Power Investment Decisions under Uncertain Carbon Policy: The Effect of Anticipated Repeal and Reinstatement of Regulations

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Abstract

Political uncertainty over global greenhouse gas (GHG) mitigation policy is likely to defer investment in cleaner technologies. It may also incentivise short-lived, high-cost interim investments while businesses wait for the uncertainty to subside. The range of possible policy responses to the issue has created uncertainty over the future of national mitigation pathways. Given that the electricity sector, globally, is a major emitter of GHGs, this represents a systematic risk to investment in electricity generation assets. This paper uses a real options analysis framework informed by a survey of experts conducted in Australia - used as a proxy to model the degree of the uncertainty- to investigate the optimal timing for investment in the conversion of a coal plant to a combined cycle gas turbine plant using the American-style option valuation method. The effect of market and political uncertainty is studied for the *Clean Energy Act 2011* in Australia. Political uncertainty is addressed bi-modally in terms of: (1) uncertainty over the repeal of the carbon pricing policy, and (2) if it is repealed, uncertainty over the reinstatement of the policy, to represent the effect of electoral cycles and the possibility of more stringent future global mitigation efforts. Results of the analysis show that although political uncertainty with respect to GHG mitigation policy may delay investment in the conversion of the coal plant, expectations over the reinstatement of the carbon pricing reduces the amount of option premium to defer the conversion decision.

Keywords: Energy investment, Real options, Australian climate policy, Political Cycles, Uncertainty

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Nomenclature

Indices	
$i = 1,2,\dots,I$	Iteration index
I	Total number of iterations
$t = 1,2,\dots,T$ and Δt	Time stage, time interval, month
T	The end of planning horizon, (480 months)
Carbon and electricity price model parameters	
$P_{c,t}$	Carbon price at time t (A$/tCO2)
μ_c	Carbon price drift rate (per annum)
σ_c	Volatility of carbon price (per annum)
$\tilde{\varepsilon}_{t,c}$	Standard normal random variable to generate carbon price volatility
$\widetilde{M}_{i,t}$	Node mode random variable for iteration i at time t
$m_{i,t}$	Node mode for iteration i at time stage t. $m_{i,t} = 0$ represents that node placed at replication i at time stage t has not fallen in repeal mode by the time t. Similarly, $m_{i,t} = 1$ represents repealed nodes and $m_{i,t} = 2$ shows reinstated nodes
$\epsilon_{r,t}$	Random number drawn from a uniform probability distribution for simulation of repeal occurrence, $0 < \epsilon_{r,t} < 1$
$\epsilon_{s,t}$	Random number drawn from a uniform probability distribution for simulation of reinstatement occurrence, $0 < \epsilon_{s,t} < 1$
$\bar{P}_{c,t}$	Expected price of carbon upon reinstatement at time t, A$/tCO2
$P_{e,base,t}$	Base price of electricity at time t, A$/MWh
$P_{e,base,avg.,t}$	Forecasted average base price of electricity at time t used in the mean-reversion process, A$/MWh
η_e	Reversion speed of the electricity price
σ_e	Volatility of electricity price
$\tilde{\varepsilon}_{t,e}$	Standard normal random variable to generate electricity price volatility
$\gamma_{i,t}$	Average emission intensity of electricity generation mix at time t, tCO2/MWh
$p_{r,t}$	Probability of repeal at time t, %
$p_{s,t}$	Probability of reinstatement at time t, %
$\varphi_{i,t}$	overall probability of repeal at time t conditional upon remaining in repeal mode from time t to the end of the planning horizon, %
$\psi_{i,t}$	overall probability of remaining in repeal mode from time t to the end of the planning horizon, %
λ_{MGA}	Emission intensity decay ratio, medium global action (MGA) scenario
λ_{CEA}	Emission intensity decay ratio, the *Clean Energy Act 2011* (CEA) scenario
Valuation parameters	
r	Required discount rate
$eNPV$	Extended/expanded net present value, result of real options analysis (ROA) analysis, A$
$sNPV$	Standard net present value, result of discounted cash flow (DCF) analysis, A$
OV	Option value, A$
$MV_{i,t}$	Market value of the coal plant for iteration i at time t, A$
$\overline{MV}_{t,k}$	Average market value of the coal plant at time t over node modes k, A$
$opv_{i,t,\tau}$	Present value of operating profits for iteration i, assuming operating from time t to time τ, A$
$\pi_{Coal,i,t}$	Operating profit of the coal plant for iteration i at time t, A$
κ	Coal plant value recovery factor, %

1. Introduction

The risk of investment in contemporary energy supply has been magnified as a result of exposure to climate change policy risk in addition to traditional risk factors. However, given the aforementioned policy risk and its potential impact on carbon and energy prices, it is not only current policy settings that will influence current investment decisions in long-lived carbon price exposed assets, but also expectations over future policy settings.

The increasing reliance on coal for electricity generation in Australia makes it a high per-capita emitter of greenhouse gases (GHGs). A long period of political negotiations culminated in 2012 with a carbon pricing mechanism. This started with a fixed price of A$23/tCO2, to be followed by an emission trading scheme (ETS) with a floating price and an emissions cap. However, lack of bipartisan support has threatened the policy's sustainability. In 2013, the recently elected Federal Government put before parliament a package of seven carbon tax repeal bills, all of which were rejected by the Senate. However, with the Senate make-up being unknown until mid-2014 these repeal bills could still be passed into law at some uncertain time in the future. Because we have access to data from a survey of experts by Jotzo et al. [1] conducted in mid-2012, we take the perspective of decision makers with the information that was available prior to the repeal bills being put before parliament.

In this paper, a case study is developed to evaluate the timing of a hypothetical brown-field conversion to a combined cycle gas turbine (CCGT) plant or abandonment of an existing coal-fired steam turbine (CFST) plant in New South Wales, Australia that expands upon the real options analysis (ROA) model presented in Shahnazari et al. [2]. This expanded model provides a more realistic framework matched with expectations among investors about the future of carbon pricing, addressing some of the knowledge gaps in the existing literature. This is the first study, to our knowledge, that accounts for reinstatement of the policy to reflect the effect of electoral cycles and/or a more stringent global effort toward GHG mitigation. Our model also develops a more realistic simulation of uncertainty over repeal and reinstatement of the carbon policy over an expected time period. As such, probability distributions of repeal and reinstatement (derived by a survey of experts) are allocated for each time stage to represent various expectations over respective carbon policy events in the future.

