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Working Paper Series

#2006-035

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Generation: A Clay-Clay-Vintage Portfolio Approach with an
Application to Climate Change Policy in the UK**

Adriaan van Zon and Sabine Fuss

October 2006

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Adriaan van Zon[†] and Sabine Fuss^{*}

Abstract

UK climate change policy has long been concerned with the transition to a more sustainable energy mix. The degree of competition in electricity markets rises as these markets become more and more liberalized. In order to survive in such an increasingly competitive setting, electricity producers have to handle as efficiently as possible the uncertainties associated with the volatility of fuel prices, but also uncertainties regarding the technological evolution of electricity production (including the development of renewable technologies). Technological uncertainty in combination with high capital costs are likely to deter investors from adopting renewable technologies on a larger scale than they are doing right now, even though they have to accept a higher degree of fuel price risk by doing so. By carefully composing a portfolio of technologies with different (co-)variances in the respective prices and rates of technical progress, risk-averse producers can effectively hedge the uncertainties mentioned above. In order to model this type of investment behaviour, we use an extended version of the van Zon and Fuss (2005) clay-clay-vintage-portfolio model that starts from the notion that investment in electricity production equipment is irreversible. However, a physical capital portfolio – in contrast to a portfolio of financial assets – can only be adjusted at the margin. This implies that it becomes extremely important to look ahead, and act on not just expectations themselves, but also their reliability. Using the extended model, we implement several features of present UK policy in order to illustrate the principles involved. We find that the reduction of risk goes together with an increase in total costs. We also find that for increasing values of risk-aversion, investors would be willing to adopt nuclear energy at earlier dates than otherwise would have been the case. In addition to this, we find that the embodiment of technical change, in combination with the expectation of a future switch towards another technology, may actually reduce current investment in that technology (while temporarily increasing current investment in competing technologies). The latter enables rational but risk-averse investors to maximise their productivity gain by waiting for ongoing embodied technical change to take place until the moment they plan to make the switch and then investing more heavily in the newest vintages associated with that technology at the time of the switch.

**UNU-MERIT Working Papers
ISSN 1871-9872**

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[†] For contact: Adriaan.vanZon@merit.unimaas.nl

^{*} For contact: S.Fuss@algec.unimaas.nl

1. Introduction

UK climate change policy started to be formulated in concise terms from the beginning of the 1990s on. In response to the Framework Convention on Climate Change in Rio (1992) the target that the year 2000 emissions should be no larger than emissions in the year 1990 was set up as a voluntary agreement. Through the privatization of the electricity market by the Conservative Government, this target could largely be met. The change in government to New Labour did not interrupt UK efforts in reducing emissions. Even though the targets introduced during the Nineties might have been too ambitious to be met immediately, numerous measures have been enacted to counteract the ongoing increase in CO₂ emissions in the UK. One example that directly affects the electricity industry is the so-called Renewables Obligation, which requires electricity retailers to acquire at least 10% of their electricity from renewable sources, but there are also a number of taxes involved in the wider emissions reduction program. In addition, nuclear electricity generation is presently considered as a potential “bridge” during the transition from fossil-fuel-based power production to a more sustainable system based on renewable energy.

With liberalized electricity markets, investors in power generation face more competition and need to internalize and hedge a large number of uncertainties. These range from the risks that are due to the volatility of fuel prices to uncertainties about how renewable technologies will actually evolve in terms of their efficiency. Due to such technological uncertainties and high capital costs, investors in the electricity sector may still be reluctant to adopt renewable technologies on a larger scale, even though, by doing so, they may have to expose themselves to a higher degree of fuel price risk. However, by carefully composing a portfolio of technologies with different (co-)variances in the respective price changes and rates of technical progress, producers can effectively hedge these kinds of uncertainties. This implies that, in general, producers will opt for a mix of technologies, including technologies that are not yet fully developed.

In addition, a portfolio-approach towards the investment problem seems to be especially suited in order to avoid irrecoverable downswings in the aggregate return on investment. To this end, we use an extended version of the van Zon and Fuss (2005) clay-clay-vintage-portfolio model that starts from the notion that investment in electricity production equipment is largely irreversible, since a physical capital portfolio – in contrast to a portfolio of financial assets – can only be adjusted at the margin. This implies that it becomes extremely important to look ahead, and act on not just expectations themselves, but also to consider the reliability of these forecasts. In addition, we add emissions and a number of other features to the model, which enables us to implement several important aspects of UK climate change policy. Our (preliminary) findings are roughly in line with the plan to use nuclear energy as a bridge to a more sustainable electricity portfolio. The latter seems to be entirely consistent

with the views of a rationally behaving risk-averse investor¹. The paper is further organised as follows. In section 2, we will briefly discuss the current electricity mix of the UK, the projections about UK emissions, and the background of UK policy for GHG emissions reductions. Then, in section 3, we will give an overview of the model that we use for our analysis. In section 4, the results will be presented and interpreted², while section 5 contains a summary and conclusion.

2. Energy Conversion and Climate Change Policy in the UK

During the 1990s the UK electricity mix, which up to that time had mainly been based on coal, became more diversified, as the share of gas in fuels used for power generation started to rise. At the end of the 1990s the share of nuclear energy fell substantially, which was due to more frequent outages at nuclear power stations for repairs, maintenance and safety case work (DTI, 2005). By 2004 still less than 4% of all electricity produced in the UK came from techniques based on renewable energy³. Fig. 1 below illustrates the proportions of the current UK electricity generation mix.

Figure 2 shows that, over the last decades, emissions from power generation have been decreasing, while electricity production has continued to increase, while CO₂ emissions per unit of power generated have decreased by almost fifty percent. This favourable trend was mainly due to the switch from coal to gas, efficiency improvements at the plant level and – over the last few years - an increasing contribution of nuclear and renewable power to the overall electricity mix (DTI, 2005). However, GHG emissions are a stock externality, and there is now wide agreement that further GHG emissions will lead to considerable (and potentially irreversible) damages related to global warming if GHG concentrations rise beyond the threshold of 550-700 ppmv (see e.g. the IPCC scenarios). Consequently, UK policy makers have taken up the challenge of realising further emissions reductions and have set out clear goals for emissions reductions in the Energy White Paper (2003).

¹ However, we should also admit here from the outset, that the data-set we have been able to obtain is very limited in terms of its coverage of technologies and time (for details see Appendix C). Nonetheless, it is the most complete data-set we could get hold of, and it serves its purpose of illustrating the principle working of the model reasonably well.

² The data, which are mainly taken from Anderson and Winne (2004) and complemented by information from the DTI, will be listed and described in Appendix C.

³ The fraction of electricity coming from oil-fired generators had been falling from the late 1970s on and was negligibly small by 2004 already.

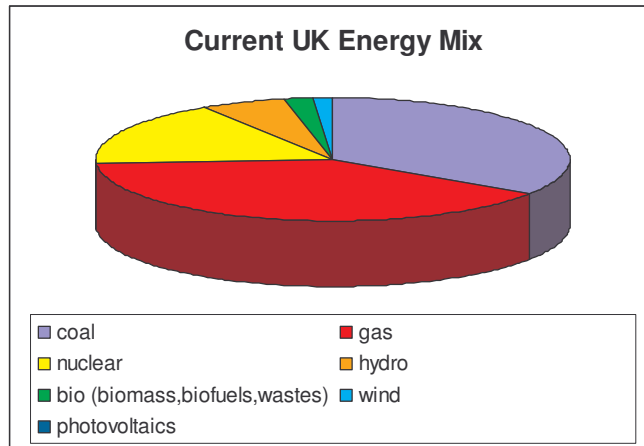


Fig. 1: UK Power Mix (based on data of installed capacity from the DTI, 2005).

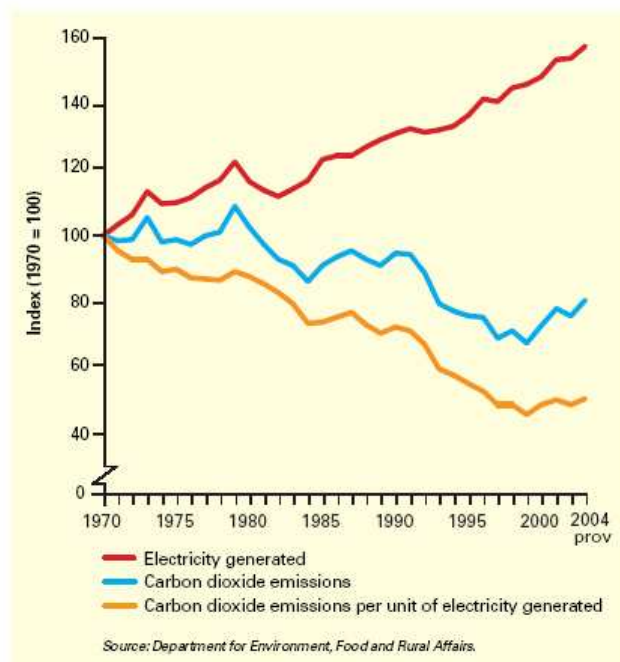


Fig. 2: Power Station Emissions of Carbon Dioxide (from DTI, UK Energy Sector Indicators 2005).

The projections about CO₂ emissions, which are used for the Energy White Paper, amount to emissions of 145 MtC by the year 2050 (the worst case scenario is 180 MtC). This is the business as usual scenario, which is regarded to be most appropriate for policy analysis⁴. The target of UK climate change policy for 2050 is to cut CO₂ emissions by 60%. That would translate to a level of 60 MtC by 2050 and 110-120 MtC by 2020. The portion that could potentially be saved due to a more

⁴ However, this projection also takes into account the effect that the Renewables Obligation and the Climate Change Levy (which is a tax that does not directly affect the electricity sector) will have had by 2010, i.e. the achievement of the 10% renewables target.

intensive use of renewables in electricity production is estimated to be 3-5 MtC. A further reduction of 2-4 MtC could be achieved through fuel switching due to the EU emissions trading scheme. These levels of potential carbon savings might seem low relative to the total level of envisaged reductions. One might argue that e.g. large-scale hydropower techniques are already very advanced and could easily provide a larger share of the electricity mix. However, there is actually very little scope for any additional large-scale hydropower systems as suitable sites are scarce. Therefore, any additional capacity relying on hydro techniques must be small-scale.⁵ Likewise, the resources for some biomass technologies are limited, e.g. for landfill gas. Furthermore, importing crops for biomass electricity generation is often not economically viable, while at the same time such imports would also cause emissions related to transportation that will reduce net potential savings. Without further improvements in UK crop yields, it is therefore fair to assume that not much more than 20% of electricity demand can be met by biomass technologies, which already take up the lion's share of renewable energy production nowadays. Similarly, wind will not constitute a higher share than 10% of demand, since there is not much scope for expansion (at least not onshore; with the advancement of offshore wind turbines, this picture will definitely change) and it cannot be relied upon during times of the day when there is no wind, also because storage possibilities are more than limited up to date.

As already indicated in the introduction, the renewables target has mainly been met through the introduction of the so-called Renewables Obligation, which requires electricity retailers to acquire at least 10% of their electricity from renewable sources. At the same time, suppliers are obliged to generate the necessary amount of renewable electricity in order to secure the supply of renewable electricity. This is monitored by the UK gas and electricity market regulator Ofgem, which creates Renewable Obligation Certificates (ROCs) that the suppliers can acquire for each MWh of renewable energy generated. Supplier compliance can then be checked by the correct amount of ROCs. This arrangement effectively allows electricity generators to meet their obligations or not. In fact, they could also “buy out” of their obligation by acquiring ROCs. The price varies around £30/MWh (DTI, 2002). Ofgem then recycles the money collected from the purchase of the ROCs back to the renewable electricity producers on the basis of the proportion of ROCs they constitute in the market. The UK has preferred to institute such a market-oriented approach to promote the use of renewables, even though the German system of feed-in tariffs has proven to be very effective in meeting targets as well. With the latter mechanism the producers receive a premium on top of the market price of electricity depending on the technology they are using. Solar techniques, for instance, receive much larger remunerations per MWh produced than e.g. large-scale hydro plants. Interestingly, Mitchell et al (2006), who look into the subject much more deeply, find that the German feed-in system outperforms the UK Renewable Obligation mechanism with respect to the effectiveness of phasing in

⁵ On the other hand, even if all rivers in the UK could be tapped, the additional amount of hydropower would not exceed another 10,000 GWh according to DTI estimates. Upper-bounds of this kind will be incorporated as a maximum installable capacity constraint in our analysis later on.

renewable energy in the long run. They attribute this to the fact that it reduces the risk associated with investing in renewables-based capacity more than the UK system⁶. If true, this is a direct indication of the practical importance of risk for technology adoption in the electricity sector.

