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A scenario-based integrated approach for modeling carbon price risk

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Abstract Carbon prices are highly dependent on government emission policies and local industrial compositions. When historical data does not exist or limited price data can only be sourced from another country, scenario analysis becomes the only tool for the modelling of future carbon prices. However, various plausible but equally possible scenarios can produce large variations in forecast carbon prices. In a traditional approach of scenario analysis, investment decisions or risk management strategies are proposed and analysed for each given scenario, optimal solutions are determined. However, when the number of scenarios becomes large, it often becomes too complex and intractable to have a clear view on the selection of investment decisions or risk-management strategies because these decisions and strategies are closely linked with each of the many scenarios. In this paper, it is proposed to use a stochastic mean-reversion model to represent future carbon price movements, but this model is calibrated to the forecast carbon prices of all the scenarios. In this approach, a single model is used to capture the underlying uncertainty and expectation of the stochastic carbon prices as projected by all the scenarios, carbon price risk can thus be modeled and

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analysed without the need for direct references to any specific scenarios. The modelling and management of long-term carbon-price risk are therefore purely dependent on future carbon price levels and volatilities of these scenarios, instead of on the scenarios themselves. Through such an approach, the optimization of investment decisions and risk management solutions can be much simpler because the forecasted carbon prices are the only input data.

Keywords Carbon trading · Carbon-price · Real-option · Forecasting · Scenario analysis · Mean-reversion models

JEL Classification C63

1 Introduction

Australia will formally start a market-based emissions-trading scheme (ETS) in 2010. The price levels for traded carbon emissions can only be known confidently after details of the national ETS have been legislated and only when the trading scheme is in operation with full liquidity. The scheme proposed by the Australian government will initially cover all sectors except agriculture and export exposed sectors, is designed to allow international trading if agreements can be reached with other countries and has several other features such as banking and borrowing of permits (Department of Climate Change 2008).

For any large businesses with direct exposure to the ETS, the impact of carbon prices needs to be quantified and effective risk-management strategies implemented. For example, if a power generation company plans to build a new coal-fired power plant, the company will need to add future carbon emission cost as part of per-unit cost of the new power plant, and when carbon prices are not currently known, and can also be expected to have a high degree of variability in the future, the company is not able to determine its cost base for the new power plant. Therefore the long run marginal cost of such a new power plant is very uncertain.

Cost are not the only financial variable that are effected by the introduction of emission trading. The future price of electricity will also change. It will need to increase in order to cover the costs of existing generators who may need to purchase emission permits. To accommodate growth in electricity demand the future electricity price will also need to reflect the long run marginal costs of new entrants who have a lower emission intensity but may have higher capital or operating costs than existing generators.

For both existing generators and new entrants, the impact of carbon prices on electricity prices needs to be studied before the company can estimate its likely future revenue to support decisions about new investments or different ways of operating their plant (such as reducing output or retrofitting plant with CO_2 capture and storage). In general, either to estimate future costs or forecast potential revenues, or for establish risk-management strategies for carbon price risk, a fundamental question is how to estimate and forecast carbon prices not only in the near-term such as 3–5 years, but also for the long-term, for example 30–40 years.

In forecasting long-term carbon prices, time-series analysis tools cannot be used to detect future trends and patterns because of the lack of historical data in Australia.

Similarly, observed carbon prices from permits traded on overseas exchanges cannot be directly relied upon due to the fact that carbon prices are largely driven by regulatory constraints and the composition of the local economies covered by an ETS. Additionally, carbon prices are highly dependent on technological advancement (e.g., carbon capture technologies) and regulatory changes (e.g., additional economic sectors to be included or not for emissions control). Given the uncertainties in terms of possible disruptive technology advances and government regulations around the proposed ETS, it is posited that scenario-based forecasting of future carbon prices can be a useful tool. In this paper, for scenario analysis, CSIRO's Energy Sector Model (ESM), a bottom-up partial-equilibrium model of the Australian stationary energy sector (for details, see Graham et al. 2007) is relied upon to provide forecast carbon prices under a variety of scenarios effecting the electricity generation sector. The results from ESM are augmented with other published modeling results from CSIRO (2006) and Hat eld-Dodds et al. (2007), which use a national and global general equilibrium model respectively, to provide a broader sectoral and global context as well as alternative modeling frameworks to our understanding of the range of future possible carbon prices.

The forecast carbon prices from different scenarios can vary considerably, particularly for long-term forecasts. Figure 1 represents the forecast prices of future carbon emission between 2010 and 2050. The assumptions for each of the scenarios can be found in Graham et al. (2007), CSIRO (2006) and Hat eld-Dodds et al. (2007), and scenario identi ers are tabulated in Fig. 1 as well. As shown in Fig. 1, there is a large variation in the forecast carbon prices from 2020. In this paper, we assume that each of the different scenarios can occur with equal probability in the future, the forecast price values of each of the various scenarios should thus be regarded as equally probable and likely to happen.

