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Longer Climate Commitments, Higher Investment Rate? The Case of Carbon Capture and Storage

Audrey Laude*

* Maitre de conférences en sciences économiques, REGARDS (Université de Reims Champagne-Ardenne)

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Climate change can only be limited through a deep transformation of the energy sector and therefore requires heavy investment. However, long-term climate targets and the means to reach them are still largely undefined, as evidenced by the Copenhagen Agreement, which has failed to impose binding commitments. More generally, the outcomes of negotiation rounds are rarely predictable. This regulatory uncertainty hampers investment because investors can too easily postpone their investment decisions. This article analyzes how this uncertainty affects investor behavior, most notably through the role of commitment period lengths. Negotiations are assumed to be set on a regular basis, e.g., every five years. We model investment decisions for a carbon capture and storage (CCS) project at a coal plant using a real option framework. We show that long commitments trigger investment, but the benefits of an additional year are higher for short commitments than for long commitments. A minimum policy cycle of 5 years has been established, but extending commitments beyond 10 years yields less relevant results, even for very carbon-sensitive projects. Similar results are obtained if long-term target ambiguity is present, as is the case when the investor does not know whether the climate policy is going to be highly or moderately stringent.

Mots clés : climate commitments, regulatory uncertainty, carbon capture and storage

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Université de Reims Champagne-Ardenne
UFR de sciences économiques, sociales et de gestion
57B Rue Pierre Taittinger
51096 Reims

Directeur : **Martino Nieddu**

Responsable de l'édition des *working papers* **: Cyril Hedoin**

Longer Climate Commitments, Higher Investment Rate?

The Case of Carbon Capture and Storage

Audrey Laude
Laboratoire REGARDS, Université de Reims, France[1]

Abstract

Climate change can only be limited through a deep transformation of the energy sector and therefore requires heavy investment. However, long-term climate targets and the means to reach them are still largely undefined, as evidenced by the Copenhagen Agreement, which has failed to impose binding commitments. More generally, the outcomes of negotiation rounds are rarely predictable. This regulatory uncertainty hampers investment because investors can too easily postpone their investment decisions. This article analyzes how this uncertainty affects investor behavior, most notably through the role of commitment period lengths. Negotiations are assumed to be set on a regular basis, e.g., every five years. We model investment decisions for a carbon capture and storage (CCS) project at a coal plant using a real option framework. We show that long commitments trigger investment, but the benefits of an additional year are higher for short commitments than for long commitments. A minimum policy cycle of 5 years has been established, but extending commitments beyond 10 years yields less relevant results, even for very carbon-sensitive projects. Similar results are obtained if long-term target ambiguity is present, as is the case when the investor does not know whether the climate policy is going to be highly or moderately stringent.

Keywords:
Climate commitments, Regulatory uncertainty, Carbon capture and storage

JEL Classification:
Q48 ; Q55 ; Q58

1 Introduction

Climate change must be addressed on an international level. The Kyoto Protocol was a first attempt to provide a global regulatory framework. The more recent Copenhagen Agreement was expected to establish clear targets and a roadmap to reach them, but the negotiations led to minimal agreement and failed to impose binding commitments. Even considering subsequent climate change conferences, the evolution of climate policy remains very uncertain.

[1] Mail : audrey.laude-depezay@univ-reims.fr

This uncertainty, referred to henceforth as regulatory uncertainty, can be defined as "*an individual's perceived inability to predict the future state of the regulatory environment*" (Milliken, 1987). In the case of climate change, the short-term aspects of regulatory uncertainty must be distinguished from its long-term aspects. The former concerns abrupt and quick changes in the regulatory framework. The outcomes of negotiation rounds indeed remain largely unpredictable for carbon market stakeholders. As a result, announcements can create regulation shocks, leading to carbon price jumps on the international carbon market. Some of these changes could affect long-term policies, but not necessarily. For instance, the climate policy is likely to be less stringent during an economic crisis because policy attention is temporarily drawn to other priorities.

The second aspect of regulatory uncertainty concerns long-term policy targets, also known as *"basis directions"* (Hoffmann et al., 2008). The choice of policy targets may evolve along with the flow of climate change information, mitigation costs and, most obviously, states' decisions. The credibility of these targets is weakened by the lack of binding commitments, as compliance depends largely on the political will of states (Bodansky, 2003). Commitments can then be easily offset by unexpected socio-economic events (Frankel, 2009). These circumstances cast doubt on the future efficacy of climate policy in the middle of this century and thus long-term carbon prices. This uncertainty applies to industries in the energy sector in particular because investments must be planned decades in advance.

As most private investors value policy predictability, they cope with regulatory uncertainty by postponing their investments (Paulsson and von Malemberg, 2004; Reedman et al., 2006). These individual decisions could lead to a global lock-in into carbon-intensive technologies (Unruh and Carillo-Hermosilla, 2006). The transformation of worldwide energy systems could slow dramatically despite the need for immediate action (IEA, 2011a).

The length of commitment periods is thus an important feature of climate policy that cannot be neglected. If long climate commitments are needed to trigger investment, some policy flexibility must still be maintained to cope with new events and information. The benefits of long versus short commitments have been discussed, most notably by Buchner (2007). Regulatory frameworks will be adapted in ways that cannot be predicted. Short commitments ensure policy flexibility in the long run, promote quick actions by firms for compliance purposes and facilitate firm-monitoring by regulators. However, short commitments are not well equipped to face the annual variability of emissions due to situational and meteorological events. Short commitments also imply more negotiation rounds and thus a loss of time, energy and money compared to long commitments. The main drawback remains a lack of long-term vision that could result in chronic underinvestment.

