and Development (R&D) expenditures lead to an innovation flow that can be absorbed by the firm.
- **Learning-by-using:** Feedbacks of users point out the limitations of the product and may lead to substantial technological progresses.
- **Learning-by-interacting**: The diffusion of knowledge results from interactions between various stakeholders like scientists, industrial actors, decision-makers and users. Progress coming from learning-by-using and from learning-by-doing may be shared by the community.
- **Economies-of-scale:** reduction costs in large-scale operations result from operational efficiencies. It is seen as a part of learning effect because large-scale production promotes technological progress.

Learning curves are the most common way to deal with technological progress into economic models. Usually, they focus on the learning-by-doing effect even if some models include a second parameter, i.e. research and development (R&D). Technological progress is then measured in terms of reductions in costs, because these improvements generally have an economic impact. Most of analyses estimate then the gain with a progress ratio (PR) which is the ratio of current cost (per unit of production) to initial cost after a doubling of production.

It is not easy to separate quantitatively the different learning effects and most modeling merged them, which constitutes an important limitation of this tool. For instance, learning curves do not often distinguish between improvements after the process implementation (learning-by-doing in the strict sense of the term) and improvements due to the building of new capacities. Another common bias is the mix-up of learning-by-doing and scale effect that overestimate the real learning rate, Sönderholm, (2007).

In the case of CCS industry, the capital cost constitutes a huge entry barrier. If a decision maker implements a CCS project, he cannot benefit of future cost reductions on capital. The value of waiting is higher than in the case of a continuous progress after the project implementation as generally assumed by learning curves. Real Options (RO) approach allows taking this issue into consideration. Moreover, technical change process is inherently uncertain. It provokes thus an additional value to delay the investment. RO are clearly more adapted to deal with risk than deterministic technological paths.

Despite their inherent limitations, learning curves are still essential for our framework. In our modeling, technological progress is exogenous, so we have to do assumptions about learning evolution. Basically, learning-by-doing and learning-by-using are not taken into consideration here, but they are partially incorporate into the learning-by-interacting effects. We use here progress ratios as a proxy of cost reductions that mix learning-by-researching and learning-by-interacting effects. However, progress ratios are insufficient by themselves because the rate of doubling capacity is unknown here, since technological change is exogenous. Building scenarios on costs evolution is thus necessary.

2.2 - CCS and BECCS

In this analysis, we focus on a variant of CCS, BECCS in bioethanol industry, whose production process is described in the next section. BECCS does not need specific technologies compared to other CCS chain (especially CCS on a coal power plant). That is why we focus only on CCS literature in this section.

Ferioli *et al.* (2009) estimate a progress ratio in energy technologies of 19% with a range of 3% to 34% and a 95% confidence interval. Yet, coal-based technologies have a lower historical PR (between 3.75 and 15.1%), see Jamasb and Köhler (2007).

As a consequence, a further analysis is required on CCS components evolution. According to IPCC (2005), the technical maturity of CCS units varies greatly. Some aspects of the technology are mature (e.g. transportation by pipeline), some others are partially demonstrate (e.g. geological storage in saline aquifers), or still in the research phase (e.g. oxyfuel combustion capture process). Storage costs progress is assumed to remain stable here. First, these processes are based on well-established gas and oil drilling technologies. Second, because they are very site-sensitive and might be subjected to a negative learning rate as nuclear industry has already met, Neij (2008). This phenomenon was certainly due to necessary improvements on safety and limited experience sharing. On the contrary, capture components are still largely unproven and are assumed to gain in efficiency, even in the case of post-combustion technologies.

In addition, the overall progress ratio of the process chain depends on the evolution of each specific components set apart. Moreover, they can influence each others. For instance, in the case of CCS, a higher capture efficiency may lead to a secure storage and thus lower monitoring costs. On the contrary, if the capture process doesn't evolve sufficiently, the whole CCS chain is likely to be penalized. This problematic is yet out of scope in our study.

Rhiahi *et al.* (2004) are among the first who intend to forecast future CCS costs through a comparison with past experience in controlling sulphur dioxide emissions (SO_2) from power plants. The corresponding PR is about 12-13%. Actually, CCS shares with SO_2 scrubbers some features: their commercial value is created by legislation and they are submitted to a large technological uncertainty. By analyzing the development of nuclear plants, LNG and SO_2 scrubbers, Rai *et al.* (2009) conclude that CCS technologies are very sensitive to their diffusion path. In addition, Baker *et al.* (2009) highlight that experts have some disagreement on CCS technologies evolution, especially regarding capture processes, even the most well-known, i.e. the post-combustion. In this study, we focus on the evolution of capture components because this process is the most likely to evolve significantly and is also the main investment cost of the whole chain. Moreover, no O&M costs decrease is assumed (no learning-by-doing effect inside the firm).

McKinsey report (2008) is referred as our benchmark in order to get high, 'best-guess' and low learning rates scenarios. In this report, the global progress ratio is around 12% per doubling capacity for CCS. Their reference case (i.e. a new coal power installation) evaluates that costs decrease from a demonstration phase (i.e. between 2015 to 2030) with a range of CCS costs of 60-90€/tCO_2 to a mature commercial phase in 2030 with 30-45€/tCO_2.