This case study represents a short-term response to carbon pricing that dampens its financial impact on the owner of a CFST asset. Given that a substantial proportion of the capital cost of incumbent CFST plants are sunk, their early scrapping and replacement with new low-emission technologies is a costly option. Therefore, brown-field augmentation of CFST with gas turbines, to benefit from a lower emission intensity and higher energy conversion efficiency, is potentially attractive as a means of preserving some of the asset value that was sunk into the original investment.

Real options theory has been employed to evaluate investment decisions in electricity markets mainly in the last two decades with a more recent uptake in green policy evaluation applications. Dixit and Pindyck [3] have shown by a simple example how ROA can support electricity planning decisions. A key element of risk management is to acknowledge the value of waiting to acquire more information about market and political conditions before committing to an investment, which will be referred to as the value of flexibility in this paper. Consequently, the notion of a 'now-or-never' investment in generation assets – as would be encapsulated by a traditional discounted cash flow (DCF) analysis – does not fully capture the temporal leeway at a potential investor's disposal. Other studies, such as Tseng and Barz [4], Deng and Oren [5], and Reuter et al. [6] have focused on short-term operational variability and flexibility and/or constraints on investment decisions. Reuter et al. [7] have compared greenfield investment in wind turbines with investment in coal plants.

Coinciding with increasing global concern regarding the anthropogenic causality of climate change, many studies have assessed the effect of uncertain forthcoming GHG mitigation regulations in terms of policy design and implementation timing on investment decisions, herein called pre-implementation studies. These studies give considerable foresight into the effect of uncertainty and volatilities in the business environment. Numerous studies have shown that market and political uncertainty can affect investment in generation technologies both in terms of choice of technologies and timing of investments. Grubb and Neuhoff [8] have identified three correlated problems eroding the efficiency and effectiveness of the European emission trading scheme (EU

ETS). They argue that design of permit allocation, uncertainty over the commitment to continuation, and the effect on relative international competitive advantage of key sectors are major factors weakening the EU ETS. Reinelt and Keith [9] explore the effect of uncertain natural gas and carbon prices on choice of generation technology and optimal timing of investment, and conclude that the interaction of regulatory uncertainty with an irreversible investment significantly raises the social cost of carbon abatement. Fuss et al. [10] find that uncertainty pertaining to volatile carbon prices in a carbon permits trading market expedites investments in carbon-saving technologies.

Numerous studies have attempted to assess the value associated with waiting to retrofit incumbent coal-fired generation with carbon capture and storage (CCS) technology in a pre-implementation mode [9-16]. To the best of our knowledge CCS technology has not been established at a commercial scale, and so there is an additional uncertainty as to whether or not it will ever leave the research and development stage, which may not have been accounted for in the literature above. Instead, this paper investigates an option that is ready to exercise immediately due to the fact that conversion from CFST to CCGT is a viable technology. Moreover, in this conversion process, some of the sunk costs associated with the original investment into a CFST plant can be preserved.

Concerns over relatively recent enacted carbon pricing regulations, among early adopters, has switched to presumptions about the continuation of the policies in light of the lack of cross-party support in the political spectrum at national and international levels. In contrast with pre-implementation studies, the literature on the effect of political uncertainty on investment decisions in the post-implementation phase, where carbon pricing policy is already in place, is limited. Hoffman [17] provides empirical evidence regarding the actual effect of EU ETS on investment decisions in the German electricity industry. His findings show that companies integrate carbon costs into their investment decisions, however, in comparison with the objectives of the EU ETS, the induced technological transition to cleaner technologies are obstructed significantly by the lack of a long-term signal to decrease emission caps. Blyth et al. [18] and Shahnazari et al. [2] have shown that the closer in time a change in policy is expected, the higher the perceived risk by the investor, and consequently the investment decision may be delayed until after the resolution of political uncertainty. Fuss et al. [10] find that political uncertainty might limit the diffusion of less carbon-intensive technologies. Boomsma et al. [19] analyse investment timing and capacity choice for renewable energy projects in the presence of feed-in-tariffs and renewable energy certificate trading and find that uncertainty regarding the change of support scheme creates an incentive to defer investment in larger projects.

Political uncertainty has been modelled in various ways. Yang et al. [20] and Shahnazari et al. [2] have used a step function to simulate political uncertainty assuming that price shocks occur with a known probability at certain times in the future. Fuss et al. [10] have modelled political uncertainty with a 50% probability of policy repeal at a known expected time. The model developed by Blyth et al. [18] represents climate change policy uncertainty as a potential step-change shock (positive or negative) to carbon prices at some fixed point in time. In the Australian study by Reedman et al. [12], a carbon tax of a known size at an uncertain date in the future is introduced, however, their approach limits the expectation of arrival of the policy to only once in a known 10 year period. In contrast, the model developed here is novel as it models political uncertainty through a range of expectations over carbon pricing policy repeal and reinstatement.

Using a real options analysis (ROA) method, this paper presents a set of results and their implications stemming from the modelling of these uncertainties in the context of the aforementioned investment decision. Moreover, price paths are informed by Treasury forecasts, assuming these data were the best available information for a decision maker to base an investment decision upon at the time the decision was made. This approach accounts for carbon price pass-through and technological changes with respect to the effect of expected carbon prices on the modelling of electricity price paths.

2. Model

It is assumed that a 400MW coal-fired steam turbine power plant has been running for 10 years, and the remaining life of the plant is 40 years from the present time. Under anticipated increasing carbon prices, the investor has the option to invest in the conversion of the plant to a CCGT power plant in response to the looming cost, or abandon the plant under high future carbon prices. The options available to the investor are: (1) to invest in the plant conversion to CCGT, (2) to abandon the plant, or (3) to take no action. However, with uncertain carbon prices in the future due to either a policy regime change or volatility in prices in the liberalized emission trading market, the investor has the option to wait and acquire information about the future, to at least be partially informed about the commitment of the government to the current policies.

