Awerbuch, Shimon; Yang, Spencer

Article

Efficient electricity generating portfolios for Europe: Maximising energy security and climate change mitigation

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Suggested Citation: Awerbuch, Shimon; Yang, Spencer (2007) : Efficient electricity generating portfolios for Europe: Maximising energy security and climate change mitigation, EIB Papers, ISSN 0257-7755, Vol. 12, Iss. 2, pp. 8-37

This Version is available at:
http://hdl.handle.net/10419/44888

ABSTRACT

This paper applies portfolio-theory optimisation concepts from the field of finance to produce an expository evaluation of the 2020 projected EU-BAU (business-as-usual) electricity generating mix. *We locate optimal generating portfolios that reduce cost and market risk as well as CO_2 emissions relative to the BAU mix. Optimal generating portfolios generally include greater shares of wind, nuclear, and other non-fossil technologies that often cost more on a stand-alone engineering basis, but overall costs and risks are reduced because of the portfolio diversification effect. They also enhance energy security. The benefit streams created by these optimal mixes warrant current investments of about €250 – €500 billion. The analysis further suggests that the optimal 2020 generating mix is constrained by shortages of wind, especially offshore, and possibly nuclear power, so that even small incremental additions of these two technologies will provide sizeable cost and risk reductions.*

Shimon Awerbuch (http://www.awerbuch.com) was Senior Fellow, Sussex Energy Group, SPRU, University of Sussex until his sudden death in a plane crash on February 10, 2007 – only a few days after presenting this paper at the 2007 EIB Conference on Economics and Finance. He was a financial economist specialising in electric utilities, energy and technology and had previously served as Senior Advisor for Energy Economics, Finance and Technology with the International Energy Agency in Paris. EIB staff who worked with Shimon will remember him as a charming, friendly, and inspiring person and as a dedicated economist enthusiastically presenting his ideas and convictions. We are very grateful to Dr. Spencer Yang – Dr. Awerbuch's co-author – for finishing their joint work.

Spencer Yang (spencer.yang@bateswhite.com) is Visiting Fellow at Sussex Energy Group – SPRU – University of Sussex – Brighton, UK. Spencer Yang is also Manager, Energy Practice, with Bates White, LLC, Washington DC, USA.

Efficient electricity generating portfolios for Europe: maximising energy security and climate change mitigation

Shimon Awerbuch

Spencer Yang

1. Least-cost *vs.* portfolio-based approaches in generation planning

Traditional energy planning in Europe and the United States focuses on finding the least-cost generating alternative. This approach worked sufficiently well in a technological era, marked by relative cost certainty, low rates of technological progress, and technologically homogenous generating alternatives and stable energy prices (Awerbuch 1993, 1995a). However, today's electricity planner faces a broadly diverse range of resource options and a dynamic, complex, and uncertain future. Attempting to identify least-cost alternatives in this uncertain environment is virtually impossible (Awerbuch 1996). As a result, more appropriate techniques are required to find strategies that remain economical under a variety of uncertain future outcomes.

Given the uncertain environment, it makes sense to shift electricity planning from its current emphasis on evaluating alternative technologies to evaluating alternative electricity generating portfolios and strategies. The techniques for doing this are rooted in modern finance theory – in particular mean-variance portfolio theory.[1] Portfolio analysis is widely used by financial investors to create low risk, high return portfolios under various economic conditions. In essence, investors have learned that an efficient portfolio takes no unnecessary risk to its expected return. In short, these investors define efficient portfolios as those that maximise the expected return for any given level of risk, while minimising risk for every level of expected return.

Portfolio theory is highly suited to the problem of planning and evaluating electricity portfolios and strategies because energy planning is not unlike investing in financial securities where financial portfolios are widely used by investors to manage risk and to maximise performance under a variety of unpredictable outcomes. Similarly, it is important to conceive of electricity generation not in terms of the cost of a particular technology today, but in terms of its portfolio cost. At any given time, some alternatives in the portfolio may have high costs while others have lower costs, yet over time, an astute combination of alternatives can serve to minimise overall generation cost relative to the risk. In sum, when portfolio theory is applied to electricity generation planning, conventional and renewable alternatives are not evaluated on the basis of their stand-alone cost, but on the basis of their portfolio cost – that is: their contribution to overall portfolio generating cost relative to their contribution to overall portfolio risk. Portfolio-based electricity planning techniques – pioneered by Awerbuch and Berger (2003), Berger (2003), Awerbuch (2000a), Humphreys and McLain (1998), Awerbuch (1995), and Bar-Lev and Katz (1976) – thus suggest ways to develop diversified generating portfolios with known risk levels that are commensurate with their overall electricity generating costs. Simply put, these techniques help identify generating portfolios that can minimise a society's energy cost and the energy price risk it faces.

This also has important security of energy supply implications. Although energy security considerations are generally focused on the threat of abrupt supply disruptions (see for instance European Commission 2001), a case can also be made for the inclusion of a second aspect: the risk of unexpected electricity cost increases. This is a more subtle, but equally crucial, aspect of energy security. Energy security is reduced when countries (and individual firms) hold inefficient portfolios that are needlessly exposed to the volatile fossil fuel cost risk.

1 Mean-variance portfolio theory (MVP), an established part of modern finance theory, is based on the pioneering work of Nobel Laureate Harry Markowitz 50 years ago. For a recent contribution see Fabozzi *et al.* (2002).

Optimal portfolio mixes are designed to minimise expected generating cost and risk, while simultaneously enhancing energy security.

The purpose of this paper is to describe a portfolio optimisation analysis that develops and evaluates optimal and efficient EU electricity generating mixes for 2020, in an environment of uncertain CO_2 prices. These optimal portfolio mixes are designed to minimise expected generating cost and risk – while simultaneously enhancing energy security – and they can be used as a benchmark for evaluating electricity generating strategies aimed at minimising CO_2 emissions. A key finding of the analysis is that compared to the projected 2020 EU business-as-usual (BAU) electricity generating portfolio, there exist optimal and efficient portfolios that are less risky, less expensive, and that substantially reduce CO_2 emissions and energy import dependency.

