Valuing Climate Change Uncertainty Reductions for Robust Energy Portfolios**

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Abstract – Climate policy uncertainty has decisive influence on energy sector strategies. Potential stranded climate-energy investments may be enormous. Remote sensing can improve our understanding of the climate system and thus better inform climate policy and reduce associated uncertainties. We develop an integrated energy-portfolio model to value these uncertainties. The operations of individual power plants are optimized using real options given scenarios of stochastically evolving CO_2 prices mimicking observation-induced climate policy uncertainty. The resulting profit distributions are used in a portfolio optimization. The optimization under imperfect information about future CO_2 prices leads to substantially lower profits for a given risk level when portfolios are to be robust across all plausible scenarios. A potential uncertainty reduction associated with an improved climate modeling supported by remote sensing will thus not only lead to substantial financial efficiency gains, but will also be conducive to steering investments into the direction of higher shares of renewable energy.

Keywords: real options, energy, policy uncertainty, robust portfolios, Earth observations.

1. INTRODUCTION

The arrival of better information and new data from remote sensing on climate sensitivity and other factors important for determining the necessary stabilization target and corresponding policy measures often leads to adaptations and adjustments in the latter and therefore to considerable uncertainty for investors in the energy sector. In a recent article, Hansen et al (2008) explain that paleoclimate evidence and ongoing climate change suggest that CO_2 will need to be reduced to much lower levels than we might have been prepared for. They claim that "the largest uncertainty in the target arises from possible changes of non-CO_2 forcings." Remote sensing can help to monitor GHGs and compare actual to reported emissions and computed scenarios. Numerical models can then be used to examine their impact on radiative forcing, which can then be translated to the appropriate policies.

1.1 Motivation

The energy sector is characterized by long-lived investments involving large sunk costs. Once a power plant, for example, is installed, it will most probably be used throughout its lifetime and maybe even beyond. Many OECD countries are now in the situation, however, that existing capacity is ageing and much of it will need to be replaced in the coming decades. In order to avoid further lock-in to fossil-fuel-based energy technologies, policymakers have been trying to incentivise a transition to a less carbon-intensive energy production regime by imposing taxes on the combustion of fossil fuels or through a cap-and-trade system with tradable permits within the European Union (EU).

In this paper we want to shed more light on decision-making in the electricity sector when investors are faced with uncertainty about CO_2 policy. This will show how important Earth observations are for better-informed decisions. To this end, we develop a new framework of analysis, where different methodologies are integrated: the investment decisions and operations at the plant level are optimized within a real options framework. This provides the profit distributions that will in turn inform the larger investor (i.e. a larger energy company, a region or even a country) of how to diversify across technologies. For this part of the analysis we have chosen a portfolio approach, which will use the Conditional Value-at-Risk (CVaR) as a risk-measure, since the more common variance approach should only be used in cases where the profit distributions are clearly normal, which does not apply in our case.
This approach builds on earlier work by Fortin et al (2008), but has one important novelty that enables us to evaluate the impact of policy uncertainty or, in other words, the value of better information. More precisely, we compute the losses from being forced to have an energy portfolio, which is robust across different scenarios. The scenarios are characterized by differences in the CO_2 price, which again depend upon the stabilization target chosen.

1.2 References to Related Work

The electricity sector bears certain features, which makes real options analysis in this context a suitable tool for investment decision-making. In particular, these features pertain to the flexibility on behalf of the investor to time the commitment of large resources optimally in the face of uncertainty about future developments (see Dixit and Pindyck (1994) for a more complete overview, also on methodological issues). Especially studies concerned with the effect of policy uncertainty have recently surged: Fuss et al (2009) use a real options model where multiple options are evaluated simultaneously, so that the effect of the individual options on each other is accounted for. The model is applied to the electricity sector, analyzing the transition from CO_2-intensive to CO_2-neutral electricity production in the face of rising and uncertain CO_2 prices and estimating the expected value of (perfect) information, i.e. the willingness of investors and producers to pay for information about the correct CO_2 price path, which rises over time. The authors find that it is preferable to have climate change policies that are stable over a certain length of time, since less frequent fluctuations reduce the expected value of information and result in smaller cumulative CO_2 emissions. Other studies are presented in an International Energy Agency book (IEA, 2007). Similarly, Reinelt and Keith (2006) employ real options to assess energy investments, where they focus on the social cost of CO_2 price uncertainty, which they find to be enhanced by investment irreversibility and alleviated by the competitiveness of technologies with relatively inexpensive carbon capture retrofit possibilities.