Climate change political uncertainty is modelled inclusively by carbon price. The model assumes a geometric random walk (GRW) process to simulate carbon price paths:

$$P_{c,t+1} = P_{c,t} e^{(\mu_c . \Delta t + \sigma_c . \tilde{\varepsilon}_{t,c})} \tag{1}$$

where, $P_{c,t}$ is carbon price at time t, μ_c is the drift parameter, σ_c is the price volatility, Δt is time steps in the model, which is 1 month, and $\tilde{\varepsilon}_{t,c}$ is a standard normal random variable. The starting carbon price and its drift rate used in this study are based on the *Clean Energy Act 2011* (CEA) policy scenario forecast values modelled by Treasury [21].

To represent the effect of carbon price shocks that are either the result of carbon policy repeal or reinstatement, simulation of the carbon price paths is complemented with two probability mass functions at each time stage t, one for repeal and one for reinstatement. In contrast to similar works, the probability distributions applied here will provide a more realistic model of the expectations over the future of the policy. First, the probability of repeal is dynamic in terms of changing probability distributions in the future representing expectations over the repeal of the policy over time. Second, there is consideration for reinstatement of the policy should repeal occur. To emphasise again, this, in turn, reflects expectations over a more serious global agreement to mitigate emissions and/or the effect of domestic electoral cycles.

For each time stage, it is assumed that dual political outcomes (repeal or no-repeal and reinstatement or no-reinstatement) take the form of a Bernoulli distribution, where the mass function probabilities are adjusted over time. The CEA policy scenario is assessed by applying subjective probabilities of repeal and reinstatement from a survey of experts conducted by Jotzo et al. [1]. The survey captured a sample of views over future carbon pricing policy settings held by people whose advice regarding this issue may have been sought by power system investment decision makers prior to the September 2013 Australian Federal election. From this survey data, we estimate a binomial proportion 95% confidence distribution using the method suggested by Clopper and Pearson [22] for each time step over the relevant portion of the planning horizon. The model is run for combinations of the lower and the upper 95% confidence bounds of the survey derived subjective probabilities of repeal and reinstatement, as well as their expected values, as shown in Fig. 1. The respective probability mass functions are derived such that the overall probability of repeal and reinstatement follow the full-sample figures obtained by the survey. Accordingly, as the survey shows, there is a 39 per cent probability of repeal (39 per cent of respondents expected the current carbon pricing to be repealed) by 2016, but 81 per cent expectation over the existence of a carbon price in 2020, leading to a 52 percent reinstatement expectation.

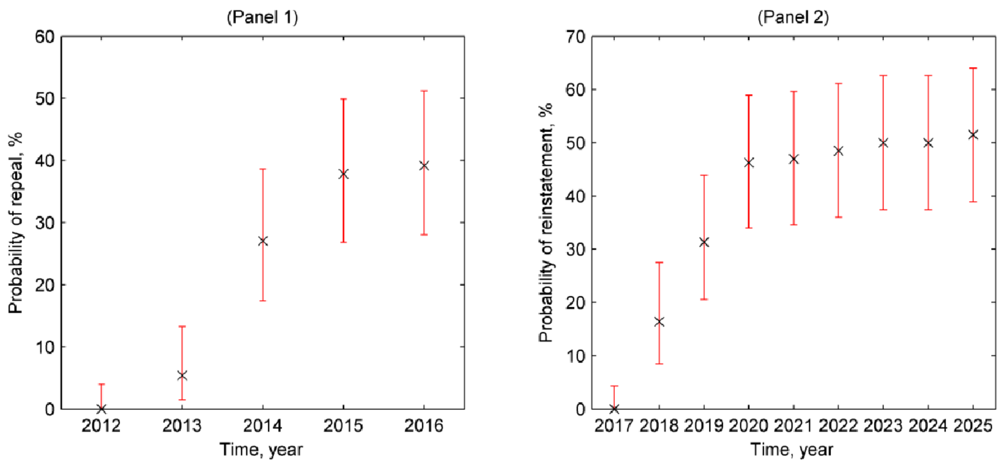

Fig. 1. Panel 1 shows 95% confidence interval for cumulative yearly probability of repeal, Panel 2 shows 95% confidence interval for cumulative yearly probability of reinstatement

Carbon (and electricity) prices will be simulated for a number of replications, i $(i = 1,2,\dots,I)$, at each time stage, t $(t = 1,2,\dots,T)$, resulting in a total of $I \times T$ decision nodes. Each decision node in the simulation takes one of three modes: (1) Mode 0: where the carbon price has not been dropped by time t, $(m_{i,t} = 0)$; (2) Mode 1: carbon price has been effectively set to zero as a consequence of the relevant policy repeal $(m_{i,t} = 1)$, and (3) Mode 2: where carbon price has been reinstated from the repeal mode $(m_{i,t} = 2)$. Accordingly, carbon prices will be generated conditional on path modes and probabilities of repeal and reinstatement as follows,

$$P_{c,t} = \begin{cases} 0 & , \quad \epsilon_{r,t} < p_{r,t}\,, m_{i,t-1} = 0 \\ P_{c,t}\ (from\ Eq.1), & \quad \epsilon_{r,t} \geq p_{r,t}\,, m_{i,t-1} = 0 \\ 0 & , \quad \epsilon_{s,t} \geq p_{s,t}\,, m_{i,t-1} = 1 \\ \bar{P}_{c,t} & , \quad \epsilon_{s,t} < p_{s,t}\,, m_{i,t-1} = 1 \\ P_{c,t}(from\ Eq.1)\,, & \quad m_{i,t-1} = 2 \end{cases} \tag{2}$$

with $\epsilon_{r,t}$, $\epsilon_{s,t}$ being random numbers between 0 and 1 generated by a random number generator with a uniform probability distribution, and where $p_{r,t}$ and $p_{s,t}$ define the probability of occurrence of repeal and reinstatement at time t, respectively. It should be noted that $\bar{P}_{c,t}$ is the level of carbon price upon reinstatement. Jotzo et al. [1] have collected the expectations of experts over the price of carbon and have found that the forward price is u-shaped with a large variance, having a 60% confidence interval ranging from zero to A$25/tCO2 in 2020. For simplicity, in this study we use the reported mean for subjective carbon prices derived from the survey for 3 distinguished time periods: (1) between 2016 and 2018: $\bar{P}_{c,t} = \$16/tCO2$, (2) between 2018 and 2020: $\bar{P}_{c,t} = \$20/tCO2$, and (3) between 2020 and 2025: $\bar{P}_{c,t} = \$28/tCO2$. Other parameters used in the stochastic modelling of the state variables are presented in Table 1.