In developing these results, we proceed as follows. Section 2 sets out the main principles of the portfolio-based approach to electricity-sector planning. Section 3 describes the data needed for applying such an approach and how we have compiled and estimated them. Using these data, Section 4 identifies optimal EU electricity generating portfolios for 2020 and it presents key features of these portfolios. Section 5 probes deeper into some of the findings, highlighting the role of nuclear energy, the scope for minimising CO_2 emissions, the economic consequences of real-world technology constraints, and the effects of carbon pricing. Section 6 summarises, concludes, and stresses the potential and limitations of our analysis.

Box 1. Electricity generating costs, risks, and correlations

Electricity generating cost and returns

Portfolio theory was initially conceived in the context of financial portfolios, where it relates expected portfolio return to expected portfolio risk, defined as the year-to-year variation of portfolio returns. This box illustrates portfolio theory as it applies to a two-asset generating portfolio, where the generating cost is the relevant measure. Generating cost (€/kWh) is the inverse of a return (kWh/€), that is, a return in terms of physical output per unit of monetary input.

Expected portfolio cost

Expected portfolio cost is the weighted average of the individual expected generating costs for the two technologies:

(1) Expected portfolio cost = $X_1 E(C_1) + X_2 E(C_2)$,

where X_1 and X_2 are the fractional shares of the two technologies in the mix, and $E(C_1)$ and $E(C_2)$ are their expected levelised generating costs per kWh.

Expected portfolio risk

Expected portfolio risk, $E(\sigma_p)$, is the expected year-to-year variation in generating cost. It is also a weighted average of the individual technology cost variances, as tempered by their covariances:

(2) Expected portfolio risk = $E(\sigma_p) = \sqrt{X_1^2\sigma_1^2 + X_2^2\sigma_2^2 + 2X_1X_2\rho_{12}\sigma_1\sigma_2}$,

where: X_1 and X_2 are the fractional shares of the two technologies in the mix; σ_1 and σ_2 are the

2. Portfolio-based approach to electricity sector planning

2.1 Portfolio optimisation basics applied to electricity sector planning

Portfolio theory was developed for financial analysis to locate portfolios with maximum expected return at every level of expected portfolio risk. Box 1 reviews the basics of this theory and explains how this paper applies it to electricity generation mixes. An important point to note here is that in the case of electricity generating portfolios, it is more convenient to optimise portfolio generating costs as opposed to portfolio returns (see Awerbuch and Yang 2007 and Awerbuch and Berger 2003). This choice does not affect the results and conclusions presented in this paper.

In the case of electricity generating portfolios, it is more convenient to optimise portfolio generating costs as opposed to portfolio returns.

Expected portfolio generating cost is the weighted average of the individual technology costs. The expected risk of an electricity portfolio – that is, the expected year-to-year fluctuation in portfolio generating cost – is a weighted average of the risks of the individual technology costs, tempered by their correlations or covariances. Each technology itself is characterised by a portfolio of cost streams, comprising capital outlays, fuel expenditures, operating and maintenance (O&M) expenditure, and CO_2 costs. It follows that for each technology, risk is the standard deviation of the year-to-year changes of these cost inputs.

standard deviations of the holding period returns of the annual costs of technologies *1* and *2* as further discussed below; and ρ_{12} is their correlation coefficient.

Portfolio risk is always estimated as the standard deviation of the holding period returns (HPRs) of future generating cost streams. The HPR is defined as: *HPR=(EV–BV)/BV*, where *EV* is the ending value and *BV* the beginning value (see Brealey and Myers 2004 for a discussion on HPRs). For fuel and other cost streams with annual reported values, *EV* can be taken as the cost in year *t+1* and *BV* as the cost in year *t*. HPRs measure the rate of change in the cost stream from one year to the next. A detailed discussion of its relevance to portfolios is given in Berger (2003).

Each individual technology actually consists of a portfolio of cost streams (capital, operating and maintenance, fuel, CO_2 costs, and so on). Total risk for an individual technology – that is, the portfolio risk for those cost streams – is σ_T. In this case, the weights, X_1, X_2, and so on, are the fractional share of total levelised cost represented by each individual cost stream. For example, total levelised generating costs for a coal plant might consist of ¼ capital, ¼ fuel, ¼ operating costs, and ¼ CO_2 costs, in which case each weight $X_j = 0.25$.

