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Biomass and CCS:
The influence of the learning effect

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Résumé

Combiner la production de Bioénergies avec les technologies de Capture et Stockage du Carbone (BECSC) peut permet d'obtenir des émissions négatives lors de la production de bioéthanol. Cependant, les coûts de l'étape de capture sont très élevés et réduisent la rentabilité. Cet article s'intéresse à deux incertitudes : le progrès technique et le prix du carbone, via une approche par les options réelles. Nous comparons les cas d'un développement rapide ou lent du CSC. Un progrès technique précoce peut découler d'une politique intensive d'investissement dans la Recherche et Développement ou dans des projets pilote, mais les réductions de coûts associées demeurent incertaines. Nous montrons que le progrès technique stimule l'investissement dans les émissions négatives mais pas avant 2030. Dans un deuxième ensemble d'expériences, nous appliquons une subvention qui rémunère les émissions séquestrées plutôt qu'évitées. En d'autres termes, cet instrument économique ne prend pas en compte les émissions indirectes issues de l'ajout de la chaîne CSC elle-même, mais il comptabilise toutes les émissions stockées par le processus. A l'inverse des innovations technologiques, cette subvention est sûre pour l'investisseur. La probabilité d'investissement est beaucoup plus élevée et le projet peut être réalisé avant 2030. Cependant, les émissions négatives dans le domaine des biocarburants via les BECSC ne semblent pas être une solution de court terme dans notre cadre d'étude, qu'elle que soit la tendance de prix testée.

Mots-clés : Options réelles, Progrès technique, Bioénergies et Capture, Transport et Stockage du Carbone.

Abstract

The combination of bioenergy production and Carbon Capture and Storage technologies (BECCS) provides an opportunity to create negative emissions in biofuel production. However, high capture costs reduce profitability. This article investigates carbon price uncertainty and technological uncertainty through a real option approach. We compare the cases of early and delayed CCS deployments. An early technological progress may arise from aggressive R&D and pilot project programs, but the expected cost reduction remains uncertain. We show that this approach results in lower emissions and more rapid investment returns, although these returns will not fully materialise until after 2030. In a second set of experiments, we apply an incentive that prioritises sequestered emissions rather than avoided emissions. In other words, thiseconomic instrument does not account for CO_2 emissions from the CCS implementation itself but rewards all the sequestered emissions. In contrast with technological innovations, this grant is certain for the investor. The resulting investment level is higher, and the project may become profitable before 2030. However, BECCS in bioethanol production does not seem to be a short term solution in our framework, whatever the carbon price drift.

Keywords: Real options; Learning effect; Bioenergy Carbon capture and storage

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1 - Introduction

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

One of the most challenging issues regards the capture process itself; it has not received extensive commercial scale testing, even though it is the only way to prove the commercial feasibility of CCS. According to most experts, further research on capture components (membranes, sorbents and solvents) is needed,van Alphen(2010). However, collaboration between industrial actors is hindered by intellectual property issues because technological innovation is perceived as a competitive advantage. A solution could be to create public-private partnerships to reduce uncertainty and increase financial resources, which are currently too low for integrated commercial-scale CCS demonstration projects (e.g., combining capture, transport and storage). These kinds of projects would improve global knowledge and know-how and thus lead to major reductions in costs. However, if these projects are delayed, the learning process and global CCS deployment could take decades.

In this study, we focused on a variant of the CCS technology portfolio, in 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 simultaneously create negative emissions and produce energy, see IPCC (2005) such as electricity and heat (IEA, 2009 ; Rhodes, 2007) or biofuels (Lindfeldt and Westermark, 2008 ; Mathews, 2007; Möllersten*et al.*, 2003). In fact, the CO_2 that is removed from the atmosphere by BECCS can 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 those resulting from energy production. According to Azar*et al.* (2006) and Read and Lermit (2005), BECCS chains can meet low emissions targets (below 450 ppm). This study focused on biofuel production. Specifically, we considered the case of sugar beet processing at a bioethanol refinery that was retrofitted with CCS. A technical and geological description of this project can be found in Fabbri*et al.* (2010).

The aims of the current study were as follows: first, we investigated whether negative emissions technology is profitable and under what conditions; second, we attempted to quantify the impact of short run versus long run learning effects on optimal investment timing; and third, we tried to find an alternative way to subsidise CCS projects that would reward sequestered, rather than avoided, emissions and compare the impact on investors' behaviours.

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 subject to a number of uncertainties, including carbon prices, energy prices and capital cost evolution. Second, capital-intensive technologies like CCS and BECCS create barriers to entry in the carbon market. Third, investors do not behave passively; they can delay their final decisions to wait for better information or market conditions. Because of these three features (uncertainty, delay and sunk costs), a real option (RO) approach seems more applicable. Coined by Myers (1977), the phrase 'real option' by analogy with financial options theory. An option is the right, but not the obligation, to undertake a business investment opportunity. Some of the most important theoretical considerations on this subject can be found in Dixit and Pindyck (1994) and Trigeorgis (1996).