To analyse the effect of electricity price uncertainty and uncertainty associated with a policy regime change, a mean adjusting and reverting (MAR) process as developed by Shahnazari et al. [2] has been used.[1] To briefly explain this process, the price of electricity is assumed to be affected by the carbon price in two ways: (1) the direct effect of carbon cost pass-through, and (2) the indirect effect of carbon price-induced restructuring of the generation mix. For this purpose, the electricity price was decomposed into the price of electricity without a carbon price, $P_{e,base,t}$, and a component that is the result of carbon price pass-through to electricity prices; this approach is similar to Koljonen et al. [23] and Laurikka [24]. It was assumed that the carbon price will be passed to electricity prices by a transformation factor γ_t,

$$P_{e,t} = P_{e,base,t} + \gamma_t . P_{c,t} \tag{3}$$

The transformation factor at any point in time is the emission intensity of the marginal plant in the generation system. However, in our study the focus is on average monthly values, so $P_{e,t}$ is an average monthly price of

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[1] For a detailed explanation of this modelling technique see Shahnazari et al. [2].

electricity and γ_t is a monthly average emission intensity of the generation mix. The base price of electricity, $P_{e,base,t}$, i.e. the price of electricity without the effect of carbon, is also influenced by the generation mix. In summary, the first term on the right hand side of Eq. 3 contains the indirect effect of carbon price on electricity price and the second term provides the direct cost of carbon price pass-through.

The average base price of electricity, $P_{e,base,t}$, in Eq. 3, is modelled through the logarithmic MRV process given below,

$$\ln\left(P_{e,base,t+1}\right) = \ln(P_{e,base,t}) + \eta_e.\left(\ln(P_{e,base,avg.,t}) - \ln(P_{e,base,t})\right) + \sigma_e.\tilde{\varepsilon}_{t,e} \tag{4}$$

where, η_e is the speed of reversion, $P_{e,base,avg.,t}$ is the average level of $P_{e,base,t}$, that the level of $P_{e,base}$ tends to revert to, $\tilde{\varepsilon}_{t,e}$ *is* a standard normal random variable, t denotes the time stage and σ_e is the volatility in electricity prices. To model the short term correlations between the price of carbon permits and electricity prices in the market, the error terms of the two price processes are correlated in Eq. 1 and Eq. 4. A covariance/correlation matrix has been used to generate linearly correlated data.

This study uses deterministic values for γ_t and $P_{e,base,avg.,t}$ based on policy scenario modelling performed by Treasury [25], however, they will be adjusted conditionally, based on the modes $(m_{i,t})$ of the prices in simulated paths. It should be noted that the average base price and emission intensity should be fed into the model as an exogenous variable, and emphasized that average emission intensity is determined by the electricity generation mix. However, the composition of the energy mix, per se, is dependent on political uncertainty. For the purpose of the current study, it is assumed that the emission intensity of the generation mix will decrease according to deterministic assumptions in the CEA scenario despite the existence of political uncertainty in paths nodes with $m_{i,t} = 0$.[2] Similar to path nodes with $m_{i,t} = 0$, upon reinstatement of prices $(m_{i,t} = 2)$, emission intensity will be decreased exponentially from the last values prior to the reinstatement, to a minimum of 0.05, with a constant decay ratio extracted from forward trend intensity curves developed by Treasury. Should a drop in prices occur $(m_{i,t} = 1)$, it is assumed that emission intensity will continue to decrease exponentially with a constant decay ratio, λ_{MGA}, to a minimum of 0.73, as extracted from medium global action (MGA) scenario forward trend intensity curves developed by Treasury.[3]

Accordingly, the average emission intensity of the generation mix is calculated for all simulated nodes conditional on the node modes, $m_{i,t}$, and $\varphi_{i,t}$,

$$\gamma_{i,t+1} = \begin{cases} \max\left[\gamma_{i,t} e^{-\lambda_{MGA}.\Delta t}, 0.73\right], & m_{i,t} = 1 \\ \max\left[\gamma_{i,t} e^{-\lambda_{CEA}.\Delta t}, 0.05\right], & m_{i,t} = 0, \ or \ m_{i,t} = 2 \end{cases} \tag{5}$$

where λ_{MGA} and λ_{CEA} are emission intensity decay ratios derived from the MGA and CEA scenarios, respectively. The average base price of electricity, $P_{e,base,avg.,t}$, may also be affected according to the generation composition. However, further investigation reveals that the base price of electricity in each of the MGA and CEA scenarios does not deviate significantly until early-2030, as forecasted by Treasury forward curves. Correspondingly, it is assumed that carbon price uncertainty does not affect the base price of electricity since the political uncertainty modelled here is taken to be resolved completely by 2030. However, upon reinstatement of carbon prices it is assumed that $P_{e,base,avg.,t}$ will exponentially increase by a growth rate derived from the mean of the average base prices for the MGA and CEA scenarios. In the case where a price path remains in repeal mode, it is assumed that the respective average base price of electricity remains constant in real terms. Parameters used in the modelling of the electricity price are presented in Table 1.

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[2] In the interest of maintaining the paper's focus on the development of the model the effect of political uncertainty on the emission intensity is not detailed here. However, a further model developed has shown that this correlation does not have a significant effect on the results of the analysis.

[3] The MGA scenario assumes countries implement the less ambitious end of their mitigation pledges made in the Cancun Agreements and Copenhagen Accord, and stabilise greenhouse gas concentrations at 550 ppm by around 2100 [21].