3 – Real Option Model

3.1 - The case study

3.1.1 -Bioethanol refinery description

Data are based on two previous works. In one hand, the description of a real bioethanol refinery in France, in a region which seems favorable to CO_2 underground storage. This first firm processes sugar beets to produce sugar and high purity alcohol for the perfume, solvents and bioethanol. Only the bioethanol production itself is studied here. An overall of this study is available in Laude *et al.* (2010). In the other hand, to deal with upper volumes, we established a study on scale effects, see Laude and Ricci (2010). We choose here an ethanol production of 4Mhl/yr. Two CO_2 sources are depicted: the cogeneration unit (fed with natural gas) and the fermentation unit. For an ethanol production of 4Mhl/yr, the volumes of CO_2 emitted are 300,000 t/yr from the fermentation unit and around 407,000t/yr from the cogeneration unit.

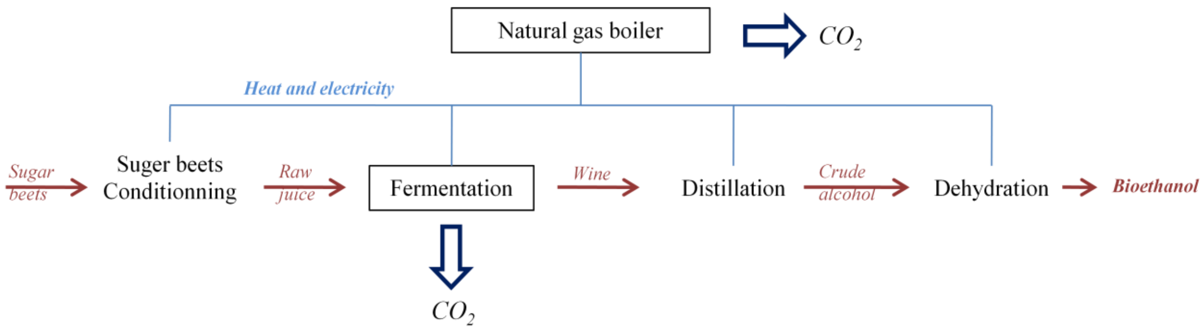

Figure 1: Description of the sugar refinery process

3.1.1 - Valuation of the CCS chain

The exhaust stream from the fermentation is assumed to be pure. Actually, this corresponds to an ideal anaerobic fermentation, where the chemical reaction yields to ethanol and CO_2 only. Because of this feature, only the cogeneration unit requires a capture process. A post-combustion process is used with an assumed capture rate of 90%. Thus the CO_2 is transported in a dense phase via pipeline. No intermediate pumping is needed to reach the wellhead at an appropriate pressure for injection, because of the short distance and the absence of elevation differentials. The storage takes place in a deep saline aquifer, at roughly 2250m below the surface. Regarding the storage facilities, we consider two vertical wells to be sufficient to achieve the maximum possible CO_2 flow rate, which is anticipated during the harvest period. Monitoring costs of the site injection had been funded and are included in capital costs. If the CCS chain is implemented on the fermentation unit, the main cost is the injection costs. If the CCS chain is also added on the cogeneration unit, the main cost becomes the capture cost.

In addition, a carbon footprint has been achieved to quantify the environmental benefits of the CCS chain, see Laude *et al.* (2010). The amount of CO_2 avoided differs from the amount of sequestered CO_2 in the subsurface. Avoided emissions are indeed determined as a result of implementing CCS such that :

$$q_{avoided} = q_{seq} - q_{CCS}$$

q_{ccs} includes the surplus of emissions due to the CCS chain for each of the cases studied. Implementing a CCS chain on the cogeneration unit increases significantly the emissions emitted by the plant, notably because of the energy penalty. The main features of this case study are summed up in Table 1.

Only avoided emissions measured the real environmental benefits of the project, so it seems quite natural to reward them only and it is what the European legislation on CCS foresees, see Directive 2010/345/EC. For that matter, we choose avoided emissions in our calibration except in a specific sensitive analysis (see subsection 4.4). However, rewarding sequestered rather avoided emissions may constitute an interesting aid for CCS development, more certain in an investor point of view than technical progress.

CCS chain on fermentation only	Capital (M€)	58
	O&M (M€) without gas	2.2
	gas consumption (MWh)	35,728
	Emissions (MTCO$_2$eq)	200,000
	Avoided emissions (MTCO$_2$eq)	190,000
CCS chain on fermentation and natural gas boiler	Capital (M€)	150.8
	O&M (M€) without gas	7.83
	gas consumption (MWh)	4,300,000
	Emissions (MTCO$_2$eq)	470,000
	Sequestered emissions (MTCO$_2$eq)	423,783
	Avoided emissions (MTCO$_2$eq)	366,667

Table 1: CCS chain features

3.2 - Real Option methodology

3.2.1 - Framework

The investment decision can occur between 2015 and 2050. At the maturity date, the bioethanol refinery is assumed to shut down or need too many modifications, which makes the CCS chain obsolete. The maximal CCS lifetime of the refinery is thus 35years. CCS is implemented at the date of decision, no time-to-build troubles are specified in our model.

