AN OPTIONS APPROACH TO UNLOCKING INVESTMENT IN CLEAN ENERGY

THE BANKING ENVIRONMENT INITIATIVE (BEI) NOVEMBER 2012

TECHNICAL ANNEX

UNIVERSITY OF CAMBRIDGE
PROGRAMME FOR SUSTAINABILITY LEADERSHIP

THE BEI IS A GROUP OF LEADING INTERNATIONAL BANKS LOOKING FOR WAYS TO DIRECT CAPITAL TOWARDS SUSTAINABLE, LOW CARBON GROWTH AND AWAY FROM ACTIVITIES THAT UNDERMINE IT

This is a Banking Environment Initiative (BEI) report. It should be cited as: Banking Environment Initiative (BEI), 2012, *An Options Approach to Unlocking Investment in Clean Energy*

About the Banking Environment Initiative (BEI)

The BEI was convened by the Chief Executives and Chairs of some of the world's largest banks in 2010 to identify new ways in which banks can collectively stimulate the direction of capital towards sustainable, low-carbon growth and away from activities that undermine it. The secretariat is provided by the University of Cambridge Programme for Sustainability Leadership (CPSL).

The BEI has been laying the foundations for an exciting new approach to tackling key sustainability issues through innovative bank-corporate partnerships. Two partnerships have been pioneered initially, drawing on CPSL's experience of developing business-led collaboratories: time-bound, problem-solving groups which focus on particular sustainability challenges.

This report is the product of the BEI Collaboratory on Clean Energy, which was delivered through a partnership between BEI members and a group of oil and gas and electric utility companies. Its central aim was to find ways to unlock greater mainstream investment in clean energy. This is complemented by an independent evidence base compiled by experts at the University of Cambridge's Judge Business School (JBS).

Acknowledgements

This report was written by **Dr Chi-Kong Chyong** (Research Associate, JBS) and **Andrew Voysey** (Senior Programme Manager for the Finance Sector, CPSL). Expert guidance and review was provided by **Professor Daniel Ralph** (Professor of Operations Research, JBS), **Dr David Reiner** (Senior Lecturer in Technology Policy, JBS), **Dr Jake Reynolds** (Deputy Director, CPSL) and **Richard Burrett** (Senior Associate, CPSL).

This report was championed and guided throughout by members of the BEI Collaboratory on Clean Energy, which comprised BEI banks (**Barclays**, **Deutsche Bank**, **Lloyds Banking Group**, **Nomura**, **Northern Trust** and **Westpac**) and energy companies (**BG Group**, **DONG Energy**, **Duke Energy**, **EDF Energy**, **RWE npower** and **Shell**).

This is the Technical Annex to the main report, which can be downloaded from www.cpsl.cam.ac.uk/bei, and should be read in conjunction with the main report.

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Acronyms

The following acronyms are used in this report:

AEO	Annual Energy Outlook
BEI	Banking Environment Initiative
CAPEX	Capital Expenditure
CAPM	Capital Asset Pricing Model
CCGT	Combined Cycle Gas Turbine
CCR	Carbon Capture Readiness
CCS	Carbon Capture and Storage
DCF	Discounted Cash Flow
EIA	Energy Information Administration (in the United States)
EIS	Environmental Impact Study
eNPV	Expanded Net Present Value
FEED	Front End Engineering and Design
GBM	Geometric Brownian Motion
MBTU	One thousand British Thermal Units: a unit of energy
Mt	Million tonnes
Mtpa	Million tonnes per annum
NPV	Net Present Value
OPEX	Operating Expenditure
pa	Per annum
PTC	Production Tax Credit
RO	The Renewables Obligation
ROC	Renewables Obligation Certificates

Options Analysis Procedure

As mentioned in the main report, there are several key steps in carrying out options analysis. **Figure 1** is taken from the main report and is reproduced here for consistency and convenience.

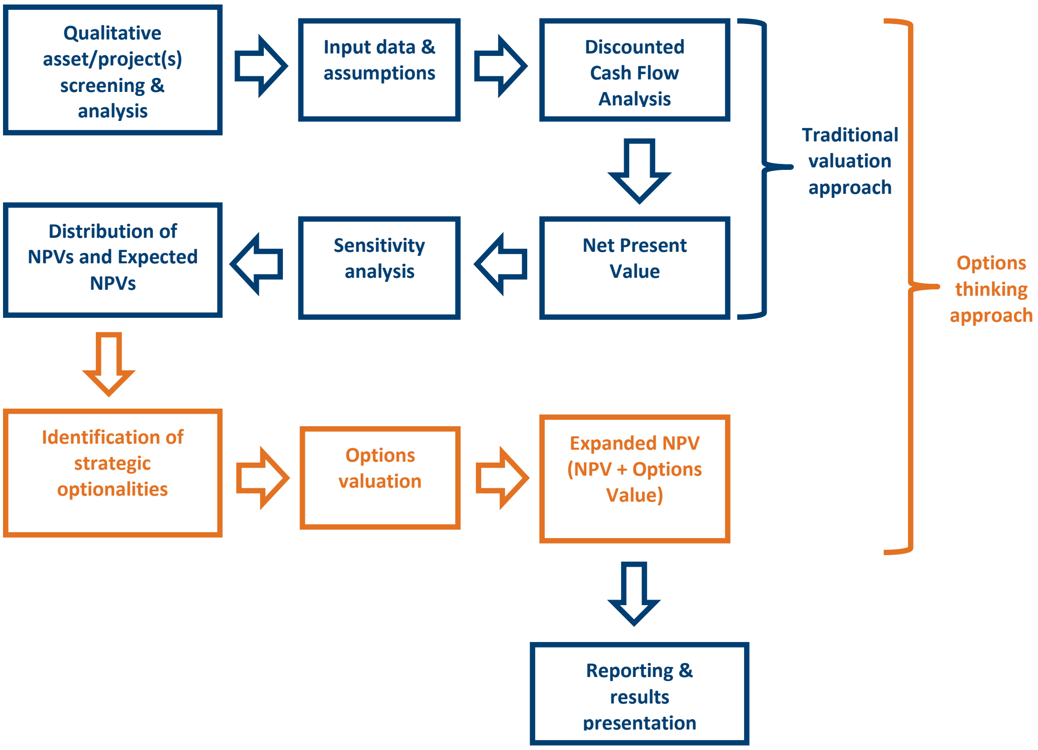

Figure 1: Flow diagram of an options approach to investment valuation, incorporating the same early steps as a Discounted Cash Flow analysis

An options approach to investment valuation builds on traditional Discounted Cash Flow (DCF) analysis and in essence consists of the following key steps, some of which are part of DCF analysis as well (

Figure *1*):

Net Present Value Analysis

For projects and assets that passed the initial management qualitative screening, a DCF model is created to analyse and derive Net Present Values (NPV) for these projects. This serves as a reference case analysis. These NPVs are calculated using a traditional approach, cost-benefit analysis, where the cost and benefit streams of the investment are projected through the course of its expected lifetime. The cumulative net benefit over the lifetime of the investment is then discounted at the appropriate rate of cost of capital (the discount rate).

Projection of cost and benefit streams could be done using time-series forecasting methods, if historical data are available. In this case, the future is assumed to behave based on past experience. Alternatively, management assumptions regarding projections of the main parameters for the NPV calculation have to be made.

Sensitivity Analysis

The NPV that we calculate using a traditional approach, DCF, is a single-point estimate, which is highly dependent on assumptions about future market conditions. This gives little confidence in its accuracy and therefore sensitivity analysis is often performed to reveal the impact of changing future market conditions on the NPV. The sensitivity analysis can be performed using Monte Carlo simulation and, as the result, an expected NPV and its distribution can be obtained. This is an important step, especially for further options analysis where we would require an estimation of volatility of the project value (underlying asset) in order to estimate an option's value. At this stage, the most important variables that contribute to the variability of the project value should be identified. For example, in our wind case studies this would be power prices and wind resources or gas prices in our gas CCS case study.

Identification of Strategic Optionalities

At this stage, some of the projects and assets that, although having a negative expected NPV, could potentially serve as a hedge and/or contribute to the overall value of the portfolio of company's assets, are prime candidates for further analysis using options analysis. The first step in this analysis is to identify embedded optionalities that these projects may contain. Sometimes, identification of strategic optionalities embedded in these opportunities might be implicitly or explicitly done during the first step of the DCF analysis (
Figure *1*). These strategic optionalities could be, among other things, the ability to expand, contract, abandon or switch the asset during its lifetime.

Options Analysis

The final step in the options analysis is to evaluate these optionalities using various methods under uncertain future market conditions. The result is an expanded NPV (eNPV) which reflects both the options value and conventional expected NPV from the DCF analysis.

In financial and real options analysis, there are multiple methods and approaches that could be used to derive an option's value, including closed-form models, like the Black-Scholes models and its variants, differential equations, multinomial lattices, Monte-Carlo path-dependent simulation approaches, variance reduction and other numerical methods. Closed-form models, binomial lattices model and partial-differential equation models are amongst the most often used techniques in the derivation of an option's value; however, in practical real options theory the binomial lattices model and closed-form models (particularly, the Black-Scholes model) have gained most attention.