Nevertheless, although numerous studies analyze private investment in a carbon market with policy uncertainty (Laurrika and Koljonen, 2006; Reinelt and Keith, 2007), little attention has been devoted to the length of commitment phases. Yang et al. (2008) found that the risk premium of investment is highest just before a regulation shock. They then suggest that long commitment periods (e.g., 10- years) may reduce an investor's global risk. Fuss et al. (2009) model carbon price jumps that follow a Poisson distribution, showing that investors prefer long stability periods with abrupt changes over small but frequent regulatory modifications. These studies use the real option (RO) approach, which is well suited for understanding the behavior of investors under circumstances of uncertainty. RO approaches are generally characterized by the right, but not the obligation, to undertake a business investment opportunity (Myers, 1977). Their main advantage is accounting for the trade-off between immediate investment and the value of waiting. RO approaches are thus particularly appropriate in the context of investment under conditions of high uncertainty and possible decision postponing. An excellent introduction to this subject is given by Dixit and Pindyck (1994).

The aim of this article is to discuss the optimal length of climate commitment, as there is a trade-off between regulatory stability and policy flexibility. To the best of our knowledge, no other RO study has estimated the benefits of each additional year of stability. Rounds of negotiation are planned on a regular basis (e.g., every 5 years) to account for the effects of several regulatory shocks. These shocks are modeled by carbon price jumps with an unknown magnitude and direction. They represent short-term regulatory uncertainty. Long-term regulatory uncertainty is modeled through an ambiguity in the long-term carbon price drift, which increases with stringent policies and decreases otherwise. Contrary to popular belief, very long commitment periods, such as 15-year commitments, do not necessary increase the investment rate compared to 10-year periods because the marginal gain of investment decreases with additional years of regulatory stability.

The investment project modeled here is a carbon capture and storage (CCS) project applied to a coal plant. This technology is considered very promising and could contribute significantly to climate mitigation (IEA, 2009; IPCC, 2005). However, CCS upfront costs are very high and the investment decision can easily be delayed. CCS projects are thus very sensitive to both carbon prices and regulatory uncertainty.

This article is organized as follows. Section 2 contains a description of the real option model and the data used, and Section 3 focuses on carbon price modeling under regulatory uncertainty. Section 4 describes and discusses our results in terms of investment probability. Section 5 presents our concluding remarks.

2 Real Option framework and data

2.1Real option modeling

As stated previously, this article models investments in carbon capture and storage projects under regulatory uncertainty. Note that CCS chains are only implemented to comply with legislation and to avoid the purchase of tradable emissions permits. This technology has no other use and leads to a decrease in plant efficiency. Coal is generally assumed to be partially diverted to additional energy needs, leading to a reduction in electricity production. However, we prefer to model an increase in coal requirements and a stable quantity of output to avoid modeling long-term electricity prices. The two approaches are strictly equivalent. The yearly cash flows, CF_t, generated by CCS implementation are given by:

$$CF_t\left(P_t^c, P_t^f, O\&M_t\right) = q^c P_t^c - q^f P_t^f - O\&M_t$$

with P^c as the carbon price, q^c as the quantity of carbon avoided, P^f as the fuel price (i.e., the price of coal), q^f as the quantity of fuel and $O\&M$ as the operation and maintenance costs. A yearly time-step is used. If I_t is the initial investment cost and r the discount rate, set at 8%, we can write the net present value (NPV) as:

$$NPV_t\left(P_t^c, P_t^f, O\&M_t, I_t\right) = \sum_t^T \frac{1}{(1+r)^t} CF_t\left(P_t^c, P_t^f\right) - I_t$$

At each time step, the decision maker has the choice of waiting or investing in CCS. In other words, an optimal investment time must be chosen to maximize the value of the investment opportunity. This scenario is an optimal stopping problem that can be solved through a discrete dynamic program with the Bellman equation:

$$V_t\left(P_t^c, P_t^f, O\&M_t, I_t\right) = \max\left\{NPV_t\left(P_t^c, P_t^f, O\&M_t, I_t\right), \frac{1}{(1+r)^t}\,\mathbb{E}\left\{V_{t+1}\left(P_t^c, P_t^f, O\&M_t, I_t\right)\right\}\right\}$$

V_{t+1} is called the continuation value and reflects the value of waiting before investing.

We use an algorithm known as the least squares method (LSM) to derive the optimal stopping time (Longstaff and Schwartz, 2001; Jonen, 2009). This method is very adaptable and robust, including when multiple or complex stochastic movements are considered. The solution is divided into three parts. First, stochastic prices are simulated through Monte Carlo simulations. Second, the algorithm is run backwards. For each simulation path, the continuation value is determined by linear regression on all paths. The continuation value is then compared to the immediate payoff: if the continuation value is lower than the immediate payoff, the decision maker must invest at this time, namely the stopping time. Third, only the earliest stopping time of each simulation is conserved, and the corresponding project values are discounted. The average of these values is the option value of the project. In the next section, we compute each experiment with 100,000 Monte Carlo simulations to guarantee convergence and reproducibility.

Please note that in the results section (Section 4), we are more interested in investment probability than in the option value. To evaluate this probability, we simply count the number of paths for which there is an optimal stopping time and divide it by the number of simulations.