The analysis of this paper will therefore not only focus on the status quo of the UK electricity generation mix and its response to uncertainty in the framework of our model, but it will also illustrate what risk would seem to imply for the way in which UK policy may succeed in meeting the (ambitious) targets that the government has set in terms of increasing the share of renewables in power generation with the ultimate goal of reducing GHG emissions in this sector.

3. The Clay-Clay-Vintage Portfolio Selection Approach

3.1 Introduction

The model used in this paper is an extension of the one developed in van Zon and Fuss (2005). It is an optimum portfolio selection approach integrated with a two-dimensional clay-clay vintage model. The first of these two dimensions refers to the kind of basic technology that is used to produce electricity, like coal-fired plants, gas-fired plants, nuclear plants, and so on. The second dimension refers to quality/productivity differences between various generations within these basic technologies, due to embodied technical change. The clay-clay assumption implies that investment is (largely) irreversible. Embodied technical progress may turn the vintage that was cutting edge by the time it was installed obsolete due to the arrival of a new vintage, a process which is nowadays generally known as creative destruction “emphasised” by Schumpeter and “popularised” in an endogenous growth setting by Aghion and Howitt (1992).⁷

There are some other studies that have made use of the ideas of Optimum Portfolio theory in order to analyze the energy sector. Awerbuch and Berger (2003), for example, use mean-variance portfolio optimization for their analysis of the EU electricity market. They examine different types of risk of which they find fuel price risk to be the dominant type. Our model however shows results for fuel price risk reductions that are qualitatively different from those regarding technological uncertainty. A further contribution to electricity planning problems comes from Madlener, Kumbaroglu and Ediger (2005). In terms of uncertainty they look at fluctuations in demand, peak load capacity, generation costs and the price of electricity, modelling the expected value of these items as discrete stochastic autoregressive moving average processes. Even though they use a dynamic

⁶ With a fixed tariff per kWh irrespective of the load profile of the technology to be deployed, the German policy effectively reduces price, volume and balancing risks to zero, while the ROC policy exposes UK electricity producers to a higher degree of uncertainty in all three respects (Mitchell et al, 2006).

⁷ However, the creative destruction aspects of technical change were already integrated in a vintage setting by Salter (1960) and Malcolmson (1975).

programming approach, their approach of maximizing the net present value of investment in a vintage model of electricity production is otherwise similar to ours. More specifically, they use their model to analyze data for the Turkish electricity sector, where a mainly gas-fired capacity had been added to installed capacity, which Madlener et al (2005) find to be a suboptimal choice in terms of risk reduction because coal prices are much less volatile than gas prices for Turkey.

Portfolio considerations have also played a role in distribution and trading of electricity. As an example, Kleindorfer (2005) uses multi-period portfolio optimization subject to a Value-at-Risk (VaR) constraint, where a VaR constraint is the "maximum loss that the portfolio is allowed to sustain over a specified period of time and at a specified level of probability." (page 2, Kleindorfer, 2005). Kleindorfer (2005) makes a distinction between sellers (i.e. those who generate electricity in the first place) and buyers (i.e. distribution companies), who engage in contracts to satisfy the demand of their retail and wholesale customers. Such purchases and sales can possibly be made for several years in advance and the participants can use a number of financial instruments such as puts, forwards, calls, etc to hedge their risks. The extent to which buyers and sellers are risk averse is founded in the pre-specified maximum loss in the VaR constraint. To conclude, Kleindorfer's (2005) focus is more on power trading than on the actual set-up of power generating capacity that we investigate.

Chaton and Doucet (2003) have a three-period model of the electricity sector, in which they also include issues of trading. However, they also take into account demand and price uncertainty and equipment availability. Equipment availability can be influenced by technological progress, for example. More work dealing with electricity generation capacity, but focussing strongly on the irreversibility of investment is done by Pindyck (1993). He investigates technical uncertainty and uncertainty with respect to construction cost.

It is important to note that, even though we focus on the risks associated with volatile fuel and investment price growth and uncertainties with respect to fuel- and capital-saving technical change, which is quite similar to the objectives of the real options models referred to above (e.g. Pindyck, 1993), we do so with a different type of method, combining OPT with clay-clay vintage modelling. As clay-clay vintage models explicitly deal with the both the cumulative character of technical change and the irreversibility of investment, we think that our approach is a valuable alternative to traditional real options modelling. In order to illustrate the approach free of too many interaction effects, we will further abstract from issues of power trading (Kleindorfer, 2005).

Our basic results (cf. van Zon and Fuss (2005)) are qualitatively somewhat different from – and maybe even “richer” - than those of others, as they are in between the “standard” predictions of OPT and real options theory. Moreover, price and technological volatility have intrinsically different effects on investment: price-volatility generates “standard” OPT outcomes, whereas technological volatility does not. The reason is that in our set-up, producers may actually postpone investment in technologies that exhibit lower degrees of technological uncertainty in our model, whereas OPT predicts that assets with a lower associated risk will make up for a larger part of the portfolio

immediately. Real options theory traditionally recommends to wait and invest later in the face of uncertainty, and to invest more when volatility is reduced. The findings in van Zon and Fuss (2005) are partly in contrast with this because by linking OPT to vintage modelling we explicitly incorporate the embodied and cumulative nature of technical change into the investment decision. Whereas in real options theory the option value of waiting and keeping the investment opportunity open falls with a decrease in the variance, our (implicit) option value is adjusted for the benefits that can be realized through the cumulativeness of technical change, where the latter can more than outweigh the immediate gains from lower variance (van Zon and Fuss, 2005). We will here first outline the basic model of van Zon and Fuss (2005) and then highlight the new features that we have added.

3.2 The Vintage Model

In our model we will be using several multi-dimensional/indexed variables. More specifically, we will be using the index f to denote a technology family (fuel type), an index v to denote the moment in time at which the vintage under consideration has been installed, and t to denote the present moment in time. The variables K^f , Y^f , X^f and F^f are the (vintage) level of investment, capacity output, actual output and fuel consumption per technology, respectively. We allow for embodied capital- and fuel-saving technical change at a proportional rate with a given expected value and a given (expected) variance of that rate. For the development of the volume of capital associated with each vintage, we then have:

$$K_{v,t}^f = e^{\delta^f (t-v)} \cdot K_{v,v}^f \quad (1)$$

where $K_{v,t}^f$ measures the volume of capital still left of a vintage that was installed at time v after $(t-v)$ periods of time have passed since its installation. In equation (1), δ^f is the (constant) exponential rate of physical decay associated with vintages belonging to family f . Hence, equation (1) states that the amount of capital associated with a vintage installed $t-v$ periods ago will fall at a rate of δ^f percent per year due to technical wear and tear. For capacity output associated with a vintage we have:

$$Y_{v,t}^f = \frac{K_{v,t}^f}{\kappa_v^f} \quad (2)$$

In equation (2) κ_v^f is the capital-output ratio associated with a vintage of family f that was installed at time v . As we assume that there is no ex post disembodied technical change, κ_v^f does only depend on v . However, embodied (capital- and fuel-saving) technical change takes place at a given expected proportional rate and with given expected variance of that rate. We therefore have:

$$\kappa_v^f = \kappa_0^f \cdot e^{\hat{\kappa}^f \cdot v} \quad (3)$$

where $\hat{\kappa}^f$ is the expected proportional rate of change of the capital-output ratio.⁸ By analogy, we postulate for the fuel-output ratio ϕ_v^f that:

$$\phi_v^f = \phi_0^f \cdot e^{\hat{\phi}^f \cdot v} \quad (4)$$

where $\hat{\phi}^f$ is the expected proportional rate of change of the fuel-output ratio.⁹ Hence, for fuel consumption per vintage belonging to family f we find:

$$F_{v,t}^f = \phi_v^f \cdot X_{v,t}^f \quad (5)$$

We can use (2) to find the "demand" for capital per vintage in function of the level of installed/required capacity (in "capital" terms):

$$K_{v,t}^f = \kappa_v^f \cdot Y_{v,t}^f \quad (6)$$

3.3 Incorporating Ex Ante Investment Decisions under Uncertainty

Given the factor requirements above, there are now two problems to solve. The first one is the problem how much to invest per technology family, given its specific characteristics. The second problem is the timing of investment. Since investment is irreversible ex post (i.e. capital costs are sunk), the investment planning process should involve both forward-looking expectations as well as a measure of risk aversion in order to accommodate this irreversibility. Therefore, we assume that producers minimize the weighted sum of the expected present value of total cost and the variance of that cost by carefully choosing a composition of their vintage portfolio in both the family dimension and the vintage/productivity dimension, because as rational, risk-averse investors they would be willing to reduce risks by spreading investments both over technologies and over time.

However, as we are using a planning period with fixed length, the irreversibility of investment would provide a bias against investment in capital-intensive technologies at the end of the planning period. Hence, we take irreversibility to mean "ex post clay during the planning period", rather than "ex post clay for all times". We implement the latter by noting that in principle the value

⁸ A negative/positive value of this rate therefore reflects capital-saving/-using technical change.

of investment should be equal to the present value of interest and depreciation charges on investment (cf. Appendix A for more details). So, in order to make the relative contribution of capital costs to total costs during the planning period comparable between vintages that are installed at different points in time during the planning period, we simply assume that the relevant capital costs are actually the present value of the interest and depreciation charges associated with a particular vintage that are incurred until the end of the planning period.

In order to calculate the portfolio variance of the present value of buying and using the vintage portfolio, we first describe how capital and fuel costs are expected to develop over time and what the corresponding variance of these expectations will be.

3.4 Expected Variance in Fixed and Variable Cost Components

The present value (further called “PV”) of capital and fuel costs for all technology families f over a planning period with length θ is given by:

$$PV = \sum_f \sum_{t=0}^{\theta} e^{-\rho \cdot t} \cdot \left(\Psi_{t,\theta}^f \cdot P_t^f \cdot \kappa_t^f \cdot Y_t^f + \sum_{v=0}^t Q_v^f \cdot \phi_v^f \cdot X_{v,t}^f \right) \quad (7)$$

In equation (7), ρ is the rate of discount, while $\Psi_{t,\theta}^f = 1 - \left(\frac{1 - \delta^f}{1 + \rho} \right)^{\theta - t + 1}$ reflects the share of initial investment outlays that can be regarded as the discounted¹⁰ flows of factor payments (i.e. interest and depreciation charges) for the years from t until the end of the planning period θ . P_t^f is the cost of a unit of investment of a vintage at installation time t with $0 \leq t \leq \theta$. In equation (7) depreciation charges are valued at historic cost-prices, rather than at replacement value¹¹. κ_t^f is the capital/capacity-output ratio associated with vintage t . Since we do not have any disembodied technical change ex post by assumption, the capital-output ratio does not change, once a vintage has been installed. Q_t^f is the

⁹ See note 7.

¹⁰ These flows during the period $t.. \theta$ are discounted back until time t . The term $e^{-\rho \cdot t}$ then takes account of further discounting costs until the beginning of the planning period, i.e. time zero. Note that for an infinitely long horizon, the share would approach a value of 1, whereas for a very short horizon, the shortest possible being 0 for investment taking place in the first year after the planning period, the share is equal to zero. So, for t approaching θ , the share is falling towards zero. For further details see appendix A.

