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Evaluating the power investment options with uncertainty in climate policy

Ming Yang [a,*], William Blyth [b], Richard Bradley [a], Derek Bunn [c], Charlie Clarke [d], Tom Wilson [d]

[a] International Energy Agency, 9, rue de la Fédération, F-75739 Paris Cedex 15, France
[b] Oxford Energy Associates, 28 Stile Road, Oxford OX3 8AQ, UK
[c] London Business School, Regent's Park, London NW1 4SA, UK
[d] Electric Power Research Institute, 3420 Hillview Avenue, Palo Alto, California 94304, USA

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Abstract

This paper uses a real options approach (ROA) for analysing the effects of government climate policy uncertainty on private investors' decision-making in the power sector. It presents an analysis undertaken by the International Energy Agency (IEA) that implements ROA within a dynamic programming approach for technology investment choice. Case studies for gas, coal and nuclear power investment are undertaken with the model. Illustrative results from the model indicate four broad conclusions: i) climate change policy risks can become large if there is only a short time between a future climate policy event such as post-2012 and the time when the investment decision is being made; ii) the way in which CO_2 and fuel price variations feed through to electricity price variations is an important determinant of the overall investment risk that companies will face; iii) investment risks vary according to the technology being considered, with nuclear power appearing to be particularly exposed to fuel and CO_2 price risks under various assumptions; and iv) the government will be able to reduce investors' risks by implementing long-term (say 10 years) rather than short-term (say 5 years) climate change policy frameworks. Contributions of this study include: (1) having created a step function with stochastic volume of jump at a particular time to simulate carbon price shock under a particular climate policy event; (2) quantifying the implicit risk premium of carbon price uncertainty to investors in new capacity; (3) evaluating carbon price risk alongside energy price risk in investment decision-making; and (4) demonstrating ROA to be a useful tool to quantify the impacts of climate change policy uncertainty on power investment.

JEL classification: F53; C61; D78; E37; G18; O16; O38; Q48; Q52; Q54

Keywords: Real options; Investment; Uncertainty; Carbon shock; Climate policy

* Corresponding author. Tel.: +33 1 40 57 67 33; fax: +33 1 40 57 67 39.
E-mail address: ming.yang@iea.org (M. Yang).

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1. Introduction

Investment in the power sector has at least three crucial characteristics. Firstly, the investment is partially or completely irreversible. Once invested, the asset may become stranded because of various risks. Secondly, without hedging, the price risks, market evolution and policy intervention uncertainties can have a substantial effect on financial performance. Thirdly, without central planning, the timing of an investment is discretionary. Profit-seeking enterprises can invest in a power plant now if they think the return on the investment is high enough to match the risks, or they can postpone the investment to acquire more information on some of those risks. In other words, investors have the option but not the obligation to invest in a project at a particular point in time.

Furthermore, because different technologies emit different amounts of greenhouse gases per unit of electricity generated, climate policy risk introduces a new factor into this investment decision. Whether climate change policies are introduced through a price mechanism (*e.g.*, permit trading scheme or carbon tax) or through some other regulatory mechanism, the current and potential future cost of emissions needs to be included in the investment analysis, even in countries where there is currently no cost for emitting greenhouse gases. One problem with incorporating these emission costs into financial appraisal is that the status of climate change policy in most countries is uncertain. Uncertainties range from general issues such as whether / when carbon constraints will be imposed to more specific issues the form of regulation, stringency of emissions controls and levels of allocation of emission permits. Confounding this issue, volatile oil prices not only add their own uncertainties into the equation, but influence the relative costs of carbon abatement opportunities.

The objective of this paper is to present the results of quantifying the cost of uncertainty in the process of climate policy evolution, through its effects on inducing greater optionality considerations in the behaviour of investors. The paper provides some illustrative results for the choice between coal and gas (with and without carbon capture) as well as nuclear power plants.

2. Methodology

2.1. Real options approach

The term “real options approach” (ROA) can be traced to Myers (1977), who first identified the analogy between investments in real assets and financial options. ROA is useful in project appraisal when the project revenue streams resulting from the investment are uncertain, when there is the possibility of learning about future market conditions that could affect the project’s profitability, and when there is the possibility to optimally choose the time to make the investment. A number of studies have been undertaken applying ROA to evaluate power project investments. Laughton et al. (2003) applied this approach to assessing geological greenhouse gas sequestration. They concluded that the use of a traditional deterministic discounted cash flow (DCF) can distort the valuation of projects, as it does not account for the complex effects of risk and uncertainty. Using ROA in an environment of uncertain CO_2 price, Sekar (2005) evaluated investments in three coal-fired power generation technologies: pulverized coal, standard Integrated Coal Gasification Combined Cycle (IGCC) and IGCC with pre-investments to reduce the cost of future CCS retrofitting. Sekar developed cash flow models for each of the three technologies, with CO_2 price as an uncertain variable. Rothwell (2006) used ROA techniques to evaluate risks to the development of new nuclear power plants. He modeled three uncertainties: price risk, output risk and cost risk. Using a Monte Carlo simulation, Rothwell derived various risk premiums, between \$383/kW and \$751/kW that would trigger investment in the United States' new nuclear power plants.

Laurikka (2006) presented a simulation model using ROA to quantify the value of Integrated Gasification Combined Cycle (IGCC) technology within an emissions trading scheme. The study designed and simulated three types of stochastic variable: the price of electricity, the price of fuel and the price of emission allowances. Laurikka concluded, (1) a straightforward application of the traditional project appraisal on a scenario of IGCC can bias results for current competitive energy markets regulated by an emissions trading scheme; (2) the potential combination of several uncertainties rendered the European Union Emission Trading Scheme (EU ETS) complex; and (3) when accounting for uncertainties, the IGCC technology is not competitive within the EU ETS.

Lin et al. (2007) used the ROA to examine how much and when greenhouse gas emissions should be reduced in a case study. On the basis of a detailed literature review on the ROA, they created a simple mathematical model for assessing environmental pollution prevention when ecological and economic uncertainty coexists, which may provide a reference or a foundation for government decision making. They studied the optimum timing for adopting pollution prevention policies by expanding the continuous time model of decision making for the greenhouse effect, taking into account environmental and economic uncertainty. One of the interestingly specific quantifications of Lin et al. (2007) is that they presented a case study in which decision makers adopt a pollution prevention policy when the pollutants reach a particular threshold of 48 million tons. This illustrates the nature of ROA in providing a framework for understanding decision triggers as environmental scenarios evolve.