Correlation, diversity, and risk

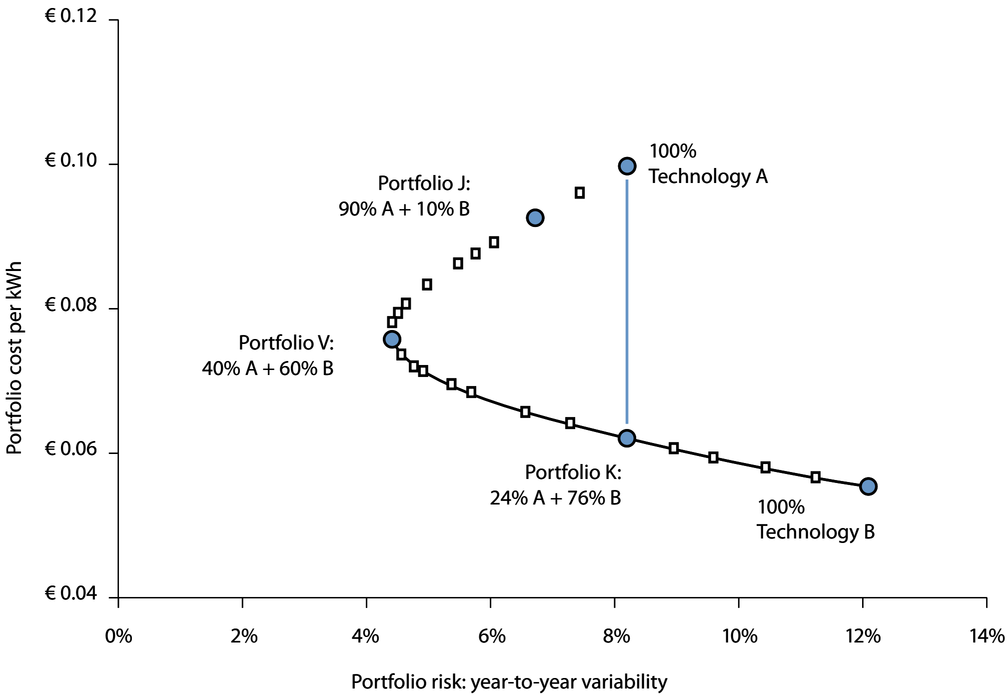
The correlation coefficient, ρ, is a measure of diversity. Lower ρ among portfolio components creates greater diversity, which reduces portfolio risk σ_p (with the notable exception discussed by Roques 2006). More generally, portfolio risk falls with increasing diversity, as measured by an absence of correlation between portfolio components. Adding a fuel-less (that is fixed-cost, riskless) technology to a risky generating mix lowers expected portfolio cost at any level of risk, even if this technology costs more (Awerbuch 2005). A pure fuel-less, fixed-cost technology, has $\sigma_i = 0$ or nearly so. This lowers, σ_p, since two of the three terms in equation (2) reduce to zero. This, in turn, allows higher-risk/lower-cost technologies into the optimal mix. Finally, it is easy to see that σ_p declines as $\rho_{i,j}$ falls below 1. In the case of fuel-less renewable technologies, fuel risk is zero and its correlation with fossil fuel costs is zero too.

For electricity planning, portfolio optimisation exploits the interrelationships among the various technology generating cost components.

Portfolio theory improves decision making in the following way. First, since the investor only needs to consider the portfolios on the so-called efficient frontier, rather than the entire universe of possible portfolios, it simplifies the portfolio selection problem. Second, it quantifies the notion that diversification reduces risk. For electricity planning, portfolio optimisation exploits the interrelationships (i.e., correlations) among the various technology generating cost components. Take for example fossil fuel prices. Because they are correlated with each other, a fossil-dominated portfolio is undiversified and exposed to fuel price risk. Conversely, renewables, nuclear, and other non-fossil options diversify the mix and reduce its expected risk because their costs are not correlated with fossil prices.

The portfolio diversification effect is illustrated in Figure 1, which shows the costs and risks for various possible two-technology portfolios. Technology *A* is representative of a generating alternative with higher cost and lower risk – such as photovoltaics (PV). It has an expected (illustrative) cost of around €0.10 per kWh with an expected year-to-year risk of 8 percent. Technology *B* is a lower-cost/higher-risk alternative – such as gas-fired generation. Its expected cost and risk are about €0.055 per kWh and 12 percent, respectively. The correlation factor between the total cost streams of the two technologies is assumed to be zero. This is a simplification since in reality the capital and variable cost of PV will exhibit some non-zero correlation with the capital and variable cost of gas generation.

Figure 1. Portfolio effect for illustrative two-technology portfolio



As a consequence of the portfolio effect, total portfolio risk decreases when the riskier technology *B* is added to a portfolio consisting of 100 percent *A*. For example, portfolio *J*, which comprises 90 percent of technology *A* plus 10 percent *B*, exhibits a lower expected risk than a portfolio comprising 100 percent *A*. This is counter-intuitive since technology *B* is riskier than *A*. Portfolio *V*, the minimum variance portfolio, has a risk of around 4 percent, which is half of the risk of *A* and one-third of the risk of *B*. This, however, illustrates the point of diversification.

Investors would not hold any mix above portfolio *V* because mixes exhibiting the equivalent risk can be obtained at lower cost on the solid portion of the line. Portfolio *K* is therefore superior to 100 percent *A*. It has the same risk, but lower expected cost. Investors would not hold a portfolio consisting only of technology *A,* but rather would hold the mix represented by *K*. Taken on a stand-alone basis, technology *A* is more costly, yet properly combined with *B,* as in portfolio *K*, it has attractive cost and risk properties. Not only is the mix *K* superior to 100 percent *A*, most investors would also consider it superior to 100 percent technology *B*. Compared to *B*, mix *K* reduces risk by one-third while increasing cost by just 10 percent (€0.005 per kWh), which gives it a higher Sharpe ratio than other mixes.[2] Mix *K* illustrates that astute portfolio combinations of diversified alternatives produce efficient results, which cannot be measured using stand-alone cost concepts. To summarise, portfolio optimisation locates minimum-cost generating portfolios at every level of portfolio risk, represented by the solid part of the line in Figure 1, that is, the stretch between *V* and *B*.

2.2 Portfolio-risk perspective *vs.* engineering-risk perspective

Having sketched the gist of the portfolio approach to electricity generation planning, it is useful to comment on the distinction between unsystematic (or firm-specific) risk, systematic (or market) risk, and risks usually considered in engineering approaches to analysing the pros and cons of alternative generation technologies.

Finance theory divides total risk into two components: unsystematic risk that affects primarily the prices of an asset (these risks can be reduced through diversification) and systematic that affect the prices of all assets. Systematic risk refers to the risk common to all securities and cannot be diversified away (within one market). Within the market portfolio, unsystematic risk will be diversified away to the extent possible. Systematic risk is therefore equated with the risk (standard deviation) of the market portfolio.

In the case of generating technologies and other real assets, diversification and portfolio risk are frequently misunderstood. With some analysts adopting an engineering approach that strives to enumerate all conceivable risks, including those that do not affect overall portfolio risk by virtue of diversification.[3] Ignoring diversification effects in this manner, however, yields a portfolio risk estimate that is systematically biased upwards.