¹¹ Note that a change in investment prices then affects only the marginal vintage in a technology family, as opposed to changing fuel prices that would affect production on all vintages in a technology family at the same time. So valuation at historic cost-prices introduces a qualitative difference between capital and fuel costs that would vanish in part if capital would be valued at replacement costs. Of course, there would still be the qualitative difference arising from capital costs being associated with capacity installed and fuel costs with capacity used.

user price of a unit of fuel f used at time t . The price of fuels does not depend on the vintage v , for which it is used. Hence, for all vintages v , Q only depends on t . ϕ_v^f is the corresponding fuel-output ratio. Y_v^f is the total capacity of vintage v at its time of installation. That amount will decrease due to depreciation, and it therefore limits actual output on a vintage v at time t , i.e. $X_{v,t}^f$, in accordance with

$$X_{v,t}^f \leq e^{-\delta^f \cdot (t-v)} \cdot Y_v^f.$$

In order to calculate the variance of the present value of total cost as given by (7), we have made several simplifying assumptions. The first one is that the (constant) discount rate also reflects the required internal net rate of return on investment. The second one is that forecasting errors are serially uncorrelated, and that (co-) variances of the growth rates of fuel and investment prices, but also of the rates of fuel-saving and capital-saving technical change, are constant. In that case, it should be noted that for constant expected values of the growth rates of prices and capital and fuel coefficients, a first order approximation of equation (7) is given by:

$$PV \approx \sum_f \sum_{t=0}^{\theta} e^{-\rho \cdot t} \cdot \Psi_{t,\theta}^f \cdot \tilde{P}_t^f \cdot \tilde{\kappa}_t^f \cdot Y_t^f \cdot (1 + S_t^{f,\hat{P}} + S_t^{f,\hat{\kappa}}) + \sum_f \sum_{t=0}^{\theta} \sum_{v=0}^t e^{-\rho \cdot t} \cdot \tilde{Q}_t^f \cdot \tilde{\phi}_v^f \cdot X_{v,t}^f \cdot (1 + S_t^{f,\hat{Q}} + S_v^{f,\hat{\phi}}) \quad (8)$$

where $S_t^{f,\hat{P}} = \sum_{j=0}^t \mathcal{E}_j^{\hat{P}^f}$, $S_t^{f,\hat{\kappa}} = \sum_{j=0}^t \mathcal{E}_j^{\hat{\kappa}^f}$, $S_t^{f,\hat{Q}} = \sum_{j=0}^t \mathcal{E}_j^{\hat{Q}^f}$ and $S_v^{f,\hat{\phi}} = \sum_{j=0}^v \mathcal{E}_j^{\hat{\phi}^f}$, and where \mathcal{E}_j^x is the forecasting error associated with variable x for time j . Variables with a tilde represent their expected values. Moreover, in equation (8), \hat{P}^f and \hat{Q}^f are the expected growth rates of investment prices and fuel prices for technology family f . $\hat{\kappa}^f$ and $\hat{\phi}^f$ are the expected rates of capital- and fuel-using technical change.¹² All forecasting errors \mathcal{E}_j^x are assumed to have zero expectation. Note the subscript v in $S_v^{f,\hat{\phi}}$. The other sums of error terms all depend just on t .

Equation (8) can now be used to calculate the (approximated) expected forecasting error in the present value of total capital and fuel costs. Given that K is the set of stochastic variables, i.e. $K = \{\hat{P}, \hat{\kappa}, \hat{Q}, \hat{\phi}\}$, while $k1$ and $k2$ are "running" elements of this set, then the expectation of its squared value will be equal to the total variance of the PV, which in turn is given by:

$$\text{var}(PV) = \sum_{t1=0}^{\theta} \sum_{t2=0}^{\theta} \sum_{f1} \sum_{f2} \sum_{k1 \in K} \sum_{k2 \in K} \min(t1, t2) \cdot m_{t1}^{f1, k1} \cdot \sigma_{f1, k1}^{f2, k2} \cdot m_{t2}^{f2, k2} \quad (9)$$

¹² See note 7.

where $\min(t1,t2)$ represents the minimum of $t1$ and $t2$. $\sigma_{f1,k1}^{f2,k2}$ is the co-variance between the growth rates of the different stochastic variables $k1$ and $k2$ for technology families $f1$ and $f2$.¹³ The “terms” $m_{t1}^{f1,k1}$ and $m_{t2}^{f2,k2}$ are defined in terms of the actual control variables of the problem, i.e. investment in individual vintages of different technology families and the corresponding production plans for those vintages. For further details, see Appendix B.

3.4 New Features

3.4.1 Introduction

In order to increase the degree of realism of the model, we have included a number of new features in the van Zon and Fuss (2005) framework. *First* of all, it is not just prices and technical change that are uncertain in this model, but also demand is no longer assumed to be known with certainty. The risk of facing higher demand than expected, is captured by the introduction of two demand scenarios, a low demand scenario (which is the standard extrapolation of known trends) and a high demand scenario (which exceeds the expectation of unchanged growth in demand).¹⁴ Weighing both scenarios by their probabilities we can determine the optimum value of investment that needs to be undertaken to be able to meet demand in all circumstances. *Second*, additional capacity may not be installed without bounds as mentioned above. In the case of hydroelectric utilities, for example, the UK has almost reached maximum installable capacity, i.e. there are not enough suitable sites left to realize additional investments. Therefore, investment is constrained here by the estimates for maximum installable capacity. *Third*, there are differences across technology families with respect to their load characteristics. While coal-fired turbines, for example, have load factors of 80% and more, wind energy and solar techniques depend on external circumstances that do not allow them to produce electricity continuously. *Fourth*, we make a distinction between base load and peak load technologies, where typically coal, nuclear and renewables are used for base load production, whereas gas can be used to meet peaks in demand. *Fifth*, the UK government has expressed interest in producing at least some output using renewable fuels. We want to include this as an explicit constraint in our model. *Finally*, as environmental concerns pertain for an important part to (cumulative) CO2 emissions, we have included these in the model, too. In this way we can see what the introduction of emission caps

¹³ In the actual calculations we will assume that all co-variances are equal to zero, as we have only relatively little data at our disposal to measure these co-variances, and our immediate purpose is to illustrate the working of the model. This has the added bonus of considerably speeding up the calculations. We implement this by requiring that $k2=k1$ and $f2=f1$ for all values of $k1$ and $f1$. See Appendix B for further details.

would mean for the technology composition of the electricity production portfolio and the timing of investment.

3.4.2 Implementation New Features

Uncertainty in demand

With respect to demand we assume that producers distinguish between different demand scenarios, in which demand grows over time at different exponential growth rates, with equally different probabilities. In all scenarios, production plans should be sufficient to meet demand. Production capacity in turn should be able to accommodate all these different production plans. We therefore have to add a demand scenario dimension to all production plans (and to all the decision variables that depend on production plans, such as e.g. emissions), and so end up with the following revised demand constraints:

$$\sum_f \sum_{v=0}^t X_{v,t}^{f,s} \geq D_t^s \quad (10)$$

In equation (10) D_t^s represents the expected time path of demand under demand-scenario s , while $X_{v,t}^{f,s}$ represents the corresponding production plans for all vintages v installed up to time t and belonging to technology family f .

Load-factors

For each vintage in each technology family, we also have to take into consideration that actual output cannot be larger than capacity output, corrected for the (maximum) load factor associated with each technology. The load factor indicates how much of capacity is effectively available for production purposes. This availability depends on down-times that are technology specific, but also weather conditions as in photovoltaic or wind-powered generators. Hence, as additional constraints we now have the “effective capacity” constraint:

$$X_{v,t}^{s,f} \leq e^{-\delta^f \cdot (t-v)} \cdot Y_v^f \cdot l^f \quad (11)$$

where l^f is the (maximum) load factor associated with technology family f . It should be noted that if there is a positive slack associated with equation (11), then this implies that capacity is underutilised, in which case actual rates of capacity utilisation will be variable and smaller than l^f .

¹⁴ Of course there could be more than two demand scenarios. But at this stage we only want to illustrate the principles involved.

Emissions

Fuel consumption generates emissions of various types, depending on the type of fuel used. Hence, we have:

$$e_{i,t}^s = \sum_f \sum_{v=0}^t \omega_i^f \cdot \phi_v^f \cdot X_{v,t}^{f,s} \quad (12)$$

where $e_{i,t}^s$ are total emissions of type i at time t under scenario s . ω_i^f are emissions of type i per unit of fuel consumption in technology family f . Caps on emissions can now be integrated in the model by means of the following constraints:

$$e_{i,t}^s \leq \text{cap}_{i,t} \quad (13)$$

where $\text{cap}_{i,t}$ is some exogenous (desired) time path for total emissions of type i .¹⁵

Minimum renewables market shares

Based on the more general emission targets, the UK government has expressed its desire to produce at least 10 percent of total electricity demand using renewables¹⁶. This is implemented as follows:

$$\sum_{f \in R'} \sum_{v=0}^t X_{v,t}^{f,s} \geq x \cdot D_t^s \quad (14)$$

where R' denotes the set of renewables and where $x=0.1$. Obviously, this target could also have been specified in terms of expected demand, rather than in terms of maximum demand¹⁷, as it has been done here. Equation (14) is of course more strongly binding as it is, if at all.

Physical limits to production capacity for specific technology families

The capacity of some renewables, like hydro, is limited by the physical availability of production possibilities. We have implemented this by including some physical constraints on aggregate renewables capacity per technology family:

¹⁵ Obviously, emission caps may depend on the scenario too.

¹⁶ See section 2.

$$\sum_{v=0}^t Y_v^f \cdot e^{-\delta^f \cdot (t-v)} \leq M_t^f \quad \forall f \in R' \quad (15)$$

In equation (15), M_t^f represents the maximum value of aggregate capacity by technology family. For hydro, biowaste and biomass taken together, as well as wind, these limits are equal to 50.8, 71.5 and 34 GWh, respectively.

Peak-load demand

Some technology families are especially suited for the production of peak-load demand, because they are easy to “switch on” at the time they are most needed. Gas-fired turbines in particular are well suited. Because peak-load demand must be serviced at any time it arises, we must require that production using the set of peak-load technology families is at least as large as the actual peak-load demand. We therefore have:

$$\sum_{f \in P'} \sum_{v=0}^t X_{v,t}^{f,s} \geq p \cdot D_t^s \quad (16)$$

where P' represents the set of technologies that can be used for peak-load production (in our case only gas), and where p represents the fraction of demand to be regarded as peak-load demand.¹⁸ Strictly speaking, equation (16) is an actual production constraint, whereas it is the highest peak that determines required capacity peak-load supply, and the average peak size (amplitude and duration) that determines cumulative production under peak-load circumstances (and the corresponding partial under-utilisation of peak-load capacity).

3.4.3 The Objective Function

For a given demand scenario, we assume that producers will want to minimize a weighted sum of the expected present value (PV) of their total production cost and its corresponding variance:

$$\Phi^s = PV^s + \lambda \cdot \text{var}(PV^s) \quad (17)$$

where λ is the relative weight of the variance of the PV of total costs in the objective function. We will further assume that λ is a non-negative constant.

¹⁷ This also goes for equation (10).

Producers are supposed to minimize (10) by choosing the optimum values of both initial vintage capacity, Y_v^f , per family f for all vintages to be installed during the planning period, and a corresponding "production plan" (i.e. $X_{v,t}^{f,s}$) for each vintage that one plans to install. Y_v^f and $X_{v,t}^{f,s}$ are chosen conditionally on the expected values and (co-) variances of the stochastic variables in this setting, i.e. investment and fuel price growth as well as the proportional rates of change of the capital- and fuel-coefficients due to embodied technical change.

Given the scenario-specific values of the objective function, the ultimate criterion for the electricity investment program is the minimisation of the *expected* value of the variance-adjusted costs of buying new and operating total (i.e. both new and "old") capacity over the entire planning period, i.e. minimisation of:

$$\Phi = \sum_s \pi_s \cdot \Phi^s \quad (18)$$

subject to all the constraints listed above. In equation (18), π_s is the subjective probability of scenario s arising.¹⁹

The full model now consists of the objective function (18) that needs to be minimized, subject to the constraints (7)-(17), and where the definition of the present value of total investment and operating costs are given by (7) and (8). Moreover, PV^s in (18) is evaluated using (8) with all "S-terms" set equal to zero in order to obtain the expected value of the present value of total cost. Equation (9) is used to evaluate $\text{var}(PV^s)$ in equation (17).