2.2 Coal Plant and Carbon Capture and Storage Data

The coal plant in the model is assumed to have been built in 2010 with a life expectancy of 40 years. The main features of the power plant, with and without capture units, are described in Table 1. These data are the average of the results from fourteen studies summed up in IEA (2011b).

There are three types of technology for capturing emissions: post-combustion, pre-combustion and oxy-combustion. We choose to focus on a post-combustion capture process using an amine-based solvent known as monoethanolamine (MEA). This capture route has been selected because it is currently one of the most explored capture routes, even though deep uncertainty remains regarding technical progress in capture route development (Baker et al., 2009; IEA, 2011b).

Parameters	**Without Capture Units**	**With Capture Units**
Net power output (MW)	582	545
Net efficiency, LHV (%)	41.4	30.9
Capacity factor (%)	83	83
CO_2 emissions (kg/MWh)	820	11
Capital cost (€/kW)	1407	2315
O&M costs (€/kW)*	56	93

Table 1: Power plant data, with and without capture units. Adapted from IEA (2011b). * O&M costs are approximated as a 4% fraction of the capital costs (with or without capture units). An exchange rate of 1.35 is used to convert US dollars into euros.

New capture technologies are being developed. The magnitude of these developments can be estimated through learning rates and by comparison with the evolution costs of other power-generating technologies (Riahi et al., 2004; Van den Broek et al., 2009). We apply cost reduction on not only capital costs but also operation and maintenance (O&M) costs. Note that technological progress increases the probability of investment but also increases the value of waiting for investors, which may result in further delay. This effect is expected to be more important for capital costs than for O&M costs. Investors continue to benefit from O&M cost reductions when CCS is implemented. In contrast, the initial investment (i.e., capital costs) could be a sunk cost after technological development. Our calibration of cost reductions is adapted from Van den Broek et al. (2009). We calculate the average of their two scenarios of projection for each decade from 2010 to 2050. The global reduction in costs is 17.30% for capital and 47.97% for O&M.

After the capture step, carbon dioxide is assumed to be transported by an onshore or offshore pipeline network of 200-300 km without any intermediate booster station. Eventually, the carbon dioxide is stored at a depth of 1500 m in a saline aquifer. As the technological development of transport and storage is assumed to be almost mature (IPCC, 2005), no specific reduction in costs is modeled. These costs are very site-sensitive but are relatively low compared to capture costs. The estimated transport and storage costs add up to a global cost of 13€/tCO_2 avoided (McKinsey Company, 2008).

Our model does not consider construction time, implying that there is no time between an investor's decision and the operation phase. We do not think that this assumption is too strong. In fact, the construction time of a coal plant is approximately 3 or 4 years (IEA, 2011b), but the construction of a CCS retrofit is less time-consuming if the coal plant is CCS ready. It then assumed that the CCS chain and the capture units can be added by retrofit, e.g., sufficient land is left for capture equipment. In this case, the construction for the capture and transport steps takes only two years and that for the storage takes less than three years. Checking the safety and capacity of the selected storage site could take more time and should be included in the definition of a ready CCS (ICF International, 2010). The construction time for CCS is expected to shorten due to progress in development and implementation (McKinsey Company, 2008).

Coal prices are based on the central scenario of DECC (2011). In 2015, coal prices are set at 121 US$, but they decrease slightly until they reach a value of 110 US$ in 2019 and remain stable until 2030. These projections are in line with the literature, including World Energy

Outlook 2011 (IEA, 2011a). After 2030, we assume an increase of 2% by year. Coal prices are stochastic in our modeling, with a yearly volatility of 3.3% (Blyth et al., 2009).

3 Carbon price modeling

This subsection describes carbon price modeling under market price uncertainty and regulatory uncertainty with a focus on its short-term and long-term features.

3.1 Carbon price modeling under market uncertainty

Market uncertainty is defined here as *"the risks involved in the volatility of a price path"* (Fuss et al., 2009), as opposed to the regulatory uncertainty modeled in 3.2 and 3.3. The two most common stochastic movements that mimic price commodity are geometric Brownian motion and the mean-reverting process. Here, the two approaches are combined by modeling a mean-reversion process along a deterministic trend (Hervé-Mignucci, 2010). These two movements capture different aspects of carbon price behavior. On the one hand, a long-term geometric drift reflects rising prices under increasing environmental constraints. On the other hand, carbon prices also depend on the marginal costs of available technologies and tend to be aligned with them (Blyth et al., 2009). In addition, other mandatory emissions markets, such as the American SO_2 market, display mean-reversion features in the long term.

Our model follows Lucia and Schwartz (2002). The logarithmic model with one factor is written as:

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

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

with P_t as the carbon price, σ as the carbon price volatility, κ as the mean reversion speed and f_t as a determinist function that describes the long-term drift. This system becomes:

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

with:

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

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

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

with P_0 as the initial carbon price and α_c as the carbon drift. It can now be stated that:

$dP_t = \left(\frac{\sigma^2}{2} + \alpha\right) P_t dt + \kappa[(\ln(P_0) + \alpha_c t) - \ln(P_t)] P_t dt + \sigma P_t dz$ (2)

where $\left(\frac{\sigma^2}{2} + \alpha_c\right)$ is the carbon price drift, $\kappa[(\ln(P_0) + \alpha_c t) - \ln(P_t)]$ reflects the mean-reversion process and $\sigma P_t dz$ characterizes the diffusion process and captures the market uncertainty. κ is the mean-reversion speed, set at 0.2 (Laurrikka and Koljonen, 2006). The half-time H is approximately 3.5 years ($H = \ln(2)/\kappa$). A relatively low carbon price volatility of 15% has been applied, as only long-term volatility, not intra-annual volatility, is considered (Blyth et al., 2009).