By ignoring diversification effects, engineering risk studies yield a portfolio risk estimate that is systematically biased upwards.

For example, year-to-year fluctuations in electricity output from a wind farm is an unsystematic risk and is probably not relevant for portfolio purposes since it is uncorrelated to the risk of other portfolio cost streams – though this unsystematic risk presents a potential risk to the owner of the wind farm. Certainly in the case of a large, geographically dispersed mix such as the EU generating portfolio, year-to-year wind resource variability can be considered random and uncorrelated to fossil fuel prices or other generating cost components. While it is possible to measure the standard deviation of the yearly wind resource at a given location, its correlation to the output of other wind farms across the continent (see Figure 2), or to many if not most other generating cost components, is arguably zero (that is, $\rho_{12} = 0$ in equation (2) of Box 1). Thus, wind variability at a particular location does not contribute significantly to portfolio risk.

2 Developed by Nobel Laureate William F. Sharpe, this ratio is a risk adjusted performance of an asset and is used to characterise how well the return of an asset compensates the investor for the risk taken.

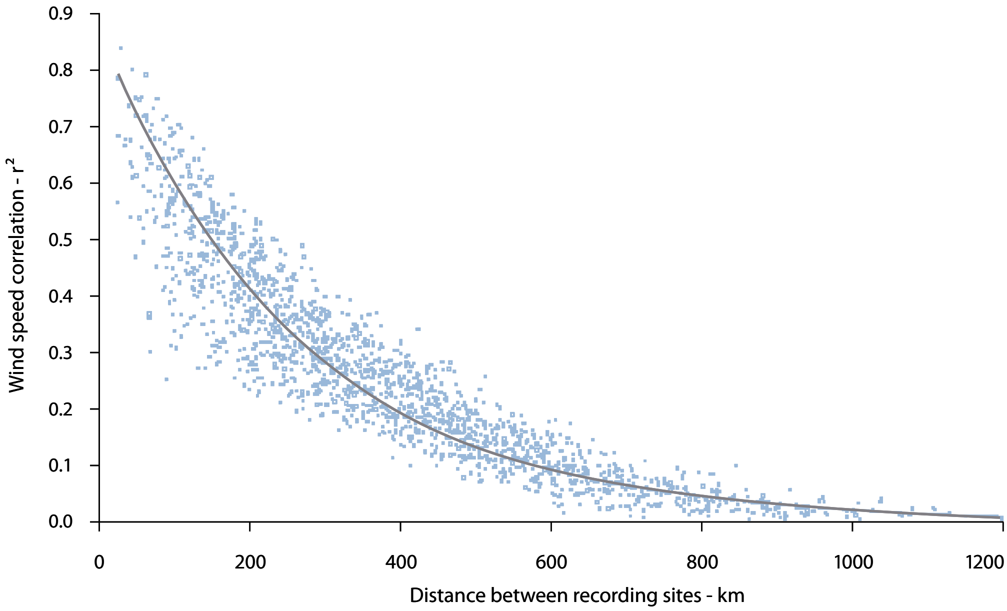
3 For example, Jansen *et al.* (2006, p. 56) develop complex *ad hoc* procedures intended to produce a 'transparent [and] comprehensive' portfolio risk measure by attempting to enumerate and combine various random risks that might affect individual generators, but which cannot be expected to affect overall portfolio risk except possibly in the case of very small generating systems.

Operating costs for wind, solar, and other passive, capital-intensive renewables are essentially fixed, or riskless, over time.

From a portfolio perspective, there is another important point to consider. Operating costs for wind, solar, and other passive, capital-intensive renewables are essentially fixed, or riskless, over time. The finance-theory aspects of these fixed-cost, riskless technologies are developed in Awerbuch (2000b).[4] Perhaps more important is that these costs are uncorrelated to fossil fuel prices. This enables these technologies to diversify the generating mix and enhance its cost-risk performance. Given sufficient geographic dispersion in the wind resources, as would be expected in an EU-wide portfolio, the operating cost of a generating system with 30 percent wind will fluctuate less from year to year than a system with no wind.[5]

The idea that enumerating all conceivable unsystematic risks is misleading in the context of a generating portfolio study holds for other engineering variances – such as annual variations in attained fuel conversion efficiency for a particular gas plant. Some analysts (Jansen *et al*. 2006, for instance) choose to include this risk. Although such yearly efficiency fluctuations might change the accountant's estimate of kWh generating costs at a given site[6], it is reasonable to assume that risk is uncorrelated, making only small contributions to overall portfolio risk.

Figure 2. Onshore wind speed correlation by distance – United Kingdom



Source: Sinden (2005)
Note: Showing 1,770 pairs of wind speed recording sites (surface wind speed), typically based on 30 years of data per pair.

4 Strictly speaking, in the case of capital costs, this statement holds only *ex post*, although, given the short lead times of renewables projects and the large proportion of manufactured components, construction-period risks for these technologies are low even *ex ante*. O&M costs for renewables arguably have the same portfolio risks as O&M costs for conventional technologies. However, because they represent a small share of total cost of renewable generation, their risk contribution is also small. This is further discussed in Awerbuch (2000).

5 Sinden (2005) and Grubb *et al*. (2007) illustrate how geographic dispersion diversifies wind variability.

6 On an accounting basis, kWh generating cost is calculated by dividing annual capital charges plus operating costs by the year's kWh output. Given a fixed capital charge and relatively fixed maintenance costs, therefore, annual wind output variability would cause year-to-year kWh costs to vary. Sunk capital costs are irrelevant in an economic sense, but fluctuations in periodic wind output might change the economic kWh cost estimate on the basis of avoided costs.