The closed-form solutions, such as Black-Scholes model, although quick and easy to implement, are difficult to explain because they tend to use highly technical stochastic calculus mathematics and are very specific in nature, with limited modelling flexibility. Therefore, in this study we use binomial lattices model to derive the option's value because this method is easy to implement, flexible and easy to explain.

The binomial lattices model is a discrete-time simulation of the value of the underlying asset (i.e. free cash flow of the project). The model replicates different values that the underlying asset can take over the course of the option lifetime in a binomial tree. The model assumes that the underlying asset, S_0, follows the binomial distribution and can either increase, u, or decrease, d, every time step Δt. It is worth noting that, as time steps becomes smaller and the distribution of the underlying asset approaches the normal distribution, the results from binomial lattices model converge with those obtained using closed-form solutions.

To calculate the value of an option in the binomial lattices model we use a risk-neutral probability approach. To summarise this, instead of using a risky set of cash flows and discounting them at risk-adjusted discount rate, we can easily risk-adjust the probabilities of specific cash flows occurring at specific times (Mun, 2002). Therefore, we can discount the cash flows at the risk-free rate because risks have now been accounted for when we used risk-adjusted probabilities on these cash flows. This is the essence of binomial lattices applied to valuing options. The results of these calculations are similar to those obtained using an alternative approach – a market-replicating portfolio approach.

In any options valuation model using a binomial lattices approach, there is a minimum requirement of at least two lattices. The first lattice should reflect the movement of the underlying asset (**Figure 2**). The second lattice is constructed to evaluate the option's value. No matter what type of options we are analysing, there is always a basic structure with the following input parameters (**Table 1**).

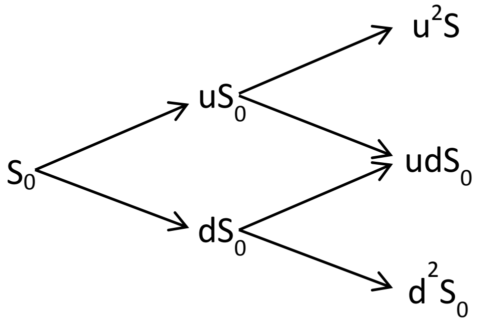

Figure 2: A two-step example of a lattice evolution of the underlying asset (S)

S	Present value of the underlying asset. This is estimated using conventional DCF analysis (NPV)
X	Present value of implementation cost of the option
T	Options time to expiration
b	Continuous dividend outflows in per cent. Since our projects are assumed to be fully equity financed there is no dividend to be paid and therefore *b=0.*
rf	Risk-free rate or the rate of return on a riskless asset.
σ	Volatility of natural logarithm of the underlying free cash flow returns in per cent. This parameter can be estimated using Monte Carlo simulation and can be conveniently derived during the 'sensitivity analysis' step of the DCF analysis (see above).
Δt	Time step
$p = \frac{e^{(rf-b)\Delta t} - d}{u-d}$	risk-neutral probabilities
$u = e^{\sigma\sqrt{\Delta t}}$	Up movement
$d = e^{-\sigma\sqrt{\Delta t}} = \frac{1}{u}$	Down movement

Table 1: Input parameters for options valuation required in binomial lattices model

Having calculated all required parameters (**Table 1**) we can then find the present value of our option in each binomial node using the following formula:

$$OV = \frac{[pOV_u + (1-p)OV_d]}{e^{rf\Delta t}}$$

Equation 1: where OV – present value of option, $OV_{u/d}$ – value of option in future up/down state, p – risk-neutral probability, rf- risk-free rate, Δt – length of time steps.

Equation 1 means that the present value of the option, *OV*, is calculated as the expected pay-off of option values in 'up state', OV_u, and in 'down state', OV_d, discounted at the continuously compounded risk-free rate, *rf*.

As we noted earlier, to estimate the option's value we should build two lattices: (i) lattice evolution of the underlying asset (**Figure 2**) with the value of the underlying asset moving up (*u*) and down (*d*), and (ii) option valuation lattice (
Figure *3*). Based on the evolution of the underlying asset tree (**Figure 2**), we use Equation 1 to estimate the present value of the option by solving it recursively.
Figure *3* shows how to estimate a two-period call option based on the lattice evolution of the underlying asset in **Figure 2**. Solving this problem recursively means that we start with the final nodes in
Figure *3* and subtract the option exercise price (*X*) from the values of the underlying asset, taken from the final nodes of the lattice tree in **Figure 2**, which is then discounted to find the present value.

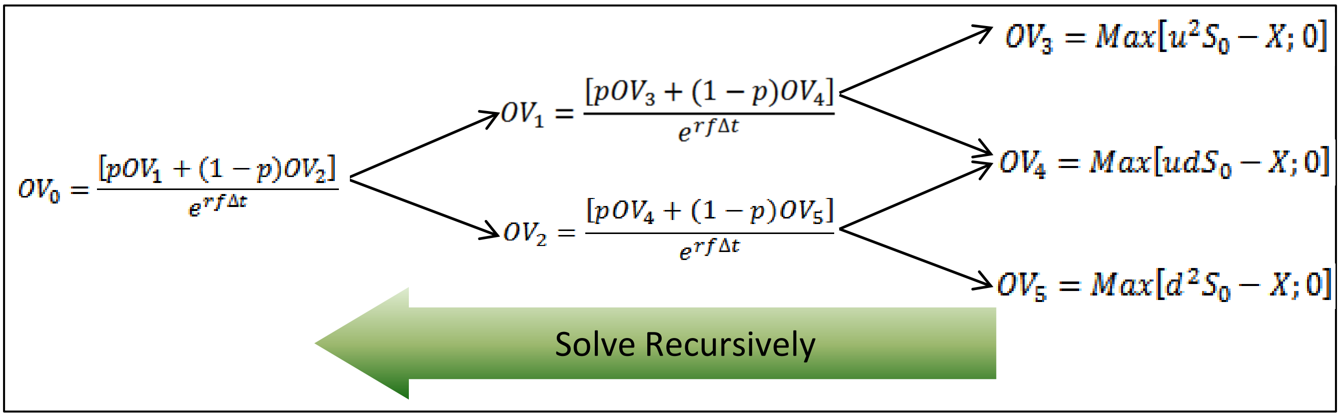

Figure 3: Option Valuation Lattice

Case Study 1: Investment in Carbon Capture Readiness (CCR) for a gas-fired power plant in the UK

Decision tree

The gas CCS case study has the following decision tree structure (**Figure 4**).

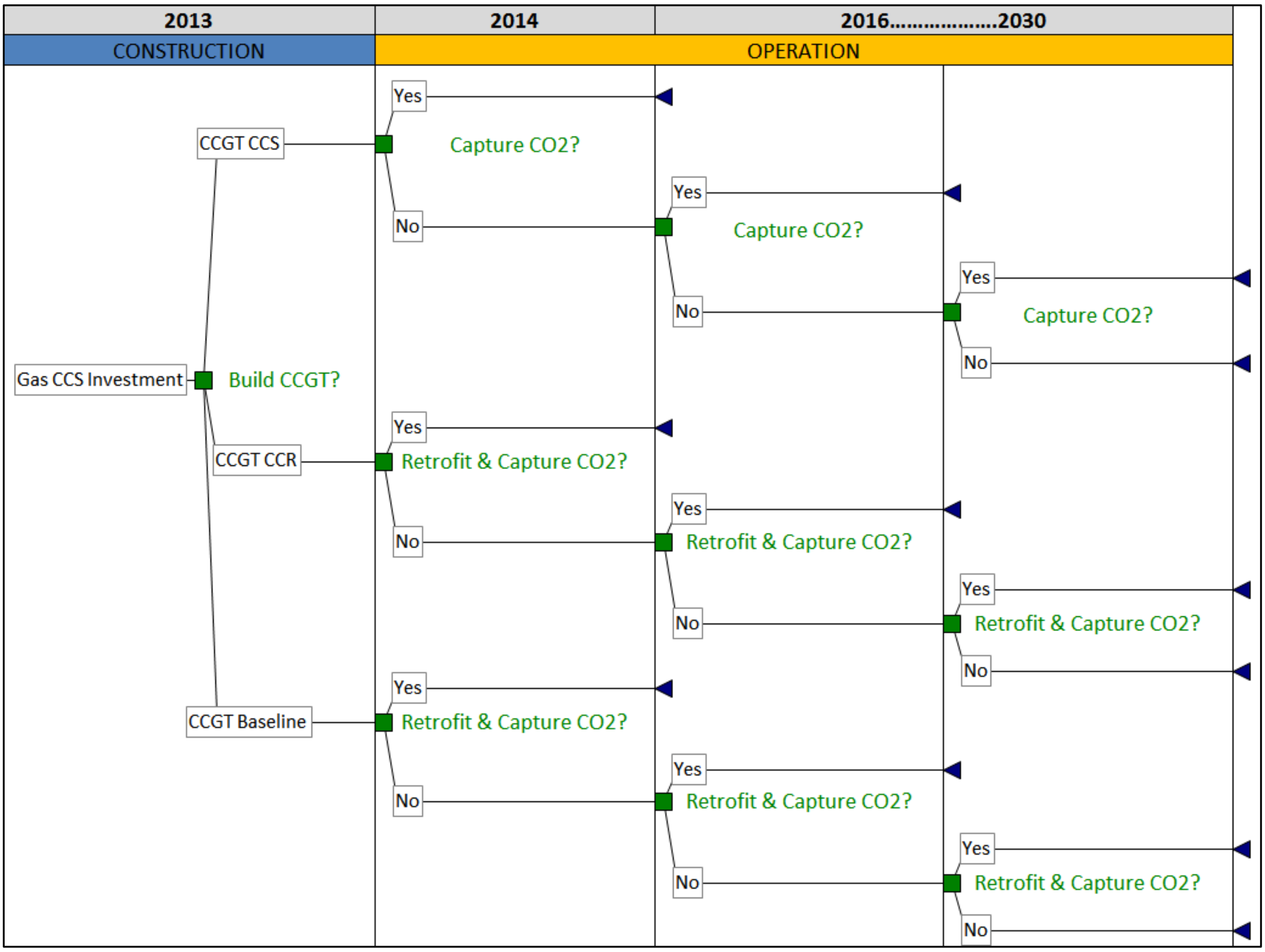

Figure 4: Decision tree for the CCS case study

Input Data and Assumptions

Data for CCGT and Capture module

The main technical characteristics of the CCGT plant under investigation are reported in **Table 2**. Costs of different CCGT plant configurations can be found in **Table 3** and costs of CO_2 pipeline and storage are outlined in **Table 4**.