Other recent applications of ROA in the energy sector include (1) Siddiqui et al. (2007), who evaluated the United States' federal strategy for renewable energy research, development, demonstration, and development; (2) Marreco and Carpio (2006), who examined the flexibility of the Brazilian power system; and (3) Kuper et al. (2006), who evaluated the influence of uncertain oil prices on energy use.

The Electric Power Research Institute of the USA (EPRI, 1999) developed the Greenhouse Gas Emission Reduction Analysis Model to evaluate the revenues, costs and expected after-tax gross margin accruing from investment in the technology of greenhouse gas reduction. The model incorporates Monte Carlo simulation, and methods of the ROA to enable an evaluation of specific GHG reduction strategies that account for individual risks and uncertainties. The model incorporates energy prices and CO_2 prices with correlations. Developed in an MS Excel environment, the model is supported by a semi-commercial software program for calculating real options, which is also the basis for the work described in this paper.

2.2. Modelling climate policy uncertainty and investment risk

In the work reported in this paper, the ROA has been used to evaluate the risks associated with uncertainty in climate change policy with an ultimate view to making recommendations on how policy could be implemented to reduce investment risk. The approach provides a useful basis for policy analysis, as it effectively allows different risk factors to be considered individually or in combination, so that the effects of policy risk, as distinct from market risk, can be isolated. The real options we investigate here are related to the flexibility that companies have to optimally time their investment in the face of regulatory uncertainty — in other words to delay their investment with the prospect of gaining better information regarding the likely outcome of the policy decisions. The ability for investors to improve likely project outcomes by waiting for additional information means that project returns for investments which go ahead immediately (*i.e.*, thereby absorbing the regulatory risk), need to be correspondingly higher in order to overcome this 'option value of waiting'. In this work, we therefore use the value of waiting as a measure of risk. Climate change policy uncertainty is represented in the investment decision by means of an uncertain carbon price. In reality, climate policy may take several forms, and does not necessarily set a direct carbon price. Nevertheless, climate policies will impose costs on investors, and we make the convenient modelling assumption that these can be represented in total as an equivalent carbon price. Some elements of policy risk are missed out as a result of this simplification. For example, in an emissions trading scheme, there may be uncertainty not only concerning the price of carbon, but also the level of free allocation of allowances. In this study, we did not take into account the effects of free allocation on the investment decision — i.e. we effectively assumed 100% auctioning of allowances. In principle, the approach outlined below could be extended to include the effects of free allocation as a subsidy to fossil-fuel generation technologies and to model the effects of allocation uncertainty as a source of risk for these plant going forward.

To capture energy market uncertainty, fuel prices are also taken to be stochastic, and various assumptions are made about price variability and correlation between the different uncertain variables. Fuel price uncertainty is included in the model in order to provide a comparison with carbon price uncertainty. We do not however model the full range of investment risks. For example technical risks such as capital cost uncertainty and demand / load factor uncertainty are not included. Again, in principle such sources of uncertainty could be incorporated into an extended ROA.

2.3. Modelling real options with dynamic programming

The approach we have taken is an optimisation of investment decision-making under uncertainty using dynamic programming, as described for example in Dixit and Pindyck (1994). The dynamic programming compares the expected outcome of investing in a project in the current year with an alternative ('continuation value') which delays investment until the timing is optimal. The calculation of the continuation value requires solving the problem from the final year of the scenario, working backwards to the first year in order to deduce the optimal investment rule over the whole possible investment horizon.

This can be described mathematically as follows. We consider a project with lifetime L which can be irreversibly initiated in any year t ($0<t<T$) for a total capital outlay of K. The cash-flow in year t without the investment is A_t, and the annual cash-flow with the investment is B_t. Since these values are uncertain, the project value will depend on the expectation $E[.]$ of these values. The total net present value V_t^{inv} of the project if investment goes ahead in year t is:

$$V_t^{\text{inv}} = \left(\sum_{n=t}^{L} d(t,n)E[B_n] \right) - K \tag{1}$$

where $d(t,n)$ denotes the discount factor applied at time t to cash flows occurring at time n. The continuation value which is the net present value of the project if one chooses not to invest in the project at period t (but assuming optimal investment opportunity depending on future conditions) is given by:

$$V_t^{\text{cont}} = A_t + d(t,t+1)E[V^*_{(t+1)}] \tag{2}$$

where V^* is the optimal net present value of the project cash flows from year $t+1$ until the end of the project lifetime under the assumption of optimal investment behaviour. The assumption of optimal investment behaviour in future years requires the comparison of V^{inv} with V^{cont} in every future year.

Since the continuation value always depends on the total expected value of the project in the following year, this procedure needs to be solved from the end of the project, working backwards. The final possible year for investing in the project is year T, at which it is assumed that the decision is a 'now or never' investment choice. In year T, V^{inv} becomes the expected value of the project over its lifetime, and V^{cont} equals zero (since there is no further opportunity to invest beyond this date). Investment will therefore go ahead in year T if $V_T^{\mathrm{inv}}>0$.

From the perspective of year $T-1$, the decision in year T will depend on the random changes in variables in the intervening year. Therefore the continuation value will be based on expectations in year $T-1$ which we denote $E_{T-1}[.]$. In year $T-1$, the continuation value becomes the current year's income A_{T-1} plus the discounted value of the expected project value given the expected outcome of the decision in year T, and the current state of information in year $T-1$.

$$V_{T-1}^{\mathrm{cont}} = A_{T-1} + d(T-1,T)\max\{E_{T-1}[V_T^{\mathrm{inv}}],0\} \tag{3}$$

Once the continuation value in year $T-1$ has been calculated, this provides a minimum value which V_{T-1}^{inv} must exceed in order for investment to proceed in that year. This provides an optimal investment rule for year $T-1$ given expectations about how prices will evolve in the intervening period. Once the optimal investment behaviour for period $T-1$ has been calculated, the same procedure can be used to derive the optimal investment rule for period $T-2$, $T-3$ and so on. Working backwards, we can derive an optimal investment rule for each year in the period $0<t<T$. Fig. 1 shows the optimization procedure described above.