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While such real options models are well suited for optimization of timing of investment and operations at the plant level, larger investors typically want to reduce risks by diversification. Portfolio frameworks have therefore been widely applied to energy sector investment before (see Bazilian and Roque (2008) for a compendium of the existing literature and the latest developments in this field).

The combination of real options modeling and portfolio optimization as such had first been implemented by Fortin et al (2008). The current paper is an extension of this work in the sense that it deals with the optimization of portfolios, which are robust across different scenarios, which can entail considerable losses depending on which scenario really materializes. Our findings indeed prove that better information about climate sensitivity and forcing by non-GHG gases leading to more stable climate policy can provide for substantial gains in terms of expected profits and reduced risks.

2. MODELING FRAMEWORK

2.1 Technologies Considered & Real Options Model

In this study we are looking at two different types of technologies that can be retrofitted with carbon capture (CCS) modules: a coal-fired power plant and a biomass-fired power plant, where the former stands representative for the fossil-fuel-fired energy technologies and the latter for renewable energy carriers, even though biomass-fired power production has the special feature that the fuel generation itself already sequesters as many emissions as are produced during combustion. Adding carbon capture facilities can thus result in *negative* emissions (Uddin and Barreto, 2007). Table A lists the relevant data of both technologies.

Table A. Power Plant Data (Source: IEA/OECD, 2005)

Parameters	Coal	Coal+CCS	Bio	Bio+CCS
Output (MWh/yr)	7,446	6,475	7,446	6,475
CO_2 (t CO_2/yr)	6,047	576	0	-6,100
Fuel Cost (€/yr)	39,510	39,510	152,612	152,612
O&M (€/yr)	43,710	60,110	43,269	59,669
Installed Cap. (MW)	1	1	1	1
Capital Cost (1,000€)	1,373	1,716	1,537	1,880

In the real options model the optimal investment plan for a single profit-maximizing electricity producer facing stochastic CO_2 prices is computed, thereby generating the profit distributions for the portfolio model. The producer has to deliver a certain amount of electricity over the course of the planning period.

For a full overview of this model, the reader is referred to earlier work in Fortin et al (2008). For the sake of saving space we will present the main equation only and describe the relevant parameters/scenarios.

The real options model considers a power plant owner with existing capacity that expires in 50 years, who has to decide, when or whether to add and how to operate an CCS module. We assume the decisions can be done on a yearly basis. The problem the investor is facing can be formulated as an optimal control problem with the investor seeking to determine his actions for each year (as a function of current state and carbon price) maximizing his profits subject to stochastic CO_2 price following a Geometric Brownian Motion (GBM) in order to allow for an upward-trending, but fluctuating price path:

$$dP_t^c = \mu^c \cdot P_t^c dt + \sigma^c \cdot P_t^c \cdot dW_c^t \tag{1}$$

with μ^c being the drift and σ^c the volatility parameter and W_t^c is the increment of a Wiener process. Let us define the yearly profit of the investor $\pi(\bullet)$ as a functions of the current state (denoted by x, representing whether the CCS module has been installed and whether it's running), the current CO_2 price and the action undertaken in that year (denoted by a). Actions available are either to do nothing or install the CCS module (in case it has not been installed yet) or to switch the module on or off (in case it has already been installed). The profit is equal to the income from selling electricity less the cost associated with running the plant and the cost of actions undertaken in that year.