Plant type	CCGT	
CO2 captured	No	Yes
Plant Outputs		
Gross power output (MW)	500	500
Auxiliary power (MW)	9	31
Net Power output (MW)	491	469.4
Net plant HHV efficiency (%)	50.80%	43.70%
Net plant HHV heat rate (GJ/MWh)	7.09	8.24
CO2 generated (tonne/hr)	202	202
CO2 emitted (tonne/hr)	202	20
CO2 captured (tonne/hr)	0	182
Emission intensity (kg/MWh)	362	42

Table 2: CCGT's Technical Characteristics
Source: (CCSI, 2011, Harland et al., 2010)

Plant type	non CCR CCGT	CCR CCGT	CCS CCGT
NGCC CAPEX, mn £	202	205	370
NGCC Fixed OPEX (mn £year)	3.6	3.6	4.2
NGCC Variable OPEX (£/MWh)	0.72	0.72	0.72
Capture CAPEX, mn £	191.5	178.6	0
Capture Fixed OPEX, (mn £/year)	0.59	0.59	0
Capture Variable OPEX, (£/MWh)	0.68	0.68	0.68

Table 3: Cost Assumptions for CCGT Plant Configurations
Source: (CCSI, 2011, Harland et al., 2010, KPMG, 2012, ZEP, 2011)

We assume a new CO_2 pipeline which runs 100km onshore and 100km offshore. The maximum capacity of the pipeline is 2.5 mtpa and storage capacity is 100Mt CO_2 40 years of plant operation. Cost assumptions for the CO_2 pipeline and storage are outlined in **Table 4**.

Pipeline	
CAPEX, £ mn	139
OPEX, £ mn/year	12.56
Storage	
CAPEX, £ mn	74.2
OPEX, £ mn/year	12.82

Table 4: CO_2 Pipeline and Storage Cost Assumptions
Source: (Serpa et al., 2011, ZEP, 2011, ScottishPower CCS Consortium, 2011)

Other input parameters

The following parameters (**Table 5**) were also used in the modelling of the CCS gas case study.

Risk-free rate (10Y UK Government Bond)	4.00%
Beta	0.51
Market Risk Premium	6.00%
Cost of Equity	5.03%
Mid-year factor	102.48%
Inflation rate	2.40%
Tax rate	23%
Depreciation method	straight line
Annual Asset Depreciation	5%
Carry Forward if no income to depreciate	yes
Depreciable Interest (of EBITDA)	100%
Residual value, £	0
UK/USD exch. rate (30.04.12)	1.6014
EUR/GBP exch rate (16.08.12)	0.7853

Table 5: Other Input Parameters for Gas CCS Case Study

Scenarios

Prices

We assume that project value are influenced by three risks modelled as a stochastic process (GBM): (i) electricity price, (ii) natural gas price, and (iii) learning rates which might result in CAPEX and OPEX reduction and improvement in operational efficiency of the capture plant (**Figure 5**). Carbon price is considered here as 'unquantifiable' uncertainty since its credibility and price path depends on multiple factors that cannot be predicted. Therefore, we treat future carbon price deterministically through scenario analysis in the model (**Figure 5**). We run and solve the model for each carbon price scenario.

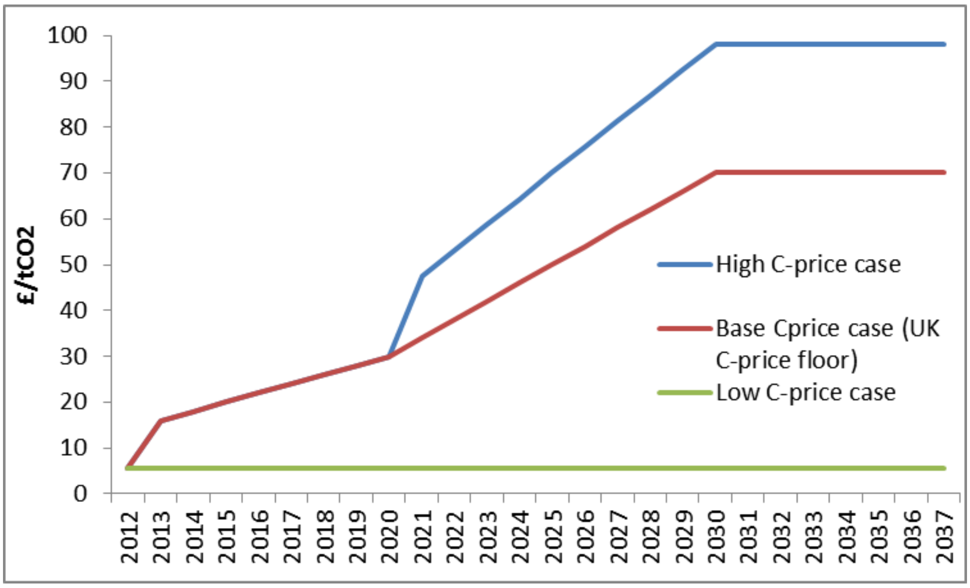

Figure 5: Carbon Price Scenarios

The UK electricity and gas prices are modelled as geometric Brownian motion process with the following parameters (**Table 6**). We assume that the gas plant is a baseload plant and therefore the electricity price under which it sells power is average spot price (i.e., average between peak and offpeak). The growth rates of both electricity and gas prices were determined based on their historical trends in the period from 1st April 2011 to 1st April 2012.

	Electricity Price	**Gas Price**
Type	APX Average Daily Spot Price	NBP Day Ahead
Initial price	47.86 (£/MWh)	56.1 (p/therm)
Volatility	7.63%	3.61%
Growth rate	0.31%	0.06%

Table 6: Parameters for Simulating Power and Gas Prices

Further, we assume that carbon price in the UK will affect the wholesale power prices as shown in **Figure 6**. This shows carbon price floor in the UK and DECC's projections of wholesale electricity prices in the UK until 2030. Clearly, it can be deduced from this figure that the UK government anticipates that higher carbon price will put upward pressure on the wholesale electricity prices.

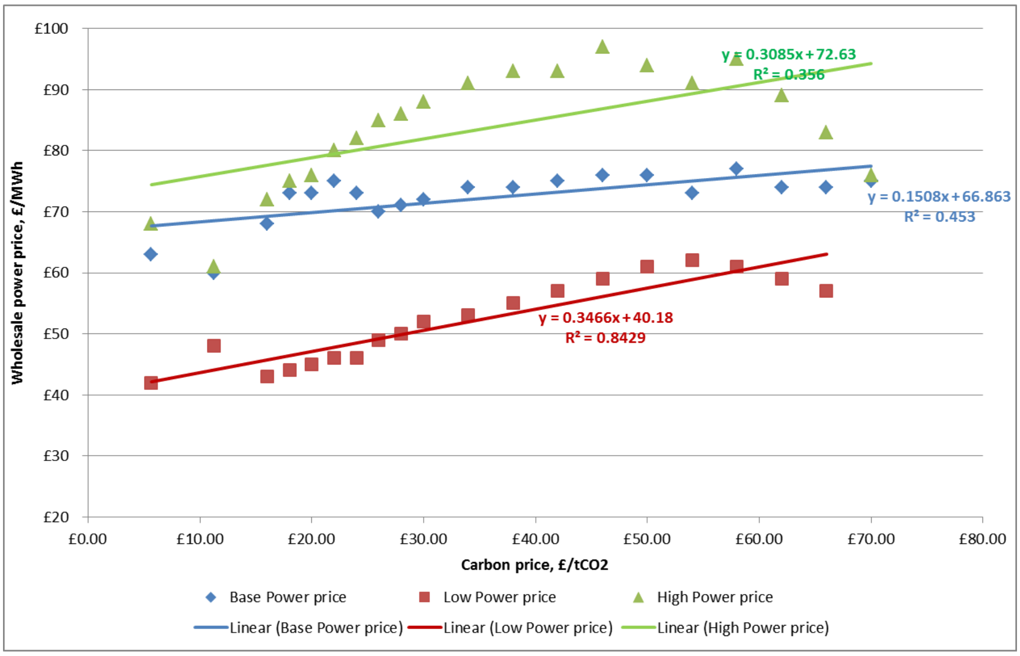

Figure 6: DECC's projections of wholesale power price and carbon price floor
Source: (DECC, 2012)

Thus, based on this consideration, we assume the following relationship between wholesale power price and carbon price:

$$p_e = \alpha p_c + p_w \tag{2}$$

where p_c is carbon price, α - slope of the linear relationship between carbon price and wholesale power prices and p_w is a default wholesale power price modelled stochastically. Thus, if there is no relationship between carbon price and wholesale power price then $\alpha=0$ and thus $p_e=p_w$. The slope parameter α is set exogenously and scenarios analysis was carried out (**Table 7**). The following scenarios were analysed with respect power and carbon price relationships (**Table 7**).