As discussed in the next section, the stochastic price processes are chosen in such a way that the expected future values for the variables can be derived from their current values. This means that the expected total revenues over the lifetime of the project can also be derived from the current values of the stochastic variables. The optimal investment rule in a given year expresses a threshold level that the annual returns have to exceed (given the prices in that year and the implication of these prices for the expected future returns) in order for investment to proceed. In other words, the optimal investment rule sets out the minimum project returns required to justify immediate investment rather than waiting. As will be shown, these minimum project returns can significantly exceed the normal positive net-present-value (NPV) rule that would be derived from the same cash-flow calculations

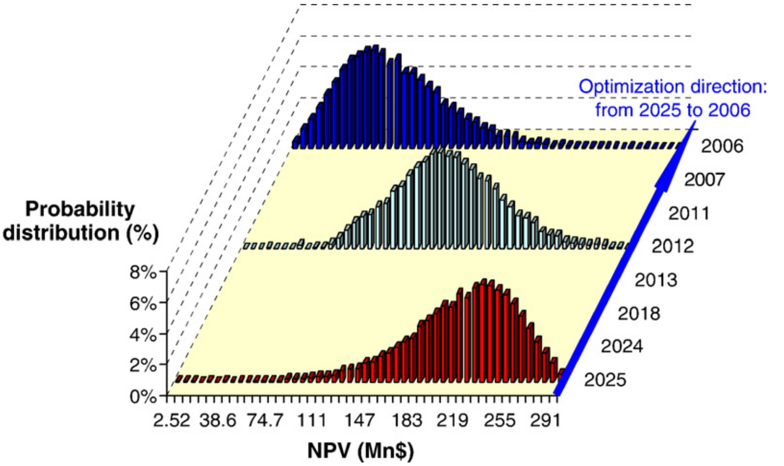

Fig. 1. Optimization of future cash flows using real options.

under certainty. The degree to which the optimal investment rule exceeds the standard positive NPV rule is a measure of the option value of optimising investment timing. It can also be interpreted as a measure of the risk premium that could be incorporated into investment decision-making as a result of price uncertainty. This risk premium can further be expressed as \$/kW at an additional cost of construction for investors and/or as surcharges in cents/kWh for electricity end-users.

2.4. Overall model structure

As illustrated in Fig. 2, the IEA's modeling methodology divides into four modules. Module 1 is a database of sorted primary data including energy prices, carbon prices and the technology of power production. Module 2 allows for the invention of scenarios and the processing of relevant data. Once treated, these data and scenarios enter Module 3's discounted cash flow (DCF) analysis and Module 4's real options analysis. In Module 3, we developed two macros to perform the traditional DCF analysis to calculate the project NPV without stochastic carbon prices and search for breakeven points where power production may switch between generation technologies. Mathematically, the NPV calculation in Module 3 can be expressed as follows:

$$\mathrm{NPV} = \sum_{t=1}^{T} \frac{C(P_c)_t}{(1+r)^t} - C_0 \quad \text{in Module 3}$$

Where:

C_0 is the unit construction costs;
P_c is the carbon price. Changing with a yearly growth rate, its yearly volatility is zero;
$C(P_c)_t$ is the cash in-flow of the project at year t. It is the function of P_c.

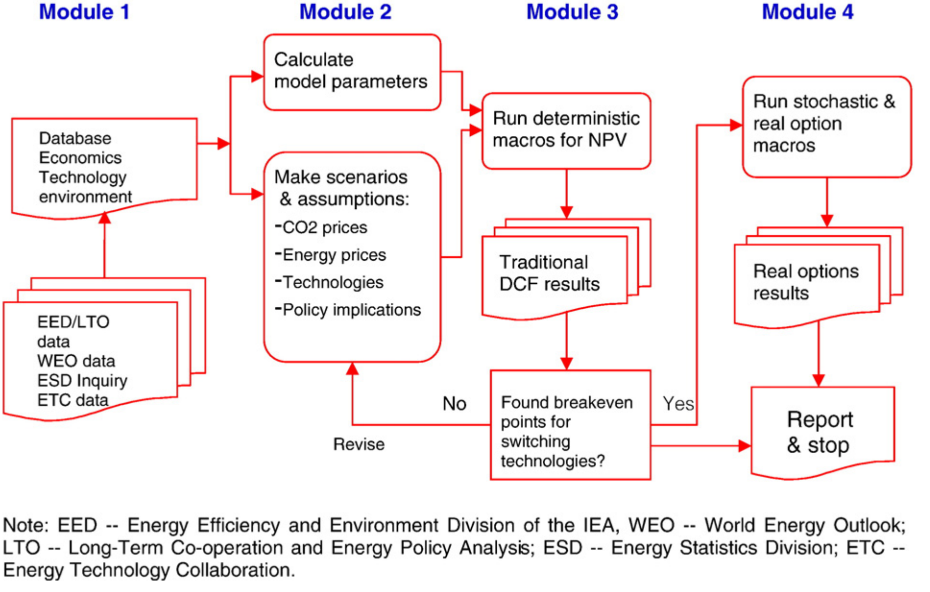

Fig. 2. Methodological framework of the modeling.

In the model, different electricity and carbon prices drive the module running the search. Once the critical points of technology switching appear, the correlating CO_2 price and other data are recorded for reporting and fed into the next module for ROA model running.

In Module 4, while setting the CO_2 and energy prices to change randomly, we calculate the stochastic NPVs for all candidate technologies in each of the planning years. The following formula is used in Module 4 to calculate the project stochastic NPV:

$$\mathrm{NPV} = \sum_{t=1}^{T} \frac{C(\text{Stochastic P}_c \text{ and } P_e)_t}{(1+r)^t} - C_0 \quad \text{in Module 4}$$

Where:

C_0 is the unit construction costs;
P_c and P_e are the carbon prices and energy prices. They change stochastically in the model;
$C(\text{Stochastic } P_c \text{ and } P_e)_t$ is the cash in-flow of the project at year t. It is the function of P_c and P_e.

We then run the real options calculator, a commercial software programme of real options analysis following the rule of optimization described in Eqs. (1)–(3) above to produce the optimal investment options for different technologies during different years. Finally, by comparing the results from Modules 3 and 4, we estimate the risk premiums in the energy sector investments. In the following section, we describe in more details about our cash flow model for NPV calculation and risk premium calculation.