As already mentioned above, we focus on the bioethanol production of the refinery, but the profitability of the bioethanol process itself is out of scope. On the contrary to electric plant, CCS implement does not lead to a reduction in the output production and that is why the two outputs are not interacting. Carbon emissions are considered as a co-product that could be made tradable on the carbon market if the CCS chain project is applied.

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 emission avoided, P^c the carbon price, q^g the natural gas consumption, P^g the natural gas price and O&M are the Operation and Maintenance costs. Carbon and gas prices are assumed to be driven by a two-dimensional geometric Brownian motions (GBM):

$$\begin{cases} dP_t^c = \alpha_c . P_t^c dt + \mu_c . P_t^c . dW_t^c \\ dP_t^g = \alpha_g . P_t^g dt + \mu_g . P_t^g . dW_t^g \end{cases},$$

where μ_c and μ_g are the carbon drift and gas drift, respectively; σ_c and σ_g are the carbon volatility and the gas volatility, respectively; W_t is a standard Brownian motion, and W_t^c and W_t^g have correlation ϱ. In the following, we denote by dP_t this two-dimensional stochastic differential equation.

CO_2 prices are difficult to foresee because they are strongly influenced by policy. As a relatively new market, the European Trade Scheme (EU ETS) has a particular behavior and its parameters cannot be calibrated with a historic data set for long term forecasts. This is the reason why we choose to study a panel of carbon drifts from 4 to 7%. Figure 2 shows the deterministic paths corresponding to each carbon drift. A drift of 6 or 7% could seem really high in comparison with most RO literature (e.g. α_c=5.68 in Szolagayova *et al.* (2008), based on previous IIASA scenarios). In the same time, for a target of 450ppm, these prices are in the range of prices investigated in the literature, according to Aldi *et al.* (2010). In addition, if the "common but differentiated responsibilities" principle is recognized, that leads to more stringent targets in Europe, for instance the aim of 75% of GHG reduction before 2050 in France. The prices are in this case in line with the assumptions of the so-called Quinet report, CAS (2008), for French forecasting.

In this article, we ignore short-term volatility and so we choose a relative moderate carbon volatility of 5%. For the same reason, natural prices have the same standard annual deviation. The corresponding drift is set at 2%. In line with Yang *et al.* (2008), natural gas and carbon prices are assumed to be correlated with a correlation rate of 0.5%. Table 2 gives an overview of the calibration.

Discount rate	r	4%
Carbon price volatility	σ_c	5%
Natural gasprice drift	α_g	2%
Natural gas price volatility	σ_g	2%
Correlation coefficient between natural gas price and carbone price	ϱ	50%
Time unit	dt	1 yr
Number of simulations	N	100,000

Table 2: Calibration of the option

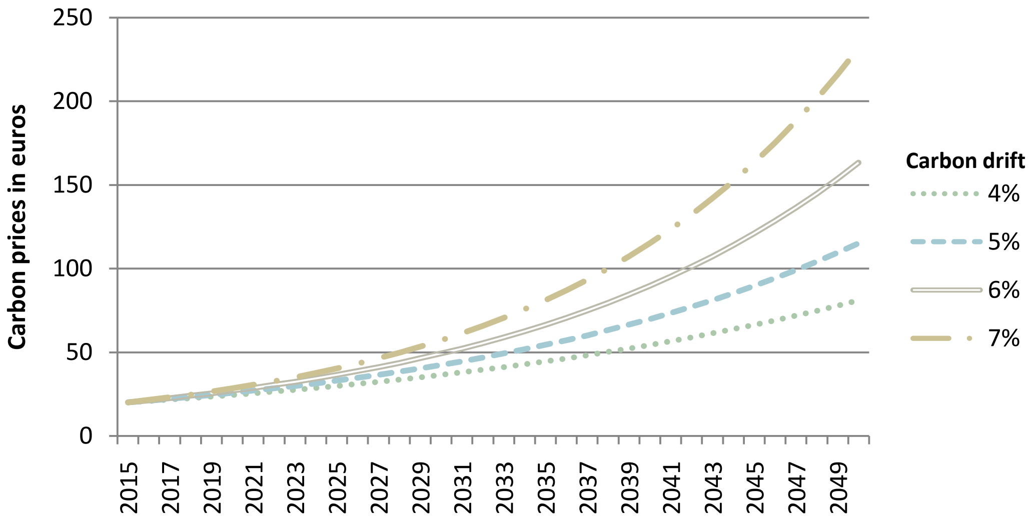

Figure 2: Deterministic carbon path, depending on the carbon drifts, from 2015 until 2050

3.2.2 Optimal stopping problem

In our real option model, the investor chooses between invest or wait at every time step. Before we proceed, let us introduce some definitions. Recursively, we define the running present value RPV_t by[1]