3. Data needed for computing optimal electricity generating portfolios

Applying portfolio optimisation to the EU generating mix requires the following inputs: (i) capital, fuel, operating, and CO_2 costs per unit of output (kWh) for each generating technology; (ii) the risk or standard deviation of each cost component; (iii) the correlation factors between all cost components. The following sub-sections will address each input and the way they are used to identify optimal portfolios. A more detailed presentation of the data and estimation can be found in Awerbuch and Yang (2007).

3.1 Technology generating cost

Figure 3 shows levelised 2020 generating cost for various technologies based on TECHPOLE performance and cost data.[7] Fossil fuel costs reflect the most recent projections of the European Commission (European Commission 2006) and the International Energy Agency (IEA 2006).

As for the cost of CO_2, a value of €35/t CO_2 has been used. This can be interpreted as an expected market price of CO_2, assuming that economic policies aimed at internalising the economic cost of CO_2 emissions yield a market price of CO_2 – for example, under the European Union Emissions Trading Scheme. Alternatively, in the absence of such policies, the cost of CO_2 can be interpreted as the shadow price of CO_2, estimated on the basis of the economic cost of CO_2 emissions and of CO_2 abatement cost.[8] As for capital cost, this study assumes full capital cost recovery for new and already installed generating capacity. Although capital costs are sunk from an economic perspective, we assume that electricity producers set prices to recover their sunk costs. This assumption may not hold in day-to-day decision-making, but over time, producers cannot remain viable unless they recover their capital costs. Thus, a full-cost recovery approach is implemented for both existing and new plants.

As Figure 3 shows, a system integration charge is added to wind generation to compensate for 'intermittency costs'. This adjustment is necessary because wind is a variable-output technology. System integration is a complex issue. Many think of wind as intermittent, although there are very few times when wind output is actually zero (Sinden 2005 and Grubb *et al*. 2007). The existing electricity network organisation and protocols do require wind integration to have some extra level of backup capacity to balance the system when wind electricity output is reduced.[9] The costs have been quantified in multiple studies with similar results (Dale *et al.* 2004, DENA Grid Study 2005, and UKERC 2006, for instance). Our analysis follows the results of the UKERC (2006) survey, which estimates the aggregate intermittency costs in the range of €7.5–€12 per MWh (£5–£8 per MWh) for 20 percent wind penetrations. Because intermittency cost estimates in Europe are somewhat lower (DENA Grid Study 2005, for instance, estimated cost at or under €10/MWh), we apply a system integration charge of €10/MWh. This analysis, however, does not include possible associated systematic risks that may become more significant for wind penetrations in excess of 20-30 percent.

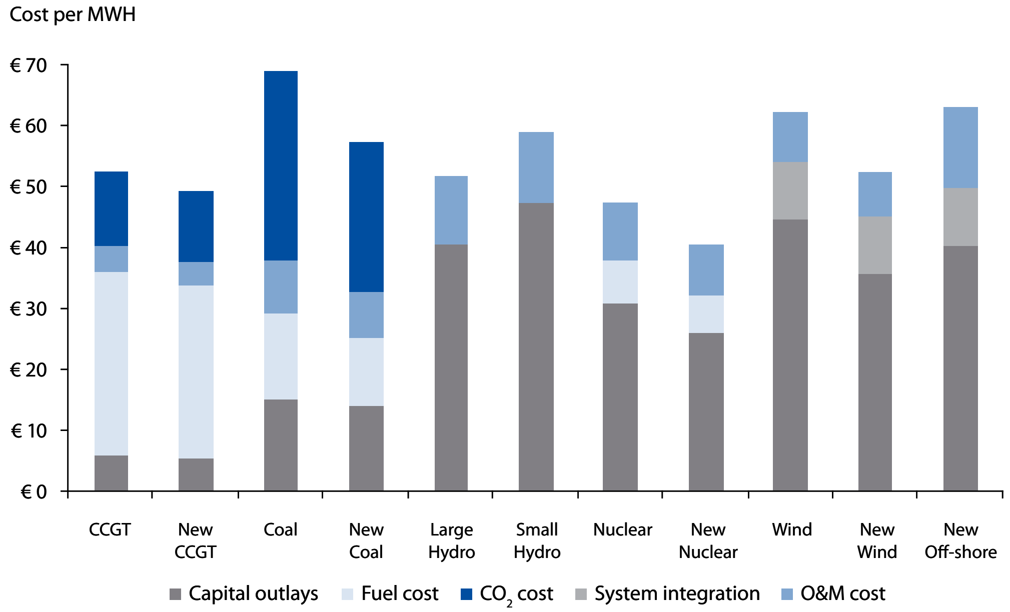
Many think of wind as intermittent, although there are very few times when wind output is actually zero.

7 TECHPOLE database, LEPII, University of Grenoble, CNRS. Fuel input cost, reflecting most recent projections of the European Commission and IEA are shown in Annex Table A1.

8 For example, in its cost-benefit analyses of energy sector projects, the European Investment Bank currently uses a baseline shadow price that rises from €25/t CO_2 in 2007 to €45/t CO_2 in 2030.

9 This being said, new electricity network protocols and information systems have even been proposed in order to exploit wind variability and obviate the need for standby reserve capacity (see – for instance – Awerbuch 2004 and Fox and Flynn 2005). These proposals generally involve matching variable output wind to interruptible load applications to prevent both system balancing and/or backup generation.

Figure 3. 2020 generating costs (€/MWh) for various technologies



Sources: Based on TECHPOLE database, LEPII, University of Grenoble; European Commission (2006), and IEA (2006).
Note: Economic costs of CO_2 assumed to be €35/t CO_2.

3.2 Technology risk estimates

Table 1 summarises our technology risk estimates, expressed as the standard deviations of the holding-period-returns (see Box 1) based on historical data for each cost component.

Construction cost risk varies by technology type and is generally related to the complexity and length of the construction period.