As can be seen from the labels in Fig. 1 many of the carbon prices based on Graham et al. (2007) differ due to a variety of domestic policy and electricity sector resource

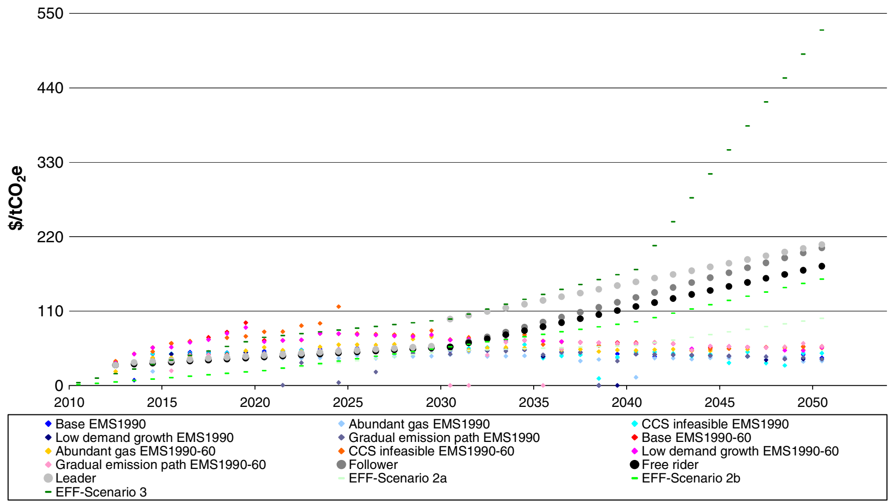

Fig. 1 Carbon price forecasts from different scenario assumptions

and technology availability conditions. The higher the domestic emission target, the lower energy demand and the more technologies and fuel options available the lower is the carbon price. For example, a deep emission cut requiring domestic emissions to fall to 60% below 1990 levels by 2050 (an “EMS 1990-60” scenario) and the condition that there is no ability to capture emissions from coal fired power stations could result in carbon prices rising to around \$100/tCO_2e by 2020 (represented as squares). On the other hand, if the emission target is for 1990 level emissions by 2050 (an “EMS 1990” scenario) and natural gas is abundant, carbon prices are projected to be as low as \$40/tCO_2e by 2020 (represented as diamonds).

The scenarios that are included from CSIRO (2006) (represented as circles and titled “Leader” “Follower” and “Free Rider”) examine the share of the global emission burden that Australia agrees to adopt finding that a higher burden (“Leader”) leads to higher costs but is offset significantly by the benefits of being able to trade emission permits with other countries when there is a greater degree of cooperation. In all of the scenarios the carbon prices converge to around \$20/tCO_2e reflecting firstly the expected international average cost of emission permits and secondly the higher costs of abatement in non-electricity greenhouse gas emitting sectors in Australia that were not taken into account in Graham et al. (2007).

The scenarios from Hatfield-Dodds et al. (2007) (shown as dashes) explore two issues. The first is the impact of all countries being subject to the same carbon price to meet a given global emission target (EFF Scenario 2a) and alternatively developed countries taking on a much larger portion of the emission reduction burden resulting in very high carbon permit prices of around \$500/tCO_2e (Scenario 3). EFF Scenario 2b is the same as Scenario 2a except that all countries, not just Australia, do not have access to technology for capturing and storing emission from coal fired power. This is projected to add \$50/tCO_2e to the global carbon price by 2050.

The different starting prices for 2010 from Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007) ranging from \$1/tCO_2e to \$35tCO_2e reflect uncertainty about how quickly the emission trading scheme will force emissions below the business-as-usual trajectory at the commencement of the scheme. Concern about the volatility of the scheme at commencement has led the Australian government to propose a price cap of \$40tCO_2e for the first five years of the scheme Department of Climate Change (2008).

In a traditional scenario analysis approach, the carbon price forecast from each of the scenarios in Fig. 1 would be studied, and corresponding risk-management strategies formulated. In this approach, risk-management decisions are clearly identified with the original scenarios selected. However, when a large number of scenarios need to be investigated, it is not easy to have a clear and intuitive grasp of such a large number of scenarios and corresponding risk-management strategies. Selecting only a manageable sub-set of most likely scenarios will however assume the risk of overlooking valuable information provided by the scenarios perceived currently as less likely, especially when there exists a large variation in the forecast price data from all the scenarios. In this paper, the focus is not on making decisions based on the most likely scenarios; rather, it is about evaluating the carbon-price uncertainties when any one of all the scenarios can happen in the future. An integrated analysis approach will be presented, and it is proposed that this approach can be more effective in analyzing a large number of scenarios such as shown in Fig. 1. For the results to be presented in the paper, we assign equal probabilities for all the scenarios in Fig. 1. However, if needed, our approach allows for including different probabilities for different scenarios by assigning different weights in formula (4) and (5) of Sect. 3 where expectations and volatilities are computed.