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

with the maturity date T (35 years), the cash flow process CF_t and the riskless interest rate r. The first time t=1 corresponds to the date of option beginning, here 2015. In the following, we denote the initial investment by I_1. Then, the profit function is given by

$$\Pi_T = CF_T - I_T, \;\; \Pi_t = RPV_t - I_t, \qquad t = T-1, \dots, 1.$$

In order to get the price of our real option, we concentrate on the following optimal stopping problem:

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

where $[1, T]$ denotes the set of all stopping times with values in {1,…, T}. In the following we focus our attention on Monte Carlo methods for solving task (1). It is well known that (1) can be solved by using 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 continuation value, i.e. the value of investing later, is defined by:

$$C_t := e^{-r\Delta t}\mathbb{E}[V_{t+1}|P_t].$$

Alternatively, we may use the DPP in terms of the optimal stopping time for solving (1) :

$$\begin{cases} \tau_T = T \\ \tau_t = \begin{cases} t\,, & \Pi_t \geq e^{-r\Delta t(\tau_{t+1}-t)}\mathbb{E}\left[\Pi_{\tau_{t+1}}|P_t\right] \\ \tau_{t+1}\,, & \Pi_t < e^{-r\Delta t(\tau_{t+1}-t)}\mathbb{E}\left[\Pi_{\tau_{t+1}}|P_t\right] \end{cases}, \qquad t = T-1, \dots, 1. \end{cases}$$

Then, the continuation value is thus:

$$C_t \coloneqq e^{-r\Delta t(\tau_{t+1}-t)}\mathbb{E}\left[\Pi_{\tau_{t+1}}|P_t\right].$$

The key idea of regression-based Monte Carlo methods is to assume a model function for the continuation value, such as done by:

$$\widehat{C_t} = \sum_{m=0}^{M-1} x_m b_m(t) \qquad (2)$$

with a basis $\{b_m(\cdot)\}_{m=0}^{M}$ specified a priori. Based on the set of simulated paths, the coefficients are determined by regression. There are a variety of regression-based Monte Carlo approaches and we refer to Jonen (2009) for an overview. Due to its simplicity and computational efficiency in higher dimensions, we concentrate on the Least Squares Monte Carlo (LSM) method proposed by Longstaff and Schwartz (2001) in this paper. By doing so, we focus our attention on the DPP in terms of the optimal stopping time and

[1] A similar framework can be founded in Alesii (2008).

approximate the optimal stopping time for each simulated path n, n=1,…,N. We apply the model function (2) and use least squares to determine the coefficients. Moreover, to reduce variance, we simulate paths by using antithetic variables. Finally, we estimate the real option price by

$$\widehat{V_0} = \frac{1}{N}\sum_{n=1}^{N} e^{-r\Delta t\tau_1^n}\,\Pi_{\tau_1^n}^n$$

where τ_1^n and $\Pi_{\tau_1^n}^n$denote the approximated optimal stopping time and the profit at τ_1^n of path n=1,…,N, respectively. In all our experiments, we choose the following basis functions:

$$\{1, CF_t, (CF_t)^2, (CF_t)^3\}.$$

3.2.3 Technical change modeling

Murto (2007) uses a Poisson process to describe capital costs evolution and he finds analytic solutions in some specific cases. Fuss and Szolgayová (2009) follow closely this model but adapt it to a discrete time model which allow to study more general cases. We retain here this global framework, adapted to an LSM algorithm.

We assume that the learning improvements happen only on the initial investment, i.e. the capital costs and not on the operation and maintenance (O&M) costs. In addition, only the capture costs may decrease since the other steps are assumed to be mature. As a result, the construction cost is split into two:

$$I_t = I^{C,T\&S} + I_t^{Cap}$$

where $I^{C,T\&S}$ is the capital costs of compression, transport and storage ; I_t^{Cap} is the capital costs of capture step. This last cost is assumed to evolve following the next stochastic process:

$$I_t^{Cap} = I_0^{Cap}.\Phi^{N_t} = I_0.e^{-\lambda.t.(1-\Phi)},$$

where I_0^{Cap} is the investment cost of capture components in 2015, N_t is a Poisson random variable with mean λ_t counting the number of innovations, and Φ is a constant reflecting the magnitude of each technical progress. Jumps can only reduce capture costs since they reflect technological progress. As a consequence, the investment expectancy is given by

$$\mathbb{E}[I_t^{Cap}] = I_0^{Cap}.e^{-\lambda.t.(1-\Phi)}\ .$$

In our modeling, the investor knows the deterministic technological path; the uncertainty is about the timing of innovations. The corresponding assumptions are indicated in the next section depending on the experiments.

4- Results

4.1 - No learning effect

The base case assumes no technical change over the whole period. The only incentive to invest is given by carbon prices, whose drift is assumed to be known by the decision maker. We first focus on a 'fermentation only' project, which means that the CCS chain regards only the emissions from the fermentation part of the firm. In sub-section 4.1.2, the same plant is studied but a CCS chain is also added on the boiler.