To our knowledge, our study is the first RO analysis of biofuel production combined with CCS. However, several studies have investigated CCS in electric plants (Abadie and Chamorro, 2008; Heydari*et al.*, 2010 ;Laurikka and Koljonen, 2006), and one focused on biomass electricity production with CCS, Szolgayová*et al.* (2008).

This paper is organised as follows: Section 2 explains the concepts of technological progress, learning effect and CCS; Section 3 describes the real option model, scenarios and calibration; and 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

Researchers, notably Grübler and Messner (1998) and Junginger*et al.* (2006), have identified different kinds of learning effects. Our work used the typology given in Kahouli-Brahmi's (2008) detailed study:

- **Learning-by-doing:** This effect refers to improvements during the production process and is based on experience, for instance, in operation and maintenance, labour efficiency and changes in production.

- **Learning-by-researching:** Research and Development (R&D) expenditures lead to an innovation flow that can be absorbed by the firm.

- **Learning-by-using:** User feedback reveals product limitations and may lead to substantial technological progress.

- **Learning-by-interacting**: Diffusion of knowledge results from the interactions between various stakeholders, such as scientists, industrial actors, decision-makers and users. The community can share the progress resulting from learning-by-using and learning-by-doing.

- **Economies-of-scale:** Reduction costs in large-scale operations result from operational efficiencies. This effect is part of the learning effect because large-scale production promotes technological progress.

Learning curves are the most common way to deal with technological progress in economic models. Usually, studies focus on the learning-by-doing effect, even if some models include a second parameter, (i.e., R&D). Because these improvements generally have an economic impact, technological progress is measured in terms of cost reduction. Most analyses estimate 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 quantitatively separate the different learning effects, and most models combine them. This limitation is significant. For instance, learning curves do not often distinguish between the improvements that are due to process implementation (learning-by-doing in the strict sense of the term) and the improvements that are due to new capacities. Another common bias is the mix-up of learning-by-doing and scale effect, which can lead studies to overestimate the real learning rate, Sönderholm (2007).

In the case of the CCS industry, capital costs constitute an important entry barrier. If a decision maker implements a CCS project, he cannot benefit from future cost reductions. The value of waiting, in this case, is higher than it is in the case of continuous progress after the project is implemented, and learning curves generally take this condition for granted. In contrast, the real options (RO) approach takes this issue into consideration. Moreover, the process of technical change is inherently uncertain and thus provokes an additional value that delays investment. The RO approach is therefore better adapted to deal with risk than are deterministic technological paths.

However, despite their inherent limitations, learning curves are essential for our framework. In our modelling, technological progress is exogenous, so we must make assumptions about learning evolution. Basically, learning-by-doing and learning-by-using were not taken into consideration in this study, but they were partially incorporated into the learning-by-interacting effects. We used progress ratios as a proxy of cost reductions that mix learning-by-researching and learning-by-interacting effects. However, because technological change is exogenous, the rate of doubling capacity is unknown. Thus, progress ratios are insufficient by themselves, and scenarios based on costs evolution are necessary.

2.2 - CCS and BECCS

Since BECCS in bioethanol industry does not need specific technologies, unlike other CCS chains (especially CCS in coal power plants), we only focus on CCS literature in this section.

Ferioli*et al.* (2009) estimated a progress ratio in energy technologies of 19% with a range of 3% to 34% and a 95% confidence interval. However, coal-based technologies have a lower historical PR (between 3.75% and 15.1%), Jamasb and Köhler (2007). Consequently, further analysis of CCS components evolution is necessary. According to IPCC (2005), technical maturity varies greatly among CCS units. While some aspects are mature (e.g., transportation by pipeline), others are only partially so (e.g., geological storage in saline aquifers) or are still in the research phase (e.g., oxyfuel combustion capture process). We assumed that storage costs remain stable because, these processes are based on well-established gas and oil drilling technologies and they are site-sensitive and might thus be subject to negative learning rates. Such negative learning rates have already been demonstrated for the nuclear industry, Neij (2008), and this phenomenon is certainly due to required safety improvements and limited experience sharing. In contrast, capture components remain largely unproven; they are assumed to increase efficiency, even in the case of post-combustion technologies.

In addition, the overall progress ratio of the process chain depends on the individual evolution of each component. Moreover, these components can influence each other. For instance, in the case of CCS, a higher capture efficiency may lead to secure storage and thus lower monitoring costs. In contrast, if the capture process does not evolve sufficiently, the whole CCS chain is likely to be penalised. However, this problem is beyond the scope of our study.