Carbon price modeling cannot be based on historical data because the carbon market is too young a market. The EU ETS (European Union Emission Trading Scheme) was launched in 2005; however, the first phase, achieved in 2007, is generally observed as a trial phase, and the second phase has been affected by the economic crisis. Moreover, the carbon market is artificial and maintained by political will.

Therefore, a wide range of carbon price drifts should be considered. In our reference case, the drift is established at α_c=4.5% to define an intermediate price scenario. However, in the sensitivity analysis and when drift uncertainty is studied, we use a wider range of drift, between α_c=3% for the lowest scenario and α_c=6% for the highest scenario. These values are in line with IIASA scenarios (Fuss et al., 2012), and the highest price profile is consistent with Quinet report prices, which were designed for French targets (Quinet, 2009). These assumptions also agree reasonably well with the carbon price profiles found in Durand-Lasserve et al. (2010) from a global perspective.

3.2 First regulatory uncertainty: short-term modeling

The outcome of a negotiation is hardly predictable, depending on not only the available information but also the economic and social context. Adjustments can be very abrupt, whether they make the regulation more binding or release the environmental constraint. This type of scenario is what we call a regulation shock. This kind of shock translates into the CO_2 market through upward or downward jumps in response to more or less stringent regulation, respectively. Some carbon paths subjected to a price jump in 2035 are depicted in Figure 1. The effects of the jumps are less significant after several years. Prices tend to approach the carbon price drift because of the mean-reversion process. Thus, regulation shocks mostly exert a temporary impact on carbon price evolution.

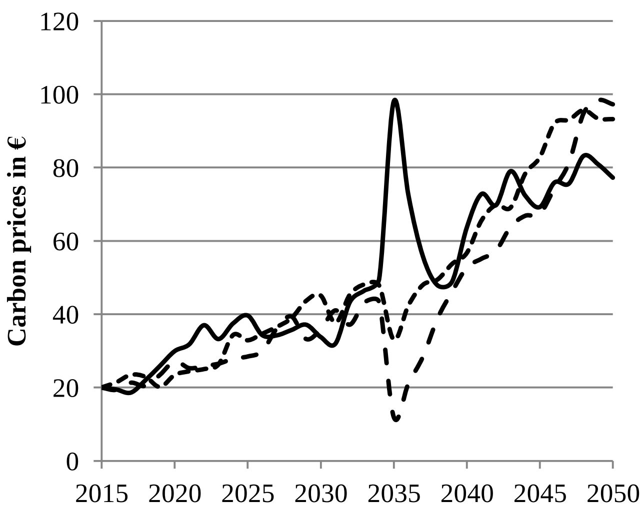


Figure 1: Example of three carbon price paths undergoing a regulatory shock. The carbon drift is set at 4.5%.

Furthermore, the regulation framework is assumed to be revised regularly, so multiple regulation shocks may occur due to successive rounds of negotiation. Jumps are modeled as periodic, occurring, for instance, every five years. An interesting feature of the model is that investors schedule the timing of potential jumps. Using the jump modeling of Yang et al. (2008), equation (2) can be re-written as:

$$dP_t = \left(\frac{\sigma^2}{2} + \alpha_c\right) P_t dt + \kappa[(\ln(P_0) + \alpha_c t) - \ln(P_t)]P_t dt + \sigma P_t dz + \eta(2dy - 1)P_{t\in\tau} \quad (3)$$

η is the maximal magnitude of jumps, and dy is a random variable following a uniform distribution on the interval [0,1]. With η set at 1, carbon prices can either double or collapse. τ is the vector of the fixed negotiation dates. The probabilities of upward and downward jumps are the same.

3.3 Second regulatory uncertainty: long-term modeling

Let us now assume that there is also regulatory uncertainty around long-term climate targets in addition to market uncertainty and the first regulation uncertainty. Some climate targets exist, but they are poorly transposed onto specific regional regulations and lack credibility in the long run. These targets could thus be easily offset by socio-economic shocks (Frankel, 2009).

If climate policy stringency is high, carbon prices should be higher, reflecting the marginal cleanup cost of the energy sector. Investors must then cope with the risk of a forecasting error on carbon price evolution. For the sake of simplicity, we assume that they must address two scenarios: low and high carbon price drifts, corresponding to a moderate versus stringent policy scenario, respectively.

The carbon price modeling under these two scenarios is the same as that described in equation (3); the only difference is that α_c may now change. There are two deterministic drifts, α_c^{up} for a hard cap and α_c^{down} for a soft cap. If the carbon price P_t^c is closer to the highest curve, its drift becomes α_c^{up} for the next year. Similarly, if the price is closer to the lowest curve, its drift becomes α_c^{down}.

Without regulation shock, the carbon price of volatility is the only source of uncertainty. The real drift signal is blurred, but less so with time. Figure 2 illustrates this convergence effect. During 2015-2020, the two deterministic curves become nearly interchangeable but gradually diverge. It is then difficult to determine which drift the carbon path follows during the first years. First captured by the lowest curve, the carbon path eventually converges on the highest curves because of volatility.