Carbon Price Pass through Effect Scenarios	Comment
0%	In this scenario it is assumed that there is no effect of carbon price on wholesale power price
23%	This scenario means that a £1 increase in carbon price increases wholesale price by £0.23. This is an average of DECC's three power price projection scenarios (**Figure 2**).
50%	In this scenario, a £1 increase in carbon price would increase the wholesale power price by £0.5.
100%	In this scenario, a £1 increase in carbon price would increase the wholesale power price by £1. This scenario is possible if we believe that fossil fuel generation will dominate the electricity system in the UK.

Table 7: Scenarios for Carbon Price Pass through Effect

The results reported in the report assume 23% pass through effect for gas CCS and offshore wind case studies. Results from sensitivity analysis regarding the pass through effect are available upon request.

CCS Technological Learning

We assume that technological learning will have an impact on improvement in capture efficiency by reducing parasitic load and reduction in capital and operational expenditure of the capture plant. This will depend on the assumed learning rate and anticipated rate of CCS deployment worldwide (**Table 8**).

$$y_i = y_0 \left(\frac{C_i}{C_o}\right)^{-b} \tag{3}$$

where y_i is capture efficiency parameter (or CCS CAPEX/OPEX) of the *i*th installed capture unit and y_0 is the initial level of capture efficiency, C_i is total global cumulative installed CCS capacity and C_0 is initial level CCS installation and *b* learning rate exponent index which denotes that with each doubling of installed capacity, the capture efficiency will be improved by $1\text{-}2^b$.

We assume the following global CCS deployment rate between now and 2035 (**Table 8**).

Global CCS deployment rate (% pa): 2013-2033	
High Case	40.00%
Base Case	10.00%
Low Case	0.00%

Table 8: Global CCS Deployment Scenarios

Note that by IEA (2011) in one of its most optimistic scenarios of CCS deployment, some 450 GW of coal power generation is assumed to have CCS by 2035, assuming that at the moment there are virtually no CCS power plants, IEA's optimistic scenario of CCS deployment would yield around 17% of CCS installations per year.

Improvements in efficiency and CAPEX & OPEX

Improvements in the CAPEX and OPEX of the carbon capture plant are assumed in this model (**Table 9**). For the capture plant, learning rate we assumed future rate of deployment of the CCS technology worldwide. We assume that only the stringent CCR option will be able to fully benefit from technological learning stemming from the learning-by-doing effect of future CCS installation. For the case of building CCGT with CCS from the outset or for the case of non-CCR CCGT, we assume 'technology lock-in' the capture plant in terms of inability to enjoy future improvements in capture efficiency (better solvents which would allow lower fuel consumption and power parasitic load from regeneration and compression of CO_2). Also, we assume no improvements in the net efficiency of CCGT plant itself or reduction of CAPEX/OPEX of the CCGT plant can be incorporated in the already installed CCGT plant. However, we assume that as gas CCS will be rolling out in the future (according to assumed scenarios outlined in **Table 8**), CAPEX and OPEX of the capture module will be reduced at assumed learning rate (**Table 9**).

	CAPEX			OPEX		
	Min	Max	Most Likely	Min	Max	Most Likely
High case	18%	51%	33%	30%	90%	66%
Base case	6%	17%	11%	10%	30%	22%
Low case	3%	9%	6%	5%	15%	11%

Table 9: Learning Rate Scenarios for Cost of the Capture Plant

Capture plant efficiency would be improved depending on the assumed learning rate (**Table 10**) and cumulative CCS installations in the future. The improvement in capture efficiency could result in additional power capacity being available for export to the grid as well as reduced fuel consumption due to improved solvent technology. We assume that initial parasitic load for a 500MW CCGT plant to be 21MW (e.g., power to run CO_2 compression) and 96 mmcm of natural gas is consumed for running the entire capture process (mostly solvent regeneration). Therefore, the efficiency improvements in the capture process would reduce both the fuel consumption (solvent regeneration) as well as parasitic power consumption.

Learning rate scenarios: Efficiency of Capture			
	Min	Max	Most Likely
High Case	11%	18%	15%
Base Case	4%	6%	5%
Low Case	2%	3%	3%

Table 10: Learning Rate Scenarios for Improvement in Carbon Capture Efficiency

The fundamental difference between CCR, non-CCR and CCGT with CCS from the outset is the ability of CCR to incorporate a range of technical operation of the capture module therefore being able to enjoy technical improvements of the CCS. CO_2 pipelines and storage are assumed to be a mature area and therefore no technological or cost reductions are assumed for this model.

Case Study 2: Investment in offshore wind farm development in the UK's North Sea

Decision tree

Figure **7** shows the decision tree for the offshore wind investment case study.

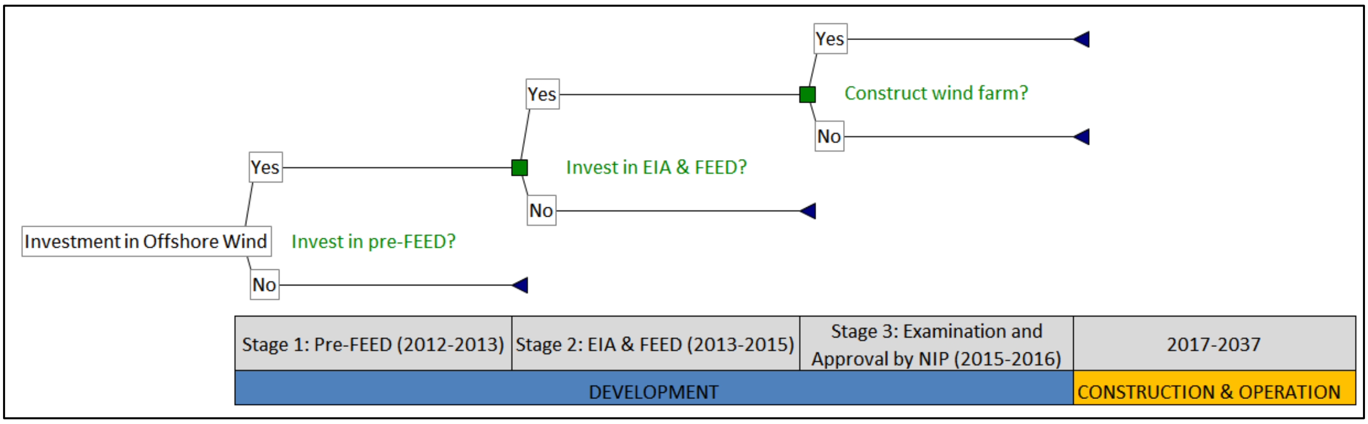

Figure 7: Decision Tree for Offshore Wind Case Study

Input Data and Assumptions

Cost Assumptions and Data

Figure 8 describes main stages for developing and operating the offshore wind power farm in the UK North Sea. General information and some assumptions are reported in **Table 11**. Cost assumptions for both development and operational phases of a hypothetical 500MW offshore wind farm in the UK North Sea is reported in **Table 12**.

Country	UK
Region	North Sea
Time of Valuation	2012
Wind farm operational lifetime, years	20
Type of turbines*	RePower 5M -100m
Number of Turbines	100
MW/Wind turbine generator	5
Total maximum installed capacity, MW	500
Construction time, days/turbine	5

Table 11: General Information about Offshore Wind Case Study

Note: *We do not have any preferences as to a particular type of wind turbines and the choice of RePower 5M -100m was solely based on publically available information regarding its power curve.