Rhiahi*et al.* (2004) were among the first to forecast future CCS costs based on previous efforts to control sulphur dioxide emissions (SO_2) in power plants. The corresponding PR is about 12 to 13%. CCS and SO_2 scrubbers share some features: their commercial value is created by legislation, and they are both subject to substantial technological uncertainties. Rai*et al.* (2009) analysed the development of nuclear plants, LNG and SO_2 scrubbers and concluded that CCS technologies are sensitive to their diffusion paths. In addition, Baker *et al.* (2009) highlighted the disagreement among experts on the subject of CCS technologies evolution, particularly with regard to capture processes (even the most well-known, post-combustion). In this study, we focused on the evolution of capture components because this process has the highest investment cost in the whole chain and is the most likely to evolve significantly. In addition, we assumed no decrease in O&M costs; in other words, there is no learning-by-doing effect inside the firm.

We used the McKinsey report (2008) to obtain high, 'best-guess' and low learning rates scenarios. In this report, the CCS global progress ratio was around 12% per doubling capacity. Their reference case (a new coal power installation) evaluated the decrease in costs from a demonstration phase (between 2015 and 2030) with CCS costs ranging from 60-90€/tCO_2 compared to a mature commercial phase in 2030 with costs of 30-45€/tCO_2.

3 – Real Option Model

3.1 - The case study

3.1.1 -Bioethanol refinery description

These data were based on two previous studies. The first investigated an existent bioethanol refinery in France, in a region that seemed favourable to CO_2 underground storage. The first firm processes sugar beets to produce sugar and high purity alcohol for perfume, solvents and bioethanol. Our study only evaluated the bioethanol production data. An overview of this study is available in Laude *et al.* (2010). To deal with upper volumes, we also evaluated scale effects (Laude and Ricci, 2010) based on an ethanol production of 4 Mhl/yr. Two CO_2 sources were used: the cogeneration unit (fed with natural gas) and the fermentation unit. For an ethanol production rate of 4 Mhl/yr, the volumes of CO_2 emitted are 300,000 t/yr from the fermentation unit and around 407,000 t/yr from the cogeneration unit.

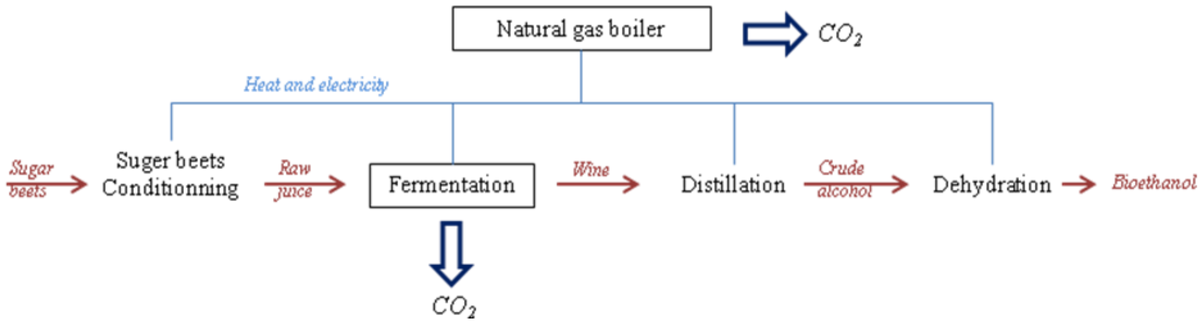

Figure 1: The sugar refinery process

3.1.1 - Valuation of the CCS chain

We assumed that the exhaust stream from the fermentation was pure to create an ideal anaerobic fermentation, in which the chemical reaction only yields ethanol and CO_2. Therefore, only the cogeneration unit requires a capture process. We used a post-combustion process with an assumed capture rate of 90%. Thus, the CO_2 was transported in a dense phase via pipeline. No intermediate pumping was needed to reach the wellhead at an appropriate pressure for injection because of the short distance and the absence of elevation differentials. The storage facilities were in a deep saline aquifer at roughly 2250m underground, and two vertical wells were sufficient to achieve the maximum possible CO_2 flow rate, anticipated during the harvest period. Funding was provided to monitor costs of the site injection, and these costs were included in the capital costs. If the CCS chain is implemented on the fermentation unit, the main costs are the injection costs. If the CCS chain is also used on the cogeneration unit, the capture costs predominate.

In addition, a carbon footprint has quantified the environmental benefits of the CCS chain (Laude *et al.*, 2010). The amount of avoided CO_2 differs from the amount of sequestered CO_2 in the subsurface as a result of implementing CCS, such that:

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

where 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 significantly increases the emissions emitted by the plant, notably because of the energy penalty. The main features of this case study are summarised in Table 1.

CCS chain on fermentation only	Capital (M€)	58
	O&M (M€) without gas	2.2
	Gas consumption (MWh)	35,728
	Emissions ($MTCO_2eq$)	200,000
	Avoided emissions ($MTCO_2eq$)	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 ($MTCO_2eq$)	470,000
	Sequestered emissions ($MTCO_2eq$)	423,783
	Avoided emissions ($MTCO_2eq$)	366,667

Table 1: CCS chain features

Only avoided emissions measure the real environmental benefits of the project, so it is reasonable to reward only these, as the European legislation on CCS suggested in Directive 2010/345/EC. Thus, we measured avoided emissions in our calibration, with the exception of a specific sensitive analysis (see Subsection 4.4). In fact, rewarding sequestered rather than avoided emissions may be an interesting tool for CCS development because it is more certain than technological progress, from an investor's point of view. Carbon price signal could be insufficient to grant investment in technologies not completely mature, as pointed by Finon (2010). So other economic incentives than permit market has to be investigated.