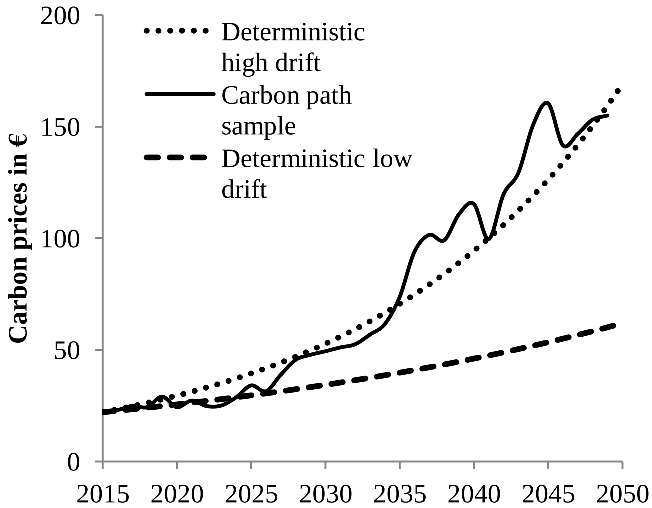


Figure 2: Example of a carbon price path under climate target uncertainty. The low (high) carbon drift is set at 3% (6%).

The two regulatory uncertainties are merged in subsection 4.3 of the Results. Regulation shocks are situational, but it is obvious that some policy decisions – modeled here as regulation shocks – can influence carbon prices in the long run. Short-term decisions give an indication of environmental constraint evolution. Upward price jumps therefore suggest that high targets are pursued. On the contrary, downward jumps cast doubt on the political will to enforce a hard emissions cap.

4 Results and discussion

Subsection 4.1 is devoted to market uncertainty and presents a sensitivity analysis. These experiments are used as a benchmark for the following analyses. Subsection 4.2 focuses on the first regulatory uncertainty, i.e., the short-term effects of negotiation rounds. Special attention is paid to the investment probability over the entire period. In subsection 4.3, the regulatory uncertainty increases as ambiguity around long-term climate targets is added.

4.1 Investment probability under market uncertainty

4.1.1 Reference case

Figure 3 gives us the frequency distribution of investment between 2015 and 2050, the maturity date. It can be observed that before 2022, no simulation leads to an investment decision. Carbon prices are simply too low, so economic conditions cannot be fulfilled, regardless of coal prices. In addition, the option value has a relatively high value of 57.8 M€. This result is in line with the CCS literature on real options, which suggests that CCS investments are not currently financially justified (Heydari et al, 2012; Rammerstofer and Eis, 2011). After 2022, the yearly probability rises, peaking in 2030, which is called the optimal date of investment. These findings are consistent with a progressive CCS setup (IEA, 2009), provoked by a global carbon price increase while capital and O&M costs decrease due to technological progress and learning. Investing after 2046 is not an appropriate strategy because there is insufficient time before the coal plant shuts down. Throughout the entire period, the probability of investment is 78.69%, meaning that for nearly 80% of the simulations, economic conditions become satisfactory for triggering investment.

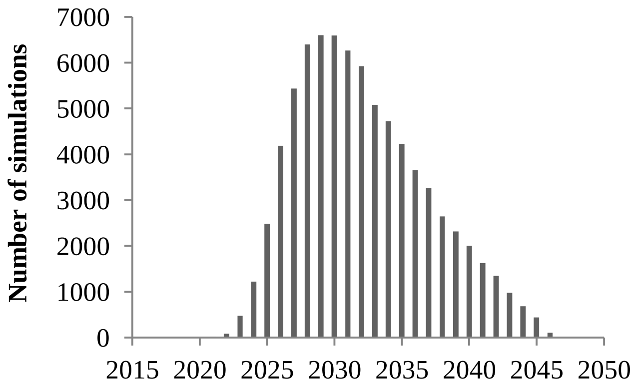


Figure 3: Frequency distribution of investment in the case of the CCS retrofitting of a coal plant. The carbon drift is set at 4.5%.

4.1.2 Sensitivity analysis

A sensitivity analysis has been conducted on the following key parameters: carbon prices, coal prices, capital costs, operation and maintenance (O&M) costs and discount rate. Modifying these parameters may have a high impact on profitability, changing the overall investment probability. Figure 4 shows the results of this analysis, expressed as a percentage of investment probability for each parameter. The vertical axis marks the probability of the reference case, i.e., 78.69%.

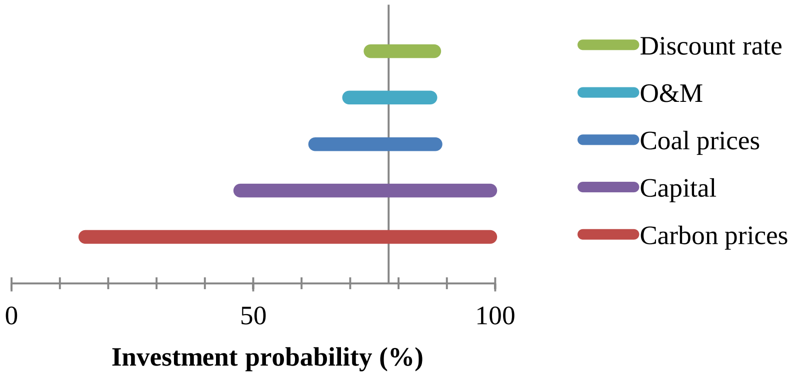


Figure 4: Sensitivity analysis of key parameters. The results are expressed as percentages of investment probability.