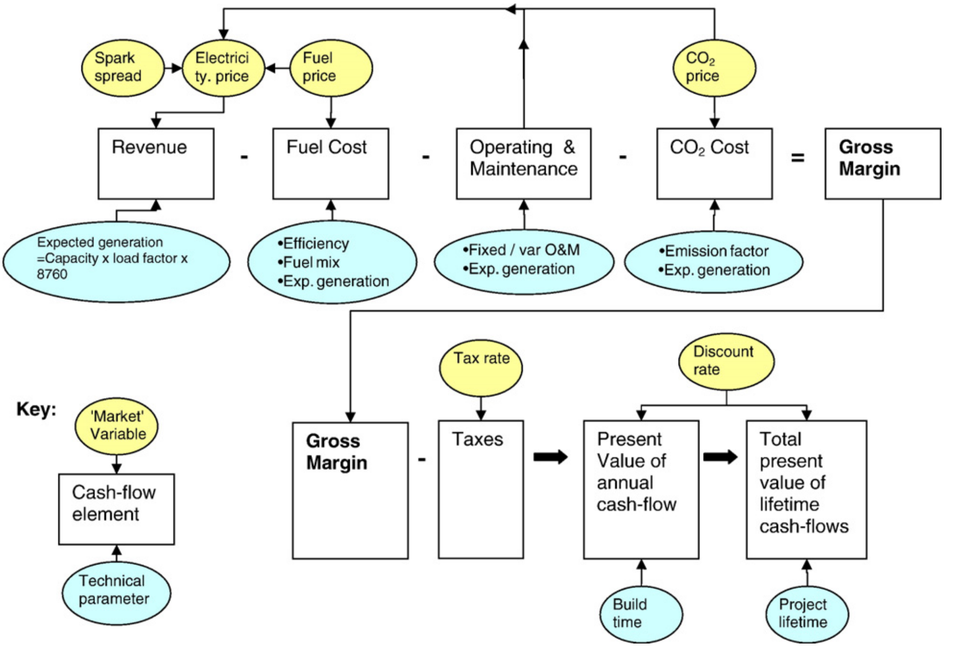

Fig. 3. Structure of cash-flow model.

The structure of the NPV cash flow model shown in Fig. 3 looks similar to that of a usual project appraisal cash flow model. It derives the project net present value by calculating the following cash flow elements: (1) revenue; (2) fuel cost; (3) operation and maintenance costs; (4) CO_2 costs; (5) tax payment; and (6) investment capital. Fig. 3 also shows where the energy market variables and technical parameters are fed in the model to calculate the cash-flow elements. Energy market variables include energy prices and the costs of capital for various power generation technologies. The technical parameters include the plant lifetime (*e.g.* assumed to be 25 years for a gas plant, 40 years for a coal plant), fuel consumption per unit of kWh generation, CO_2 emissions per kWh of output, and capacity factor assumptions for the power plants.

The model measures the total revenues minus the total operating costs adjusted for tax and build time and discounted to give the total present value of cash-flows over the expected lifetime of the plant. For simplicity, this final output from the cash flow is referred to from here on as the gross margin. If this gross margin is larger than the capital costs for the investment, the NPV would be positive. However, this does not necessarily indicate that the project would go ahead. Rather, the investment will only go ahead if the expected value of the project exceeds the continuation value in any given year of the scenario. In general, the greater the level of uncertainty, the greater the continuation value, since the range of possible future values of the project will be greater, and so the possibility to optimise the value of the project through delay will be greater.

There are three key characteristics in this model that make its results significantly different from others. First, energy price and CO_2 price are evolved as Monte Carlo variables. Each of them can be set individually as a random variable, or both of them simultaneously, to capture the uncertainties resulted from the energy market and climate change policy. Second, we use a multi-stage dynamic ROA to optimizing the investment decision. Third, we define a way to calculate carbon risk premium in this study. We focus on these three characteristics below. More detailed descriptions of the framework and the model are available in a working paper by Yang and Blyth (2007).

2.5. Modelling stochastic energy and carbon prices

The input energy (including electricity, gas and coal) prices to the model are assumed to be stochastic. This means that in any given year of the run, expectations of the future value of these variables can change according to their current value which has some element of randomisation. Price uncertainties are modelled following the approach described by Dixit and Pindyck (1994 p65). Fluctuating fuel prices are treated as a combination of short-run volatility, with a mean which itself is uncertain and can drift according to a random walk process. In most of our results, we ignore the short-term volatility element, and simply model fuel price primarily through a long-run random walk process. Changes dx in price x from one period to the next are assumed to follow a geometric Brownian motion path over time:

$$\mathrm{d}x = \alpha x \mathrm{d}t + \sigma x \mathrm{d}z \tag{4}$$

where α is a drift parameter representing the expected growth rate in the price over time, σ is the variance parameter presenting the standard deviation of the probability of future prices, and dz is the increment of Wiener process, a factor to be selected at random from a normal distribution.

Gas prices are modelled with an annual standard deviation of ±7.75%, and coal prices with a ±1.8% standard deviation. This gives a standard deviation from the expected mean after 15 years of ±30% for gas prices, and ±7% for coal prices, approximately in line with the IEA's high and low price scenarios (IEA, 2004). The expected (mean) price levels are USD5.2/GJ (55 US cents per therm) for gas and USD 1.9/GJ for coal price throughout the modelling period. These standard deviations are low relative to normal measures of annual price volatility in most markets, but these values and the geometric Brownian motion process are chosen to reflect longer-term uncertainty, not short-run volatility. The model was tested using an additional element of short-run volatility assuming a mean-reversion process for volatility where the mean was allowed to vary according to geometric Brownian motion. The results were not significantly different from when the short-run volatility element was omitted, indicating that it is long-term price uncertainty rather than short-term price volatility *per se* which adds an investment risk premium.

In this study, all uncertainty relating to climate change policy is expressed through the carbon price. We can distinguish between three different types of price variation for carbon: short-term mean-reverting, long-term random-walk drift and policy-related price shocks.

We make the same simplifying assumption for CO_2 as we make for fuel price, namely that short-term volatility, where prices fluctuate quite rapidly according to conditions in the market, is mean-reverting and does not significantly alter the investment decision. We therefore do not explicitly include this type of variation in the price process for carbon.