3.2 - Real Option methodology

3.2.1 - Framework

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

As mentioned above, we focused on the bioethanol production of the refinery, but the profitability of the bioethanol process was not addressed. As opposed to electrical plants, CCS implementation does not reduce output production, which is why the two outputs do not interact. Carbon emissions are considered co-products that could be 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 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. We assumed that carbon and gas prices are driven by 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 $\mu_g$are the carbon drift and gas drift, respectively; σ_c and $\sigma_g$are the carbon volatility and gas volatility, respectively; $W_t$is a standard Brownian motion; and W_t^candW_t^ghave correlation ϱ. In the following section, dP_t denotes this two-dimensional stochastic differential equation.

CO_2 prices are difficult to predict because they are strongly influenced by policy. As a relatively new market, the European Trade Scheme (EU ETS) has a particular behaviour and its parameters cannot be calibrated with historic data from long-term forecasts. Therefore, we chose 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 high in comparison with most RO literature (e.g., α_c=5.68 in Szolagayova*et al.*(2008), based on previous IIASA scenarios).

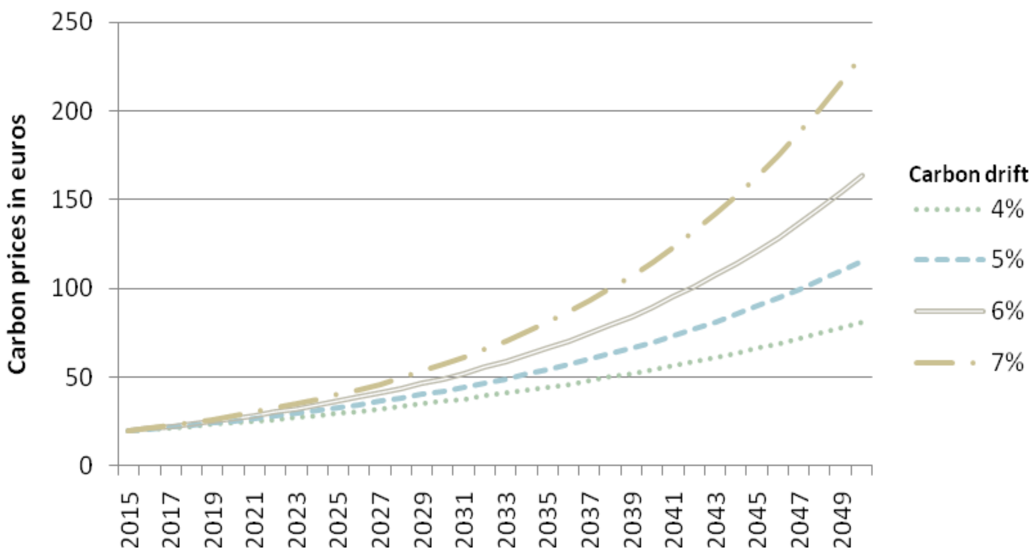

Figure 2: Deterministic carbon path, depending on the carbon drifts, from 2015 until 2050

At the same time, these prices are in the range of prices investigated in the literature for a target of 450 ppm, Aldi*et al.* (2010). In addition, recognising the principle of "common but differentiated responsibilities" has created more stringent targets in Europe (e.g., the aim of 75% GHG reduction before 2050 in France). The prices in this case are in line with the assumptions of the Quinet report, CAS (2008), for French forecasting.

This study did not deal with short-term volatility and chose a relatively moderate carbon volatility of 5%. For the same reason, market prices had the same standard annual deviation. The corresponding drift was set to 2%. In line with Yang *et al.* (2008), we assumed that natural gas and carbon prices are correlated with a correlation rate of 50%. Table 2 gives an overview of the calibration.