The optimal control problem can be solved recursively by dynamic programming, where the corresponding Bellman equation is:

$$\begin{aligned} V(x_t, P_t^c) = \max_{a \in A(x_t)} \{\pi(x_t, a(x_t, P_t^c), P_t^c) + \\ + e^{-r} E[V(x_{t+1}, P_{t+1}^c) | x_t, P_t^c]\} \end{aligned} \tag{2}$$

$V(\bullet)$ is the value function; T=50 is the planning horizon. V equals zero at the end of the plant's lifetime.

The optimization problem can then be solved recursively. The first part of the sum in equation (2) is the immediate profit upon investment; the second part is the value from waiting, which is computed using Monte Carlo simulation. This method was chosen, since it remains computationally efficient for a high degree of complexity and is rather precise when the discretization of the price is sufficiently fine. The output of the recursive optimization part is a table listing the optimal action for each time period, for each possible state and for each possible carbon price in that period. For the analysis of the final outcome, we can then simulate (10,000) possible CO_2 price paths and extract the corresponding decisions from the output table. By plotting the profits for all 10,000 price paths, we obtain the final distributions needed.

2.2 Framework for Robust Portfolios

Defining CVaR according to Rockafellar and Uryasev (2000), let f(x,y) be the loss function depending on the investment strategy $x \in \Re^n$ and the random vector $y \in \Re^m$, and let p(y) be the density of y. The probability of f(x,y) not exceeding some fixed threshold level α is $\psi(x,\alpha) = \int_{f(x,y)\le\alpha} p(y)dy$. The β-VaR is defined by $\alpha_\beta(x) = \min\{\alpha | \psi(x,\alpha) \ge \beta\}$ and the β-CVaR is defined by $CVaR_\beta(x) = \phi_\beta(x) = (1-\beta)^{-1} \int_{f(x,y)\ge\alpha_\beta(x)} f(x,y)p(y)dy$, which is the expected loss given that it exceeds the β-VaR level, where β is the confidence level. Both VaR and CVaR are applicable to profits as well as to losses, because one may consider returns as negative losses (and losses as negative returns). In the following, losses are defined as negative returns and thus we will report -VaR and -CVaR to indicate respectively the lower threshold for returns and expected returns in case they are lower than that threshold.

Let us consider n different technologies (here two) for investment. Values y_i, i = 1,…,n reflect the profits for each technology. We assume the vector $y = [y_1,\ldots, y_n]^T \in \Re^n$ of NPV profits to be a random vector having some distribution and describe the investment strategy using the vector $x = [x_1,\ldots, x_m]T \in \Re^n$, where the scalar value x_i reflects the fraction of capital invested into technology i. The return function depends on the chosen investment strategy and the actual profits; computed as $x^T y$. As the actual profit is unknown, there is a specific degree of risk associated with investment strategy x. To measure this risk and find the corresponding optimal *x*, our optimization is based on minimizing CVaR with a loss function $f(x, y) = - x^T y$, i.e. negative profits. Following Rockafellar and Uryasev (2000), we approximate the problem of minimizing CVaR by solving a piece-wise linear programming problem and reduce this to a linear programming problem with auxiliary variables. A sample $\{y_k\}^q_{k=1}$, $y_k \in \Re^n$ of the profit distribution is used to construct the LP problem. Concerning the investment strategy in the sense that it should deliver a specified minimum expected profit (or limited expected loss), the LP problem is equivalent to finding the investment strategy minimizing risk in terms of CVaR:

$$\min_{(x,\alpha,u)} \alpha + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} u_k$$
$$\text{s.t. } e^T x = 1, m^T x \ge \pi, x \ge 0, u_k \ge 0, \qquad (3)$$
$$y_k^T x + \alpha + u_k \ge 0,\ k = 1,...,q\ .$$

where $u_k \in \Re^n$, k=1,…,q are auxiliary variables, $e \in \Re^n$ is a vector of ones, q is the sample size, $m=E(y) \in \Re^n$ is the expectation of the profit vector. π is the minimum portfolio profit[1] and α the threshold of the loss function β.