Longer-term price uncertainty (e.g. relating to technology cost uncertainty and other market variables) is modelled using a geometric Brownian motion price process as described by Eq. (4) with annual standard deviation of ±7.75%. The total range (standard deviation) of prices after

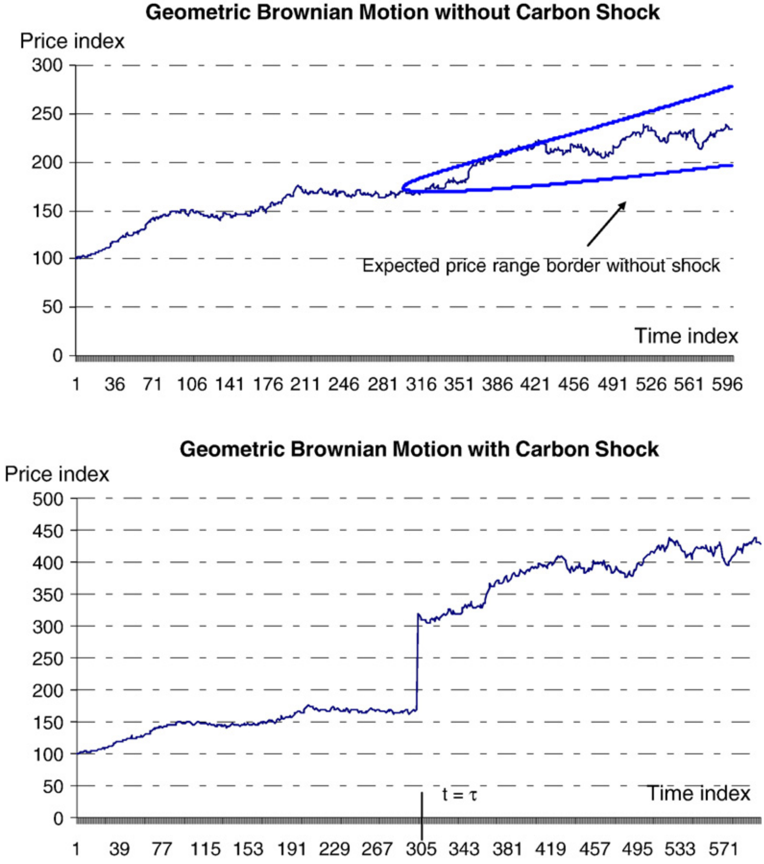

Fig. 4. Illustrative comparison of carbon prices with and without shock.

15 years would be ±30%. This is chosen to match the range of gas price uncertainty used in the model. The expected mean carbon price is taken to be \$25/tCO_2 throughout the modelling period.

We have developed a special step function to simulate carbon price shock or climate change policy uncertainty in addition to its annual stochastic price variation. This represents an 'information event' or carbon price shock resulting from a policy announcement such as might arise at the beginning of a new allocation period in an emissions trading scheme, or the announcement of a new regulatory intervention. The possible shock in carbon price due to such an event is assumed to occur in one particular year of the run τ. Prior to year τ, prices vary according to geometric Brownian motion. The price in year τ has an additional randomised component representing the price shock. Prices in year $\tau+1$ and beyond continue according to geometric Brownian motion starting from the new position after the shock. This means that the uncertainty associated with the price shock (representing policy uncertainty due to special event) is assumed to be resolved after year τ, so that prices continue with some annual variability at the new level determined by the level of the price shock. Our carbon price modelling was derived from Dixit and Pindyck (1994 p65) by adding a step function $\eta x(2\mathrm{d}y-1)$. See formula (5). We use x_c to represent carbon price. Parameters α, σ dz are the same as in Eq. (4). Parameter dy is a uniform random variable with a value between 0 and 1 designed to simulate the shock of carbon price at the particular event $t=\tau$. The value of the step function is an additional to Wiener process of the carbon price variation at $t=\tau$. The coefficient η defines the size of the price shock, and is typically set to a value of 1 in most runs. The term $\eta x_c(2\mathrm{d}y-1)$ therefore represents a price shock in the range ±100% (*i.e.*, anywhere between a doubling of prices or a collapse of prices to near zero). The year in which the shock occurs can be varied — we compare results where the shock occurs after 5 years versus a case where the shock occurs after 10 years.

$$\mathrm{d}x_c = \begin{cases} \alpha x_c \mathrm{d}t + \sigma x_c \mathrm{d}z + \eta x_c(2\mathrm{d}y - 1), & \text{when } t = \tau \\ \alpha x_c \mathrm{d}t + \sigma x_c \mathrm{d}z, & \text{when } t \neq \tau \end{cases} \tag{5}$$

Fig. 4 demonstrates the modelling effect of Eq. (5). It consists of two charts: Geometric Brown Motion without Carbon Shock and Geometric Brown Motion with Carbon Shock. The two curves are identical if the step function ($\eta x_{t-1}(2\mathrm{d}y-1)$ is taken away. As indicated above, we assume the shock takes place at $t=\tau$. The two lines starting at $t=\tau$ in the chart without shock form an expected price range or area. However, if carbon price shock happens, the price range or area will likely be completely changed. See the chart with carbon price shock.

The expected value of carbon in the model depends on the investment option being considered. The main aim of the modelling is to understand the effects of uncertainty, not whether a particular investment is cost-effective under any particular carbon price scenario. We therefore set carbon prices close to a level where the investment would be considered just financially viable under a normal NPV rule. We then introduce the stochastic price variations and run the model to find the new optimal investment rule which can be compared with the NPV rule to provide an analysis of the effect of uncertainty on investment risk premiums.

Correlation between different stochastic variables can be introduced into the model by ensuring that there is correlation in the selection of the randomisation elements dz_i for the different variables i. The key correlation that needs to be considered is between gas prices and CO_2 prices (since electricity prices in any case incorporate variability in these two inputs). It is plausible to assume that gas and CO_2 prices will be partially correlated in an emissions trading scheme because of the role of these prices in the dispatch decisions of power generators. When gas prices are high, the generators will tend to prefer to dispatch coal-fired plant, thereby pushing up carbon prices. On the other hand, CO_2 prices may respond to a whole range of other stimuli. In the runs presented here, we assume a moderate correlation coefficient of around 0.5.

Electricity prices are assumed to follow the short-run marginal costs (SRMC) of existing plant operating at the margin of the electricity system. Three different assumptions are made about what type of plant the SRMC is based on:

1. Coal-fired plants are always on the margin and entirely determine SRMC.
2. Gas-fired plants are always on the margin and entirely determine SRMC.
3. The marginal plant in the electricity system will be that which has the greatest SRMC, chosen by the model (between a coal plant and a gas plant) depending on the outturn fuel and CO_2 costs in any given year. In this case, it is assumed that there is a mix of existing coal and gas plants in the system, so that 80% of the time marginal demand will be met by the plant with higher SRMC for that year, and 20% of the time marginal demand will be met by the plant with lower SRMC for that year (*i.e.*, during off-peak times). The merit order may change from one year to the next during the run depending on what happens to the stochastic CO_2 and fuel prices.