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

Table 2: Calibration of the option

3.2.2 Optimal stopping problem

In our real option model, the investor chooses to invest or wait at every time step. In what follows, we introduce some definitions. Recursively, we define the running present value RPV_t by:

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

in which the maturity date is T (35 years); the cash flow process is CF_t; and the riskless interest rate is r. The date that options begin – 2015 – is represented by t=1. A similar framework can be found in Alesii(2008). If we denote the initial investment by I_0, then the profit function is given by:

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

To obtain the price of our real option, we use the following optimal stopping problem:

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

where $[1, T]$ 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 continuation value, the value of investing later, is defined by:

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

Alternatively, we can use the DPP in terms of the optimal stopping time to solve (1):

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

In this case, the continuation value is as follows:

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

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

$$\hat{C}_t = \sum_{m=0}^{M-1} x_m b_m(t) \qquad (2),$$

with a base $\{b_m(\cdot)\}_{m=0}^{M}$specified beforehand. Based on the set of simulated paths, the coefficients are determined by regression. There are a variety of regression-based Monte Carlo approaches, for an overviewsee Jonen (2009). Due to the method's simplicity and computational efficiency in higher dimensions, we chose the Least Squares Monte Carlo (LSM) method proposed by Longstaff and Schwartz (2001). By doing so, we consider the DPP in terms of the optimal stopping time and 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 with 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 modelling

Murto (2007) used a Poisson process to measure capital costs evolution and found analytic solutions in specific cases. Fuss and Szolgayová (2009) followed this model closely but adapted it to a discrete time model to study more general cases. We retained this global framework and adapted it to an LSM algorithm.

We assume that the learning improvements only occur with the initial investment (i.e., the capital costs), and not with O&M costs. In addition, we only allow the capture costs to decrease because the other units are assumed to be mature. As a result, the construction cost is split in two: $I_t = I^{C,T\&S} + I_t^{Cap}$,

where $I^{C,T\&S}$ refers to the capital costs of compression, transport and storage, and I_t^{Cap} refers to the capital costs of the capture step. This last cost is assumed to follow the 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 that reflects the magnitude of each technical progress. Jumps can only reduce capture costs because they reflect technological progress. As a consequence, the investment expectancy is given by

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

In our model, the investor knows the deterministic technological path and does not know the timing of innovations. The corresponding assumptions are indicated in the next section for each experiment.

4- Results

4.1 - No learning effect

The base case assumed no technical change over the whole period. The only incentive to invest was given by carbon prices, and we assumed that the decision maker knows the prices' drift. We first focused on the 'fermentation only' project, in which the CCS chain only measures the emissions from the fermentation part of the firm. In Subsection 4.1.2, the conditions are the same, except a CCS chain was applied to the boiler.

4.1.1 - Fermentation only

The discount cash flow method gives a first indication of the project's profitability. In this case, the project starts in 2015. Since carbon and natural gas prices are deterministic, the only way to incorporate a risk measure is through the discount rate r. If a rate of 4% is applied, the net present value (NPV) is always positive, regardless of the carbon drift. Thus, the project is always accepted. According to the Lebègue report (2005), this rate is accurate for a long term public project (more than 30 years) Nonetheless, this rate is low compared to the rates that are usually chosen for private project appraisal. At r =8%, for instance, the project is considered profitable as soon as α_c is equal to or greater than 5%. When an RO approach is implemented, the results show an increase in global investment rates with higher carbon drifts. 'Investment rate' refers to the number of simulations in which the decision maker decides to invest. This indicator measures the probability of project success before the option ends. Fermentation is nearly insensitive to carbon drift. The global investment rate is higher than 80% when α_c equals 4% and almost reaches 100% when α_c is set to 7%.

Another important indicator is the 'optimal date'. Each simulation has a corresponding date of investment. The 'optimal date' is the date on which the most investments are implemented (considering the whole set of simulations). In other words, the optimal date is the date with the highest probability of investment. In our experiments, the project was generally implemented after one year (2016). Thus, this it appeared to be extremely profitable with relatively little risk.

4.1.2 - Negative emissions

It is notable that the last case only required a compression step. That is, no specific capture component was required. Nevertheless, to obtain negative emissions, it was necessary to implement a post-combustion process. Unfortunately, the costs are far greater in this case, resulting in a dramatic fall in profitability. The capture costs represent 62% of all capital costs. As a consequence, the NPV is negative at every carbon drift, even for a low discount rate of 4%. From the 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. At α_c=6%, the probability of investment is around one third and at α_c =7%, it is roughly three-quarters. The optimal date of investment is positively affected by a carbon drift increase. This finding is intuitive because the output price drives the investments, raises the incentive and lowers the value of waiting. At α_c =6%, the optimal date occurs after 19 years, and, when α_c equals 7%, it happens 18 years after the option opening.

The investment profile provides more detailed information on decision maker behaviour (Figure 3). For instance, at the middle drift of 5%, the optimal date is 23 years. This result is not very relevant because the rate is too low and the peak of investments is not clear. In addition, the investments that are linked to a carbon drift of 4% are effectively invisible. For this reason, we decided to focus on 6% and 7% carbon trends. These carbon drifts are clearly higher than most projections of GHG shadow prices and correspond to a very low stabilisation target (450 ppm or less). Although it might have been obvious that carbon prices are the main driver of investment, we observed that the project was highly sensitive to this factor, unlike the project with CCS applied only to fermentation. Moreover, the profile became progressively less flat in the upper carbon trends. At 7%, the peak of investment was almost three times that at 6%.