In this paper, it is proposed to use a single stochastic model to represent the underlying stochastic future carbon prices as forecasted by the various scenarios contained in Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007). The stochastic model should statistically exhibit the inherent stochastic features of all the scenarios as expressed through the forecast carbon prices.

In this paper, a mean-reversion model is calibrated to the variation or volatility in the forecast carbon prices from different scenario assumptions: Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007). Accordingly, the calibrated mean-reversion model captures the variation or volatility of the forecast carbon prices as well as their expected future mean values. The model essentially quantifies the variability and expected average future prices in the original scenario assumptions. The calibrated model can therefore be regarded as an integrated model that encapsulates future carbon price levels and their variability as predicted by the different scenarios. The model can be conveniently used to simulate future stochastic carbon prices for evaluating investment decisions, for example through a real-option valuation approach. Risk-management strategies can be structured directly around carbon price uncertainties instead of scenario assumptions. Through such an approach, investment decision trees can be embedded within optimisation processes, and any risk-management solutions are calculated directly off carbon price levels, not pertinent to any particular scenario assumptions.

2 Mean-reversion model for future carbon prices

The price of carbon traded on the future Australian ETS can be expected to be determined by the usual demand-and-supply mechanism from all market participants. We can also expect the carbon price to behave very similarly to the prices of other commodities currently traded on exchanges around the world, such as the WTI crude oil on the New York Mercantile Exchange, or copper on the London Metal Exchange.

For commodities, their prices are generally modeled with some form of mean-reversion feature. The rational for mean-reversion is that the price of a commodity tends to be pulled back to its production cost plus a margin; for example, when the commodity price is much higher than its production cost and an additional margin, more competitors will move in, the volume of production will also be expanded by existing players to try to profit from the high price, subsequently, the increased production will make the supply exceed the demand, and the price of the commodity will fall due to oversupply; conversely, when the price is much smaller than the production cost plus a margin, the volume of production will be reduced to cut down on loss, demand not met by diminishing supply will then drive up the price, the commodity price thus exhibits a reversion to a mean value which should be the production cost plus a margin. For carbon emission prices, we will adopt a mean-reversion model.

To prevent the carbon price from the possibility of being negative, we use a log-normal mean-reversion spot model:

$$d \ln S = [\theta(t) - a \ln S]dt + \sigma(t)dZ \tag{1}$$

to describe the spot price movement of the carbon price at time t, a is the mean reversion rate, $\theta(t)$ is the value of the mean reversion level multiplied by the reversion rate, and σ is the volatility of the logarithmic value of the carbon spot price. Z is a Wiener process of zero mean value and of a variance of dt.

If a new variable X is defined, and it has an initial value of zero and follows the stochastic equation:

$$dX = -aXdt + \sigma dZ \tag{2}$$

then a new variable Y is also defined so that:

$$dY = (\theta(t) - aY)dt$$

Therefore, $X = \ln S - Y$ and also $S = e^{X+Y}$.

Since $X = 0$ at $t = 0$, $Y|_{t=0} = \ln S_0$. The stochastic variable X can then be used to represent the carbon price S via $S = e^{X_1+Y_1}$, and Y can be determined by ensuring the model reproduces the expected forecast carbon prices at any future time t. The mean-reversion level for ln S can then be calculated as:

$$\frac{\theta(t)}{a} = Y(t) + \frac{1}{a}\frac{dY(t)}{dt} \tag{3}$$

For the carbon price model (1), when futures prices and implied volatilities of vanilla options Hull and White (1994) on some of these futures prices are available and very liquid in the market, the market data can be used to calibrate the parameters in Eq. (1). The model (1) thus calibrated represents the carbon price process in the risk-neutral world (see Hull 2002), and the calibrated mean-reversion level is the mean-reversion level in the risk-neutral world. It is noted that parameter $\theta(t)$ is determined by formula (3), and the value $Y(t)$ in the formula (3) is calculated iteratively during calibration when the expectation of S in the risk-neutral world is matched to input market futures prices at time t.