4. Simulation Results

4.1 Introduction

Technology characterisation

In this section we present the results obtained using a number of simulations that are meant to highlight the working of the model. Before we describe the outcomes of the various experiments, however, we first want to broadly categorise the various production technologies in terms of the growth rates and variances of their capital and fuel costs, but also in terms of the growth rates of their capital and fuel productivity and the corresponding variances. To this end, the data in Appendix C have been summarized in Table 1.

¹⁸ We have assumed $p=0.1$ for all simulations.

¹⁹ It should be noted that we could also introduce risk aversion at this level of decision making, by amending (18) to include the variance in Φ_s . For reasons of simplicity, we have not done this here.

| | Coal | Gas | Nuclear | Hydro | Biomass | Biowaste | Wind | Pv |
|----------------------------|----------|----------|----------|----------|----------|----------|---------|----------|
| δ | 0.0333 | 0.0400 | 0.0333 | 0.0250 | 0.0400 | 0.0400 | 0.0400 | 0.0333 |
| Load-factor | 0.8 | 0.8 | 0.8 | 0.5 | 0.8 | 0.8 | 0.3 | 0.22 |
| κ_0^{20} | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| φ_0 | 2.76 | 2.166 | 2.65 | 0 | 4.187 | 4.187 | 0 | 0 |
| P_0 | 136.98 | 51.370 | 251.141 | 171.232 | 205.480 | 205.480 | 136.986 | 456.621 |
| Q_0 | 6.522 | 10.16 | 4.151 | 0 | 4.060 | 0 | 0 | 0 |
| $\hat{\kappa}$ | -0.0099 | -0.0163 | -0.0047 | -0.0064 | -0.0463 | -0.04 | -0.0219 | -0.0086 |
| $\hat{\varphi}$ | -0.0017 | -0.0029 | -0.0029 | 0 | -0.0042 | 0 | 0 | 0 |
| \hat{P}^{21} | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| \hat{Q} | 0.025 | 0.040 | 0.018 | 0 | 0 | 0 | 0 | 0 |
| $\sigma_{\hat{\kappa}}^2$ | 0.000570 | 0.000938 | 0.000017 | 0.000160 | 0.000001 | 0.00931 | 0.00083 | 0.026800 |
| $\sigma_{\hat{\varphi}}^2$ | 0.000114 | 0.000118 | 0.000089 | 0 | 0.000256 | 0 | 0 | 0 |
| $\sigma_{\hat{P}}^{22}$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| $\sigma_{\hat{Q}}^2$ | 0.011240 | 0.018820 | 0.001620 | 0 | 0 | 0 | 0 | 0 |

Table 1. Input data

The corresponding (admittedly somewhat impressionistic) technology characterisation is listed in Table 2. Such a characterisation may be of help to interpret the results obtained in the various simulation runs outlined further below. From that table, it follows that the combination of low load-factors and medium to high capital costs are likely to make wind and photovoltaic generation unattractive substitutes for carbon based technologies, but for the fact that they do not generate any CO₂ emissions. In addition to this, wind has a high variance in capital-saving TC because the data also take into account the highly risky offshore wind technologies. Biomass/biowaste has similar cost properties as wind and photovoltaics, but savings prospects through technological change are more positive than with wind and photovoltaic generation. This also goes for the load factor that helps to reduce the relative impact of capital costs on total costs. Hydro is an established technology in the sense that there is little or no (capital-saving) technical change, but also little variance in technical change. Nuclear energy is a relatively sure bet: technical change is relatively slow but certain. This counteracts to some extent the high capital costs, next to relatively low fuel costs and low variance in the price-growth of nuclear fuels. The latter does not hold for gas that in addition also suffers from

²⁰ By construction through a suitable choice of units of measurements.

²¹ Assumption due to lack of data.

²² Assumption due to lack of data.

high capital costs. So gas could be expected to have a relatively low share a priori, save for the fact that technical change is relatively fast, but also relatively uncertain. However, with a CO2 emission cap, and given the fact that gas is a peak-load fuel, the share of gas in total electricity production must remain significant. Finally, coal is a “middle of the road” type of fuel with medium capital and fuel costs and medium or low rates of technical change and variances of those rates.

| Parameters | Coal | Gas | Nuclear | Hydro | Biomass | Biowaste | Wind | Pv |
|---------------------------|--------|--------|---------|------------------|---------|----------|--------|------|
| Capital cost | medium | low | high | medium | high | high | medium | high |
| Fuel cost | medium | high | medium | nr ²³ | medium | low | low | low |
| Fuel cost growth | medium | high | low | nr | nr | nr | nr | nr |
| Variance fuel cost growth | medium | high | low | nr | nr | nr | nr | nr |
| Fuel-saving TC | low | medium | medium | nr | high | nr | nr | nr |
| Variance fuel-sav. TC | medium | medium | low | nr | high | nr | nr | nr |
| Capital-saving TC | low | medium | low | low | high | high | high | low |
| Variance capital-sav. TC | low | medium | low | low | low | high | high | high |
| Load factor | high | high | high | medium | high | high | low | low |

Table 2. Characterization of technology families

Simulation runs

In the following subsection we first describe the base-run, i.e. the outcomes associated with the investment program for a planning period of 30 years that fits all the constraints that were described in more detail in section 3, except that it does not contain a CO2 emission cap. The base-run has been obtained for a value of $\lambda = 0$. That implies that the variance of the cost of the entire investment program is not an issue. The base-run results are labelled R0 and they are discussed in section 4.2. There are 4 other runs, called R1-R4 that redo the base-run but then for values of λ equal to 0.000015, 0.00003, 0.000045 and 0.00006. The results associated with these runs are presented in section 4.3. They show how increasing risk aversion would influence the optimum composition of the capital stock in terms of technology families. Section 4.4 contains the run that is based on a value of $\lambda = 0.000015$, i.e. R1 and on a cap on CO2 emissions defined by the emission path that grows at a constant proportional rate from a level of 150 MtCO2 to a level that is about 25% lower than in R0 at the end of the planning period, i.e. to a level of $(1-0.25) \cdot 350 = 245$ MtCO2. Section 4.5 contains a run, i.e. R6, again with $\lambda = 0.000015$, but also a doubling of the expected variance in the growth rate of gas prices, from the beginning of the planning period. Finally, section 4.6 contains the results of a run (R7) that pertains to a large shock in the variance of the rate of fuel-saving technical change for

²³ nr means not relevant in this case.

nuclear energy. We do this to see whether renewables could take over, more or less on their own, from nuclear energy in these circumstances.

4.2 The Base-Run

These are the results for the base run, using the data from appendix C, but disregarding the variance in fuel prices and rates of technical change by setting $\lambda = 0$. For the low growth (1.5%) demand scenario (S1) and the high demand growth (2.5%) scenario S2, we have plotted the actual production shares for both scenarios, as obtained in the base-run.

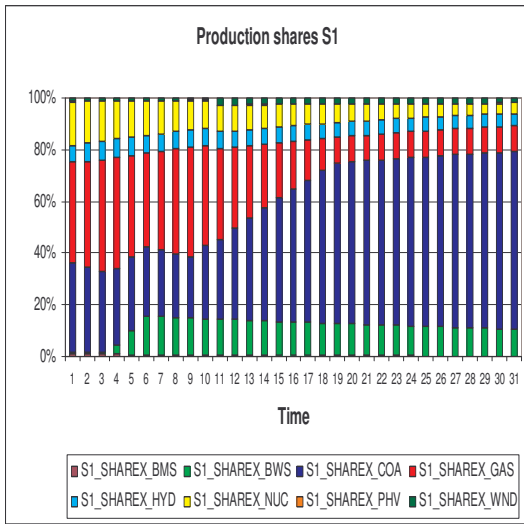


Fig. 4.2.1

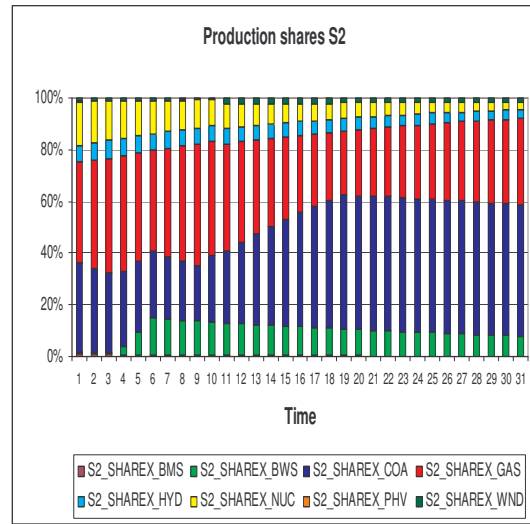


Fig. 4.2.2

In both scenarios, we start out with the same distribution over technologies in the beginning. However, it is clear that gas-based generation takes over to meet the additional demand in the case of the second scenario. This increased production from gas-based electricity generation goes at the expense of coal, but also of hydro and nuclear by a smaller margin. This can be explained by the fact that gas has the lowest investment prices and can be installed at less additional cost than any of the other technologies. This more than outweighs the disadvantage of being more expensive in terms of fuel, since the high demand scenario has a much lower probability of occurring than the standard scenario S1. Indeed, gas is also a peak-load fuel, and as such its higher share in S2 is not very surprising.

In Figures 4.2.3 and 4.2.4 we present the underlying capacity composition. Without any risk aversion, the weight of the variance in the objective function is equal to zero. In other words, all technologies become perfect substitutes, with gradually evolving costs characteristics per fuel technology driving the intertemporal variations in the composition of the technology portfolio. Total unit costs evolve according to increases in investment and fuel prices, but may also shrink as a result

of either capital- or fuel-saving technical change. Other features that matter in this respect are related to constraints on maximum installable capacity, peak- and base-load characteristics and initial conditions (i.e. production using “old” vintages may go on as long as variable (fuel) costs are lower than total unit costs on “new” vintages (this is essentially Malcolmson’s scrapping condition, cf. Malcolmson (1975)).

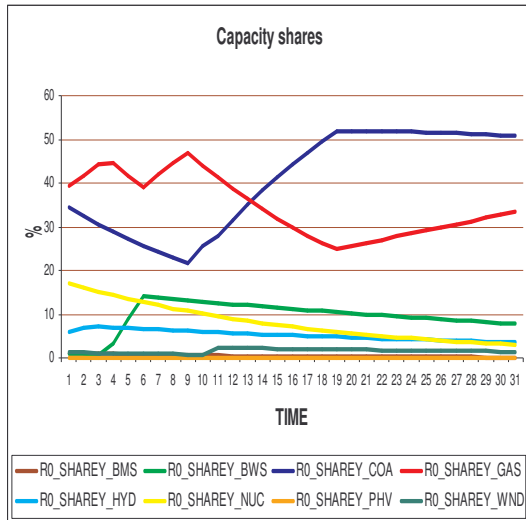


Fig. 4.2.3

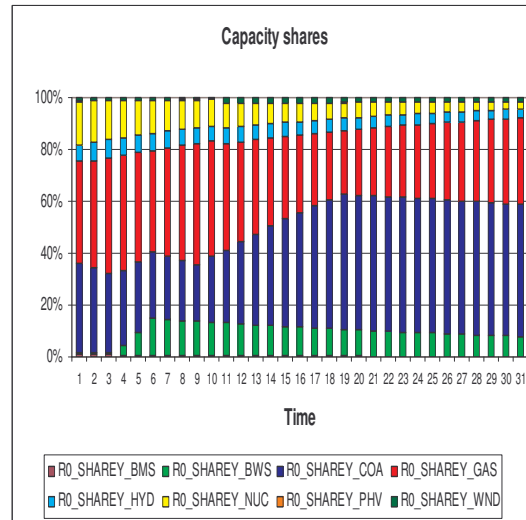


Fig. 4.2.4

Fig. 4.3.2 illustrates the points made above more clearly. Without risk aversion, the technologies are perfect substitutes to the extent that the cheapest alternative is always what should be invested into, when the present value of total unit costs for one technology falls below those of another one. In the beginning gas and hydro are the only technologies that undergo some investment, which is observable from their increasing capacity shares. The other technologies actually see a decrease in their capacity shares, which is due to depreciation, so there is no net investment in those technologies.