4.1.1 - Fermentation only

The discount cash flow method gives us a first indication of the project profitability. In this case, the project is supposed to start in 2015. As carbon and natural gas prices are deterministic, the only way to incorporate a risk measure is done through the discount rate r. If a rate of 4% is applied, the net present value (NPV) is always positive, whatever the carbon drift which means that the project is always accepted. This rate is accurate for very long term public project (more than 30 years) according to the Lebègue report (2005). Yet, this rate is very low compared to those usually chosen for private project appraisal. For instance, at r =8%, the project is considered profitable as soon as α_c is equaled or upper to 5% .

When an RO approach is implemented, results show that the global investment rate increase with higher carbon drifts. 'Investment rate' refers here to the number of simulations for which the decision maker decides to invest. This indicator catches the probability of project success before the option ends. In the case of fermentation, it is almost insensitive to carbon drift. The global investment rate is higher than 80% with α_c equals to 4% and almost reach 100% if α_c is set to 7%.

Another indicator is referred as 'optimal date' thereafter. Actually, there is a date of investment for each single simulation. The optimal date is the date for which there is the most investments implemented over the whole set of simulations. In other words, the optimal date is the date with the highest probability of investment. Regarding the current experiments, the project is generally implemented after one year (2016). This project seems extremely profitable and not very risky.

4.1.2 - Negative emissions

It should be noted that in the last case, no specific capture component is needed but only a compression step. Nevertheless, to obtain negative emissions, it is now necessary to implement a post-combustion process. Unfortunately, the costs are far more important which results in a dramatic fall of profitability. Regarding the relative investment costs, capture costs represent indeed 62% of the whole capital costs. As a consequence, the NPV is negative at every carbon drift, even for a low discount rate of 4%. In a RO perspective, global investment rates reach only 0.3% and 5.8% of success over the whole period, for carbon drifts at 4% and 5% respectively. The impact is more striking for higher carbon drifts, since a major progression is noticed. At α_c=6%, the probability of investment is around one third and at α_c =7%, it is set at roughly three-quarter.

The optimal date of investment is positively affected by a carbon drift increase. This is an intuitive result since the output price drives the investments, thus the incentive is higher and the value of waiting diminishes. At α_c =6%, the optimal date happens after 19 years, and if α_c equals 7%, it happens 18 years after the option opening.

The investment profile provides more detailed information on decision maker behavior, see Figure 3. For instance, at the middle drift of 5%, the optimal date computed is 23 years. This last result is not very relevant because the rate is very too low and the peak of investments is not obvious. In addition, the investments linked to a carbon drift of 4% are quite simply invisible. This is the reason why we are going to generally focus on 6% and 7% carbon trends in the next sections. These carbon drifts are clearly higher than in most projections of GHG shadow prices and clearly match with very low stabilization target (for instance 450 ppm or even less). Even if it was obvious that carbon prices are the main driver of investment, we see here that this project is highly sensitive to this factor, unlike the project with CCS applied only on fermentation. Moreover, with upper carbon trends, the profile becomes less and less flattened. At 7%, the peak of investment is almost three times the one of 6%.

Investment rates do not give any indication on the expected avoided emissions of this project. If the project is implemented in 2015, the gain is easily computed: the project leads to a reduction of 12,5Mt of CO_2 avoided over its lifespan. The expected environmental benefits, over the 100 000 simulations, is computed with the next formula:

$$Q_E = \frac{q_E}{N} \cdot \sum_{t=0}^{T} \left[\sum_{k=0}^{t} \left(\mathcal{N}_E(k) \right) \right],$$

where Q_E is the global quantity of avoided emissions, q_E the annual avoided emissions if the investment is done, N the number of simulations, $\mathcal{N}_E$ the number of accepted projects at date k (determined by the optimal date of investment for each simulation).

At α_c =6%, the expected emission reduction is only 1.5MtCO_2, but it rises to approximately 4.0 MtCO_2 with a carbon drift of 7%. We have to highlight that environmental benefits (in expectancy) almost double between α_c =6% and 7%, because of the higher level of investment.