Because the Australian ETS is not yet in operation, futures prices and options on these futures are not available. To determine the parameters in model (1), this paper proposes to use the forecast carbon price data from the different scenarios of Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007) as input data to calibrate the model (1). Because the scenario assumptions incorporate future technological advancement, the forecast carbon prices would be more reliable than using historical data from the European Union Emissions Trading Scheme (EU-ETS) because disruptive changes in technologies and government regulations can not be reflected by available historical data.

The scenarios of Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007) are regarded as plausible and equally probable scenarios that can happen in the physical world, not in the risk-neutral world. When scenario-based forecast data is used to calibrate model (1), the calculated mean-reversion level is not in the risk-neutral world, but in the risk-adjusted world because the forecast data is the expected outcomes produced from plausible scenarios in the current risk-averse world. Therefore, the drift rate in model (1) should be adjusted for market risk if the model is used for evaluating options or investment returns. The historical carbon price data from the EU-ETS can potentially be used to estimate the historical market price of risk for carbon, and this estimated market price of risk can then be used for model (1).

3 Calibration to forecast carbon prices from different scenarios

Let $\hat{S}_i^k$ be the forecast carbon price at future time t_i from the k-th scenario. The expected future price is therefore calculated as:

$$F_i = E(S^k) = E\left(\hat{S}_i^k\right) = \frac{1}{N}\sum_{k=1}^{N} w_k \hat{S}_i^k \tag{4}$$

Here, at time t_i under the kth scenario, the carbon price $\hat{S}_i^k$ is deterministic, the expected future carbon prices is calculated as the expectation of carbon prices of all the scenarios $k = 1, \ldots N$. w_k is the weighting of the kth scenario and it is a reflection of the probability when the kth scenario is expected to occur. w_k satisfies the relationship: $\sum_{k=1}^{N} w_k = N$.

In standard financial market applications, model (1) is calibrated to market traded volatilities of vanilla options and these volatilities are normally quoted through the Black-Scholes formula (see Graham et al. 2007). In the current application, the volatilities of the forecast carbon prices are calculated by assuming the prices follow a geometric Brownian motion (see CSIRO 2006). The volatility Vol at time t_i is thus calculated as:

$$\text{Vol}_i^2 = \frac{1}{N-1}\sum_{k=1}^{N} w_k \left(\ln \hat{S}_i^k - A_i\right)^2 \tag{5}$$

Where $A_i = \frac{1}{N}\sum_{k=1}^{N} w_k \ln \hat{S}_i^k$ is the average value of the logarithmic carbon prices forecasted for time t_i.

The forecast carbon prices for different scenarios (Graham et al. 2007; CSIRO 2006; Hatfield-Dodds et al. 2007) are used to calculate the expectation and volatility of forecast carbon prices. Equation (4) is used to calculate the expected future carbon prices between 2012 and 2050. Figure 2 plots the carbon prices from 2008 to 2050. For simplicity, we assume that the price between 2008 and 2012 is constant and equals the carbon price of 2012.

The volatility or the standard deviation of the logarithmic carbon prices forecasted by the scenarios of Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007) are calculated via (5), and it is plotted here in Fig. 3 where the volatility is expressed in percentage per year. As shown in Fig. 3, volatility is very high (almost