In all three cases, the SRMC calculates fuel costs based on assumed plant efficiencies for existing plant of 38% for a coal plant and 48% for a gas plant, fixed operating and maintenance costs of \$3.33/MWh for a coal plant and \$1.5/MWh for a gas plant, and CO_2 costs based on emissions factors of 94.6 tCO_2/TJ input fuel for a coal plant and 56.1 tCO_2/TJ input fuel for a gas plant. The final price of electricity comprises the SRMC element plus an additional spark spread[1] of \$5.5/MWh which is assumed to vary stochastically, according to geometric Brownian motion with a 20% annual volatility, zero correlation with gas prices and moderate (37%) correlation with CO_2 price variations. These assumptions about the price formation process for electricity are relevant to competitive markets where electricity prices are determined by the cost of generation of the marginal plant in the system. In price-regulated markets, a firm's revenue will be determined by the costs of generation of each individual plant in their fleet. This would lead to a different risk exposure.

2.6. Calculation of risk premiums

The risk premiums of climate policy uncertainty impact on power investment were calculated under two scenarios. In the first scenario, we used the traditional project evaluation method, namely discounted cash flow without taking into account price uncertainty, ADB (2002). In this method, investment capital, project operation and maintenance costs, future carbon price, energy price and project revenue were all taken as non-stochastic, at their expected values, subject to deterministic rates of growth. With these certain values, we calculated the project cash flow and discounted it to get the net present value ($NPV_{certain}$) of the project. In the second scenario, we use the ROA with carbon and energy prices set as uncertain variables. The distribution of the project $NPV_{uncertain}$ including the option to optimise the timing of the investment decision is derived by hundreds of thousands of Monte Carlo simulations. More details on the calculation of the NPV distribution and all other equations of the whole model can be found in Yang and Blyth (2007). By comparing the expected NPVs of

[1] The spark spread is the nominal trading contribution of a gas-fired power plant from selling a unit of electricity, having bought the fuel required to produce (at 48% efficiency) this unit of electricity. All other power plant costs (operation and maintenance, capital and other financial costs) must be recovered from the spark spread.

the two scenarios, we derived the premium of carbon price, *i.e.*, climate policy, uncertainty. In a simplified mathematical equation, it can be expressed as follows:

$$\mathrm{RP(USD/kW)} = \frac{(\mathrm{NPV_{uncertain}} - \mathrm{NPV_{certain}})(\mathrm{USD})}{\mathrm{Capacity(kW)}} \quad (6)$$

Where: RP (USD/kW) is the risk premium of the project investment, ($NPV_{uncertain} - NPV_{certain}$) represents the additional revenue of the project in USD, which is required to trigger investment at year *t*, and the Capacity is the total additional capacity in kW due to the investment.

3. Scenarios, assumptions and technology data

To identify the relative importance of CO_2 price uncertainty and fuel price uncertainty, the model was run separately for three different scenarios: (1) keeping CO_2 prices constant with stochastic fuel prices; (2) keeping fuel prices unchanged with CO_2 prices changing randomly; and (3) with both CO_2 and fuel prices varying stochastically. The model was also run with three different assumptions about which type of plant would be on the margin of the system and therefore setting electricity prices: (1) coal plants determine prices; (2) gas plants determine prices; and (3) the model determines the marginal plant (either coal or gas) depending on the prevailing fuel and CO_2 prices in any year.

Table 1 shows some of the technology data assumptions. These are based on the average of plant costs given in NEA-IEA (2005), with minor modifications for coal and gas plants based on discussions with power companies which co-operated in the work. More significant modifications were made regarding costs for a nuclear plant. Taking a simple average of costs from NEA-IEA (2005), nuclear would be the cheapest option even under a scenario with zero carbon price. Since the aim of the analysis was to determine the effects of carbon price uncertainty, costs for nuclear power were raised to an expected level where the financial case for all three technologies (coal,

Table 1
Technical assumptions used in the model

Project specific assumptions	New coal	New gas	New nuclear
Project lifetime (Years)	40	25	40
Capacity retrofitted (MWe)	1350	1350	1350
Capital ‘overnight’ cost ($/kW)	1320	589	2528 [b]
Construction period (years)	3	2	6
Capacity/load factor [a]	85%	85%	85%
Average generation efficiency	46%	57%	33% [c]
CO_2 emissions factor for fuel (tCO2/TJ input energy)	95	56	0
Fuel costs ($/MWh)	15	22	10
Fixed operation and maintenance costs ($/kW-Yr)	42.5	42.5	99 [b]
Variable operation and maintenance costs ($/MWh)	3.3	1.5	0.4

Notes for table:

[a] Load factors for coal-fired, gas-fired and nuclear power plants are usually different. In this case study, we used the same value (85%) assuming that all the power plants will be able to run as base-load plants. This way, we put all the power plants in the same operation level to better compare the impacts of climate policy uncertainty on different technologies.

[b] Overnight cost is the cost of a construction project if no interest was incurred during construction, as if the project was completed “overnight.” Capital and fixed O&M costs are increased by $840/kW and $32/kW-yr respectively representing 2 standard deviations above the average in NEA-IEA (2005).

[c] Fuel cycle costs for nuclear are included in the variable operating and maintenance costs.

gas and nuclear) were approximately equivalent under our fuel and CO_2 price assumptions. Although this meant raising capital and operating costs for nuclear power by two standard deviations relative to the mean in NEA-IEA (2005), these figures are still lower than other recent estimates used for policy analysis purposes (*e.g*. DTI, 2006).

The technology data includes assumptions about the build time for each technology. This is taken to be the delay between committing capital to the project and generating revenue. Capital is assumed to be spent at a constant rate over this period. The discount rate used throughout for the cash-flow for evaluating present values of future costs and revenues is 7%. Capital costs are assumed to be subject to an annual depreciation tax shield of 13.3% of capital costs against a corporation tax rate of 31%. Final cash-flows and risk premiums are evaluated post tax.

In this study, we did not explicitly consider technical risks. The capital and operating costs of each technology, as well as their performance characteristics (efficiency, load factor, etc.) were assumed to be known with certainty. In principle however, the methodology described in this paper could be extended to analyse the effects of these important additional sources of risk.

4. Results

Fig. 5 shows the relative importance of fuel and CO_2 price risks for the three different power generation technologies under the three different scenarios and the three price-setting assumptions. As mentioned, the risk premium shown here is the additional net present value (expressed in USD per unit of plant capacity) required to overcome the option value of waiting and to justify immediate investment in the face of future uncertainties. In these results, the uncertain regulatory event that causes a possible shock to CO_2 prices is assumed to occur in year 11 of the run. The risk premiums for CO_2 therefore relate to a period of 10 years of relative price stability before this possible shock occurs.