Now let us consider a problem similar to (3), where the sample $(y_{ks})^q_{k=1}$, $y_{ks} \in \Re^n$ of the profit distribution depends on the scenario number s=1,…,S. We consider a minimax setup, where an investor wants to hedge against the worst possible.

$$\min_{(x,\alpha,u)} v$$
$$\text{s.t. } v \ge \alpha_s + \frac{1}{q(1-\beta)} \sum_{k=1}^{q} u_{ks},\ e^T x = 1,\ m_s^T x \ge \pi_s, \qquad (4)$$
$$x \ge 0, u_k \ge 0, y_{ks}^T x + \alpha_s + u_{ks} \ge 0,\ u_{ks} \ge 0,$$
$$k = 1,...,q,\ s = 1,...,S.$$

where $y_{ks} \in \Re^n$ are samples of NPV profits y_s for scenario s and v $\in \Re^n$ are auxiliary variables. The solution (x_*, α_*, u_*) yields the optimal x, so that the corresponding CVaR reaches its minimum across all scenarios, i.e.

$$\beta - \text{CVaR}(x_*) = \min_x \max_s \beta - \text{CVaR}_s(x). \qquad (5)$$

3. RESULTS: ENERGY SECTOR LOSSES DUE TO UNCERTAINTY

3.1 Scenarios Considered and Parameters

Table B. Parameters

μ^c			P_0^c (€/ton)	σ^c	r
scen.1	scen.2	scen.3			
0.00636	0.01716	0.0397	12	0.04	0.05

Table B sets out the parameters used in the analysis, before we present the results in detail. Note that the starting CO_2 price, P_0^c, and the volatility parameter, σ^c, are equal for all scenarios. Scenarios are thus defined by their trend only (μ^c): scenario 1 corresponds to a stabilization target of 670 ppm and is thus the least strict target with the lower increase in CO_2 prices. Scenario 2 aims at 590 ppm and scenario 3 at 480. The trends have been computed on the basis of the GHG shadow prices estimated for the year 2060 in the GGI Scenario Database (IIASA, 2007).

3.1 The Benchmark Case

Table C presents the results from the real options optimization – the characteristics of the profit distributions in terms of payoff and risk. Note that we report the –CVaR here; the variance is actually increasing for biomass as stabilization targets get stricter.

Table C. Descriptive statistics

	Coal		Biomass	
Scenario	Exp. Profit (10^6 €)	-CVaR (97%)	Exp. Profit (10^6 €)	-CVaR (97%)
1	1.177	1.050	0.523	0.228
2	1.099	1.007	0.808	0.351
3	0.984	0.847	1.836	0.942

It is clear that coal is the more profitable technology for looser targets (scenario 1) and biomass gets more attractive only as CO_2 prices increase more rapidly. Therefore, it does not come as a surprise that the portfolio in scenario 1 is dominated by coal. For scenarios 2 and 3 the target gets stricter and the share of biomass grows (see Fig. 1).

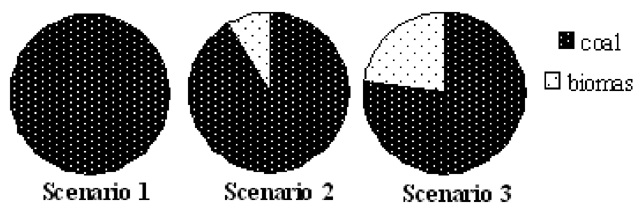

Figure 1. Portfolio shares per scenario.

3.1 Minimax Portfolios

Table C summarizes the outcomes for optimizing portfolios that are either based on the expectations of one scenario (the benchmark case) or that have to be robust across 2-3 scenarios.