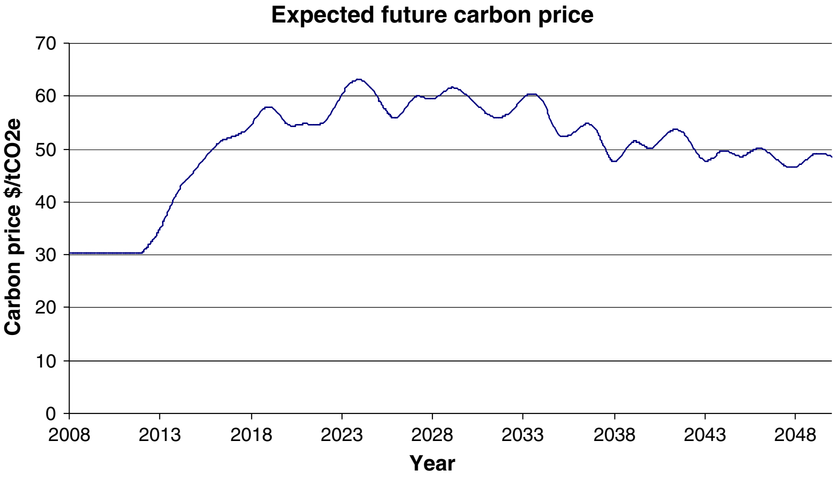

Fig. 2 Expected future carbon prices from long-term scenario analysis

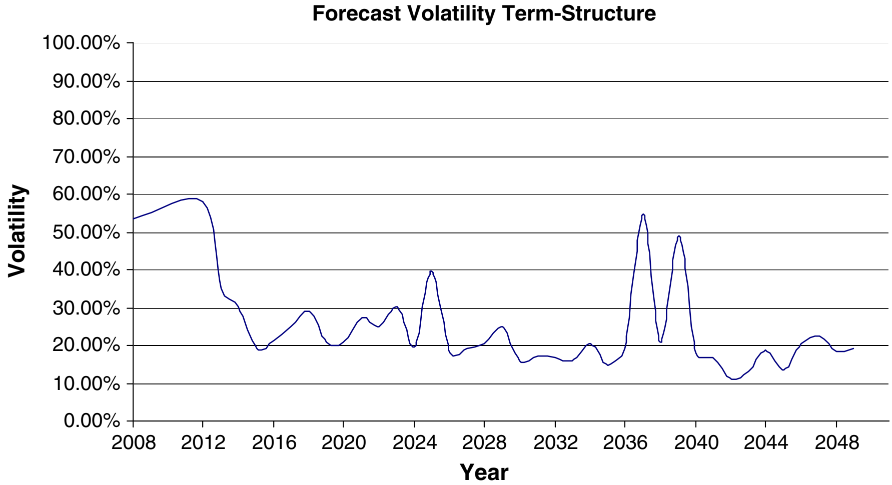

Fig. 3 The volatility of forecast carbon price from long-term scenario analysis

60%) around year 2012, the year when the scenario simulations are started. Between the year 2036 and 2040, the calculated volatility of the forecasted carbon prices from the different scenarios of Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007) surges to around 50%.

The expected values and volatilities of carbon prices as forecasted through different scenarios are used as input data to calibrate the mean-reversion model (1). Once the mean-reversion model is calibrated, the future expected carbon prices as shown in Fig. 2 can be reproduced by the calibrated model (1). The forecast volatility term-structure is matched through an optimisation scheme to minimise the difference between Vanilla option prices produced by the model (1) and those by the

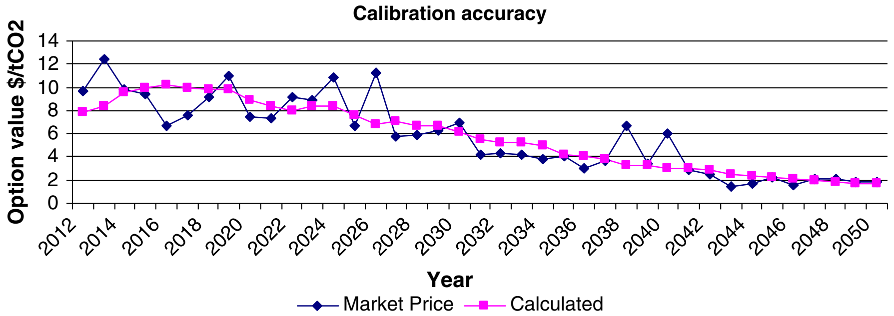

Fig. 4 The option prices as calibrated by the mean-reversion model

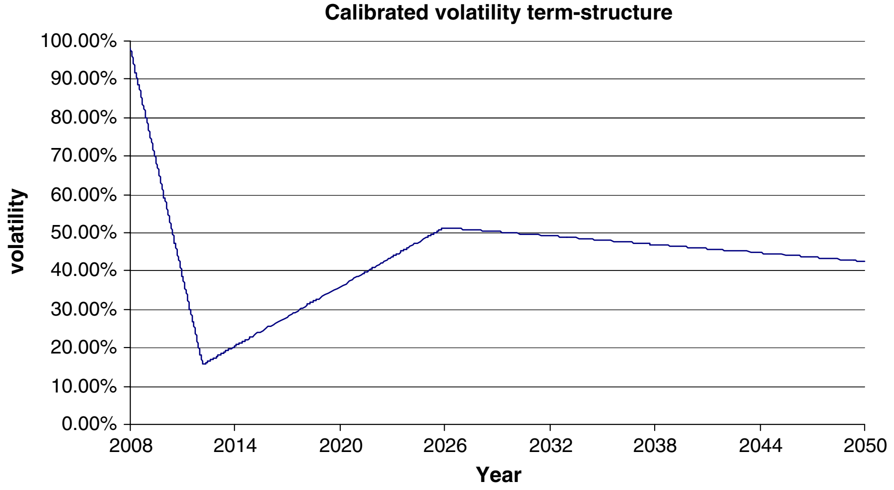

Fig. 5 The calibrated future volatility values

Black-Scholes model (Hull 2002) with the forecast volatilities as input. The accuracy of the calibration is demonstrated through the model prediction for options prices in comparison with the equivalent option prices calculated from the variances of scenario forecasts. Figure 4 shows the differences in the options values:

For the calibrated volatility, four volatility values are used to construct a volatility term-structure along the time axis. The calibrated volatility value σ is piecewise linear in time, and it is plotted below.