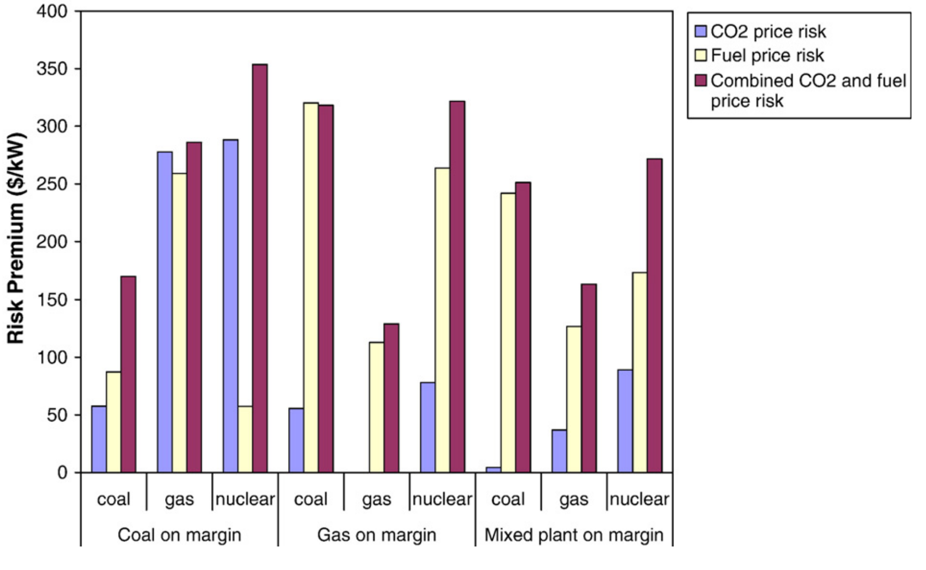

Fig. 5. CO_2 and fuel price risks with regulatory risk event of 10 years.

4.1. CO_2 price risk

In most of the cases shown in Fig. 5, CO_2 price risk is not very significant. The exceptions are for gas and nuclear plants when a coal plant is on the margin. If a coal plant is at the margin of the merit order (see the left-hand block of the results in Fig. 5), CO_2 prices are assumed to be passed through to electricity prices at a rate determined by the high emission levels of a coal plant. Gas and nuclear power investments would in this case be strongly affected by changes in CO_2 price. This is not the case for a coal plant, since changes in CO_2 price would affect both costs and revenues by a similar amount, leaving overall profitability relatively insensitive to changes in CO_2 price.

When a gas plant is on the margin (see the central block of results in Fig. 5), the rate of feed-through of CO_2 prices to electricity prices is significantly lower because of the lower emission levels of a combined cycle gas turbine (CCGT) plant compared to a coal plant. Therefore the CO_2 price risk for coal and nuclear plants is quite low.

When the marginal plant is allowed to vary (*i.e.*, “mixed plant on margin” results on the right of Fig. 5), CO_2 price risk is still quite low, as this case is actually closer to the 100% gas plant on the margin case than the 100% coal plant on the margin case under the assumptions made in the model.

4.2. Fuel price risk

Coal prices are assumed in the model to be relatively stable, so fuel price risk is mostly created by uncertainty in gas price, and the possibility for this to feed through to the electricity price. In the case where a coal plant is always on the margin, the electricity price is unaffected by gas price uncertainty, so the fuel price risk for coal and nuclear plants is low. The fuel price risk for a gas plant in this case is high because gas price fluctuations would affect the generation costs without any corresponding change in the revenues.

In the case where a gas plant is always on the margin however, the fuel price risks for a new gas plant are low because fluctuations in fuel prices would show up in corresponding fluctuations in the revenue, leaving overall profitability relatively insensitive to fuel price changes. Coal and nuclear plants would be heavily exposed in this case to gas price fluctuations via the feed-through of these fluctuations to the electricity price.

The fuel price risk is reduced slightly in the case with mixed plant on the margin because for some fraction of the time a coal plant would be setting the electricity price, thereby reducing on average the expected level of price fluctuations.

4.3. Combined CO_2 and fuel price uncertainty

The combined risk is not a simple addition of the fuel and CO_2 price risks, since it has to take account of the correlation between the two sets of prices. An interesting example is to compare gas power and nuclear power investments under the “coal on margin” case. The nuclear plant investment has high CO_2 price risk but low fuel price risk, giving a combined risk premium only slightly greater than the CO_2 price risk premium. The gas power investment has high CO_2 risks and high fuel price risks, but the combined total is not much higher than the sum of the individual components. The reason is that there is assumed to be some correlation between gas prices and CO_2 prices. Therefore, when gas prices are lower than expected (favouring the investment in a gas plant), the CO_2 prices will also tend to be lower than expected, offsetting some of the benefits of the low gas price.

In any case, it is interesting to note that in all three cases of different assumptions of the marginal plant, nuclear power investments appear to be amongst the most risky. The reason is that

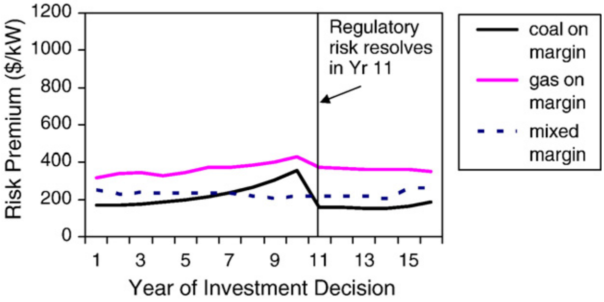

Fig. 6. Coal plant — evolution of risk premium overtime.

CO_2 and fuel price uncertainties are expected to be reflected in electricity prices, and will therefore directly affect nuclear plant revenues. For the two fossil-fuel technologies, fuel and CO_2 prices can affect both costs and revenues which makes the profitability (difference between revenues and costs) less sensitive to fluctuations in these prices.

4.4. Risk premiums under different assumptions of electricity price-setting

Figs. 6–8) show how the risk premiums (for coal, gas and nuclear power respectively) evolve over time if the decision to build a plant is taken closer to the time of the uncertain regulatory event leading to a possible CO_2 price shock. The vertical axis shows risk premium in USD/kW, the same units as for Fig. 5. The horizontal axis indicates the year in which the decision to build is taken. The possible (stochastic) CO_2 price jump occurs in year 11. The figures show the combined CO_2 and fuel price risk premiums under the three different assumptions about electricity price-setting. Under the stochastic price variations assumed in the model, fuel price risks remain approximately constant over time, whereas CO_2 price risks increase as the date of the possible CO_2 price shock is approached, and then decrease again after the price shock (*i.e.*, once the regulatory uncertainty is assumed to have been resolved). CO_2 price risks therefore become relatively more important when there is less time available between the build decision and the date of the possible price shock.