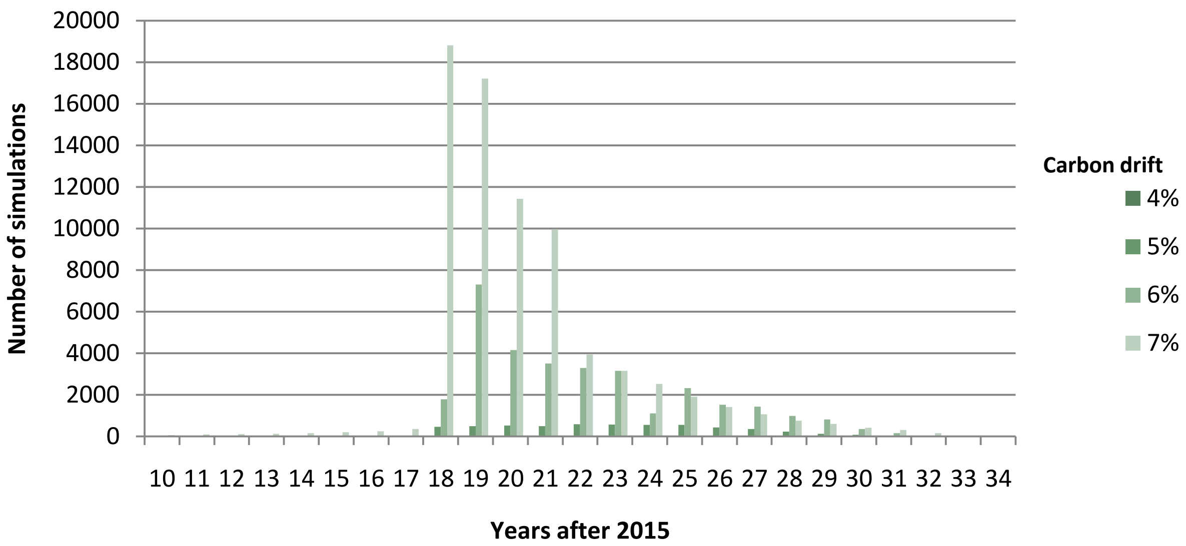

Figure 3: Frequency distribution of investment for the reference case, depending on carbon drifts

4.2 - Learning effect in the long run

According to Fuss *et al.* (2009), learning effect creates an additional value of waiting and thus tends to delay the investment implementation. The decision maker foresees the reduction in costs and is very likely to invest only after innovation emergence. With a low learning rate of 33% over the period, this actually happens. At the highest carbon drifts of 6 or 7%, the global optimal date is delayed of one year. However, if the learning rate is set at 50%, there is no additional delay for the 6% scenario and at 7%, the optimal date returns to 18 years. At a learning rate of 66% and with α_c sets at 7%, the optimal date is closer from today by two years (16th years of waiting). The existence of a turning point means that the reduction in cost appears in average sufficiently soon to trigger investments.

For low carbon drifts (i.e. α_c =4% and 5%), the increase of investments is important in relative rate but it does not change much the interpretation. For the highest learning rate, at α_c =5%, the number of projects accepted roughly doubles, while the investment rate rises from 5.8% without learning to 13.2% with a low learning.

At a higher carbon drift (α_c=6%), the increase is weaker in relative terms but the critical level of 50% of investment rate is reached. If the carbon drift is now set at 7%, the investment rate reached 90%. The probability of success is clearly improved. On Figure 4, investment profiles are drawn for low, middle and high learning rates. This reveals that higher learning rates tend to spread the investments decision and not only to move the global optimal date. Actually, the 66% learning rate almost encompasses the two other curves.

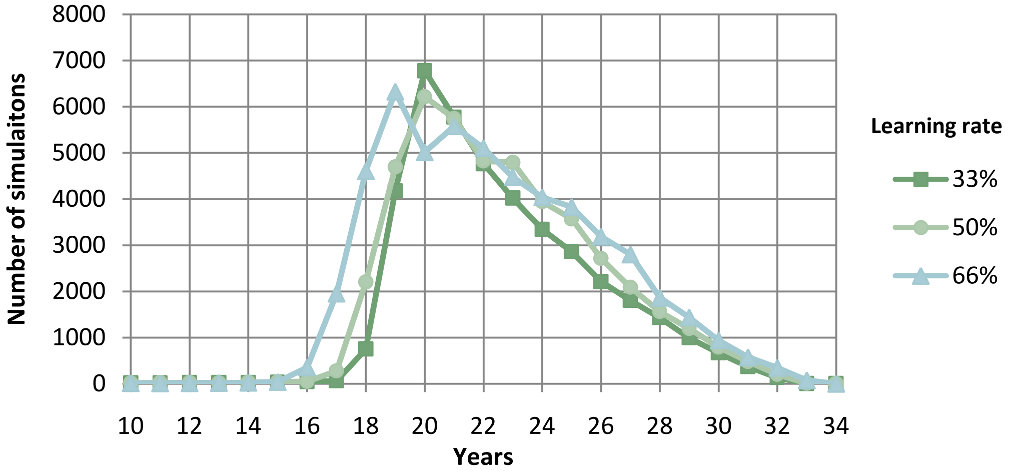

Figure 4: Long run learning effect on investment with a carbon drift of 6%

This incentive on investment also creates a further environmental benefit. For instance, at α_c =6% and for the highest learning rate, the expected avoided emissions is now of 2.39MtC0$_2$, i.e. 860.000 extra CO_2 tons.

4.3 - Early deployment

In the previous section, we have shown that learning effect is necessary to reach a higher profitability of success, especially for α_c =6%. We now explore the impact of an early deployment on private investors behavior, as assumed in the McKinsey report (2008). More precisely, in this set of experiments, technical change happens only on the first fifteen years of the option availability. After 2030, no more cost reduction is assumed, nor for capture components neither for transport and storage. Such a learning is possible only if technology oriented subsidies outside of the carbon market are granted, see Blyth *et al.* (2009), but the induced technological change is still uncertain.