From the calibration of model (1), the mean-reversion level is calculated as defined by (3). The future mean-reversion level can be viewed as the price level around which the future carbon price fluctuates. From the calibration, the mean-reversion rate is also obtained as $a = 0.0854543$ per year (8.5%/year). Figure 6 plots the future mean-reversion price level.

Once the volatility term-structure (Fig. 5), the mean-reversion level (Fig. 6) and the mean-reversion rate a are determined through calibrating model (1) to the forecast carbon prices, we can employ the model (1) to simulate future carbon prices because

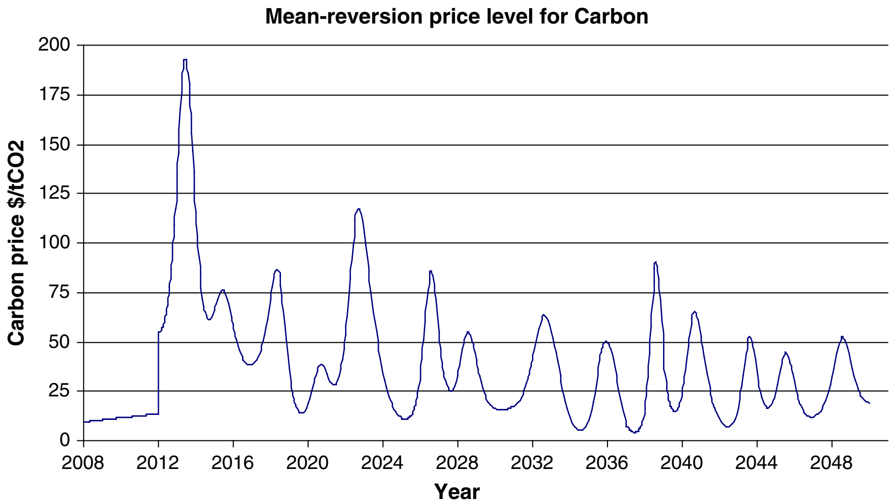

Fig. 6 The future mean-reversion level of future carbon prices

it captures the inherent stochastic features of future carbon prices as predicted by the plausible scenarios of equal probability.

4 Assessing carbon price risk via mean-reversion model

Once the mean-reversion model (1) is calibrated, it can be used for evaluating investment risks dependent directly on future carbon prices. For example, the calibrated mean-reversion model can now be used to simulate or forecast future carbon prices because the transition probability function is now known. Investment returns/costs that are dependent on the simulated carbon prices are therefore known at all future dates, and the present value of these future returns/costs can be calculated as the expectation of all the future returns/costs. In this paper, the focus is on developing a framework for using a single stochastic model to represent the vast amount of forecast data from a large number of scenarios. In a follow-up paper, details of valuing future returns/costs as part of investment decision-making processes will be provided, in which, the approach developed here will be used to establish the value of investments in tree plantations to pro t from selling carbon off-set certificates on the Australian ETS.

There are generally two ways to use the calibrated stochastic model (1) to produce future carbon prices: a). through Monte-Carlo simulations, b). through trinomial trees.

4.1 Monte-Carlo simulation of carbon prices

Because the mean reversion model (1) is calibrated to the forecast carbon prices from various scenarios of Sect. 1, the calibrated model (1) represents the underlying stochastic features of the future carbon prices as predicted by the various scenarios. Model

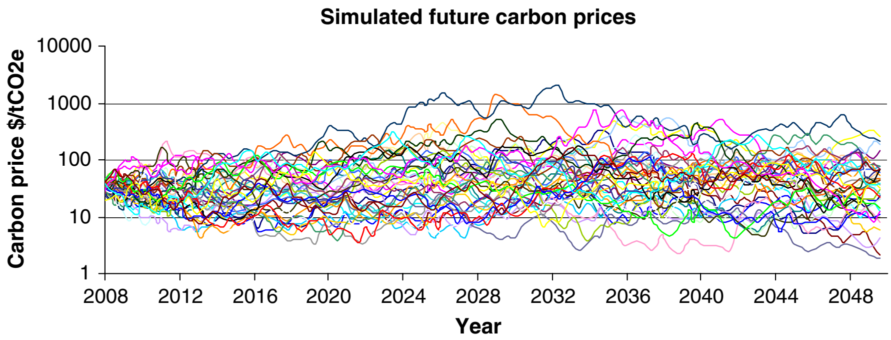

Fig. 7 The future carbon prices through Monte-Carlo simulations

(1) can be used directly through Monte-Carlo simulations to study or estimate costs or risks directly dependent on the future carbon prices. For the Monte-Carlo simulations, a simulation path can be constructed through the following equation:

$$\ln S_{i+1} = \ln S_i + [\theta_i - a \cdot \ln S_i](t_{i+1} - t_i) + \sigma_i \sqrt{t_{i+1} - t_i} \cdot \phi(0, 1) \tag{6}$$

where the path starts from today's known carbon spot price S_0, t_i is the i-th discrete time nodal point, θ_i/a is the mean-reversion level as calculated by formula (3) for time t_i, and volatility σ_i is a direct output from model calibration. $\phi(0, 1)$ is a random value of normal distribution with zero-mean and unit variance.

Figure 7 plots a total of 40 samples of simulated future carbon prices from 2008 to 2050. Each of the Monte-Carlo simulation paths is created by using (6).

Along each of the simulated paths, the calculated carbon price S_i at time t_i can be used as an input to determine costs and payoffs for investments or to inform decision-making through a real-option valuation approach, such as for the expansion/abandonment/suspension of an existing power generator.

4.2 Using tree representation of future carbon prices

Using binomial or trinomial trees for evaluating real options is often more effective and it is also easier to implement because the valuation of investment and decisions can be visualised in an intuitive tree structure, and the tree structure has a fixed number of possible carbon price levels for which investment decisions or payoff functions can be clearly stated.

Figure 8 shows the trinomial tree structure that represents the calibrated mean-reversion model (1). As shown in Fig. 8, at the beginning time $t_0 = 0$, the spot carbon price is $\$30.40/tCO_2$ which is the estimated spot carbon price for Australian ETS, at the final time $t_i = 40$ years, the future carbon prices range from $\$1.85/tCO_2$ to $\$500/tCO_2$. Such a large variation in carbon prices at future dates is due directly to the volatility values of the future carbon prices and more importantly to the time span of forty years. The extremely small or large carbon prices are not due to a particular scenario combination, these extreme price levels are automatically generated to

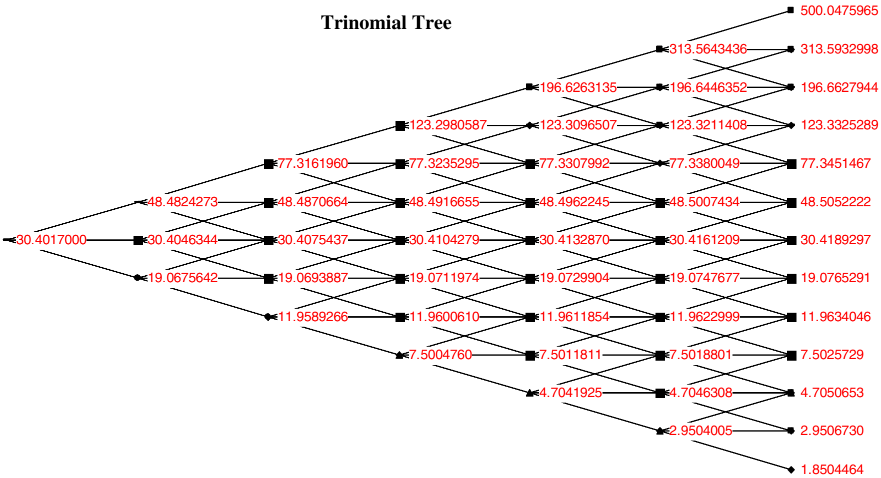

Fig. 8 Future stochastic carbon prices ($/t CO_2) as represented by a trinomial tree

construct the carbon price tree consistent with input forecast carbon price data shown in Fig. 1.

From each carbon price point at time t_i on the trinomial tree, the carbon price can move to three possible values at the next time interval t_{i+1}. There is a probability value associated with each of the three paths from t_i to t_{i+1}: P_{ik}^U is the probability from S_i^k to S_{i+1}^{k+1}, P_{ik}^M is from S_i^k to S_{i+1}^k, which is the central branch. P_{ik}^D is the probability from S_i^k to S_{i+1}^{k-1}. For details of how these probabilities are determined, please refer to Wilmott (1998). The probability values are used in real-option valuation procedures to calculate expected payoffs in the future. Fig. 9 is a schematic display of the carbon price tree grid from t_i to t_{i+1}:

The calibration process determines the probability values for all carbon price points at time t_i to the next time slice t_{i+1}. Additionally and importantly, the expectation