One may wonder why wind and biomass do not constitute a higher share of capacity here. This is in part due to the constraints that we have imposed on these technologies (and also hydro). Since it has not proven economically viable to import biomass, while domestic supplies will be limited in the future, we have applied an upper bound on the use of this technology. Investment in wind does occur after technical change has sufficiently reduced capital costs. However, the share stays rather constant afterwards, for the reason that we have excluded the much more expensive alternative of offshore wind turbines in this analysis, even though it becomes more and more infeasible to build additional windmills onshore, especially in the more densely populated areas of the UK.

This leaves us with the composition of electricity generation equipment shown in the picture below. Overall, we can say that gas still constitutes the lion’s share of the electricity mix, followed by coal, whereas wind and bio-wastes have gained at the expense of nuclear power, hydropower, biomass and solar photovoltaic generation.

4.3 Introducing Risk Aversion

In this section we present the results associated with the introduction of risk aversion. We redo the base-run, but now for values of λ equal to 1.5×10^{-5} , 3×10^{-5} , 4.5×10^{-5} , 6×10^{-5} . In Figures 4.3.1 and 4.3.2 below, we show how total costs and the corresponding square root of the variance evolve in function of λ .

From Figure 4.3.1 it is clear that total costs are increasing in risk aversion, as one would expect. This follows from the fact that we started out with a cost-minimizing portfolio under the no-risk aversion assumption of the base run. Any change from that position must increase costs, therefore. From Fig. 4.3.2 it can be seen that there are decreasing returns to risk aversion, in the sense that for ongoing increases in the coefficient of risk aversion, the corresponding decreases in the “standard deviation” of total costs (as a fraction of total costs) will become ever smaller, as the curve in Fig. 4.3.2 is convex and falling. This also goes for the plot of the variance against costs given in Figure 4.3.3. Further decreases in variance can only be realized at ever increasing total costs, so further reductions in variance become ever more costly the lower variance becomes.²⁴

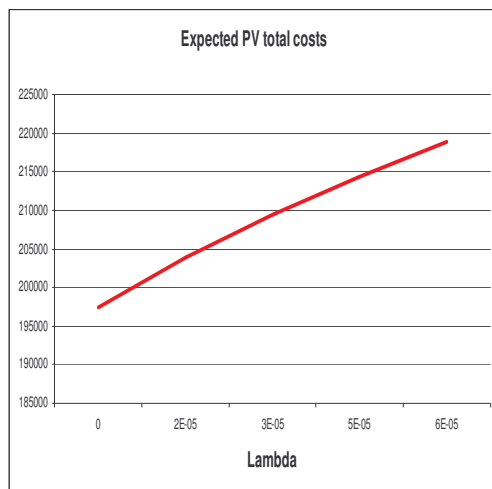


Fig. 4.3.1

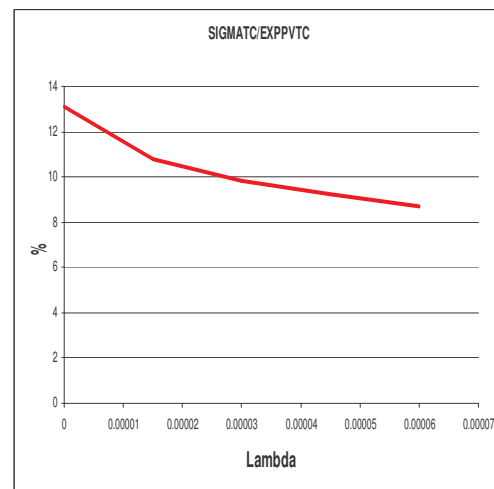


Fig. 4.3.2

²⁴ It should be noted that at a value of $\lambda = 1.5 \cdot 10^{-5}$, the standard deviation of total costs relative to total costs is of the order of 10%, which looks like a reasonable order of magnitude a priori.

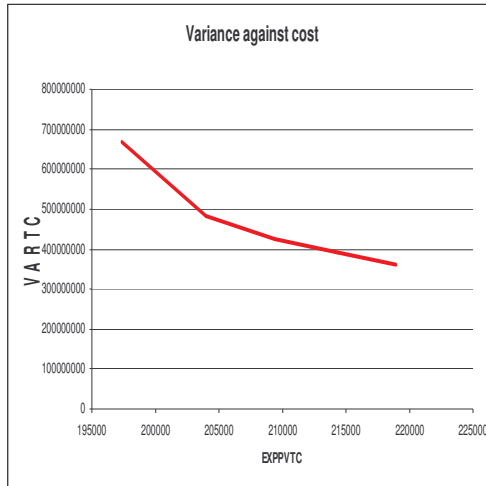


Fig. 4.3.3

In Figures 4.3.4 to 4.3.6 we show what happens to the shares of coal, gas and nuclear in total capacity output, as the reduction in variance can essentially only be brought about by a reshuffling of the technology portfolio and the associated production plans. In Fig. 4.3.4 one can see that the swings in the share of coal during the base-run are stretched out more evenly over time. Shares are lower at the end of the planning period and higher at the beginning. For gas, shares fall structurally below the base run in the beginning, picking up at the end again, thus also levelling out fluctuations in shares to some extent. However, one should recall that gas is a fuel with a relatively high variance both with respect to fuel price growth and with respect to technical change. Hence, while smoothing out fluctuation is always a good strategy when it comes down to variance reduction, reducing the portfolio shares of high variance technologies is an especially good option in this case. In Fig. 4.3.5 we see both principles at work.

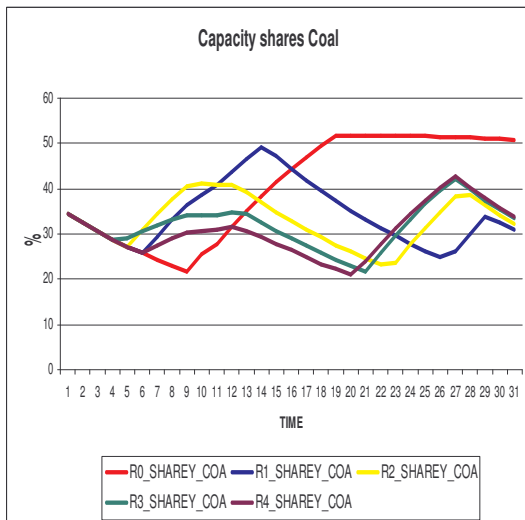


Fig. 4.3.4

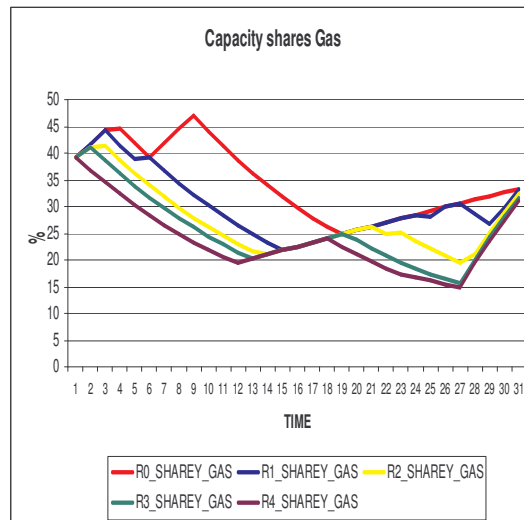


Fig. 4.3.5

Fig. 4.3.6 shows that risk-averse investors would gladly accept nuclear power as a bridge to a “care free” future. Of course, concerns about the negative externalities associated with CO2 emissions, should be weighed against the legitimate concerns about the processing and quasi-permanent storage of nuclear waste material, and the threats of micro-proliferation amongst terrorist groups. Nonetheless, nuclear energy is widely regarded as a means to buy time to find the ultimate solution to our energy problems through carbon sequestration in combination with a more intensive use of renewables. Note from Fig. 4.3.6 that the lower the degree of risk aversion, the later the moment in time within the planning period at which people are starting to build the bridge. However, one should note that they may want to postpone building such a bridge or calling it off altogether, if the risks involved in decommissioning nuclear power plants would also be taken into account, for example by the introduction of dismantling costs, that are highly uncertain. However, the variance data that we have been able to compile suggest that nuclear energy is a fairly “risk-free” alternative, which might raise some doubts.

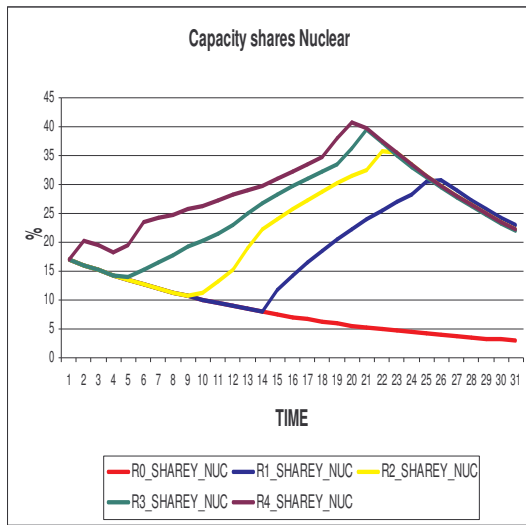


Fig. 4.3.6

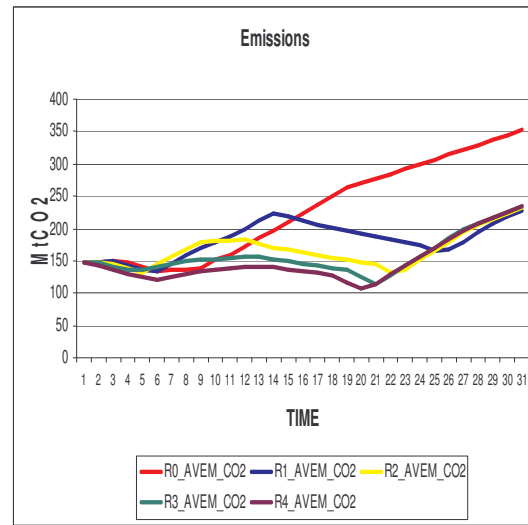


Fig. 4.3.7

In Fig. 4.3.7 we show what happens to emissions due to the reshuffling of the technology portfolio. The figure contains the probability weighted averages of total emissions in both demand scenarios S1 and S2. The one in the base run, i.e. “R0”, generates the highest emissions at the end of the planning period, mainly because coal is still an important portfolio ingredient by then. This is shown quite clearly in Fig. 4.3.7, where fluctuations in emissions follow those in the share of coal in total capacity quite closely (cf. Fig. 4.3.4).

4.4 CO₂ Emission Caps

We now combine R1 (with a value of $\lambda = 1.5 \cdot 10^{-5}$) with a cap on CO₂ emissions. It should be noted on beforehand that even a relatively slight degree of risk aversion generated a reshuffling of the technology portfolio such that in R0, emissions at the end of the planning period were way below emission levels in the base run (by more than 25 percent). This means that our time path for emissions that begins at 150 MtCO₂ and ends at $(1-0.25) \cdot 350 = 245$ MtCO₂ will not be binding at the end of the planning period (see also Fig. 4.3.7). But it will be binding in the middle-regions of the planning period, as we can see quite clearly from Fig. 4.4.1. In this Figure, the flat stretch of emissions for run R5 coincides with the emissions constraint being binding. How the corresponding emission reductions are brought about can be seen from Fig. 4.4.2.