Under all the three price-setting assumptions, when the build decision is being taken in Year 1, the overall risk premium is dominated by fuel price risk which is assumed to be constant over time. In the coal-on-margin case, CO_2 price risk starts to become more important, leading to an increasing overall risk premium if the build decision is taken from Year 6 onwards. In the gas-on-

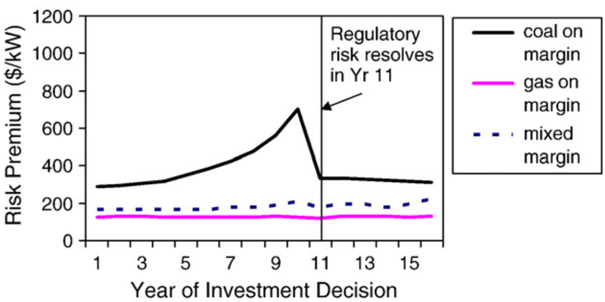

Fig. 7. Gas plant — evolution of risk premium overtime.

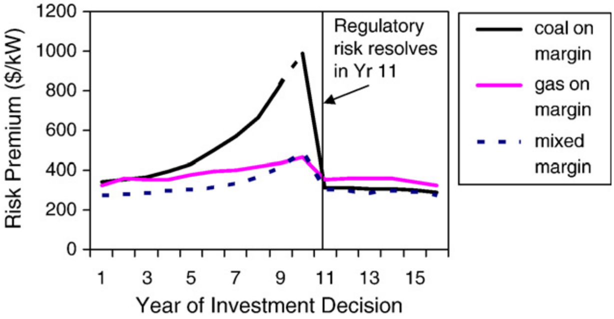

Fig. 8. Nuclear plant — evolution of risk premium overtime.[2]

margin case, overall risks remain dominated by gas-price risk, and the CO_2 price risk only leads to a slight rise in the total risk. In the mixed-margin case, the average emissions rate of the marginal plant turns out to be very close to the total emissions rate for the new coal build, so the CO_2 price risk appears very low throughout because the rate of CO_2 pass-through to costs and revenues are closely matched under these particular assumptions. This result also justifies why a power company would like to invest in diversified power generation technologies to minimize its risk.

For a gas plant, CO_2 risks are only really significant when a coal plant is on the margin. In this case, the overall risk premium increases strongly as the date of the possible price shock is approached. When a gas plant or mixed plants are on the margin, the risk premium stays relatively low throughout.

Nuclear plants are more sensitive to CO_2 price uncertainty in general because there is no balancing of risks between costs and revenues of the cash-flow. The risk premium increases when time is approaching towards Year 10 under all three price-setting assumptions, but most dramatically under the coal-on-margin case which has the highest rate of pass through of CO_2 costs to electricity costs.

On the basis of our assumptions and the results in Figs. 6–8, the option values of waiting for the investments in coal, gas and nuclear power are in the ranges of \$180/kW–\$400/kW, \$160/kW–\$690/kW, and \$210–\$900/kW, depending on which technology is running on the margin and on the amount of time between the year when a company builds the plant and the year when the government announces a new regulation on climate change.

5. Conclusions

In this study, climate policy risk is modelled as the market price for CO_2 emissions, which could be subject to trends or interventions. Although the computational model is quite detailed, and the ROA implemented through extensive stochastic price scenarios and multi-stage dynamic programming, relatively simple case study examples suggest the following conclusions:

1. Policy uncertainty becomes increasingly important if there is only a small amount of time available between the investment decision and the possible price shock representing the policy uncertainty of specific climate change policy events. The reason is that the value of waiting for resolution of the uncertainty increases if there is only a short time to wait.

[2] The data point for year 10 under the 'coal-on-margin' assumption is an extrapolation, as the model could not determine a risk premium value for that year of the run.

2. The risk premium created by policy uncertainty depends on how the uncertainty feeds through to electricity prices. CO_2 price risks will generally be more important if electricity prices follow the generation costs of a coal plant, as these will pass through CO_2 costs (and therefore cost uncertainties) at a higher rate.
3. Nuclear plants appear to be the most exposed to CO_2 and fuel price risks of the three technologies investigated. For investments of a coal plant and a gas plant, variations in the price of CO_2 and fuel affect both costs and revenues, thus dampening the effect of these variations on profitability. Nuclear plants are nevertheless exposed to the full revenue risk, with no offsetting through the variability in costs.

These conclusions depend on a number of key assumptions. Firstly, the electricity price formation process is crucial. This study is relevant to a situation where electricity prices are set in a competitive market, assuming that prices are determined by the cost of generation of the marginal plant in the system, and that all other power plants are price takers. In an alternative situation where revenues are based on regulated prices, a firm may instead receive revenues related to the actual costs that individual power plants incur. In this situation, the investment risks to the firm may be very much lower than those indicated in this paper, and a nuclear power plant in particular may face less commercial risk.

A second important assumption is that all policy risk is represented through the CO_2 price uncertainty. This is a convenient surrogate for analytical purposes. However, in emissions trading markets where there is free allocation, there will be additional uncertainty relating to the level of this free allocation, which effectively acts as a transfer of assets between the issuer of allowances (i.e. government) and the generators. The rules over allocation to fossil-fuel generators can certainly influence the choice of generation technology. In particular, free allocation to new entrants acts as a subsidy to fossil-fuel generators. Uncertainty in these rules can be an additional source of regulatory risk that has not been addressed in this paper, although the methodology described could be extended to consider this source of risk.

Finally, the paper did not consider technical risks such as uncertain costs, performance or load factor. The purpose of the study was to investigate the magnitude and effects of regulatory risk, and the authors did not aim to provide a full risk analysis of different investment options. Nevertheless, the real options methodology described here could be extended to include these important sources of risk, and this could be a fruitful area of further work.

The overall conclusion of this work is that the quantitative valuation of policy risk can add an important dimension to the analysis of climate change policy because of the potentially significant incremental effect of risk on incentives for investment. Risk premiums calculated in the illustrative examples were in some cases a substantial proportion of the capital costs of the investment, and could be sufficient to tilt investment choice away from those suggested by simple deterministic and expected NPV analyses.

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