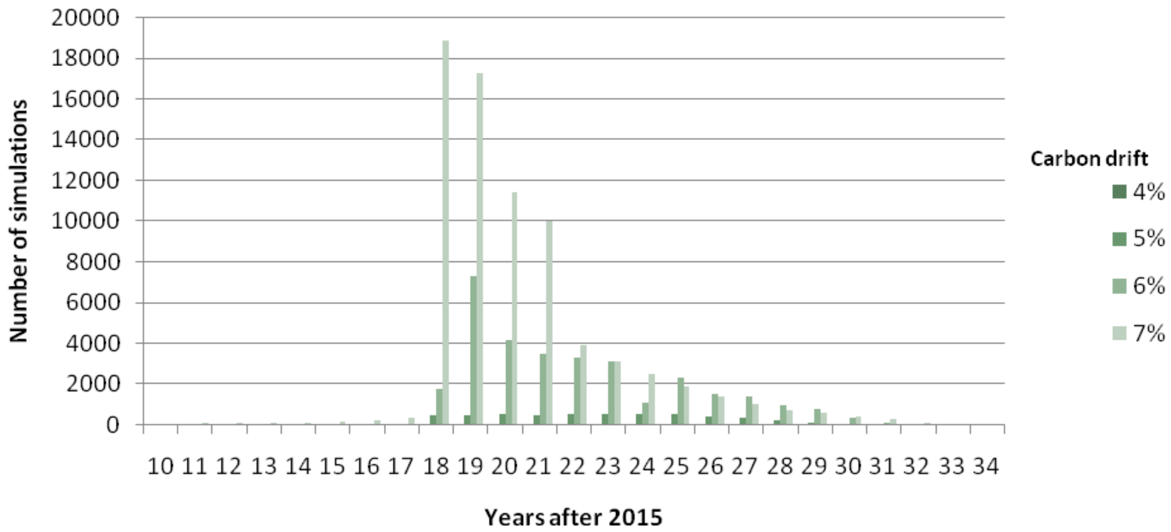

Figure 3: Frequency distribution of investment for the reference case, depending on carbon drifts

Investment rates do not give prediction of avoided emissions for this project. If the project is implemented in 2015, the gain is easily computed; the project leads to a reduction (or avoidance) of 12.5Mt CO_2 over its lifespan. The expected environmental benefits, over the 100 000 simulations, is computed with the 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 is the annual avoided emissions if the investment is undertaken; N is the number of simulations; and $\mathcal{N}_E$ is 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 1.5 $MtCO_2$, but it rises to approximately 4.0 $MtCO_2$ when the carbon drift is 7%. In addition, it is noteworthy that the expected environmental benefits almost double between α_c =6% and 7% because of the higher level of investment.

4.2 - Learning effect in the long run

According to Fuss *et al.* (2009), the learning effect creates an additional value of waiting and thus tends to delay investment implementation. The decision maker foresees the reduction in costs and is likely to invest only after innovation emergence. This prediction is met when the learning rate is low (33%) over the period. At the highest carbon drifts (6% or 7%), the global optimal date is delayed by 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 set at 7%, the optimal date is shortened by two years to the sixteenth year. The fact that a turning point exists means that the cost reduction appears sufficiently soon to trigger investments.

For low carbon drifts (i.e., α_c =4% and 5%), the increase in investments, although relevant, does not significantly change the result. For the highest learning rate, at α_c =5%, the number of projects accepted roughly doubles, and the investment rate rises from 5.8% without learning to 13.2% with low learning.

At a higher carbon drift (α_c=6%), the increase is relatively weaker, but the critical level of 50% of investment rate is reached. If the carbon drift is now set at 7%, the investment rate reaches 90%. The probability of success is clearly improved. Figure 4 shows investment profiles for low, middle and high learning rates, revealing that higher learning rates tend to spread the investment decisions in addition to moving the global optimal date. In fact, the 66% learning rate curve almost encompasses the two other curves (for 33% and 50% learning rates).