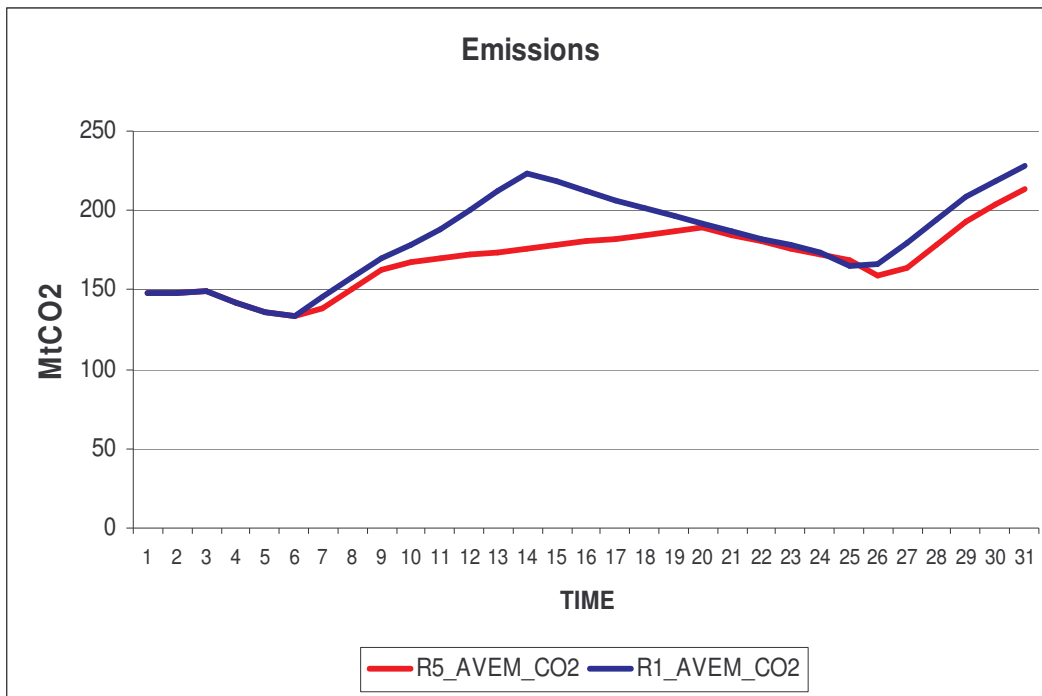


Fig. 4.4.1.

In Fig. 4.4.2 we show the absolute differences between the percentage capacity shares in runs R5 and R1. The carbon content of electricity production is reduced in period 6 by a simultaneous reduction in coal and an increase in gas. The more binding the CO₂ emission cap becomes the more additional carbon-free capacity is installed, in this case nuclear power. Then, as emissions are reduced anyhow from period 15 on (see Fig. 4.4.1), the technology distribution of power production almost reverts to normal, except that the share of nuclear energy is slightly above the base run, and those of gas and coal are correspondingly lower. This also leads to slightly lower emissions at the end of the

planning period, simply because once nuclear has been installed it will stay around for a relatively long time, since capital costs are sunk in the beginning, and old technologies are replaced by new ones only if the total unit costs on the new technologies drop below the unit variable cost on the old technologies. We see therefore that a temporary binding emission constraint can induce semi-structural emission reductions, because the composition of the capital stock changes. In addition, due to the ex post clay character of technologies themselves, and the “near clay” character of the technology portfolio as a whole, the capital stock only slowly adjusts to a situation where the caps are no longer binding.²⁵

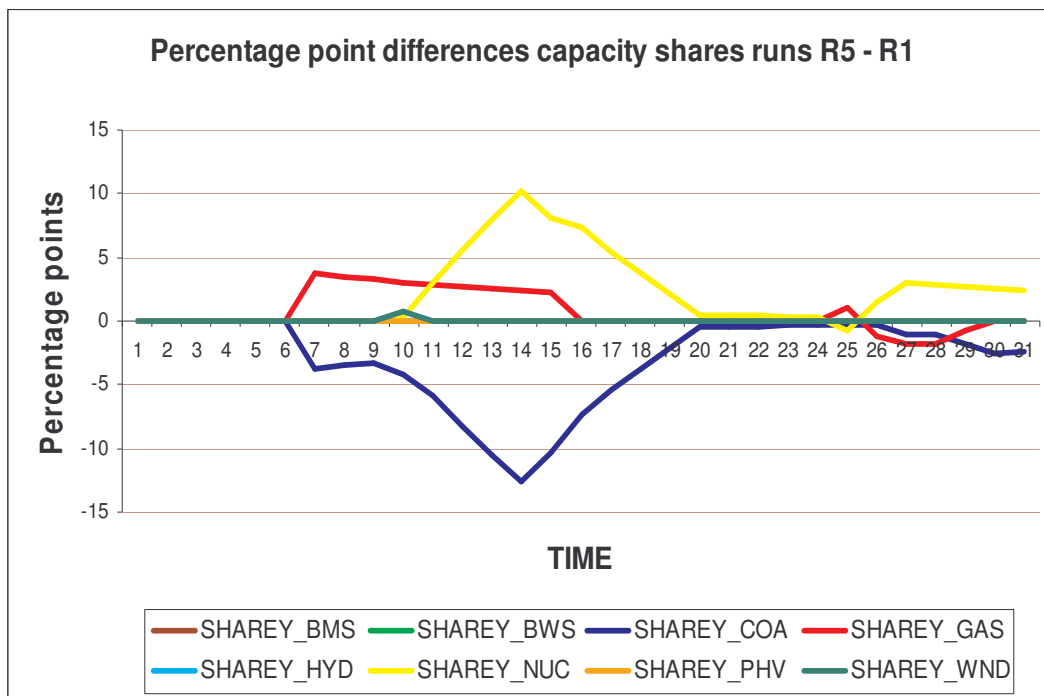


Fig. 4.4.2

4.5 Fuel Price Variance

In experiment R6 we have increased the variance of fuel price growth by 100% in the case of gas, for a value of $\lambda = 1.5 \cdot 10^{-5}$. So, in order to see what such an increase in fuel price growth variance implies, we have to compare runs R6 and R1, since in the latter case we do not have any

²⁵ It should be noted, that in our experimental setting this adjustment of the capital stock is taking place as quickly as is technically feasible, since the optimisation program “knows” when the CO2 emission constraints will become non binding, and can adapt ex ante (by a suitable adjustment of the portfolio) to this situation by choosing a more carbon intensive portfolio than otherwise would have been the case.

CO2 emission caps either. The absolute differences between capacity shares in this case are presented in Fig. 4.5.1 below.

We see that the increase in gas price growth variance significantly reduces the portfolio share of gas. Bio-waste and somewhat later coal take over, and after a slight dip in the middle of the planning period, nuclear energy is phased in as well. At the end of the planning period, gas has become a very unattractive portfolio component indeed, and coal and nuclear energy have permanently taken over.

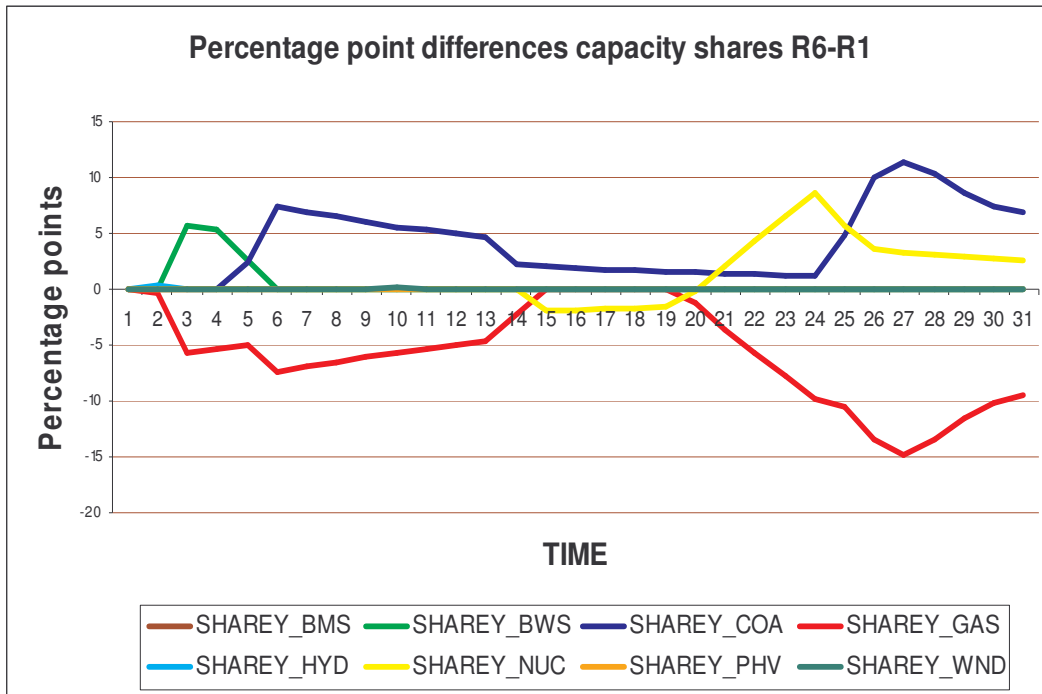


Fig. 4.5.1

4.6 Increases in Technological Variance

For technological uncertainty to have the largest possible impact, it is necessary to implement it as increased variance in the rate of fuel-saving technical change, as fuel consumption associated with a specific vintage is a continuous process, whereas investment takes place at just the moment of installation of that vintage. We have chosen nuclear energy for increased uncertainty with respect to technological change, first of all because controlled fusion has been a technological promise for over 50 years, and it still is. The second reason is that in our simulations, nuclear energy consistently appears to be the “saviour of last resort”. This leads us to wonder whether renewables would stand a chance to take over this role, if nuclear energy would become less attractive for some reason. In order to find this out, we have performed an experiment, in which we have increased the variance of fuel-

saving technical change in nuclear energy production by a factor of 100 (since fuel costs are relatively unimportant in nuclear energy production as compared to coal and gas fired power plants, we need a relatively large shock for its effect to become noticeable).

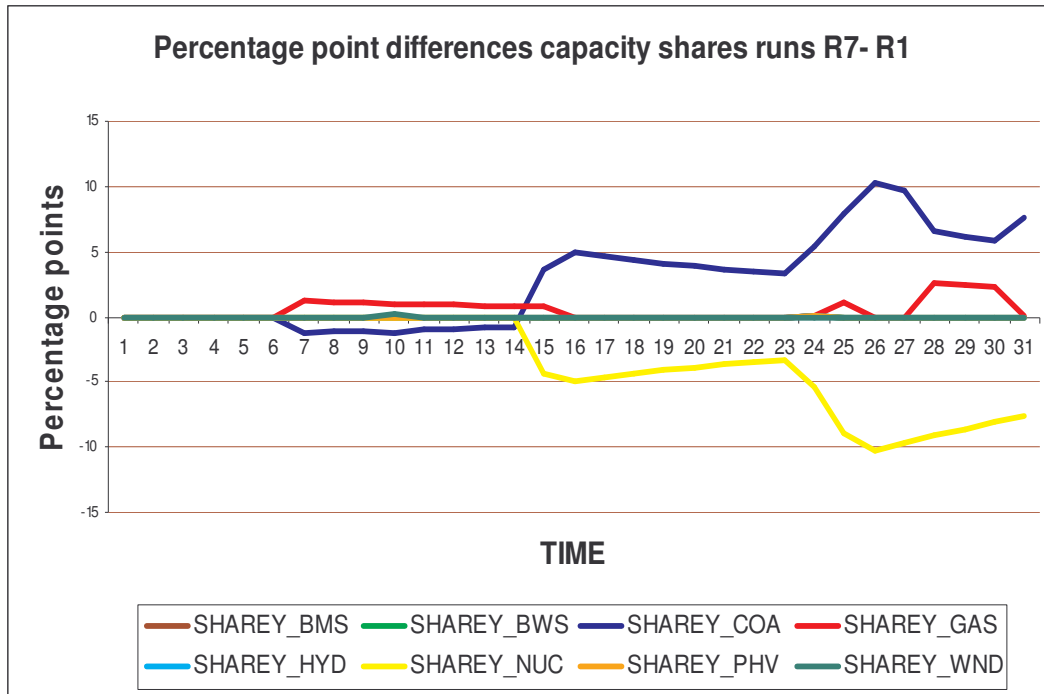


Fig. 4.6.1

Run R7 is the same as R1, except for the shock in the variance of fuel-saving technical change. The results are presented in Figure 4.6.1. In that Figure, we see that the change in the variance of technical change in nuclear energy production, although implemented from the beginning of the planning period, takes a while before it has an impact. This is due to the fact that nuclear had not been invested in during the first half of the planning period in R1 in the first place. Only from the period onward where there was investment in nuclear in R1 (i.e. in year 14), do we see a negative deviation from the results w.r.t. R1 therefore. Another result to note is the negative deviation in coal before period 14, which is compensated by an increase in gas capacity. Since investors are fully aware of the drop in nuclear at the beginning of the planning period already and they know that they will have to compensate this drop by investing more heavily in coal, they actually have an incentive to decrease their installed capacity of coal earlier on because this will enable them to install a larger amount of more modern and productive vintages when the time has come to replace nuclear capacity. In other words, by reducing coal earlier on, investors create room for more advanced capacity later on. The gap is closed by gas, since gas has relatively low instalment cost and can therefore easily make up for the lack of coal in the short run.