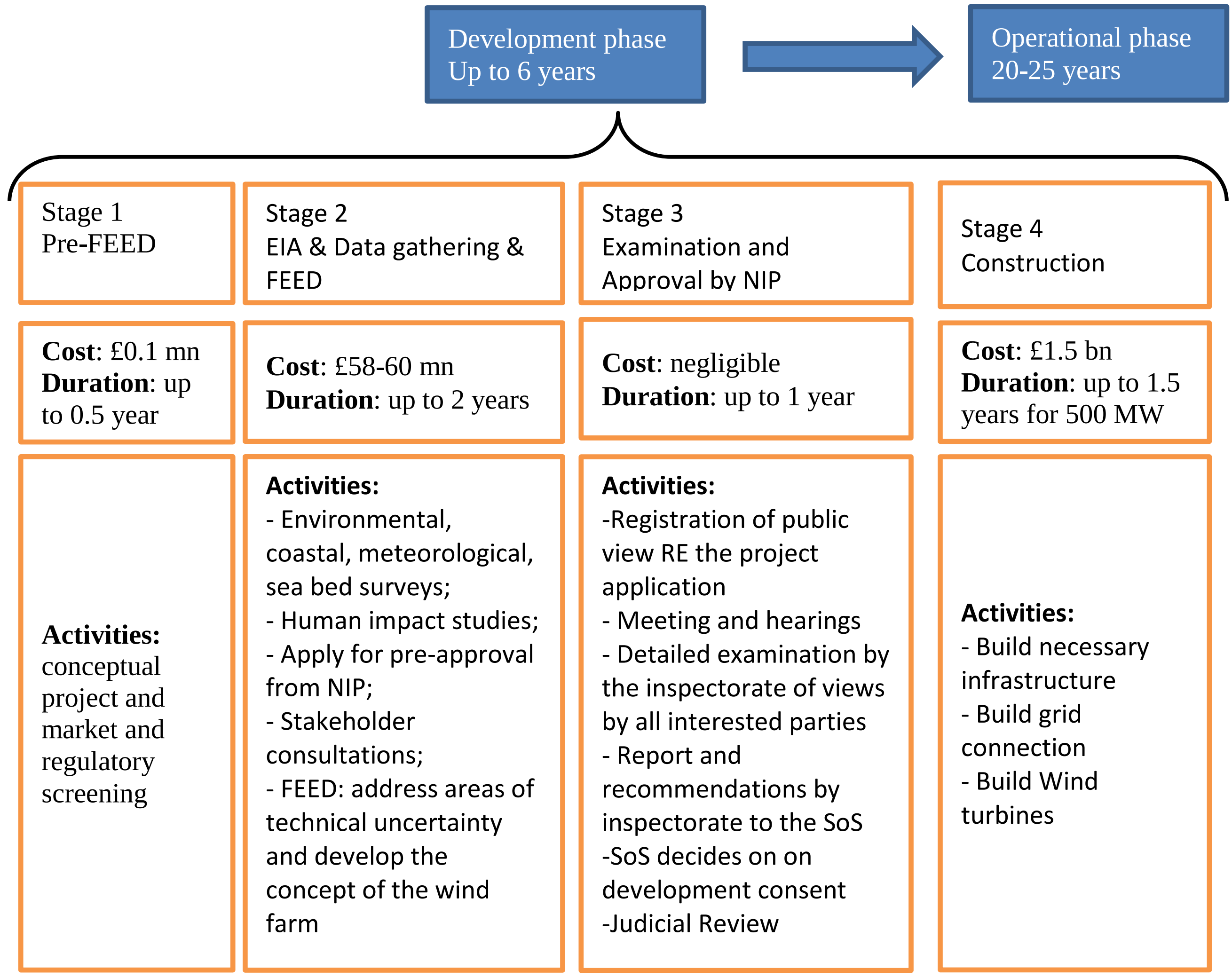

Figure 8: Wind Farm Development Phase
Sources: (NIP, 2012, BVG Associates, 2012)

Stages	**Description**	**Cost**
	Development	
Environmental surveys	Environmental surveys assess any environmental impacts that a wind farm may have on species that live, use or frequent the offshore environment in the sea and in the air.	Combined environmental survey costs for a typical 500MW wind farm are in the region of £4 million
Coastal process surveys	Coastal process surveys examine the impact of the wind farm development on sedimentation and erosion of the coastline.	Equipped and manned survey vessels will be in the order of £4-£6k/day plus mobilisation, logistics, weather delays etc, plus final reporting charges.
Met station surveys	Met stations are erected at a proposed wind farm site to monitor and analyse all aspects of meteorological and oceanographic conditions at the site.	Around £3-5 million including installation for a single met station with the cost rising the deeper and further offshore the location.
Sea bed surveys	Sea bed surveys analyse the sea floor of the proposed wind farm site to assess its conditions	Around £9 million for a 500MW wind farm.

	and characteristics.	
Front-end engineering and design	Front end engineering and design (FEED) studies address areas of technical uncertainty and develop the concept of the wind farm in advance of contracting.	Of the order of £1 million for a 500MW wind farm.
Human impact studies	This is an assessment of the impact that a proposed wind farm may have on the community living in and around the coastal area near the wind farm. This includes visual and noise assessment of the proposed wind farm and the socio-economic impact that coastal infrastructure, such as ports, will have. Studies on human impacts usually form part of an Environmental Impact Assessment (EIA).	£100k
Construction		
Wind turbines (5MW)	The turbine converts kinetic energy from wind into three phase AC electrical energy. The turbine's main components are nacelle, rotor and tower. The cost of turbines includes the above costs	£6mn
Balance of plant	It includes all the components of the wind farm, outside the turbine, such as cables, turbine foundation, offshore substation, electrical system etc.	Around 30% of wind farm capital costs (or £500 mn)
Installation and commissioning	All installation and commissioning of balance of plant and turbines, including land and sea-based activity.	In total, around £400 million for a typical 500MW wind farm.
Operations		
O&M cost	Provide support during the lifetime operation of the wind farm to ensure optimum output.	O&M costs of the order of £25-40 million for a typical 500MW wind farm.

Table 12: Cost Assumptions for the UK Offshore Wind Case Study
Source: (BVG Associates, 2012)

All other parameters used in this analysis are similar to the ones reported in **Table 5** for the gas CCS case study.

Wind Speed Modelling

Wind speed is modelled in this analysis stochastically using a Weibull probability density function. This particular distribution is regularly used by wind energy engineering since it conforms well to the observed long-term distribution of mean wind speeds for many sites. The Weibull probability distribution expresses the probability of *p(x)* to have a wind speed *x* during the year as follows (Hiester and Pennell, 1981):

$$p(x) = \left(\frac{k}{C}\right)\left(\frac{x}{C}\right)^{k-1} \exp\left[-\left(\frac{x}{C}\right)^{k}\right] \tag{4}$$

The Weibull distribution function works for $k>1$, $x\geq 0$, and $C>0$, where k is the shape factor and would typically range from 1 to 3, C is the scale factor, which is defined as follows (Hiester and Pennell, 1981):

$$C = \frac{\bar{x}}{\Gamma\left(1+\frac{1}{k}\right)} \tag{5}$$

where $\bar{x}$ is the average wind speed and Γ is the gamma function.

Therefore, in order to derive wind speed distribution profile at a particular location based on the Weibull distribution all we need is to find average wind speed at that location. For our illustrative offshore wind case study, we choose Dogger Bank location since this location is under consideration for a large-scale deployment of offshore wind power by private energy utilities in the UK North Sea. Using NASA's Atmospheric Science Data Centre database we obtained, using specific geographical coordinates of the Dogger Bank location, average wind speed for this location (**Table 13**).

Location	Dogger Bank, UK North Sea	Notation
Latitude	54.902°N	
Longtitude	1.822°E	
Average Wind Speed*	6.2 m/s	$\bar{x}$
Wind Speed Measurement height*	10 m	H
Annual average atmospheric pressure*	101.3 kPa	P
Standard atmospheric pressure	101.3 kPa	P_0
Annual average absolute temperature*	10.4 C	T
Standard absolute temperature (288.1 K)	14.95 C	T_0

Table 13: Site characteristics for Offshore Wind Case Study
Notes: * estimated using NASA's Atmospheric Science Data Centre database (Atmospheric Science Data Centre, 2008)

It is known that wind speed varies for different heights and since we assume a 5MW turbine with 100m tower, the average wind speed for this particular height should be estimated. We use the following power law equation to estimate average wind speed at 100 m height based on the average wind speed measured at 10 m height (**Table 13**):

$$\frac{\bar{x}}{\bar{x}_0} = \left(\frac{H}{H_0}\right)^{\alpha} \tag{6}$$

where $\bar{x}$ is the average wind speed at hub height H, x_0 is the average wind speed at measured height H_0, and α is the wind shear exponent. For open water locations α=0.1. Using the average wind speed measured at 10m height (**Table 13**) in Equation 6 to derive the average wind speed at 100m height, $\bar{x}$, and then this value in Equation 5 and 4, the following wind speed distribution for the Dogger Bank location was obtained (**Figure 9**):

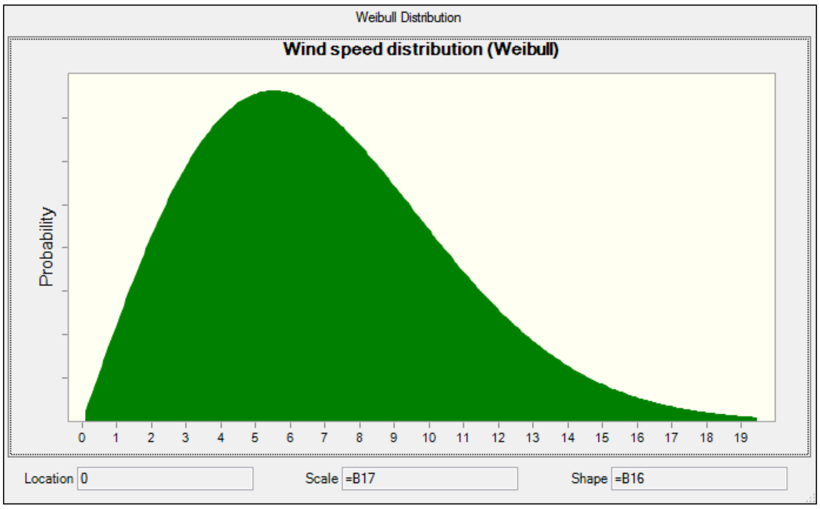

Figure 9: Estimated Wind Speed Distribution at Dogger Bank Location for UK Offshore Wind Case Study

Next, using the estimated wind speed distribution (**Figure 9**) and the RePower 5M-100 turbine power curve (**Figure 10**) we can calculate unadjusted power output, E_U. Note that, according to the power curve shown in **Figure 10**, the wind turbine starts generating power at 4 m/s or higher and it is switched off not to get damaged if the wind speed is getting too high (more than 14 m/s). These two conditions have been taken into account in the wind speed modelling. Further, unadjusted power output, E_U, does not account for the effect of location-specific atmospheric pressure and temperature conditions. Therefore, necessary adjustment should be made to derive gross energy production, E_G, of a turbine at particular location:

$$E_G = E_U \frac{P}{P_0} \frac{T_0}{T} \tag{7}$$

where E_U is the unadjusted energy production, P is the annual average atmospheric pressure at the location, P_0 is the standard atmospheric pressure of 101.3 kPa, T is the annual average absolute temperature at the location, and T_0 is the standard absolute temperature of 288.1 K.