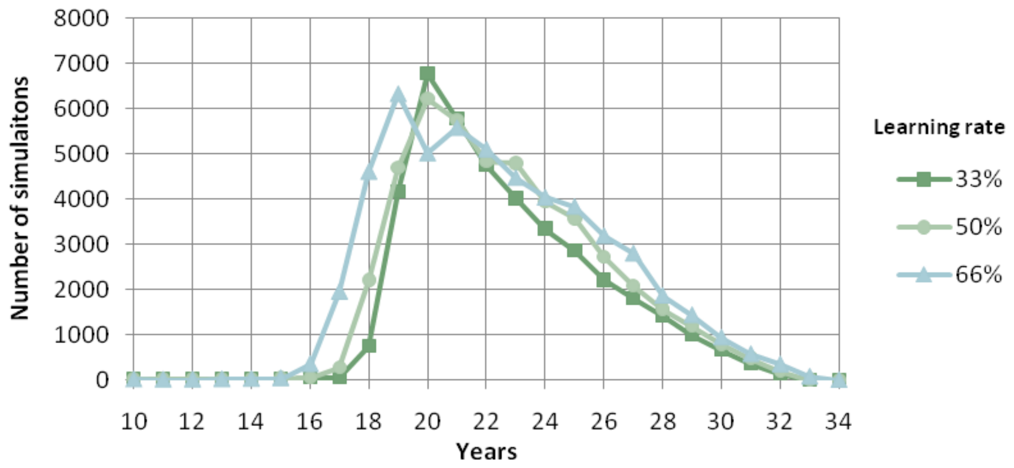

Figure 4: Long run learning effect on investment when the carbon drift is 6%

This investment incentive also creates an environmental benefit. For instance, at α_c =6% and for the highest learning rate, the expected avoided emissions is 2.39 $MtC0_2$ (i.e., 860.000 extra CO_2 tons).

4.3 - Early deployment

The previous section showed that the learning effect is necessary for higher success probability, especially when α_c =6%. This section explores the impact of early deployment on private investors' behaviour, based on the McKinsey report (2008). In this set of experiments, technical change happens only during the first fifteen years of options availability. After 2030, we assume no more cost reduction for capture components or transport and storage. Such learning is possible only if technology-oriented subsidies outside the carbon market are granted (Blyth *et al.*. 2009).

This new framework does not observe investment delays, regardless of the learning progress applied. This result was expected because, without learning, the optimal date occurs after 15 years of waiting. Thus, an early learning effect may do nothing but shorten the time frame of the investment decision.

More precisely, for the highest learning rate, we observed that at α_c=6% the investment peak happens three years earlier, than the base case. At α_c=7%, the gain increases to four years. Compared to a learning progress spread across the period, the time saved is three years and two years, respectively. When the highest carbon drift is considered, the influence of deployment in the long run versus the short run is relatively weak. In fact, even with a medium technical change spread across the period, the carbon prices are so high that the optimal date is brought forward to the time even when postponed learning was investigated.

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

This finding implies that carbon drift remains the most important driver of investment. However, early CCS development has an influence on emissions reduction. With a carbon drift of 6%, a low learning rate (33%) leads to 2.01 $MtCO_2$ avoided emissions, and a high learning rate (66%) leads to 3.01 $MtCO_2$. These results must be compared to the finding for the highest learning progress in the long run: 2.39 $MtCO_2$. Although the improvements in investment rate are admittedly moderate, an early learning effect does provide a clear increase in avoided emissions.

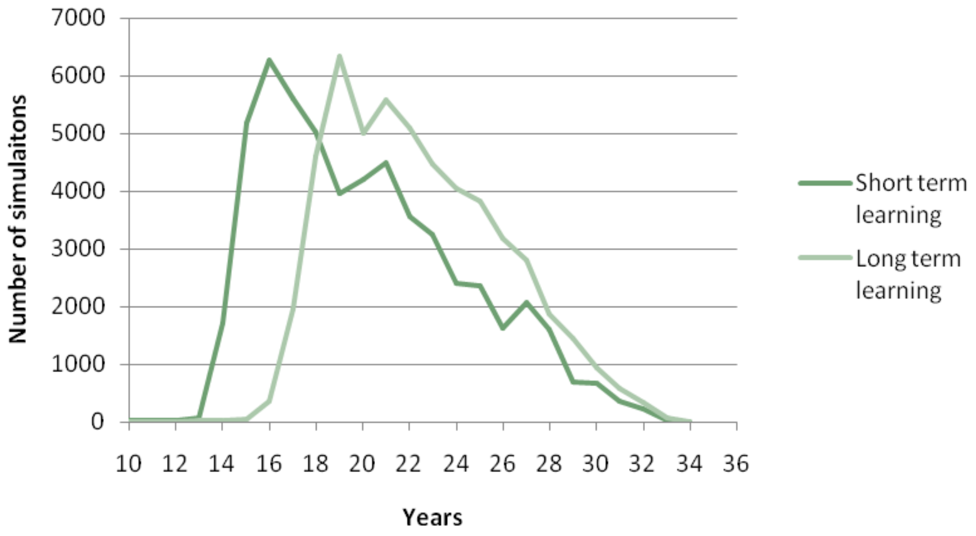

Figure 5: Comparison between early and spread-out deployment, with a high learning rate and a carbon drift of 6%

4.4 - Avoided emissions versus sequestered emissions

Regardless of the scenario, rewarding sequestered emissions, rather than avoided emissions, increases the number of investments and provokes an earlier decision peak. Without any learning effect, the investment rate grows from 34% to 58% at a carbon drift of 6%. For a drift of 7%, the investment rate increases to 92% (versus 76%). In the same period, the optimal date occurs two years and five years earlier, respectively. Thus, the impact of rewarding sequestered emissions is considerable. For both indicators, the effect is similar to a high and early learning effect. In terms of environmental benefit, the gain is 3.28 $MtCO_2$ and 6.27 $MtCO_2$, respectively.Moreover, rewarding sequestered emissions could trigger early investment and, therefore, create an additional incentive for earlier projects. If a small but early learning effect is added, at a carbon drift of 6% and 7%, the investment rate is 69% and 96%, respectively, and the optimal dates are 15 and 12 years after options begin. If the carbon drift remains at 6%, the amount of avoided emissions increases to 4.24 $MtCO_2$.