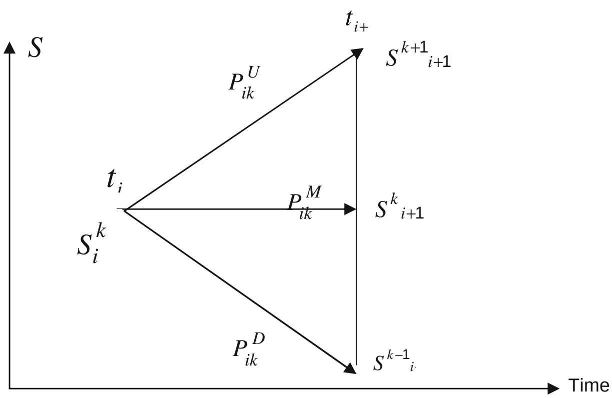

Fig. 9 Illustration of probabilities and stochastic paths within a trinomial tree

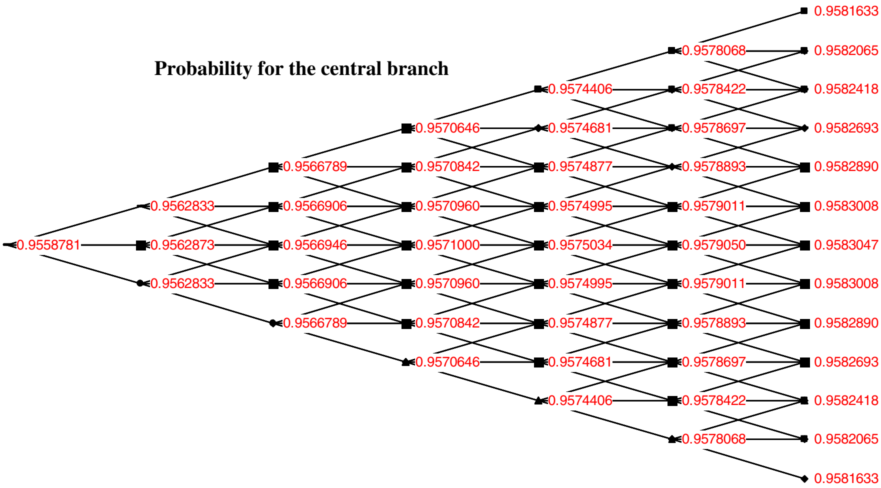

Fig. 10 Probability P_{ik}^{M} values of the calibrated trinomial tree

(or the mean value) of carbon prices at each time t_i in the tree exactly matches the expectation (or the mean value as calculated by (4)) of the carbon prices forecasted by the different scenarios. It should be noted here that to match the expectation as calculated by formula (4), $Y(t)$ in (3) is first determined, and formula (3) is then used to calculate $\theta(t)$. The calibrated tree is therefore self-consistent with the scenario forecast data of Graham et al. (2007), CSIRO (2006) and Hatfield-Dodds et al. (2007).

The following Fig. 10 illustrates the central branch probability values P_{ik}^{M} from a grid S_i^k at t_i to the next grid S_{i+1}^k at t_{i+1} (as illustrated in Fig. 9). The probability values on these tree nodes are used directly to calculate today's expectations of future investment returns linked to the carbon prices at these future dates. After discounting by using a risk-free interest-rate, these expectations are today's prices of the future investment returns.

Because the trinomial tree is fully defined by the calibrated model (1), and probabilities of moving from one carbon price point to the next are known, such as shown in Fig. 10, the probability values can be used directly to evaluate the expectations of future investment payoffs. Through model (1) and by using the trinomial tree such as the one shown in Fig. 8, investment decision-trees or risk-management solutions can be designed and implemented, and these solutions are dependent on the carbon prices, but are not linked to any specific scenarios.

5 Conclusion

This paper presents an approach of using a single stochastic model to represent the different forecast carbon prices due to a large number of plausible but equally probable scenario assumptions. In particular, a mean-reversion model is used to capture the major stochastic features exhibited in the long-term forecast carbon prices of these scenarios. The model thus provides an integrated platform for assessing and quantifying the uncertainties of future carbon prices as demonstrated by the forecast data from the various scenarios.

Once the stochastic model is calibrated to the forecast carbon prices from the scenarios, either Monte-Carlo simulation or trinomial tree methods can be used to construct risk-management strategies or to evaluate investment costs/payoffs as functions of carbon prices. Real-option valuation strategies Wilmott (2000) for existing power plants or new low-emission electricity generation technologies can be readily implemented. Additionally, the presented model can be easily used to calculate the current dollar values of planting trees to participate in trading carbon-offset certificates on the ETS.

This paper presents the first stage of work in modelling the impact of emissions trading on energy prices, in particular, on long-term electricity prices. As part of the same work, and in a separate document, the modeling of future electricity prices will also be reported. The second stage of the work will be the modeling of carbon-electricity prices through a two-factor model.

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