In this new framework, no more delay of investment is noticed, whatever the learning progress applied. This is an expected result since without learning the optimal date is gotten after 15 years of waiting. An early learning may thus nothing but bring closer the investment decision.

More precisely, for the highest learning rate, we observe that at α_c=6%, the investment happens in average three years earlier compared to the base case. At α_c=7%, the gain is up to four years. In comparison with a learning progress spread all over the period, the time saved is respectively of three years and two years. Regarding the highest carbon drift, the influence of deployment in the long run versus in the short run is weak. Actually, even with a medium and spread technical change, the carbon prices were so high that the optimal date has been already brought forward when a postponed learning was considered.

Results show also how investment rate is affected by an early learning effect. The difference between the two kinds of learning is not obvious at first sight, since it rises from one or two more hundred simulations in the whole option period. Investment profiles for α_c =6% and the highest learning rate are drawn in Figure 5, for postponed and early deployments. The two peaks have approximately the same value (a little bit more than 6% of investments this year), but the early curve is not simply a translation since the 'short term' distribution tends to have a longer tail on the right-hand side.

This implies that the most important driver of investment is still the carbon drift. However, early CCS development has an influence on the reduction in emissions. With a carbon drift of 6%, a low learning (33%) leads to 2.01MtCO_2 avoided and a high learning (66%) to 3.01MtCO_2 avoided. These results have to be compared with the highest learning progress on the long run which was 2.39 MtCO_2. Even if improvements on investment rate are moderate, an early learning effect provides a clear increase of avoided emissions.

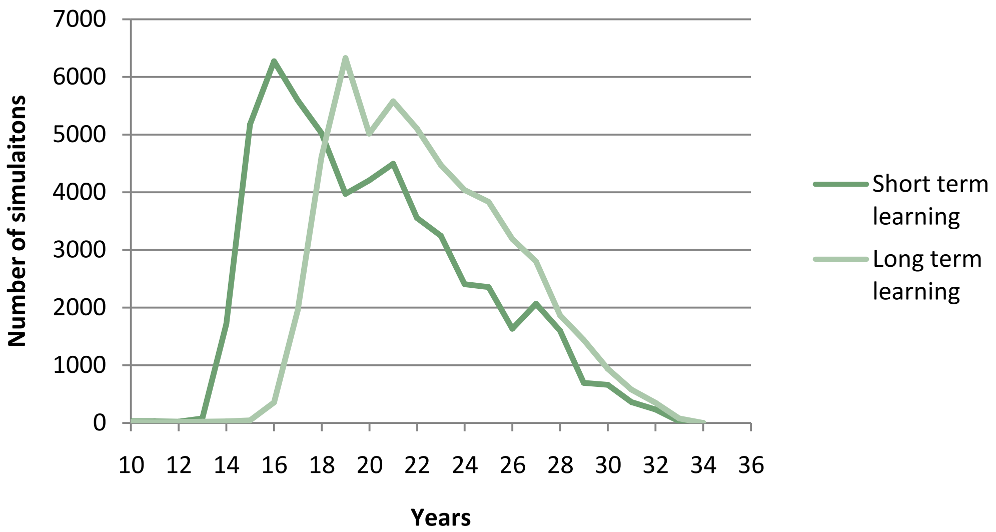

Figure 5: Comparison between early and spread deployment, with high learning rate and a carbon drift of 6%

4.4 - Avoided emissions versus sequestered emissions

Whatever the scenarios investigated, rewarding sequestered emissions rather avoided emissions increases the number of investments and provokes an earlier peak of decision. Without any learning effect, the investment rate grows up to 58% with a carbon drift of 6%. Remember that it was previously set at 34%. For a drift of 7%, the investment rate is now up to 92% (versus 76%). In the same period, the optimal date gets closer respectively of two years and five years. The influence of rewarding sequestered instead of avoided emissions is considerable. For the two indicators, it is similar to a high and early learning effect. In terms of environmental benefit, the gain is respectively of 3.28MtCO_2 and 6.27MtCO_2.

Moreover, reward sequestered emissions could trigger early investment and so create an additional incentive for earlier projects. If a small but early learning effect is added, at 6% and 7% the investment rate is respectively of 69% and 96% and the optimal dates are 15 and 12 years after option beginning. If the carbon drift is still 6%, the amount of avoided emissions increases until 4.24MtCO_2.

The option values at the beginning of the option (2015) for experiments regarding this negative emission project are summed in Table 3. It shows that the value of waiting grows with carbon drifts in every case, reflecting the progressive increase in project value. The option value raises also with higher learning rates as expected. However, when combining high learning rates and carbon drifts, the option value in case of long term learning seems sometimes upper the corresponding early learning rates. This is because the project is valuable earlier. It is also noticeable that the assumption of sequestered emissions rewarded almost doubles option values in comparison with an early learning rate of 66%.