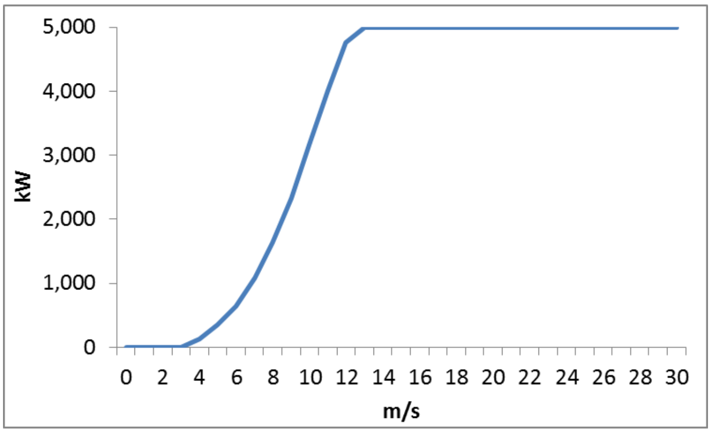

Figure 10: Assumed Power Curve for RePower 5M-100 Turbine Model

The final step in the wind power modelling procedure is to estimate 'net' power output by a turbine, E_C, i.e., by taking into account different losses as follows:

$$E_C = E_G c_L \tag{8}$$

where c_L is defined as follows:

$$c_L (1 - \lambda_a)(1 - \lambda_{S\&T})(1 - \lambda_d)(1 - \lambda_m) \tag{9}$$

where λ_a is the array losses, $\lambda_{S\&T}$ is the airfoil soiling icing losses, λ_d is the downtime losses, and λ_m is the miscellaneous losses. These loss parameters are assumed as follows (**Table 14**):

Array losses, λ_a	15.0%
Airfoil losses, λ_d	1.0%
Miscellaneous losses, λ_m	6.0%
Availability (downtime losses), λ_d	98.0%

Table 14: Energy Loss Parameters for Offshore Wind Turbine
Source: (CETC, 2004)

Taking all of the above discussion into account we can simulate net power output, E_C, and calculate the wind plant capacity factor, which represents the ratio of the average power produced by the plant over a year to its rate power capacity (**Figure 11**).

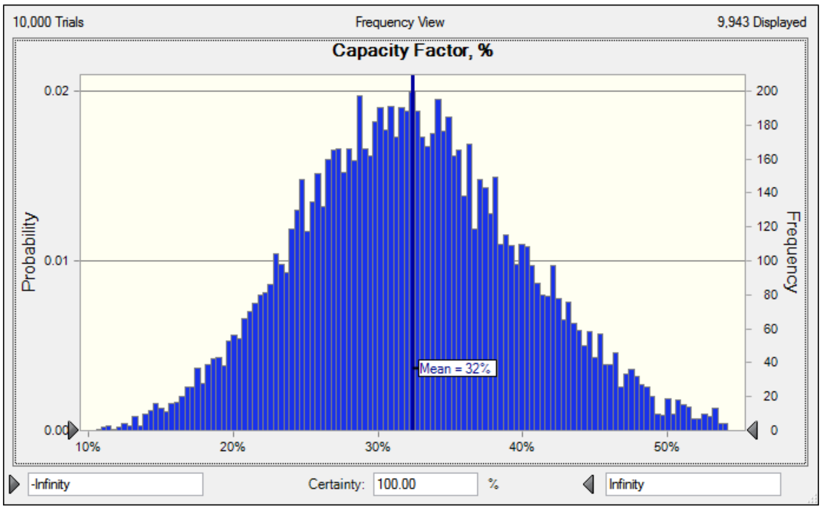

Figure 11: Estimated Distribution of Wind Capacity Factor at the Dogger Bank Location

Scenarios

For the offshore wind case study we assume the following scenarios regarding government support (Renewable Obligation Certificate, ROC) (**Table 15**):

ROC Scenarios	Comments
1.8 ROCs	In this scenario it is assumed that the wind farm would receive 1.8 ROCs per 1MW of power generated and sold. This support scheme is assumed to be valid over the entire lifetime of the wind farm, i.e., 20 years.
1 ROC	In this scenario it is assumed that the wind farm would receive 1 ROCs per 1MW of power generated and sold. As above, this support scheme is valid over the entire lifetime of the wind farm, i.e., 20 years.
No ROCs	In this scenario it is assumed that there is no government support.

Table 15: ROC Scenarios for Offshore Wind Case Study

ROCs have a market price and we assume that for the above scenarios the wind farm generator would sell their eligible ROCs at market prices. As can be seen from **Figure 12** ROC market price was always higher than the government's buy-out price.

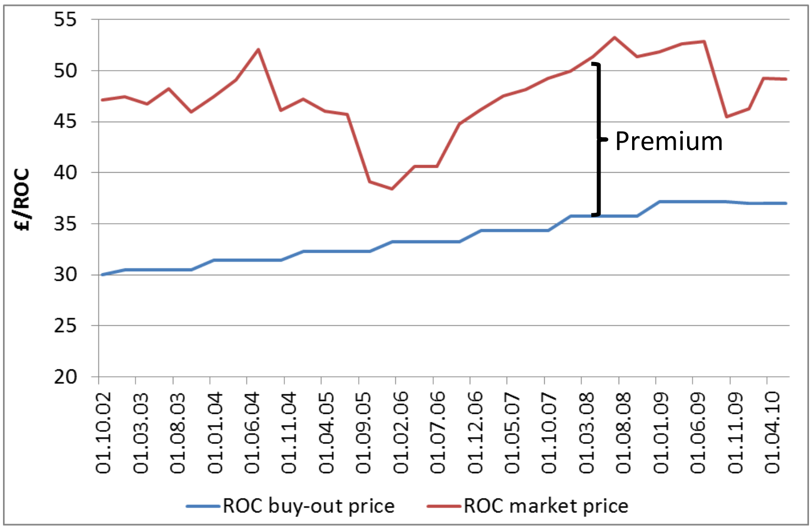

Figure 12: ROC Buy-out price and ROC Market Price

Therefore, in order to simulate ROC market price we assume that the ROC market price consists of the government's official buy-out price and a premium, which depends on market conditions. That is we assume: ROC price = buy-out price + 'premium'. The buy-out price is fixed at the current level (£40.71/ROC) throughout the modelling timeframe; however, the market premium is modelled using geometric Brownian motion process with the following parameters:

Initial Premium	£1.31/ROC
Volatility	60%
Growth rate	0%

Table 16: Parameters for Simulation of ROC Market Price Premium

Regarding simulation of power prices we modelled the UK wholesale electricity price as geometric Brownian motion process with the same parameters we used in the gas CCS case study (see **Table 4**). Further, similar to the gas CCS case study, we assume that carbon price in the UK will affect the wholesale power prices as shown in the **Figure 6** and we analyse these effects through carbon price pass through effect scenarios described above in the gas CCS section (see **Table 7**).
It should be noted that the results for the offshore wind case study reported in the main text of this study assume Base case carbon price and 23% carbon pass through effect onto wholesale power price.
We also assume technological learning for offshore wind power which would result in an annual reduction of CAPEX and OPEX. The learning rate (annual cost reduction rate) is modelled stochastically assuming a uniform distribution with lower bound of -5% and upper bound of 0% (which means no cost reduction).

Case Study 3: Investment in onshore wind farm development in the US Midwest

Decision tree

The US onshore wind case study has the following decision tree structure (**Figure 13**).