Table 1
Parameters for price paths modelling

Parameter	Symbol	Unit	Value
Initial electricity price	$P_{e,base,1}$	A$/MWh	42[a]
Electricity price volatility	σ_e	per annum	1.344[b]
Carbon price volatility	σ_c	per annum	0.0287[c]
Electricity price reversion speed	η_e	-	0.54[b]
Correlation coefficient between carbon and electricity price	-	-	0.7[d]
Emission intensity decay ratio, CEA scenario	λ_{CEA}	per annum	0.026[a]
Emission intensity decay ratio, MGA scenario	λ_{MGA}	per annum	0.005[a]
Average base price of electricity growth rate (after reinstatement)	-	per annum	0.039[a]
Decision horizon (or converted plant life)	T	years	40
Nominal rate of return	r	%	9.48[e]
Inflation rate	-	%	2.5[a]

[a] Data taken (or derived) from the Treasury modelling, see references [21, 25]
[b] Electricity price model parameters extracted from historical price data from 1999 to 2012 in the National Electricity Market, NSW, Australia
[c] Similar to Fuss et al. [10] data is taken from GGI scenario database, International Institute of Applied System Analysis, see reference [26]
[d] Similar to Szolgayová et al. [11], a further investigation of the model also shows that it does not affect the direction of the results.
[e] Data form ACIL Tasman report, see reference [27]

A backward dynamic programming technique is applied by starting at the latest decision point and working back to the first decision point, comparing the value of the options to exercise the conversion, abandon the plant or take no action versus the continuation value, to obtain the optimal exercise policy in order to maximise the sum of the discounted expected future cash flows. The method to obtain the optimal actions resembles the procedure explained in detail by Shahnazari et al. [2], using the Monte Carlo simulation method developed by Longstaff and Schwartz [28] (also known as the least square method) to calculate optimal investment rules.

The output of the least square Monte Carlo method is a distribution of optimal investment timing along with the extended net present value. The value of the option to wait, OV, is evaluated after estimating the standard net present value ($sNPV$) for the investment decision, calculated using a traditional DCF method as shown by Eq. 9:

$$eNPV = sNPV + OV \tag{6}$$

It should be stressed that the DCF methodology presented here uses the same simulated price paths as the ROA method. The option value ratio (OVR) developed by Shahnazari et al. [2] is used as a decision metric. It is the percentage of option value (OV), as calculated by Eq. 9, to the value of the project, $sNPV_{Conv.,1}$, and measures the magnitude of the value of holding and waiting to exercise the option.[4]

To model the replacement or abandonment decision, an estimate of the market value of the incumbent coal plant, $MV_{i,t}$, is required. Generally, the market value is a function of the probability of repeal, the probability of reinstatement and the expected time to these respective events. It should be noted that the value of the plant at any time stage t is determined by the information that is at hand, as well as expectations about the future. As such, the market value takes three forms depending on the status of the carbon price in each decision node:

(1) where a node has not been repealed before ($m_{i,t} = 0$) the market value of the plant is assumed to be the average present value of the operating profits produced by the plant, estimated deterministically and weighted by the overall probability of repeal and reinstatement,

[4] For a detailed explanation of this metric (OVR) see the previous study by Shahnazari et al. [2].

(2) where a path node is in repeal mode ($m_{i,t} = 1$) the market value of the plant is assumed to be the average present value of the operating profits produced by the plant, estimated deterministically and weighted by the overall probability of remaining in repeal mode ($\psi_{i,t}$) and reinstatement ($1 - \psi_{i,t}$), and,

(3) where a decision node is in reinstatement mode ($m_{i,t} = 2$) the market value of the plant is assumed to be the average present value of the operating profits produced by the plant estimated deterministically.

The steps to formulate the market value of the CFST plant, $MV_{i,t}$, is described below,

$$MV_{i,t} = \begin{cases} (1-\varphi_{i,t}).\overline{MV}_{t,0} + \varphi_{i,t}.\left[\psi_{i,t}.\overline{MV}_{t,1} + \left(1-\psi_{i,t}\right).\overline{MV}_{t,2}\right] & m_{i,t} = 0 \\ \left(1-\psi_{i,t}\right).\overline{MV}_{t,2} + \psi_{i,t}.\overline{MV}_{t,1} & m_{i,t} = 1 \\ \overline{MV}_{t,2} & m_{i,t} = 2 \end{cases} \tag{7}$$

For each simulated path i, the overall probability of repeal at time t, conditional upon the path remaining in repeal mode to the end of the planning horizon, is defined as below derived from the survey data,

$$\varphi_{i,t} = P(\widetilde{M}_{i,T} = 1 | m_{i,t} = 0) \tag{8}$$

where $\widetilde{M}_{i,t}$ is a random variable taking node modes (0,1 and 2) for iteration i at time t as sample space, and $m_{i,t}$ is the realisation of $\widetilde{M}_{i,t}$ at time t. Note that at any decision time t, $\widetilde{M}_{i,T}$ $(t < T)$ is a random variable. To put it another way, $\varphi_{i,t}$ is the probability of repeal at any time after t, for iteration i, conditional on remaining in repeal mode to the end of the planning horizon T.

Similarly, the overall probability of a repealed path remaining in repeal mode is defined as below, assuming that the repeal has already occurred,

$$\psi_{i,t} = P(\widetilde{M}_{i,T} = 1 | m_{i,t} = 1) \tag{9}$$

To calculate the average present value of the plant, $\overline{MV}_{t,k}$, the present value of cash flows, $opv_{i,t,\tau}$, are estimated for each iteration i , starting from time stage t to each succeeding termination time stage τ up to the end of the plant life,

$$opv_{i,t,\tau} = \textstyle\sum_{z=t}^{\tau} \pi_{Coal,i,z}.e^{-r(z-t)}, \tau = t, t+1, \dots, T \tag{10}$$

Each $opv_{i,t,\tau}$ represents the present value of profits accrued from operating the plant in the aforementioned period. The maximum of $opv_{i,t,\tau}$ over each iteration i for various termination times τ yields a forward looking/deterministic value, $mv_{i,t}$, of the plant,

$$mv_{i,t} = \max(opv_{i,t,t}, opv_{i,t,t+1}, \dots, opv_{i,t,T}, 0) \tag{11}$$

Finally, an average of $mv_{i,t}$ over all iterations that fall in each path mode, k, at the end of the planning horizon, T, represents an estimate of $\overline{MV}_{t,k}$,

$$\overline{MV}_{t,k} = \underset{t}{\text{average}}(\forall mv_{i,t} | m_{i,T} = k), k = 0,1,2 \tag{12}$$

$MV_{i,t}$ calculated by the above model, in Eq. 7 is then scaled by a recovery factor, $\kappa_{recovery}$ (initially set to 50%) ,to represent the amount of the plant value that can be recovered through a sell-off/scrapping transaction.

Availability and auxiliary usage are assumed to be similar in both plants to limit the results of the model that are specifically sensitive to emission rates and efficiencies, allowing outputs to be comparable to each other. It is also assumed that a typical 400MW CCGT generation train consists of a 267MW gas turbine coupled with a 133MW steam turbine. Hence, in a typical coal plant conversion, approximately one third of the CFST plant's asset value (1 steam turbine unit) is transferred to the converted plant to achieve the same total output.