The discount rate, operation and maintenance costs and coal prices are the three parameters that modify the probability of CCS investment the less. The discount rates tested vary between 4% and 10%, but the corresponding impact is low: the probability is 74.75% for a rate of 10% and 87.39% for a rate of 4%. O&M costs are also subjected to a variation of ± 50%. The investment probability then oscillates between 69.77% and 86.66%. The relative impact of the O&M costs is limited, around ± 10% compared to the reference case. This finding is not very surprising given that O&M costs represent only a small fraction of capital costs (4%) and are expected to decrease greatly due to technological progress. For coal prices, we use the low and high scenario previously. The high scenario leads to a probability of 62.76% and the low scenario to a probability of 88.00%.

Figure 4 illustrates that capital costs have a more significant influence on investment probability. With a 50% increase in costs, the probability drops to 47.28%. In contrast, a 50% decrease in costs boosts investment to near certainty (99.01%).

Carbon prices, the main driver of investment, are simulated with a wide range of carbon price drifts, i.e., between α_c=3% and α_c=6%. The investment probabilities for these price drifts are 15.25% and 99.58%, respectively, for the entire period. The results are extremely sensitive, and their progression is not linear with respect to carbon drift. A small change in the drift has a much larger effect when the drift has been set relatively low. For example, the investment probability is 35.84% for α_c=3.5% but 97.30% for α_c=5.5%. The fact that decision makers are very sensitive to carbon prices is not surprising given that carbon prices are the only outcome of CCS projects. These findings indicate that uncertainty around the carbon drift, as a result of long-term target uncertainty, may have a significant influence on investors' decision-making.

4.2 Investment probability and regular rounds of negotiations

4.2.1 The reference case

Regulation shocks are now added via carbon price jumps that occur regularly. Concerns about an abrupt decline in carbon prices make investors more cautious than they were in the first set of experiments.

The length of commitments is referred to as Δt hereafter. The investment probability is computed in one-year increments, between 1 and 17 years. The option period lasts 35 years, from 2015-2050, but there is only one jump over the entire period for Δt above 17 years. Regulation cycles have been limited to cases with at least two jumps because we are interested in the periodicity of negotiation rounds.

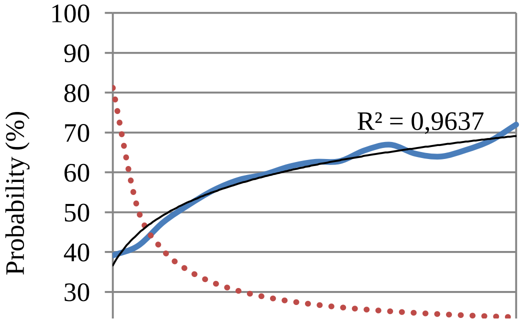


Figure 5: Investment probability (blue), trend line (black) and derivative (dotted line) for a carbon drift of 4.5%. Δt is the length of climate commitments.

A first set of simulations is launched with a carbon drift of $\alpha_c = 4.5\%$. In Figure 5, the investment probability is drawn for every Δt. The investment probability increases with commitment length. In other words, the longer the climate commitments, the more likely the decision maker is to invest in the project. For the longest commitment, Δt = 17 year, the probability of occurrence is 72.00%. This value is close to the probability value without regulation shocks (78.69%), so this probability of occurrence is 91.50% of this maximal probability. In contrast, the investment probability falls if the regulatory framework is unstable. Under conditions of yearly shocks – the worst-case scenario – the investment probability drops to 39.14%. While this value is very low, it is not null because there is still some chance that several upward jumps may occur, leading to very high carbon price profiles.

The shape of the probability curve is not linear and, at first glance, seems logarithmic. The trend line confirms this observation, as the correlation coefficient is above 96%. The derivative of this last curve is taken to calculate the variation in probability resulting from an additional year of stability. The variation is most important for Δt under 3 years. The investment probability increases from 39.14% for yearly shocks to 47.49% for Δt =3 year, which is far from the maximal probability. The regulatory framework is too unstable to properly trigger investment, and the commitment length must be extended to at least 5 years. In this latter simulation, the project has slightly more than a 50% chance (exactly 51.81%) of being fulfilled.

Building a selection criterion to determine the sufficient threshold of regulatory stability is difficult. To compare these results with the following experiments, we treat 80% and 90% of the maximal probability under regulatory uncertainty as two subjective but useful indicators. In this case, the 80% threshold corresponds to 57.60% (0.8*72.00%) of investment probability and 6-year periods of stability. In comparison, a threshold of 90% is exceeded in a 15-year period, with 64.8% of investment. Nevertheless, periods greater than 10 years do not seem accurate, as the gain of an additional year of stability is low. For example, if Δt= 11 years, the investment probability increases by less than 1% for each additional year.

4.2.2 Sensitivity analysis

We analyze here the effects of regulatory uncertainty in cases of low and high expected profitability. The results for carbon drifts of $\alpha_c = 3.5\%$ and $\alpha_c = 5.5\%$ are presented in Figures 6a and 6b, respectively. In both scenarios, the probability curves are logarithmic, as confirmed by the high correlation coefficient with respect to the trend lines.