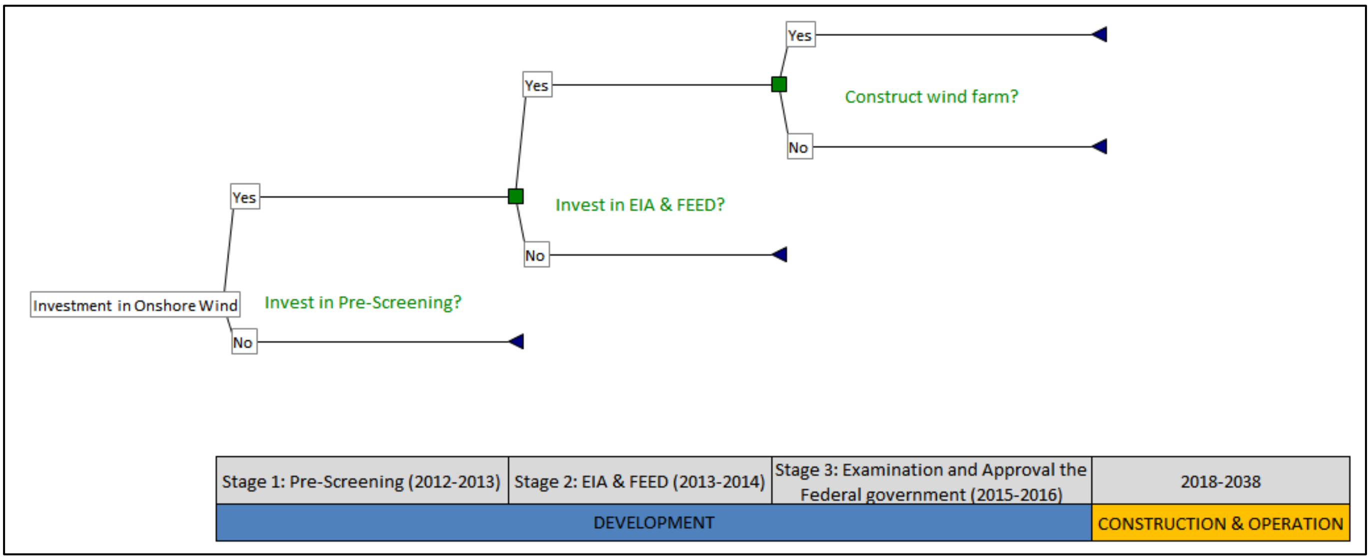

Figure 13: Decision Tree for Onshore Wind Case Study

Input Data and Assumptions

Cost Assumptions and Data

Figure 14 below describes main stages for developing and operating the onshore wind power farm in the US Midwest region. General information and some assumptions are reported in **Table 17**. Cost assumptions for both development and operational phases of a hypothetical 500MW onshore wind farm in the US Midwest region is reported in **Table 18**.

Country	US
Region	Wyoming, Rawlins
Time of Valuation	2012
Wind farm operational lifetime, years	20
Type of turbines*	GE -2.5 MW
Number of Turbines	200
MW/Wind turbine generator	2.5

Table 17: General Information about US Onshore Wind Case Study

Note: *We do not have any preferences as to a particular type of wind turbines and the choice of GE -2.5 MW was solely based on publically available information regarding its power curve.

Development phase
Up to 6 years

Operational phase
20-25 years

Stage 1 Pre-Screening	Stage 2 Wind analysis, EIS, stakeholder consult, Permitting	Stage 3 Sign major Project Documents (PPA, Interconnection, Turbine Supply, O&M, BOP Contract), Procure Approvals and Financing	Stage 4 Construction
Cost: <$1mn **Duration**: up to 0.5 year	**Cost**: <$25 mn - $35mn **Duration**: 1-2 years	**Cost**: <$50 mn - $100mn **Duration**: 1-2 years	**Cost**: $0.9-$1.0 bn **Duration**: up to 1.5 years for 500 MW
Activities: - Pre-market screen of subsidies, opportunities and development strengths -IRR requirements. - Preliminary wind analysis (regional based wind modelling) / assessing wind + transmission hot spots	**Activities:** -Wind studies - Environmental impact assessment: wildlife, legal precedent - Stakeholder consultations; landowners; - Right of way assessment: land acquisitions required? -Procure development loans? -Potential returns? - Interconnection / transmission studies (queue cost is market dependent e.g. CALISO / NYISO / $100k transmission study)	**Activities:** -Sign off-take, interconnection and procure approval if regulated -Environmental and other development approvals procured -Project/tax equity financing -Turbine order -Updated financial analysis - Independent Engineers report ($150k - $225k) - Final transmission study ($100k)	**Activities:** - Build necessary infrastructure - Build grid connection - Build Wind turbines

Figure 14: US Onshore Wind Farm Development Phase
Sources: Company reports

Stages	Description	Cost
	Development	
Pre-Screening	Screening for state subsidies and renewable portfolio standards. Early review of market opportunities, development strengths and long-term power/commodity prices. Establish required return parameters.	Modest cost. Less than $1mn.
Wind analysis, EIS, stakeholder consultations	Wind studies and completion of environmental assessment. Site development including assessment of right of way and land acquisitions required. Stakeholder consultation with local and state politician and interest groups. More detailed estimate of potential returns. Evaluate cost to get through next phase and secure loans.	Less than $25mn
Sign PPA, Procure Approvals and Financing	Virtually all wind development is backed by off-take agreement that is with an investment grade utility or is required due to renewable portfolio standard. Availability of federal tax incentives is considered for financing alternatives. The PTC (production tax credit) started 2.2 cents/kwhr in 1992 and is adjusted for inflation. The PTC applies to the first 10 years of production. It is set to expire at year-end 2012 though is likely to be extended in the lame duck session. Section 1603 of the tax code also established the ITC (investment tax credit) construction cost cash grant in place of the PTC which is a 29% cash payment at operation for projects in service by 31 December 2012 where construction started prior to 2012. These options facilitate raising project/tax equity financing and turbine orders. The approvals phase also becomes more intensive and time consuming here.	Less than $50mn
	Construction	
Wind turbine, infrastructure and grid connection	The turbine is the largest part of the cost. Completion of grid connection and necessary infrastructure.	$2,000/kw
	Operations	
O&M cost	Average cost of top-quartile projects from 2010 outside of California. Average capacity factor assumed 27%. NB: Capacity factors increasing as wind turbines get bigger, thus increasing the “swept” area of the wind turbines.	$7.89/MWhr

Table 18: Cost Assumptions for the US Onshore Wind Case Study

Sources: Company reports

Other input parameters

The following parameters (**Table 19**) were also used in the modelling of the US onshore wind case study.

Risk-free rate (10Y UK Government Bond)	1.75%
Beta	0.51
Market Risk Premium	6.00%
Cost of Equity	3.93%
Mid-year factor	101.95%
Inflation rate	0.85%
Tax rate	35%
Depreciation method	straight line
Annual Asset Depreciation	5%
Carry Forward if no income to depreciate	yes
Depreciable Interest (of EBITDA)	100%
Residual value, $	0

Table 19: Other Input Parameters for US Onshore Wind Case Study

Wind Speed Modelling

The procedure for modelling wind speed is similar to the one described for the UK offshore wind case study. In order to derive wind speed distribution profile at a particular location based on the Weibull distribution we need to find average wind speed at that location. For our illustrative US onshore wind case study, we choose Wyoming, Rawlins because it has one of the highest wind power potentials in the United States and therefore attracts a lot of commercial interests. Similar to the UK offshore wind case study, we use NASA's Atmospheric Science Data Centre database to obtain we obtained average wind speed as well as other relevant information for this location, using specific geographical coordinates of this location (**Table 20**).

Location	Wyoming, Rawlins	Notation
Latitude	41.79°N	
Longtitude	-107.234°E	
Average Wind Speed*	4.4 m/s	$\bar{x}$
Wind Speed Measurement height*	10 m	H
Annual average atmospheric pressure	78.2 kPa	P
Standard atmospheric pressure	101.3 kPa	P_0
Annual average absolute temperature	5.2 C	T
Standard absolute temperature (288.1 K)	14.95 C	T_0

Table 20: Site characteristics for US Onshore Wind Case Study

Notes: * estimated using NASA's Atmospheric Science Data Centre database (Atmospheric Science Data Centre, 2008)

Using the input parameters in **Table 20** as well as equations as outlined in the UK Offshore section above, the following wind speed distribution curve for the Wyoming, Rawlins location has been obtained (**Figure 15**):

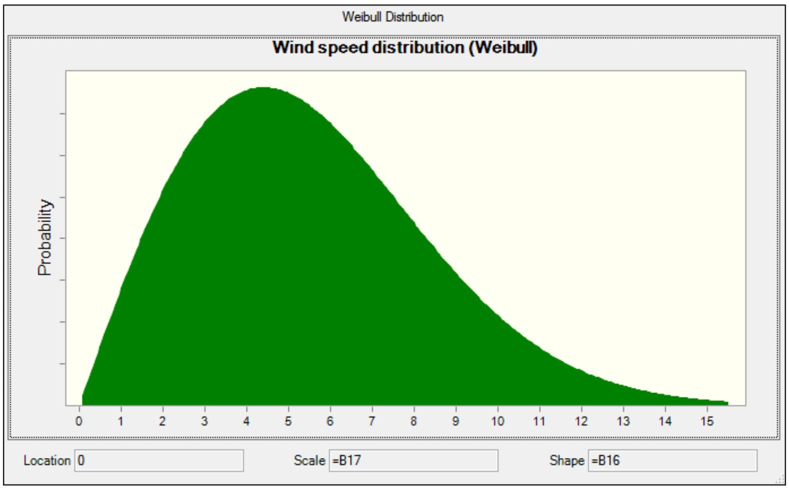

Figure 15: Estimated Wind Speed Distribution at Wyoming, Rawlins Location for US Wind Case Study

Then, using the estimated wind speed distribution (**Figure 15**) and the GE 2.5xl turbine power curve (**Figure 16**) we can calculate unadjusted power output, E_U, for this turbine operating at the Wyoming, Rawlins location.