The option values at the beginning of the option period (2015) for experiments in this negative emission project are summarised in Table 3. The value of waiting grows with carbon drifts in every case, which reflects a progressive increase in project value. The option value rises with higher learning rates, as expected. However, when the effects of high learning rates and carbon drifts are combined, the option value in the long term learning case seems to be above the corresponding early learning rates. This finding occurred because the project becomes valuable earlier. It is also notable that rewarding sequestered emissions almost doubles option values compared to 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 assumptions about learning rates

4.5- Sensitivity analysis of the scale effect

We have already mentioned that scale effects are often merged with other learning effects in economic modelling because learning curves generally measure technological progress per doubling of capacity. In this section, we distinguish between these two aspects. The firm analysed above is bigger than most European bioethanol plants but this production scale can be found in Brazil. Even if our study is designed for sugar beets, our results could be used as a benchmark to predict profitability and the optimal date(s) for a large-scale sugar cane refinery. When emissions from the fermentation process are doubled (compared to the base case scenario of this article), the investment rates clearly increase even if moderate or high carbon drifts must exceed 50%. Without learning and at α_c=6%, the carbon drift is set to 45%. The most significant improvement occurs in relation to the optimal dates. In the best cases, the optimal date is reduced to only twelve years of waiting.

In contrast, the firm studied in Laude *et al.* (2010) was smaller and only produced 600 000hl/yr of bioethanol. We studied a French bioethanol plant and obtained data on the balance of carbon and energy. In this case, the investment rate hardly exceeded 50%, except when an early CCS deployment was assumed with a large learning rate and maximum carbon drift. We found additional improvements when we investigated double fermentation emissions (around 100,000 $MtCO_2$/yr and producing more than 1 Mt of ethanol). Without learning, the probability of success at α_c=6% and α_c=7% computes to 16% and 55%, respectively, and the optimal dates are 21 and 18 years, respectively. Under the best conditions (early high learning and α_c =7%), the waiting period is about 15 years, and investment reaches 76% (versus 91% in the base case).

5 - Conclusion

Bio-energy firms are usually smaller than fossil-based plants. Thus, CCS implementation on these plants derives fewer benefits from effects of scale, which increase capital costs in relative terms. Nevertheless, only BECCS can create negative emissions and produce energy at the same time. Furthermore, in the case of biofuel production, BECCS could help to mitigate the controversy over carbon balance, as long as sustainable criteria are applied to land use.

The model illustrates the behaviour of a single decision maker who can implement a CCS project on a bioethanol refinery with two sources of emissions: the fermentation process and the natural gas boiler that provides heat and electricity. Negative emissions can only result from the separation of the two kinds of emissions. A post-combustion process is required to capture the CO_2 produced by combustion and is therefore likely to evolve. Most economic models use learning curves to deal with technological change, but learning curves generally consider the technical progress of the whole sector. Moreover, this kind of model is not suitable to study the impact of sunk costs from capital investment.

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

This study has several major conclusions. First, only fermentation projects are profitable in the short run, even when we assume a moderate carbon drift of 4%, because no capture process is needed. In these scenarios, the optimal date of installation is 2016. In contrast, post-combustion components must be implemented on the boiler to create negative emissions. As a result, negative emissions are not feasible in the short term, regardless of the scenario applied. Our results suggest that when technological learning is spread over the option period, the investment decision is postponed because the investor waits for lower costs. However, if the carbon drift is very high, small technological improvements trigger the investment and bring the date closer. At a similar learning rate, an early deployment has little influence on the investment rate compared to long term learning. The optimal date improvement is more significant and results in substantial environmental gains.

Our model cannot take into account feedback effects on investment decision at a global scale. For instance, when CCS deployment is postponed, each decision maker tends to wait for technological improvements, which may decrease the global investment rate.

One way to improve our results would be to reward sequestered emissions rather than avoided emissions. However, this method could be controversial because cap-and-trade systems, and especially the ETS, are based on evidence of avoided emissions. Moreover, other market stakeholders would bear the cost of this grant unless state members provided a subsidy for the additional avoided emissions. We have shown that this measure could reach a probability of success that is over 50% with a carbon drift of 6%. If we assumed a small learning curve in the short run, the rate of investment is close to 70%, and the optimal date is 2030. At a carbon drift of 7%, the investment rate reaches 96%, and the optimal date is 2027. It should be noted that the learning effects described in this article would be more significant in studies of an electric plant (whether or not it is fuelled with biomass) because the capture costs would be higher in relative terms and may even reach 80% of the whole capital investment.

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