This experiment is therefore a good illustration of the workings of the model, not only in the technology dimension (i.e. diversification over technology families leads to substitution of coal for nuclear, which becomes less attractive through less certain prospects of technical change), but also in the quality or time dimension (i.e. it pays off to wait for ongoing technical change to take place and reap the full benefits of being able to install higher quality vintages when investment becomes necessary and thus to substitute investment in coal today for investment in coal at a later point in time).

5. Summary and Conclusion

In this paper we have presented the outcomes of some simulations with a model based on van Zon and Fuss (2005). The latter model integrates elements from optimum financial portfolio theory with a vintage model of production for the electricity sector. The main ideas behind that model are that technological change is embodied in machinery and equipment, and that once installed, the fuel consumption characteristics of power generation equipment cannot be changed ex post. Productivity improvements in electricity production then require investing in the newest equipment that is available on the market: without investment productivity improvements can simply not be realised.

However, electricity producers are risk-averse. So, investing in a piece of equipment with a given fuel efficiency, exposes them to variations in production costs caused by fluctuations in fuel prices. Likewise, capital costs can fluctuate. Because investment is irreversible, electricity producers need to look ahead, and invest sooner rather than later if the future seems very uncertain, given the demand for electricity they are facing. In that case they would want to change their equipment portfolio in favour of vintages with relatively certain consumption characteristics (i.e. the vintage one can invest in now or in the very near future).

Using this vintage portfolio model, we distinguish between eight broad technology families, i.e. coal, gas, nuclear, hydro, biomass, bio-waste, wind and photovoltaic generation. We introduce production targets for renewables, as well as peak- and base-load distinctions between technology families. Moreover, we allow for uncertainty in demand by specifying different demand scenarios with different probabilities of being realised. We link uncertainty surrounding the cost of an investment program over a fixed planning period of 30 years, to uncertainty about fuel price growth and uncertainty about the development of fuel- and capital-saving technical change during that planning period. By investing in the newest vintages of each technology and formulating production plans for the entire vintage capital stock, electricity producers can control aggregate uncertainty. Because production technologies are clay-clay, changes in the capital stock only come about through investment and disinvestment at the margin: the room to manoeuvre is limited in a vintage setting, as it is the case in reality.

We have performed a number of simulation experiments. We find that in the base-run without any risk aversion, carbon emissions in the UK electricity sector range from about 150 MtCO₂ at the beginning of the planning period to 350 MtCO₂ at the end of the planning period. We then increase the degree of risk aversion, and find that expected costs will increase, whereas the expected variance of the expected costs of the entire vintage investment program will decrease. The corresponding standard deviation as a fraction of the expected costs also decreases, but less and less so for increasing values of the degree of risk aversion. As in optimum portfolio theory, we find that the relation between the costs of the entire investment program and the corresponding variance exhibits decreasing returns to variance: a larger variance generates a less than proportionally higher rate of return in ordinary portfolio theory, and in our case a less than proportionally smaller expected cost of the investment program. We find that changes in fuel price growth variances or technological variances have the expected effect. Increased variance with respect to some technology family reduces investment in that family, while increased risk aversion reduces fluctuations in investment over time.

We find that with increased risk aversion, electricity production becomes more diversified over technologies to such a large extent that carbon emissions would be significantly reduced, mainly by switching towards nuclear energy production, rather than renewables. In an experiment where we introduce a cap on CO₂ emissions, nuclear energy turns out to be the “saviour of last resort”, but also gas increases in importance. When we “punish” nuclear energy production by increasing its technological variance we find that gas and coal take over, rather than renewables. We also find that the anticipation of a switch towards another technology in the future makes producers want to invest less in that technology now and more in a substituting technology. In this way, they can benefit more from the cumulative nature of (ongoing) embodied technical change at the moment they will actually execute the switch. Nonetheless, the fact that gas and coal will take over from nuclear energy in this case, suggests that, given the data we have been able to use, none of the renewables is strong or promising enough²⁶ to take over from nuclear energy or coal. This will only occur, when initial costs are lower or when technological uncertainties surrounding renewables are reduced, or both.

²⁶ Note that some of the renewables such as hydropower would be advanced enough to take up a larger share of electricity production; however, hydropower is severely constrained through geographical feasibility.

Appendix A: Irreversible Investment and Capital Cost Adjustment in the Context of a Finite Planning Period

As we have assumed a finite planning period, capital goods installed at the end of the planning period are used for shorter periods of time than those installed at the beginning of the planning period, *ceteris paribus*. Hence, in terms of total costs, fuel costs will have a relatively large impact on vintages installed in the beginning of the planning period while capital cost will have a relatively large impact on vintages installed at the end. Of course, this depends on the notion that all capital costs have to be borne at the moment of installation. This is legitimate in case of an infinite lifetime of equipment (and hence an infinite planning horizon) and if the interest rate matches the discount rate. For, in the latter case, the present value of all interest and depreciation charges adds up to total initial investment outlays. We can turn this result around, and simply assume that the total present value of interest and depreciation charges over the remaining part of the planning period for a vintage installed at some point in time during the planning period will represent the *relevant* (as opposed to *total*) capital costs associated with the vintage under consideration. This assumption would remove the bias against installing relatively capital-intensive equipment at the end of the planning period.

To show how this would work, assume that the rate of interest equals the rate of discount and is given by ρ , whereas the rate of exponential decay is δ . Then, if depreciation at historic cost prices has its impact at the end of a period, while interest payments also have to be made at the end of a period, we can write the present value of the total flow $\Psi(T, \theta)$ of interest and depreciation charges for a one dollar outlay on investment at time T up to and including time $\theta \geq T$ as:

$$\Psi(T, \theta) = \sum_{t=T}^{\theta} (\rho + \delta) \cdot (1 - \delta)^{t-T} \cdot (1 + \rho)^{-(t-T+1)} = \frac{\rho + \delta}{1 + \rho} \cdot \sum_{t=T}^{\theta} \left(\frac{1 - \delta}{1 + \rho} \right)^{t-T} = \frac{\rho + \delta}{1 + \rho} \cdot \sum_{t=T}^{\theta} a^{t-T} \quad (\text{A.1})$$

where $a = (1 - \delta)/(1 + \rho)$. Using (A.1), we find that:

$$\begin{aligned} \Psi(T, \theta) &= \frac{\rho + \delta}{1 + \rho} \cdot \{1 + a + a^2 + \dots + a^{\theta-T}\} \Rightarrow \Psi(T, \theta) - a \cdot \Psi(T, \theta) = \frac{\rho + \delta}{1 + \rho} \cdot (1 - a^{\theta-T+1}) \Rightarrow \\ \Psi(T, \theta) &= \frac{\rho + \delta}{1 + \rho} \cdot (1 - a^{\theta-T+1}) / (1 - a) = (1 - a^{\theta-T+1}) = 1 - \left(\frac{1 - \delta}{1 + \rho} \right)^{\theta-T+1} \end{aligned} \quad (\text{A.2})$$

For $\theta \rightarrow \infty$, we find that $\Psi(T, \theta) \rightarrow 1$. For investment just after the planning period has ended, i.e. for $T = \theta + 1$, we find that $\Psi(\theta + 1, \theta) = 0$.

Appendix B: Variance Calculations

We can obtain equation (9) by noting that the expected forecasting error of the present value of an investment program associated with technology family f , i.e. PV^f , will be given by:

$$\begin{aligned} \mathcal{E}^{PV^f} = PV^f - E(PV^f) &\approx \sum_{t=0}^{\theta} e^{-\rho \cdot t} \cdot \Psi_{t,\theta}^f \cdot \tilde{P}_t^f \cdot \tilde{\kappa}_t^f \cdot Y_t^f \cdot (S_t^{f,\hat{p}} + S_t^{f,\hat{k}}) + \\ &\sum_{t=0}^{\theta} \sum_{v=0}^t e^{-\rho \cdot t} \cdot \tilde{Q}_t^f \cdot \tilde{\varphi}_v^f \cdot X_{v,t}^f \cdot (S_t^{f,\hat{q}} + S_v^{f,\hat{\phi}}) = \\ &\sum_{t=0}^{\theta} a_t^f \cdot (S_t^{f,\hat{p}} + S_t^{f,\hat{k}}) + \sum_{t=0}^{\theta} \sum_{v=0}^t b_{v,t}^f \cdot (S_t^{f,\hat{q}} + S_v^{f,\hat{\phi}}) \end{aligned} \quad (\text{B.1})$$

where $a_t^f = e^{-\rho \cdot t} \cdot \Psi_{t,\theta}^f \cdot \tilde{P}_t^f \cdot \tilde{\kappa}_t^f \cdot Y_t^f$ and $b_{v,t}^f = e^{-\rho \cdot t} \cdot \tilde{Q}_t^f \cdot \tilde{\varphi}_v^f \cdot X_{v,t}^f$. Again, the variables with a tilde represent the expected values of these variables.

It should be noted that equation (B.1) can be rewritten as:

$$\mathcal{E}^{PV^f} = \sum_{t=0}^{\theta} S_t^{f,\hat{p}} \cdot a_t^f + \sum_{t=0}^{\theta} S_t^{f,\hat{k}} \cdot a_t^f + \sum_{t=0}^{\theta} S_t^{f,\hat{q}} \cdot \sum_{v=0}^t b_{v,t}^f + \sum_{t=0}^{\theta} \sum_{v=0}^t b_{v,t}^f \cdot S_v^{f,\hat{\phi}} \quad (\text{B.2})$$

Except for the final term on the *RHS* of (B.2), the forecasting error in the present value of investment and operating costs for technology family f depends on a number of terms that themselves depend just on t . However, the last term of the *RHS* of (B.2), i.e. $\sum_{t=0}^{\theta} \sum_{v=0}^t b_{v,t}^f \cdot S_v^{f,\hat{\phi}}$, can be rewritten as a sum of terms that also depends on t only. In that case it is relatively straightforward to calculate the variance of \mathcal{E}^{PV^f} .