Other sources of costs in this analysis, such as capital costs, are considered to be deterministic. The effect of technical improvements, exchange rate, productivity and commodity variation over the decision horizon has been reflected through forward curves provided by the Australian Energy Technology Assessment (AETA) report 2012 [29]. Fuel and operating and maintenance forecast prices are assumed to be deterministic and data from the Treasury model [21] and an ACIL Tasman report [30] are used. Moreover, it is assumed that once the decision to convert the plant has been made, the plant is built and operated immediately, ignoring construction times. However, this assumption does not affect the quality of the results as they will only shift the pattern of the outputs without considerable impact on their interpretation. Technological data for CFST and CCGT plants collected from AETA 2012 and ACILTasman [30] are shown in Table 2.

Table 2
Power plant data for the CFST and the CCGT plants

Parameter	Unit	CFST	CCGT
Nominal capacity	MW	400	400
Availability	%	83	83
Auxiliary	%	3	3
Sent-out electricity	MWh	2803200	2803200
Emission intensity	tCO2e/MWh	1	0.368
Thermal efficiency (as gen.)	%	33.3	49.5
Fuel consumption	GJ/year	31441297	21151418
Fixed O&M	A$/year	19,400,000	3,880,000
Variable O&M	A$/year	3,363,840	11,212,800
Capital cost of conversion (typical)	A$/kW	-	1,062
Remaining life	year	40	-
Economic life	year	50	40
Part of coal plant used in conversion	%	33.3%	-

3. Results

The results of the simulation are expressed in a region of high confidence centred on the $eNPV$ and $sNPV$ obtained when the model is run with the expected value of subjective probabilities of repeal and reinstatement as inputs. The region of high confidence is based on the 95% confidence intervals for those model inputs, as outlined in Section 2. This is in effect a sensitivity analysis informed by the estimated distribution of the subjective binomial probabilities of repeal and reinstatement.

Although, the model can be run with various combinations of probability of repeal and reinstatement within the respective confidence intervals, the boundaries of the region of high confidence in the results of the ROA and DCF can be found by using three distinctive combinations of probability of repeal and reinstatement:

(1) least probable repeal scenario, where the probability of repeal is taken from the lower bound of the estimated confidence interval and the probability of reinstatement is taken from the upper bound of the relevant estimated confidence interval,
(2) base-case scenario, where the original data taken from the survey performed by Jotzo et al. [1] is used for both probabilities of repeal and reinstatement , and
(3) most probable repeal, where the probability of repeal is taken from the upper bound of the estimated confidence interval and the probability of reinstatement is taken from the lower bound of the relevant estimated confidence interval.

It should be noted that the higher the magnitude of uncertainty, the more opportunities there are to take advantage of flexibility in decision making. This adds to the potential for a broadening gap between the results of the ROA valuation and the DCF analysis, i.e. the flexibility option premium. Accordingly, among the three scenarios above it is expected that scenario (3) will reveal the highest OVR ratio, as the overall probability of repeal is the highest for all scenarios. Conversely, scenario (1) is expected to yield the lowest OVR, as it has the lowest overall probability of repeal for all scenarios. From another viewpoint, the uncertainty with respect to repeal of the policy, as quantified by the probability of repeal distribution over the planning horizon, is in the favour of the incumbent coal plant. However, any probability of reinstatement works in the opposite direction. Intuitively, the most supportive circumstance for the continuation of the incumbent CFST plant operation is scenario (3), with the highest overall probability of repeal. A similar argument can be made for the most supportive circumstance for conversion to the challenger technology, i.e. CCGT, yielding scenario (1) with the lowest overall probability of repeal.[5]

3.1. Calculation of implied confidence region

The results of the modelling for the base-case scenario (2) are shown in Fig. 2. Use of the standard $NPV > 0$ decision criterion would trigger an immediate conversion to a CCGT plant at time $t = 1$. Note that although the abandonment of the plant yields a positive NPV, it is less than the expected payoff from converting the plant. However, there is an opportunity cost of immediate investment that is related to the higher returns that could be attained through delayed investment. The $sNPV$, $eNPV$, option premium, OV, and OVR results are listed in Table 3. The OVR obtained for this scenario is about 7.4%, representing a premium that is accrued to the investor that delays the investment decision. The ROA technique explicitly estimates extended NPV with the number of iterations, I, set to 1000. As shown in Fig. 2, Panel 6, about 19% of the iterations indicated that abandonment of the CFST plant was optimal towards the middle of the planning horizon. In the case where the optimal outcome for an iteration did not involve plant abandonment, the result of each iteration was allocated to one of 40 bins shown in Fig. 2, Panel 5. No iterations indicated 'no action', i.e. that the optimal decision was to continue with production from the CFST plant. The bulk of the iterations indicated that the optimal decision was to convert to a CCGT plant early in the planning horizon. Nevertheless, the distribution of optimal conversion and abandonment time do not provide a decisive criterion that can advise the optimal investment choice with relevant timing, as the optimal decision cannot be derived from the diagram because the expected $eNPV$ is a weighted average of all the iterations. Although the majority of iterations recommended immediate conversion of the plant, a significant number suggested abandonment of the plant towards the middle of the planning horizon.

[5] It should be noted that CFST and CCGT plants are both non-zero emission technologies. Although the repeal of the carbon pricing policy works in favour of both plants, it drives the optimal decision to continue with the operation of the CFST plant.