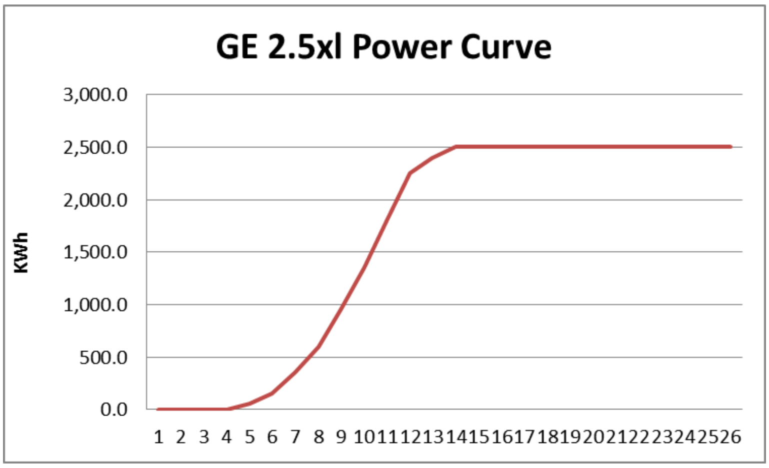

Figure 16: GE2.5xl Power Curve

Energy loss parameters for this case study are similar to the ones assumed for the UK offshore wind case study (**Table 14**). Thus, we have simulated net power output for this onshore wind case study and calculated the wind plant capacity factor, which represents the ratio of the average power produced by the plant over a year to its rate power capacity (**Figure 17**).

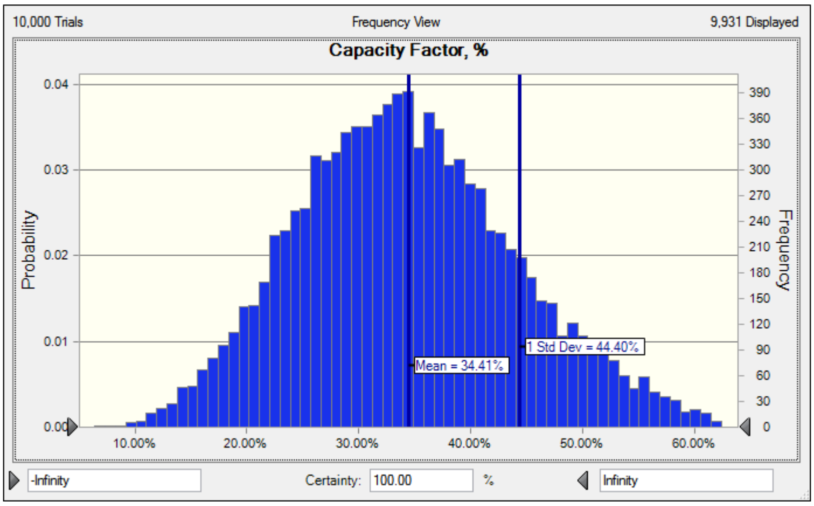

Figure 17: Estimated Distribution of Wind Capacity Factor at the Wyoming, Rawlins Location

Scenarios

The US wholesale electricity price is modelled as geometric Brownian motion process with the following parameters (**Table 21**). The initial price is an average of the 2011-2012 quarterly year ahead forward price for the NEPOOL market. Growth rate for wholesale power price is assumed to follow inflation rate as reported in Table 19.

	Electricity Price
Type	APX Average Daily Spot Price
Initial price	52.2 ($/MWh)
Volatility	28.81%
Growth rate	0.85%

Table 21: Parameters for Simulating Power for the US Onshore Wind Case Study

As was noted in **Figure 14**, majority of investment in the onshore wind power in the US is driven by government subsidies, such as Production Tax Credit, PTC. The level of support through this scheme is currently $22/MWh of power generated for the first 10 years of wind farm operation. However, this support scheme for wind power in the US is set to expire by the end of 2012 and its renewal is so far unclear. We have analysed potential impact of different scenarios of PTC (**Table 22**) on the investment in the US onshore wind power. The price level for these scenarios are assumed to follow uniform distribution with lower bound of $11/MWh and upper bound of $33MWh. Due to limited space in the main text of this study the results of different PTC scenarios on the value of onshore wind investment were not reported there but can be seen in **Figure 18**.

Timing	Comments
2014-2024	In this scenario it is assumed that the PTC would be extended in 2013 and valid from 2014 to 2024
2017-2027	In this scenario it is assumed that the PTC would be extended in 2016 and valid from 2017 to 2027
2021-2031	In this scenario it is assumed that the PTC would be extended in 2020 and valid from 2021 to 2031
2025-2035	In this scenario it is assumed that the PTC would be extended in 2024 and valid from 2025 to 2035
No PTC	In this scenario it is assumed that PTC is not extended during the whole life-time of the onshore wind project (until 2037)

Table 22: Production Tax Credit Scenarios for the US Onshore Wind Case Study

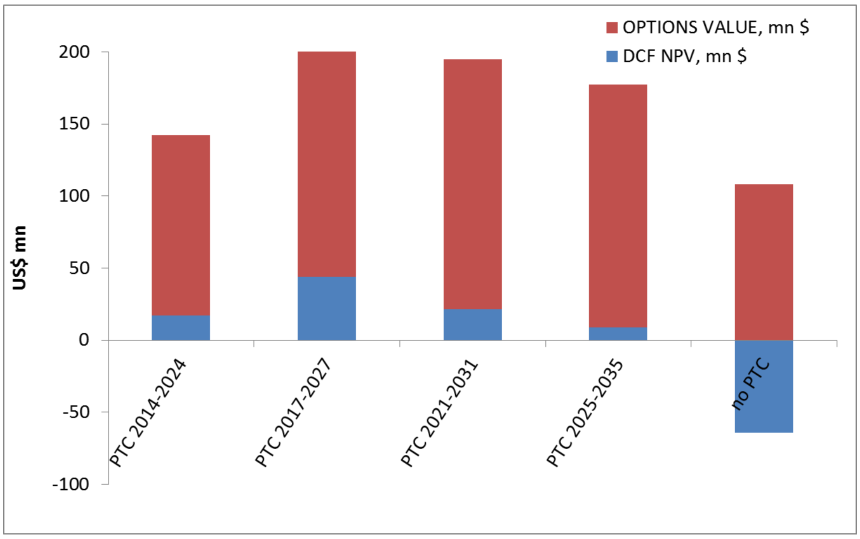

Figure 18: Effect of Different PTC Scenarios on the value of US Onshore Wind Investment

In the current US energy market environment, onshore wind power investment has been challenged by the rapid development of unconventional gas resources which over-flooded the US market with cheap gas, thereby threatening to price wind generation out of the market because of the price-setting impact of gas prices on wholesale electricity prices. In this study we also analysed potential impact of various scenarios of development of the US gas market on the investment in the onshore wind power because there remains significant uncertainty about whether low gas price can be sustained, not least because of the threat of stricter regulation of unconventional gas extraction or potential large-scale export gas projects from the US. For this analysis we have devised the following scenarios (**Table 23**) of the wholesale power price growth rates, assuming that gas is price-setting in the US wholesale power markets. These growth rate scenarios were then used in the simulation of power price dynamics using Brownian motion process.

Gas Price Scenarios	Wholesale power price growth rate, % pa (2017-2037)
Low Gas Price Scenario	0.43%
Base Gas Price Scenario	0.85%
High Gas Price Scenario	3.57%

Table 23: Gas Price Scenarios for the US Onshore Wind Case Study

In the Base gas price scenario it is assumed that the shale gas supplies would be abundant and very cheap; therefore the wholesale power price would only grow based on the dynamics of the inflation rate, which is assumed to be 0.85% pa through to 2037. The Low gas price scenario assumes that, in addition to the cheap gas price due to shale gas abundance in the US, the inflation rate would actually be very low (half the current rate of 0.85% pa) – 0.43% pa. In the High gas price scenario it is assumed that shale gas supplies falls substantially which would drive both gas and power prices up substantially to the pre-shale gas boom period (2005-2008). The annual growth rate of wholesale power price in the US during that period (2005-2008) was estimated to be 3.57% pa. The limited supplies of shale gas in this scenario could, for example, be because the US government would allow shale gas to be exported or shale gas fracking would be banned, thereby putting higher pressure on power price to increase as fast as it was during the pre-shale boom period. It should be noted that the results of the US onshore wind power case study reported in the main text of this report does not assume that PTC would be extended. Thus, these results are solely based on gas and power price dynamics as reported in **Table 23**. Further, similar to the UK offshore wind case study, we assume technological learning for onshore wind power technology which would result in an annual reduction of CAPEX. The learning rate (annual cost reduction rate) is modelled stochastically assuming a uniform distribution with lower bound of -5% and upper bound of 0% (which means no cost reduction).

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