For a carbon drift of 3.5%, the investment probability without regulation shock is very low, i.e., 35.96% compared to the reference case. When regulation shocks are added, the probability begins at 22.07% and increases until it reaches 37.36%. This result may seem surprising because this latter value slightly exceeds the probability without shock. The carbon drift is so low that price jumps could serve as an opportunity to raise prices sufficiently to enhance investment probability. Globally, the probability curve tends to be flatter than in the reference case. The threshold of 80% of the maximal probability is obtained for 4-year periods, and the 90% threshold is obtained for 7-year periods. Moreover, the benefits of an additional year of stability are below 0.6% of investment for periods longer than ten years. An unstable regulatory framework has less of an impact on investment decisions because the profitability is very low anyway.

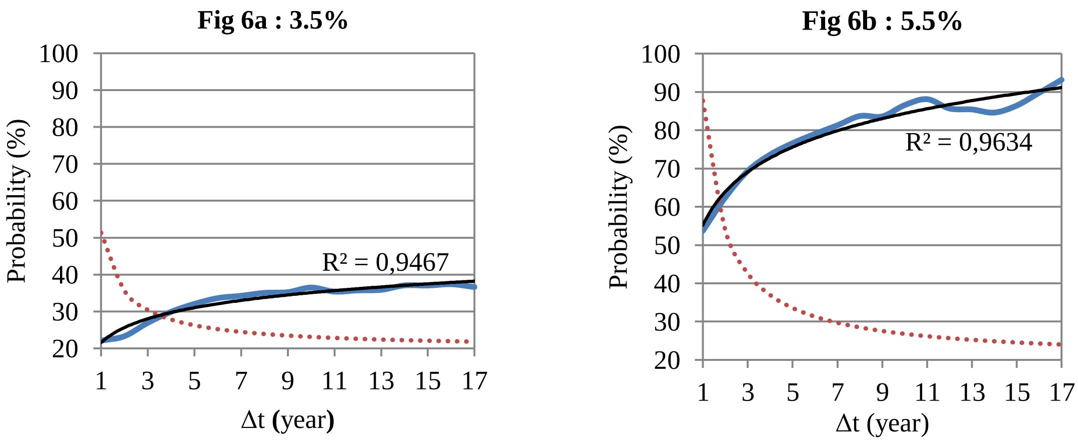


Figure 6: Investment probability in % (blue), trend line of investment probability (black) and the derivative of investment probability trend (dotted line). Carbon price drifts of 3.5 % and 5.5% are shown in Figures 6a and 6b, respectively.

A carbon price drift of $\alpha_c = 5.5\%$ is now assumed (see Figure 6b). Without any shock, the investment probability is 97.24%, which implies that the investment is almost certain over the entire period. The maximal probability with regulatory uncertainty, 93.16%, occurs for the 17-year period. This value is nearly halved to 53.72% when yearly shocks are applied. Higher probabilities of investment are reached quickly when commitment lengths are extended. For

4-year periods, 80% of the maximal probability is exceeded, i.e., 74.53%. For 9-year periods, the 90% threshold is obtained.

The negative effects of an unstable regulatory framework are less significant for high or low carbon price drifts than for intermediate ones. Relative to the reference case, the 80% threshold is obtained three years earlier and the 90% threshold is exceeded at least six years earlier. These drifts are two extreme cases, so investors guess fairly quickly whether the CCS project is going to be profitable or not.

4.3 Regulatory uncertainty on long-term climate targets

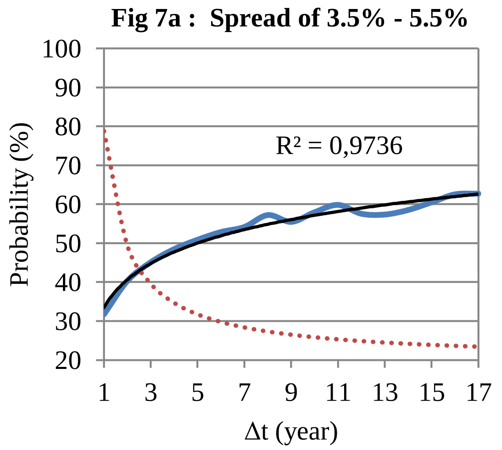
In this subsection, the second regulatory uncertainty regarding long-term climate targets is added. Two scenarios are studied. First, we assume a wide spread of carbon drift with an upper trend of 3.5% and a lower trend of 5.5% (see Figure 7a). Second, the spread between the drifts is enlarged and carbon drifts become either 3% or 6% (see Figure 7b). The shape of the investment probability curves is still logarithmic for both scenarios. An intermediate spread with carbon drifts of 4% and 5% has been tested as well, but the results were very close to the narrowest spread and are not presented here.

For the narrow drift spread, the investment probability without regulation shock is 66.95%. This value is close but slightly lower than the average value of the probability calculated separately for drifts of 3.5% and 5.5%, which is 67.30%. It is also lower than the probability of an intermediate drift, such as 4.5%, whose investment reaches occurred in almost 80% of the simulations. This difference is due to the ambiguity around long-term targets, which creates further price uncertainty. The maximal probability with price jumps is then reduced to 64.77%. The 80% threshold of investment potential is obtained for 6-years periods, and the 90% threshold is obtained for 14-years periods. The marginal gain for an additional year of stability is below 1% for commitment lengths greater than eleven years. These results are similar to the results for a unique intermediate carbon drift.