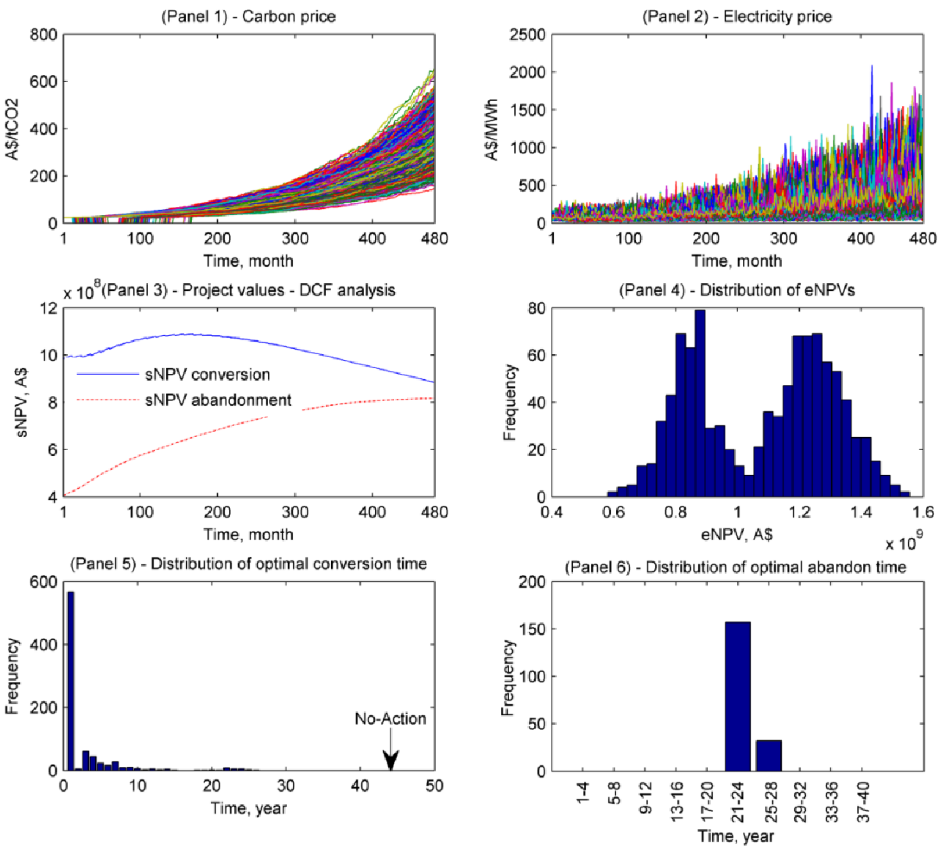

Fig. 2. Model output for optimization of timing of the investment options. Panel 3: DCF technique recommends conversion of the plant immediately ($\boldsymbol{at\ t = 1}$) as $\boldsymbol{sNPV_{Conv.,1} > 0}$.

A visual inspection of the distributions of optimum exercise times, such as those presented in Fig. 2, Panel 5 and Panel 6, along with the corresponding OVR values can assist the investor in identifying the optimal decision. An OVR threshold can be inferred from a set of various probability distributions of repeal and reinstatement. If the OVR values are less than the threshold, the optimal decision is to immediately exercise the optimal investment choice (conversion or abandonment). For example, in cases where the OVR is significantly close to zero there is a single significant peak at the beginning of the planning horizon, which indicates that it is optimal to begin immediate investment in conversion. Conversely, where OVR values substantially deviate from zero there is no single significant peak and the majority of iterations suggest either delaying the decision to convert, abandoning the plant or taking no action.[6] As such, the result of the simulation for the base-case scenario suggests that the investor has to delay the investment decision, considering a significant 7.4% OVR and the non-existence of a single peak either in the conversion or the abandonment distribution of optimal investment times.

Table 3
Project values for the base case and implied confidence region boundaries, A$

	$eNPV$	$sNPV_{Conv.,1}$	OV	OVR,%
Scenario (1) ,lower boundary	1.12×10^9	1.08×10^9	4.05×10^7	3.7%
Scenario (2) ,base-case	1.08×10^9	1.01×10^9	7.48×10^7	7.4%
Scenario (3) ,upper boundary	1.02×10^9	8.81×10^8	14.1×10^7	16.0%

Similar to the base case (2), the model was run for scenarios (1) and (3), representing the lower boundary and upper boundary of the confidence region, respectively. Table 3 presents the results of the analysis for all three scenarios. It can be deduced that a higher overall repeal probability, as in scenario (3), results in a higher OVR.

[6] A more detailed discussion of this procedure can be found in a recent study by Shahnazari et al. [2].

In other words, larger option premiums were attained by waiting when the overall probability of repeal was relatively high. A lower overall probability of repeal, as in the scenario (1), increased both the $eNPV$ and the $sNPV$, however, the option premium decreased as compared to the base case scenario. Note that the overall probability of repeal is 10.1% in scenario (1), 19.9% in scenario (2) and 31.3% in scenario (3). Also, note that the $eNPV$ as estimated by the ROA exceeds the $sNPV$ estimated by the standard DCF method in all scenarios. A further investigation of the results of the simulation for scenarios (1) and (3) also shows that delaying the decision to convert or abandon the CFST plant is the optimal recommendation. Although the OVR is relatively low, particularly in scenario (1), the distribution of optimal decisions does not show a single peak. The investor is better off to delay the decision to convert or abandon the plant, however, upon deferment, high flexibility option premium is not expected.

A comparison of the orders of the magnitude for the OVRs and the distribution of optimal decisions in this study, with those of previous findings by Shahnazari et al. [2], suggest that OVR values obtained in this study are considerably lower, owing to expectations over the reinstatement of the carbon pricing policy. These lower option premiums might switch the preference of investors to one of indifference with regards to investment in conversion or abandonment of the plant (or in extremely low OVR cases, the preference might change to immediate investment in the conversion of the CFST plant). This is completing the results suggested by Shahnazari et al. [2], where political uncertainty was modelled by a price shock representing carbon pricing policy repeal at known time periods with various probabilities. This finding can be justified by the fact that when there is a common expectation over reinstatement of carbon pricing, the effect of the expected policy repeal is substantially weakened. Fuss et al. [10] find that under a price shock with a known probability and time of occurrence, investors tend to postpone their decision until the year in which uncertainty regarding the commitment of the government is resolved. They find that a large option value exists, which will be forgone should the investor make the decision to invest immediately. Yang et al. [20] have found that in the case of gas- and coal-fired plants, political uncertainty creates a risk premium that would increase the carbon price required to trigger investment in CCS technology. However, their model of uncertainty remains limited to a price shock event similar to Fuss et al. [10] and Shahnazari et al. [2] without consideration of expectations surrounding the reinstatement of carbon pricing.

To assess the effect of reinstatement expectations, the base-case scenario (1) was modelled setting the reinstatement probabilities at zero. Results of this experiment, as listed in Table 4, showed that the OVR=17.6%, which is more than double the OVR in the original base-case scenario (1). This experiment validates our finding that expectations over the reinstatement of carbon pricing can dampen the effect of expected carbon price policy repeal on the investment decisions.