Let us start with capital, or construction, cost risk. This varies by technology type and is generally related to the complexity and length of the construction period. A World Bank analysis covering a large number of projects estimates the standard deviation of construction period outlays for thermal plants (for instance, coal-fired power stations) at 23 percent and 38 percent for large hydro plants (Bacon *et al.* 1996). For the purpose of our analysis, we apply the thermal plant value to the construction-period risk of nuclear plant (but we will consider alternative values in Section 5.1). To some extent, this is an arbitrary simplification. Many believe these risks are significantly higher. Others, however, believe such risks will resolve themselves with experience. The estimates for wind, gas, geothermal, and solar risk were determined from developer interviews as reported in Awerbuch *et al.* (2005). Construction cost risk of existing capacity was estimated at around zero percent. This suggests that 'new' vintage assets are riskier than old ones – for example, risks for a new, not yet constructed coal plant are greater than those for an existing coal plant.

Fuel cost risks have been estimated on the basis of historical (1980-2005) European fossil fuel import prices taken from an IEA database. Annual price observations were used because they eliminate seasonal variations that could potentially bias the results. In practice, electricity producers buy fuel through spot and contract purchases so that the cost of fuel in any calendar period is best measured as the total fuel outlays divided by total fuel delivered. The HPR standard deviations of fuel cost range from 0.14 for coal to 0.24 for oil. Obviously, renewable technologies and geothermal require no fuel outlays and there is thus no fuel cost risk.

Table 1. HPR standard deviations for generating technology cost streams (in %)

	Construction	Fuel	O&M	CO_2
Coal	23.0	14.0	5.4	26.0
Oil	23.0	25.0	24.2	26.0
Gas-CC turbine	15.0	19.0	10.5	26.0
Nuclear	23.0	24.0	5.5	–
Hydro-large	38.0	0.0	15.3	–
Hydro-small	10.0	0.0	15.3	–
Wind	5.0	0.0	8.0	–
Wind-offshore	10.0	0.0	8.0	–
Biomass	20.0	18.0	10.8	–
PV	5.0	0.0	3.4	–
Geothermal	15.0	0.0	15.3	–

Source: Own calculation.

Notes: HPR ≡ holding-period-returns; for definition of HPR see Box 1; they measure the year-to-year fluctuation of the underlying cost stream; as a result, the standard deviation is expressed in % while the cost stream itself is measured in €/kWh; construction cost HPRs for existing capacities are not shown as they are estimated at about zero.

The risks of operating and maintenance outlays are difficult to estimate.

The risks of operating and maintenance outlays are difficult to estimate. Typically, estimates can be found in corporate records. But often, these records are not publicly available. Even if they were, maintenance policies may not keep the records in a format suitable for the analysis carried out here. In addition, companies design these records to promote overall corporate objectives, which can result in biased numbers. For example, during periods of poor financial performance, corporate managers may choose to defer maintenance in order to meet specified corporate objectives – such as reducing O&M expense. Thus, maintenance outlays might be arbitrarily recorded as capital improvements and be depreciated over time. In the case of rate-regulated utilities, there is a significant incentive to charging these outlays to capital improvements because they earn a regulated rate of return.

The US Energy Information Agency and the Federal Energy Regulatory Commission databases maintain records covering every generator operated by a regulated utility. This data was used to estimate the HPR standard deviations for O&M costs (along with the correlations between these costs discussed in the next subsection). By using this data, we implicitly assume that the maintenance volatility for a large portfolio of generating assets in the United States will not differ materially from those that would be found for a similar European portfolio. As Table 1 shows, different technologies show different year-to-year fluctuations in maintenance outlays – ranging from 3.4 percent for photovoltaics to 24.2 percent for oil.[10]

This takes us to the risk associated with the last cost category, that is, the cost of CO_2 emissions, which is relevant for fossil fuel technologies. As Table 1 indicates, the HPR standard deviation for CO_2 has been estimated at 26 percent. The approach underlying this estimate will be presented next in the context of discussing the correlation between the cost of different fuels, the correlation between O&M costs of different technologies, and the correlation between the cost of fossil fuels, on the one hand, and CO_2 cost on the other. A more comprehensive presentation of the technology cost and risk estimation can be found in Awerbuch and Yang (2007).

10 In principle, the O&M cost category should include outlays for property taxes, insurance, and other non-maintenance categories. These would most likely exhibit lower risk and potentially dampen the results of Table 1. Because the focus in this paper is on CO_2 risk, we did not pursue this O&M issue further.

3.3 Correlation coefficients

We start here with a brief description of our approach to estimating the HPR standard deviation for CO_2 and the correlation between CO_2 cost and fuel prices. Our estimates are derived using both analytic techniques and Monte Carlo simulation. The analytic approach to estimating CO_2 risk and correlation follows the spirit of Green (2006), who expresses CO_2 price in terms of gas and coal prices. This relationship is used to derive the HPR standard deviation of CO_2 as well as its correlation with fossil fuels. The Monte Carlo approach uses a series of simulations that provide a second set of CO_2 risk and fossil fuel correlation estimates. In the Monte Carlo analyses, we used the volatility and other trends from 18 months of actual data to simulate 20 years of trading. This and its correlation to coal, gas, and oil provides an estimate of annual risk factors for $CO_{2.}$

Both methods provide a range of estimates of CO_2 risk and correlations. We compared the analytical and Monte Carlo results and performed various sensitivity analyses to test the reasonableness and robustness of these estimates. The HPR standard deviation for CO_2 that we use in the portfolio optimisation model (26 percent) is shown in the last column of Table 1.[11] The CO_2 cost/fuel cost correlation coefficient used in the portfolio optimisation is shown in the second-last column (or row) of Table 2 below.

As gas becomes more expensive, electricity generation shifts to coal, putting upward pressure on CO_2 prices – be they market prices or shadow prices.

As can be seen from these correlation coefficients, there is a negative correlation between CO_2 and coal prices and a positive correlation between CO_2 and gas. This is the expected result. Intuitively, as gas becomes more expensive, electricity generation shifts to coal, putting upward pressure on CO_2 prices – be they market prices or shadow prices. Conversely, rising coal prices shift generation to gas, which emits about half as much CO_2. As a result, the price of CO_2 falls with rising coal prices.