Experiment	Learning rate (in %)	Carbon drifts 4%	5%	6%	7%
No learning	0%	0.07	2.14	20.84	82.01
Learning in long run	66%	0.23	4.20	28.83	89.44
	50%	0.16	3.36	26.13	87.45
	33%	0.12	2.79	23.66	85.31
Learning in short run	66%	0.27	4.52	28.22	86.90
	50%	0.18	3.72	26.74	86.37
	33%	0.13	3.02	24.65	85.33
Sequestered emissions	0%	0.65	9.40	52.85	142.20

Table 3: Option values (in M€) of the negative emission project under various assumption on learning rates

4.5- Sensitivity analysis of scale effect

We have already mentioned that scale effects are often merged with other learning effects in economic modeling, since learning curves generally describe technological progress per doubled of capacity. In this section, these two aspects are distinguished. The firm previously analyzed in this article is bigger than most European bioethanol plants. However, larger installations than our base case can be found in Brazil. Even if our study is designed for sugar beets, our results could be seen as a proxy of profitability and optimal date for a large-scale sugar cane refinery. With doubling emissions on fermentation process compared to the base case scenario of this article, investment rate clearly increased even if moderate or high carbon drifts are still necessary to exceed 50%. Without learning and at α_c=6%, it is set to 45%. Actually, the most important improvement results in optimal dates. In the best scenarios, the optimal date is brought to only twelve years of waiting.

On the contrary, the firm studied in Laude *et al.* (2010) is smaller, only 600 000hl/yr of bioethanol are produced. Actually, it was a real French bioethanol plant that allows us to describe the whole process and so get data for the carbon and energy balance. In this case, the investment rate hardly exceeds 50% except if an early CCS deployment is assumed with a large learning rate and the maximal carbon drift. If a doubling on fermentation emissions (around 100 000tCO_2/yr) is investigated, which means more than 1Mt of ethanol proceeds, some improvements can be found. Without learning, at α_c=6% and α_c=7%, the probability of success is computed at respectively 16% and 55% and the optimal dates are respectively 21 and 18. In the best conditions (early high learning and α_c =7%), the waiting is about 15 years and the investment reach 76% (against 91% in the base case).

5 - Conclusion

Bio-energy firms are usually smaller than fossil-based plants. Thus, CCS implementation on these plants benefits less from effects of scale, which increase capital costs in relative terms. Nevertheless, only BECCS may create negative emissions and produce energy in the same time. Furthermore, in the case of biofuels production, BECCS could reduce the controversy about carbon balance, as long as sustainable criteria are applied on land use and land change.

The model illustrates the behavior of a single decision maker who can implement a CCS project on a bioethanol refinery with two sources of emissions: the fermentation process itself and the natural gas boiler that provides heat and electricity. Negative emissions can only result from the sequestration of the two kinds of emissions. CO_2 capture on combustion part requires a post-combustion process which is likely to evolve. Most economic models use learning curves to deal with technological change but this modeling is not convenient to study the impact of sunk costs issued from capital investment. Actually, learning curves take generally into consideration the technical progress of the whole sector.

One of the most important features of our model, is that learning is seen as an inherently uncertain phenomenon. The investor knows only the global learning curve trend for capture process. This analysis uses several complementary indicators to estimate the project potential: investment rate as an indicator of success probability, the peak of optimal date (sometimes completed by the investment profile) for the optimal investment timing and the expected amount of avoided emissions as a measure of environmental benefits.

The major conclusions of this article are the following: Projects on fermentation only are profitable even when assuming a moderate carbon drift of 4%, because no capture process is needed. In these scenarios, the optimal date of installation is 2016. On the contrary, post-combustion components have to be implemented on the boiler to get negative emissions. As a result, negative emissions are not an available option in the short term, whatever the scenario applied. If the technological learning is spread over the whole option period, results suggest that the investment decision is postponed, because the investor is waiting for a diminution in costs. However, if the carbon drift is very high, small technological improvements trigger the investment and bring the date closer. At similar learning rate, an early deployment has only a little influence on investment rate compared to long term learning. The benefit is on optimal dates is more significant which results on substantial environmental gains.

Our modeling cannot take into account feedback effects on investment decision at a global scale. For instance, if CCS deployment is postponed, each decision maker tend to wait for technological improvements which may worse the global situation by decreasing the global investment rate.

An interesting way to improve our results consists in rewarding sequestered emissions rather than avoided emissions. This could be controversial since cap-and-trade systems and especially the ETS are based on the evidence of avoided emissions. Moreover, the cost of this grant would be borne by the other market stakeholders, unless that State members give a corresponding subsidy for the additional avoided emissions. We have shown that this measure could help to reach probability of success over 50% with a carbon drift of 6%. If a small learning is assumed on the short run, the rate of investment is closed to 70% and the optimal date is 2030. At a carbon drift of 7%, investment rate reaches 96% and the optimal date is 2027. It should be noted that the learning effects described in this article, would certainly be more important if an electric plant was considering (fed or not with biomass), since the capture costs would be higher in relative terms and may even reach 80% of the whole capital investment.

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