The investment decision should be re-evaluated upon unfolding events and partial resolution of uncertainty. For instance, after the 2013 elections in Australia, where the coalition won office, expectations over reversion of the proposed ETS and carbon tax were elevated due to political attempts to fulfil pledges to repeal the *Clean Energy Act 2011*. This study extends the model of political uncertainty to include distributions of repeal and reinstatement over the planning horizon. In the current case study, should the conversion of the CFST plant have not been exercised upon the arrival of a new political event, then the investment decision (conversion, abandonment or no-action) has to be reconsidered with a new set of probabilities of repeal and reinstatement. In contrast, the model of political uncertainty in other studies have been limited to a single shock, assuming that all uncertainty is resolved in the period between the present time (beginning of the planning horizon) and policy shock event. While their price shock model makes the results more transparent, it ignores an ongoing uncertainty over political decisions. For instance, Fuss et al. [10] suggest that in cases where the optimal decision is to delay the investment, the investor would postpone the investment until after the resolution of uncertainty at the expected price shock. Our model of uncertainty suggests that the investment decision should be re-assessed upon significant (and relevant) political events.

3.2. Sensitivity analysis

The sensitivity analysis of results of this study is conducted for two potential impacting factors: (1) the discount rate and (2) the salvage value recovery factor. We chose the effect of the discount rate as we believe that it's analysis was limited in the context of the current study. The other factor is exclusively introduced in this study and therefore needs to be elaborated on in more detail. Results of these analyses are shown in Table 4.

Table 4
Sensitivity analyses results, A$

	$eNPV$	$sNPV_{Conv.,1}$	OV	OVR%
Effect of discount rate, $r = 7.5\%$				
lower boundary	1.69×10^9	1.64×10^9	4.82×10^7	2.9%
middle	1.61×10^9	1.54×10^9	6.73×10^7	4.3%
upper boundary	1.49×10^9	1.33×10^9	15.2×10^7	11.4%
Effect of salvage value recovery factor, $\kappa = 75\%$				
lower boundary	1.23×10^9	1.20×10^9	2.72×10^7	2.3%
middle	1.19×10^9	1.15×10^9	4.43×10^7	3.9%
upper boundary	1.11×10^9	1.03×10^9	8.92×10^7	8.7%
Effect of no-reinstatement				
base-case (see section 3.1)	1.12×10^9	0.95×10^9	16.7×10^7	17.6%

3.2.1. Discount rate

Results of the sensitivity analysis for a discount factor $r = 7.5\%$ show that a decrease in the discount rate generally increases both the $eNPV$ and $sNPV_{Conv.,1}$, but the gap between them decreases, i.e. OVR decreases as the discount rate decreases. The increase in $eNPV$ and $sNPV_{Conv.,1}$ is simply explained by the fact that the present value of any future cash flow received by the option holder decreases with a higher discount rate. The decrease in OVR can be explained by the fact that delaying the investment decision magnifies the opportunity cost of delaying the decision (foregone payoff) that could otherwise have been attained if the investment had been made earlier in the planning horizon. Moreover, notice that towards the end of the planning horizon the gross margin of operating the CCGT plant is eroded by the high price of carbon since CCGT is not a completely carbon-free technology.

3.2.2. Salvage value recovery factor

Recovery of the salvage value of the coal plant was scaled by a factor set at $\kappa = 50\%$ in the base-case scenario. A further investigation of the model shows that a higher recovery factor set at $\kappa = 75\%$ can affect the results of the analysis. Generally, a higher salvage value recovery factor decreases the OVR. This effect can be explained intuitively by the fact that the investor is better off selling the incumbent CFST plant for a higher value that is, in effect, a certain payoff. Note that the conversion of the plant can be assumed as selling the old plant and installing a CCGT. $eNPV$ and $sNPV$ results are also greater than those of the scenarios in Table 3. This can be explained by a higher payoff within iterations where abandonment is the optimal recommendation.

4. Conclusion

In this paper we have analysed three decision options for an investor under uncertain future carbon prices: (1) to invest in conversion of an incumbent CFST power plant to a CCGT plant, (2) to abandon the operation of the CFST plant, and (3) to take no action and continue the operation of the existing CFST plant. The option to convert the CFST plant to the cleaner CCGT plant offers natural insurance against the risk of high future carbon prices. Real options analysis has been employed to account for the flexibility in delaying the decision to abandon or convert the plant until after (partial) resolution of the political uncertainty.

Political uncertainty has been modelled by the allocation of probability distributions of repeal and reinstatement derived from a survey of expert's expectations over the respective status of the carbon pricing policy in Australia conducted in mid-2012. Accordingly, this study takes an investor's perspective with the best information available at the time of the survey. As such, modelling of the uncertainty has complemented other studies in this context by addressing expectations over reinstatement of the carbon pricing policy when policy repeal is anticipated. The model of uncertainty developed is also more realistic in terms of being dynamic in contrast to numerous other studies that simulate uncertainty with a shock event in a single period. The long-term correlation between carbon and electricity prices was addressed through short and long-term mechanisms. Market value of the incumbent CFST plant was modelled conditional on the status of the carbon policy to represent the effect of expectations over the future of the carbon price on the market value of the CFST plant. Results of the ROA and the DCF methods were compared to obtain a factor, OVR, to provide investors with a metric that can be used to recommend the optimal investment timing.

All in all, the results of this analysis suggest that the carbon pricing regulatory framework and expectations over the future of the policy might encourage immediate investment in conversion of incumbent CFST plants to CCGT plants. In contrast to our earlier findings [2], an additional expectation that the policy will be reinstated, either as an outcome of alternating political cycles or a more serious global effort to mitigate carbon emissions, might substantially alleviate the effect of an upcoming carbon policy repeal to delay investment in cleaner technologies. In effect, the expected re-establishment makes the anticipated repeal short-lived.

This work provides a ROA framework that incorporates market and political uncertainty in future carbon prices that can be used by both decision makers and policy makers. For decision makers, the framework allows for a more thoroughly informed investment strategy to be developed, based upon a range of electricity generation technologies. For policy makers, the framework offers a means through which they can test reactions to potential changes, allowing them to understand the implications that implementation would have. It also provides a tool that can be used to re-evaluate the dynamically changing situation should new information arise, allowing policy makers to be more pro-active in their actions.

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