Table 2 also shows the correlation coefficients for the various fuels, indicating a positive correlation between fuels – with the notable exception of biomass. Although the data used for this analysis do not obtain a negative fuel correlation for nuclear, a number of researchers (Awerbuch and Berger 2003 and Roques 2006) find a negative correlation between nuclear and fossil fuels, suggesting a greater diversification potential than that resulting from our analysis.

The estimated O&M correlation coefficients are shown in Table A2 in the Annex.

Table 2. Fuel and CO_2 HPR correlation coefficients

	Coal	Oil	Gas	Uranium	CO_2	Biomass
Coal	1.00	0.27	0.47	0.12	-0.49	-0.38
Oil	0.27	1.00	0.49	0.08	0.19	-0.17
Gas	0.47	0.49	1.00	0.06	0.68	-0.44
Uranium	0.12	0.08	0.06	1.00	0.00	-0.22
CO_2	-0.49	0.19	0.68	0.00	1.00	0.00
Biomass	-0.38	-0.17	-0.44	-0.22	0.00	1.00

Source: Own calculation.

11 While our CO_2 risk estimates are statistically robust, it is important to note that they are based on just 18 months of CO_2 trading. Because the results of the CO_2 risk and correlation estimates were relatively consistent over various unrelated estimation procedures, we are relatively confident in applying them to the analysis.

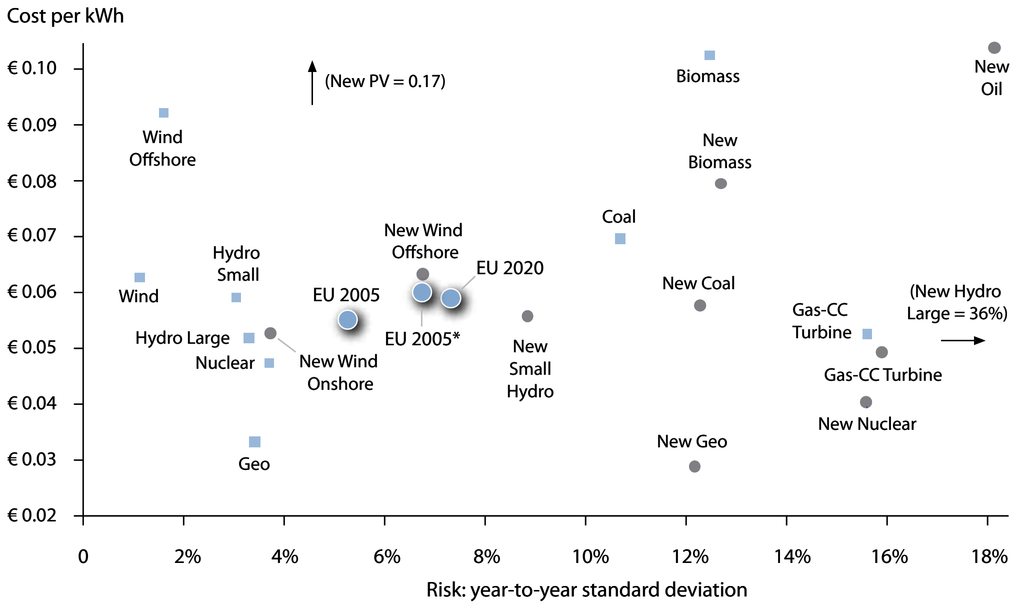
3.4 Total technology cost and risk

The previous sub-sections described the cost and risk inputs for the various generating technologies. These are combined using equation (2) in Box 1 to produce a total HPR standard deviation for each technology, where the weights (X_1, X_2, … etc.) are given by the proportional values of the levelised cost components, that is, capital, fuel, O&M, and CO_2 outlays.

Figure 4 shows the costs per kWh for each of the generating technologies in 2020 along with its risk, with the added assumption that CO_2 costs €35 per tonne. For comparison, Figure 4 also shows the cost-risk combination of the projected EU 2020 BAU mix; in addition, it pictures two variants of the EU 2005 mix: one assuming CO_2 cost of €15 per tonne and the other €35 per tonne. The former reflects the approximate price of CO_2 in 2005 and the latter enables a direct comparison between the 2005 mix and 2020 BAU mix. This comparison shows that relative to the 2005 mix, the 2020 BAU mix slightly reduces electricity generating cost from 5.98 €-cents to 5.87 €-cents per kWh. This cost reduction is attained by increasing expected risk from 6.8 percent to 7.3 percent. Compared to the 2005 EU mix, the 2020 BAU mix represents a cost-risk trade-off that few investors would make: a cost reduction of less than 2 percent would come with an increase in risk of almost 9 percent.

The business-as-usual EU electricity mix for 2020 represents a cost-risk trade-off that few investors would make.

Figure 4. Cost and risk of existing and new EU generating alternatives in 2020



Source: Own calculation.
Notes: Estimates for individual technologies and the EU 2020 BAU mix are based on a CO_2 emission cost of €35/t CO_2. For comparison, the Figure shows the actual EU 2005 generation mix for €35/t CO_2 (EU 2005*) and for €15/t CO_2 (EU 2005). See text for details.

The results also show that compared to existing vintages, new vintages exhibit lower cost and larger risk (in Figure 4, new vintages lie to the southeast of existing vintages). The cost decline is because new-vintage technologies increase energy efficiency and, thus, lower cost. For example, electricity produced by new coal plants cost 5.8 €-cents per kWh, which is 1.2 €-cents less than for existing coal plants. Risk for new vintages increases because the construction-period risk of existing vintages are sunk or zero while new generating assets yet to be constructed are exposed to construction-period risk. The largest differences between the new and existing vintages show up in capital-intensive technologies such as nuclear, wind (especially offshore), and geothermal.