To show this, we first have to rewrite $\sum_{t=0}^{\theta} \sum_{v=0}^t b_{v,t}^f \cdot S_v^{f,\hat{\phi}}$, as stated above. Dropping the unchanging superscripts f and $\hat{\phi}$, it should be noted that this sum can be re-organised in a tabular form as shown in Table B.1. From this Table one can immediately see that the sum of all the elements in a given row can be expressed as a function of t only, since for any row t we must have that the sum of the elements it contains is equal to $S_t \cdot \sum_{v=t}^{\theta} b_{t,v}$. Consequently, the sum over all elements can be

written as $\sum_{t=0}^{\theta} S_t \cdot \sum_{v=t}^{\theta} b_{t,v}$.

| $v \setminus t$ | 0 | 1 | 2 | 3 | .. | θ |
|-----------------|---------------------|---------------------|---------------------|---------------------|----|------------------------------------|
| 0 | $b_{0,0} \cdot S_0$ | $b_{0,1} \cdot S_0$ | $b_{0,2} \cdot S_0$ | $b_{0,3} \cdot S_0$ | .. | $b_{0,\theta} \cdot S_0$ |
| 1 | 0 | $b_{1,1} \cdot S_1$ | $b_{1,2} \cdot S_1$ | $b_{1,3} \cdot S_1$ | | $b_{1,\theta} \cdot S_1$ |
| 2 | 0 | 0 | $b_{2,2} \cdot S_2$ | $b_{2,3} \cdot S_2$ | | $b_{2,\theta} \cdot S_2$ |
| 3 | 0 | 0 | 0 | $b_{3,3} \cdot S_3$ | .. | $b_{3,\theta} \cdot S_3$ |
| .. | .. | .. | .. | .. | .. | .. |
| θ | 0 | 0 | 0 | 0 | 0 | $b_{\theta,\theta} \cdot S_\theta$ |

Table B.1

Defining $b1_t^f = \sum_{v=0}^t b_{v,t}^f$ and $b2_t^f = \sum_{v=t}^{\theta} b_{t,v}^f$, we find that the forecasting error of the expected present value of the variance adjusted costs of the investment (and production) program per technology family f is given by:

$$\mathcal{E}^{PV^f} = \sum_{t=0}^{\theta} \{a_t^f \cdot (S_t^{f,\hat{P}} + S_t^{f,\hat{K}}) + b1_t^f \cdot S_t^{f,\hat{Q}} + b2_t^f \cdot S_t^{f,\hat{\Phi}}\} \quad (\text{B.3})$$

Using the same notation as in equation (9) in the main text, we define $m_t^{f,\hat{P}} = m_t^{f,\hat{K}} = a_t^f, m_t^{f,\hat{Q}} = b1_t^f, m_t^{f,\hat{\Phi}} = b2_t^f$. In that case, (B.3) can be rewritten as:

$$\mathcal{E}^{PV^f} = \sum_{t=0}^{\theta} \sum_{k \in K} m_t^{f,k} \cdot S_t^{f,k} \quad (\text{B.4})$$

where, as before, K is the set of stochastic variables for all technology families, i.e. $K = \{\hat{P}, \hat{K}, \hat{Q}, \hat{\Phi}\}$, and k represents the individual elements of this set. The corresponding forecasting error for the investment and operating costs over the entire technology family portfolio would consist of the sum of (B.4) over all f , in which case we get (B.5):

$$\mathcal{E}^{PV} = \sum_{t=0}^{\theta} \sum_f \sum_{k \in K} m_t^{f,k} \cdot S_t^{f,k} \quad (\text{B.5})$$

Taking the expectation of $(\mathcal{E}^{PV})^2$, we find that:

$$VAR(PV) = E(\varepsilon^{PV})^2 = \sum_{t1=0}^{\theta} \sum_{f1} \sum_{k1 \in K} \sum_{t2=0}^{\theta} \sum_{f2} \sum_{k2 \in K} m_{t1}^{f1,k1} \cdot E(S_{t1}^{f1,k1} \cdot S_{t2}^{f2,k2}) \cdot m_{t2}^{f2,k2} \quad (B.6)$$

Under the assumption that the individual forecasting errors of all the stochastic variables are serially uncorrelated, whereas the contemporaneous co-variance of two different stochastic variables (indexed by $\{f1,k1\}$ and $\{f2,k2\}$) is constant and given by $\sigma_{f1,k1}^{f2,k2}$, it follows that the expectation part of (B.6) can be written as $E(S_{t1}^{f1,k1} \cdot S_{t2}^{f2,k2}) = \min(t1,t2) \cdot \sigma_{f1,k1}^{f2,k2}$, which implies that (B.6) can be rewritten as:

$$\text{var}(PV) = \sum_{t1=0}^{\theta} \sum_{t2=0}^{\theta} \sum_{f1} \sum_{f2} \sum_{k1 \in K} \sum_{k2 \in K} \min(t1,t2) \cdot m_{t1}^{f1,k1} \cdot \sigma_{f1,k1}^{f2,k2} \cdot m_{t2}^{f2,k2} \quad (B.7)$$

Since our main purpose is just to illustrate the principles involved, we have assumed that all co-variances between different variables are equal to zero in order to simplify matters as much as possible. Hence, only the variances of the stochastic variables are assumed to be non-zero. This can easily be implemented by means of a slight modification of (B.7):

$$\text{var}(PV) = \sum_{t1=0}^{\theta} \sum_{t2=0}^{\theta} \sum_{f1} \sum_{f2=f1} \sum_{k1 \in K} \sum_{k2=k1} \min(t1,t2) \cdot m_{t1}^{f1,k1} \cdot \sigma_{f1,k1}^{f2,k2} \cdot m_{t2}^{f2,k2} \quad (B.8)$$

Appendix C: Data Used ²⁷

Data for the first two categories (initial costs and parameters and emissions) have been taken directly from Anderson and Winne (2004) and have only been rescaled in order to make the magnitudes match. The rest of the data mainly comes from the DTI (2006) or is calculated from the data given there.

The fuel price growth rates are calculated for the period from the 3rd quarter of 2004 up to the 3rd quarter of 2005, where the source is again the DTI data for coal, gas and oil²⁸. Due to lack of data, an average of international uranium prices has been used from the Energy Information Administration²⁹.

The growth rate of investment prices is assumed to be relatively low compared to fuel price growth and constant across technologies because there were no consistent estimates available. It seems reasonable to do that because differences in rates of change usually arise due to differences in technological change, which is already accounted for in this model and because of differences in government subsidies and taxes, which are not considered at this point.

Fuel-saving and capital-saving rates of technical change have been computed from the changes in fuel use per unit of electricity produced and the changes in the capital output ratio. These in turn have been derived from the DTI data, which account accurately for fuel use, power generation by technique and capacity installed³⁰.

The (co-)variances of the rates of technical change are based on the time series of growth rates from the same source. Further data concern demand, which has been increasing at a rate of 0.8% on average extrapolating from the last five years. For the high demand scenario, demand growth is taken to be above average. The low demand scenario is associated with a higher probability of occurrence (70%). In addition, the discount rate is equal to 7.5%.

²⁷ Investment price co-variances could not be estimated, which is why they are taken to be stable across and within technology families, growing at a common rate with constant variance.

²⁸ http://www.dti.gov.uk/energy/inform/energy_prices/tables/table_331.xls

²⁹ EIA, <http://www.eia.doe.gov/emeu/international/electricityother.html>

³⁰ (<http://www.dti.gov.uk/energy/statistics/source/electricity/page18527.html>, May 2006)

| | Coal | Gas | Nuclear | Hydro | Biomass | Biowaste | Wind | PV |
|-------------------------------------|-----------|-----------|----------|----------|----------|----------|----------|----------|
| Initial Costs and Parameters | | | | | | | | |
| Variable (\$ cents/kWh) | 1.8 | 2.2 | 1.1 | 0 | 1.7 | 0 | 0 | 0 |
| Fixed (\$/kW) | 1200 | 450 | 2200 | 1500 | 1800 | 1800 | 1200 | 4000 |
| Load Factor | 0.8 | 0.8 | 0.8 | 0.5 | 0.8 | 0.8 | 0.35 | 0.22 |
| Plant Lifetime | 30 | 25 | 30 | 40 | 25 | 25 | 25 | 30 |
| Installed Capacity (MW) | 25054 | 28048 | 11852 | 4248 | 722.2 | 610.7 | 933.2 | 8.2 |
| Emissions | | | | | | | | |
| Unit CO2 Emissions (g/kWh) | 870 | 350 | 0 | 0 | 0 | 0 | 0 | 0 |
| Unit NOx Emissions (g/kWh) | 0.9 | 0.09 | 0 | 0 | 0.9 | 0.9 | 0 | 0 |
| Unit SO2 Emissions (g/kWh) | 0.5 | 0 | 0 | 0 | 0.5 | 0.5 | 0 | 0 |
| Coefficients | | | | | | | | |
| Fuel Use per GWh | 2.76 | 2.166 | 2.65 | 0 | 4.187 | | 0 | 0 |
| Capital-Output Ratio (GW/GWh) | 0.000106 | 0.000105 | 0.000108 | 0.000114 | 0.0002 | | 0.000137 | 0.000408 |
| Growth Rates | | | | | | | | |
| Fuel Price Growth Rate | 0.0259657 | 0.0666857 | 0.018887 | 0 | 0 | 0 | 0 | 0 |
| Fuel Price Growth Variance | 0.0112447 | 0.0188231 | 0.00162 | 0 | 0 | 0 | 0 | 0 |
| Investment Price Growth Rate | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |
| Investment Price Growth Var. | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| Fuel-Saving TC | -0.00167 | -0.00289 | -0.00291 | 0 | -0.00422 | 0 | 0 | 0 |
| Fuel-Saving TC Variance | 0.000114 | 0.000118 | 8.88E-05 | 0 | 0.000256 | 0 | 0 | 0 |
| Capital-Saving TC | -0.0099 | -0.0163 | -0.0047 | -0.0064 | -0.0463 | -0.04 | -0.0219 | -0.0086 |
| Capital-Saving TC Variance | 0.00057 | 0.000938 | 1.74E-05 | 0.00016 | 0.000001 | 0.00931 | 0.00083 | 0.0268 |

Table C.1: Data Set (from Anderson and Winne (2004), complemented by data taken from <http://www.dti.gov.uk/energy/statistics/> May 2006).

References

- Aghion, P., and P. Howitt (1992): "A Model of Growth Through Creative Destruction," *Econometrica*, 60(2), 323-351.
- Anderson, D., and S. Winne (2004): "Modelling Innovation and Threshold Effects in Climate Change Mitigation," Working Paper 59, Tyndall Centre.
- Awerbuch, S., and M. Berger (2003): "Applying Portfolio Theory to EU Electricity Planning and Policy-Making," Working Paper EET/2003/03, International Energy Agency.
- Chaton, C., and J. Doucet (2003): "Uncertainty and Investment in Electricity Generation with an Application to the Case of Hydro-Québec," *Annual Operations Research*, 120(1), 59-80.
- Dixit, A., and R. Pindyck (1994): *Investment under Uncertainty*. Princeton University Press, New Jersey.
- DTI (2003): "The White Paper on Energy, Our Changing Climate," retrieved from <http://www.dti.gov.uk/energy/policy-strategy/energy-white-paper/page21223.html>.
- DTI (2005): "UK Energy Sector Indicators 2005," retrieved from <http://www.dti.gov.uk/energy/statistics/publications/indicators/page17171.html>.
- DTI (2006): All additional statistics are retrieved from <http://www.dti.gov.uk/energy/statistics/index.html>.
- Energy Information Administration: "Other International Electricity Data," retrieved from <http://www.eia.doe.gov/emeu/international/electricityother.html>.
- Kleindorfer, P., and L. Li (2005): "Multi-Period VaR-Constrained Portfolio Optimization with Applications to the Electric Power Sector," *The Energy Journal*, 26(1), 1-26.
- Madlener, R., G. Kumbaroglu, and V. Ediger (2005): "Modelling Technology Adoption as an Irreversible Investment under Uncertainty: The Case of the Turkish Electricity Supply Industry," *Energy Economics*, 27(1), 139-163.
- Malcolmson, J.M. (1975), "Replacement and the Rental Value of Capital Equipment Subject to Obsolescence", *Journal of Economic Theory*, Vol. 10, pp. 24-41.
- Mitchell, C., Bauknecht, D., and P.M. Connor (2006): "Effectiveness through Risk Reduction: a Comparison of the Renewable Obligation in England and Wales and the Feed-in System in Germany," *Energy Policy*, 34, 297-305.
- Pindyck, R. (1991): "Irreversibility, Uncertainty and Investment," *Journal of Economic Literature*, 29(3), 1110-1148.
- Pindyck (1993): "Investments of Uncertain Costs," *Journal of Financial Economics*, 34(153-76).
- Salter, W.E.G. (1960), "Productivity and Technical Change", Cambridge University Press, Cambridge.
- Schumpeter, J. (1942): "Socialism, Capitalism and Democracy," Harper and Row, New York.

Van Zon, A., and S. Fuss (2005): “Irreversible Investment and Uncertainty in Energy Conversion: a Clay-Clay Vintage Portfolio Selection Approach,” Working Paper, University of Maastricht/UNU-MERIT

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