Table D. Expected profits in 10^6 € and –CVaR risk (*robust across these scenarios)

	actual scenario					
	1		2		3	
*	exp. profit	-CVaR	exp. profit	-CVaR	exp. profit	-CVaR
1	1.177	1.061	1.099	1.021	0.984	0.871
2	1.121	1.046	1.075	1.05	1.056	1.049
3	1.03	0.963	1.034	0.979	1.176	1.062
12	1.126	1.049	1.077	1.049	1.05	1.034
13	1.122	1.047	1.075	1.05	1.055	1.047
23	1.121	1.046	1.074	1.05	1.057	1.05
123	1.122	1.047	1.075	1.05	1.055	1.047

Fig. 2 shows three different portfolio profits in three different scenarios to make these results more transparent. The first bar in each scenario (dotted) refers to the portfolio, which has been optimized for the first scenario only (i.e. the benchmark case from the previous section). Obviously, this one performs best in the scenario that it has been optimized for, therefore. Should scenarios

[1] The values for required expected profit are in fact not binding: setting required profits high would exclude technologies that could have been interesting alternatives from the point-of-view of their risk profiles.

2 or 3 materialize, profits will be progressively smaller. This already underlines the importance of having the right information for finding the optimal portfolio. The second bar (checked) represents the portfolio, which is robust across the first and the second scenario, where the latter involves a stricter stabilization target. This one also performs best in the first scenario, but the drop if scenarios 2 or 3 turn out to be the case is smaller relative to the "non-robust" portfolio. This effect is even more pronounced for the portfolio, which has to be robust across all three scenarios (diamond pattern).

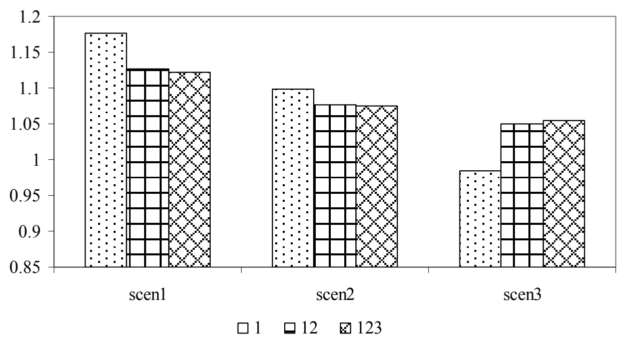

Figure 2. Expected profit (in 10^6 €) across scenarios (scen).

These results show that robust portfolio optimization in the form of our minimax-approach is a valuable tool to reduce the impact of missing information: should other scenarios than expected materialize, the investor who has optimized only for scenario 1 will experience a much larger drop in profits than the one that has been using the minimax-criterion. However, this "security" comes at the cost of accepting lower overall profits in the first two scenarios. It is thus clear that missing information causing uncertainty about stabilization targets or the adaptation of a target due to a prior lack of data leads to optimization under imperfect information and thus large losses in profits. Table D furthermore confirms that the robust portfolios perform better in terms of lower –CVaR risk in the alternative scenarios.

From a policymaker's perspective it is also interesting to note that the robust portfolios all have shares of biomass below 10%, which indicates that even if scenario 3 would have been a possibility, the chance that the other scenarios might also turn out to be true drives down investment in biomass. This further stresses the need for more precise data and information that enable the formulation of a clear and transparent stabilization target, which will not have to be adapted drastically.

4. CONCLUSION

A lack of information and data, which could be overcome through remote sensing, causes uncertainty about the appropriate stabilization target that policymakers have to base their decisions concerning climate policy upon. The EU has established a permit trading scheme, where the price rises and is inherently unstable. We have tried to model this situation by letting the CO_2 price follow a stochastic process (a GBM) and computed profit distributions for two types of power plants that are exposed to CO_2 price fluctuations to a different extent, so that diversification considerations would lead them to adopt renewable energy for stricter targets, while loose targets favor a fossil-fuel-dominated portfolio. A portfolio optimization using these profit distributions as input, has shown that expected profits are prone to drop substantially, if a scenario different from the one used in the optimization turns out to become reality. Robust portfolios (using a minimax-criterion) can partly overcome this problem by minimizing this drop, but this goes at the expense of higher profits in most scenarios. In other words, the investor has to accept low profits for relatively small improvements in risk.

It is clear that it is therefore of paramount importance to obtain the best information possible about climate sensitivity, changes in non-CO_2 forcing and the correspondence between actual and reported CO_2 emissions to come up with a clear and stable target and enable optimization under the most complete information possible.

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