For the widest drift spread, the picture is slightly different. The two drifts of 3% and 6% are extreme cases, and this ambiguity sparks a very high degree of uncertainty, specifically in the beginning of the investment period. The investment probabilities of the corresponding fixed drifts were indeed 15.25% in the lowest scenario and 99.58% in the highest scenario. The average of these values is 57.42%, which is higher than the probability when there is no shock, i.e., 41.75%. This value is also less than the value in the narrowest spread and, consequently, less than the value in the reference case. If yearly shocks are assumed, the investment probability drops to 27.93%. The highest probability is superior to the one without shock, i.e., 47.30%. Upward jumps can become an opportunity to access very high carbon paths, especially in the case of two consecutive upward jumps.

The 80% and 90% thresholds are exceeded in 4-year and 8-year periods, respectively. These commitments are shorter than they are for the narrow spread or the reference case. In other words, a wider spread of drifts leads to a reduction in investment probability, but the adverse impact of regulatory instability is lower than it is with a narrower spread. This explanation is based on our carbon price modeling. The two drifts are better separated for a wide spread than for a narrow spread, leading to lower intermediate carbon prices. The price signal is less blurred, and the decision maker knows sooner if he/she should invest or give up definitively.

Comparing the two spreads, the marginal gain of an additional year of stability is smaller for the widest spread. For example, the probability variation between a commitment length of six and seven years is only 0.87%, compared to 1.47% for the 3.5% - 5.5% spread. Even with climate target uncertainty, our conclusions are close to those for fixed carbon drifts. Longer climate commitments trigger investment, notably when the probability of investment is close to a one-in-two chance. Reducing the regulatory instability is of particular interest for projects whose profitably is highly sensitive to carbon prices.



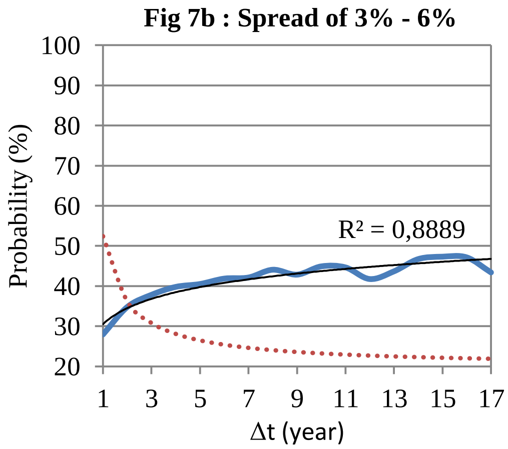


Figure 7: Investment probability in % (blue), trend line of investment probability (black) and the derivative of the investment probability trend (dotted line). Figure 7a describes the double drift 3.5%-5.5%, and Figure 7b describes the double drift 3% - 6%.

5 Concluding remarks

In this article, a real option model is used to discuss the desirable length of climate commitments from an investor’s perspective. Our carbon price modeling considers market price uncertainty as well as abrupt changes in regulation and the long-term ambiguity around climate targets. We focus on a carbon capture and storage (CCS) chain applied to a coal plant. CCS appears to be a good opportunity for investors because the project is achieved in almost 80% of the simulations, without regulation uncertainty and under a moderate evolution of carbon prices, i.e., an increase of 4.5% per year. The project is, however, postponed by fifteen years on average.

Some important lessons have emerged from this analysis. We have shown that longer commitment periods help trigger investment because the investment probability grows regardless of the carbon price scenario considered. The relation between investment and length is not linear but logarithmic. This finding implies that an additional year of regulatory stability is more beneficial for shorter periods than for longer policy cycles.

Another major contribution of this article is the finding that regulatory instability discourages the CCS project modeled under moderate carbon price scenarios. Indeed, the profitability is low on average and downward jumps can cause it to collapse. Conversely, the project is barely profitable under a low-price scenario even without any regulation shock. Under a high-price scenario, the profitability is so high that downward jumps have only a transitional effect.

It is not possible to determine an optimal lifetime for climate commitments without including the value of policy flexibility. Nevertheless, for periods less than 5 years, the investment probability dropped considerably. This length can therefore be interpreted as the minimum lifetime for climate agreements. For 7-year periods, 80% of the full investment potential is reached, even in the most sensitive cases. To reach 90% of the investment potential without regulation shock, one needs very long commitments under an intermediate price scenario. If a trade-off between commitment length and policy flexibility is necessary, we believe that 10-year policy cycles are more accurate because the benefit of additional stability years is almost negligible for commitments longer than 11 years.

A second regulatory uncertainty has been studied in the analysis of long-term climate targets. This uncertainty is modeled by a price spread between low and high carbon price drifts. This price spread reflects a larger uncertainty for investors and results in a decrease in the investment probability. For low and high drifts of 3.5% and 5.5%, respectively, the results are similar to those in the intermediate scenario. Ten-year cycles appear to be an appropriate timeframe for climate agreements, even with both types of regulatory uncertainties.

Replicating our experimental method using other technologies such as nuclear plants or wind power might have reinforced our findings. We believe, however, that our findings hold despite the use of only one example technology. CCS projects are indeed a well-adapted case study, as investment decisions are highly sensitive to carbon prices yet likely to be undertaken under moderate price conditions. Therefore, different investment profitability levels have been assessed for different price scenarios.

Finally, it appears that to enhance investment, the most important parameter is the long-term carbon drift. Precise long-term targets, i.e., for the mid- to end-of-the-century targets, as well as a roadmap to reach them are therefore needed. Spacing regulation shocks is a way to encourage investors to make a decision on risky projects, and this decision-making can partially limit the negative effects of policy flexibility.

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