CO_2 prices also increase the risk of the fossil alternatives to the extent that the holding-period-return risk of the CO_2 exceeds that of fossil fuels.

Not unexpectedly, the inclusion of CO_2 charges increases the generating cost of fossil alternatives relative to non-fossil technologies. CO_2 prices also increase the risk of the fossil alternatives to the extent that the HPR risk of the CO_2 exceeds the HPR risk of the fossil fuel. As shown in Table 1, the HPR standard deviation for CO_2 is 26 percent as compared to 14 percent for coal fuel and 19 percent for natural gas fuel. Observe that with €35/t CO_2, the standard deviation of existing coal technology rises from 5.6 percent to 10.7 percent, while the risk of existing gas generation increases much less from 14.3 percent to 15.7 percent (see Table 3). The increase for new coal is also smaller than for existing coal because the risk of new coal includes the construction-period risks, reducing the fractional share of CO_2 outlays (that is, the weight of CO_2 outlays in equation (2) of Box 1).[12]

Table 3. The effect of CO_2 costs on coal and gas generating cost-risk

	CO_2 cost per tonne					
	€0.00		€15.00		€35.00	
	Cost (€/MWh)	Risk (%)	Cost (€/MWh)	Risk (%)	Cost (€/MWh)	Risk (%)
Coal	3.8	5.6	5.1	6.2	6.9	10.7
Coal – New	3.3	11.7	4.3	10.3	5.8	12.3
Gas-CC	4.0	14.3	4.6	14.9	5.3	15.7
Gas-CC – New	3.8	14.7	4.3	15.2	4.9	16.0
Oil	8.2	20.2	9.2	18.8	10.6	17.8
Oil – New	8.0	20.8	8.7	19.3	10.2	18.3

Source: Own calculation.

In the case of oil-fired electricity generation, the HPR fuel price risk is 25 percent (slightly lower than CO_2). Because of the low correlation between CO_2 and oil (0.19 as shown in Table 2), the inclusion of CO_2 charges reduces overall risk of this technology as the proportional weight of CO_2 outlays rises as a share of total costs.

The general outcome is that our 26 percent estimate for the CO_2 HPR risk and our estimated CO_2-fossil fuel correlations, along with the addition of CO_2 charges, do not significantly raise total HPR risks of new fossil generating assets and in some cases lowers them. This is contrary to widely held beliefs. Of course, higher CO_2 risk estimates (or higher correlation with fossil fuels) will affect even new assets to a greater extent.

4. Portfolio optimisation of EU electricity generating mix

4.1 Efficient multi-technology electricity portfolios – an illustration

As previously stated, the aim of this study is to evaluate whether there exists feasible 2020 generating mixes that are 'superior' to the 2020 EU-BAU mix by virtue of reducing risk or the cost of

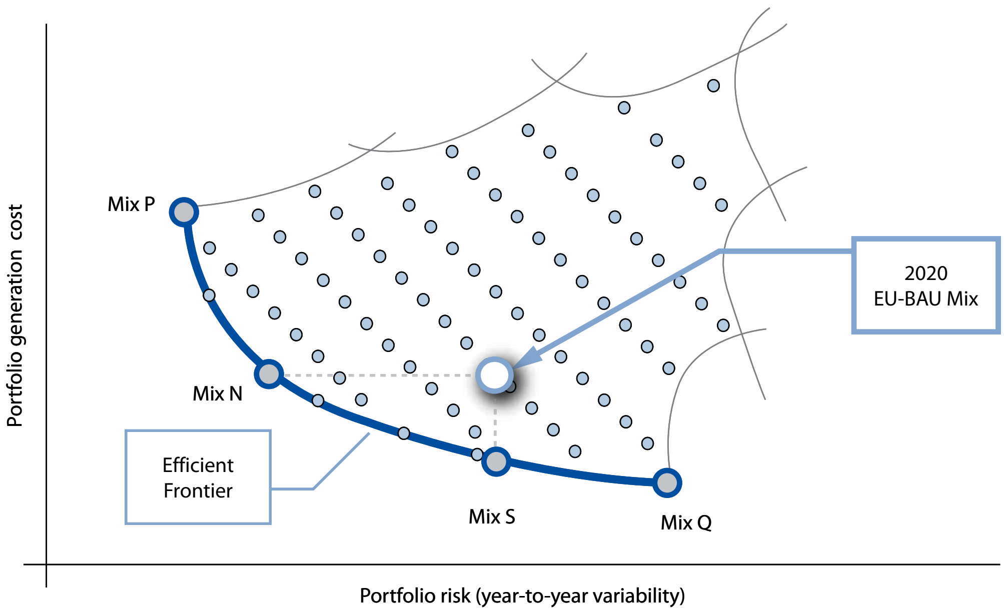
12 Note that the risk for new coal decreases slightly as CO_2 costs move from €0 to €15 per tonne; this is undoubtedly caused by the negative correlation between CO_2 cost and coal prices. As CO_2 cost rise to €35, however, the magnitude of the price overwhelms the negative correlation, and overall risk rises again.

producing electricity. To prepare for the interpretation of the results of our portfolio optimisation model, it is useful to offer a general illustration of possible results.

Figure 5 shows an infinite number of different generating mixes that could meet the 2020 electricity needs with a unique mix of the various technology options. The different portfolios all have different cost-risk as represented by the blue dots. Interestingly, technology shares do not change monotonically in any direction in Figure 5 so that two mixes with virtually identical cost-risk characteristics (that is, two mixes located close to each other in cost-risk space) can have radically different technology generating shares. Indeed, Awerbuch and Berger (2003) show that costs and risks of the EU generating mix projected for 2010 are virtually identical to a mix consisting of 100 percent coal. Likewise, radically different mixes can have nearly identical cost-risk characteristics, that is, they could be virtually co-located in the risk-cost space. The intuition for this is straightforward: there are many ways to combine ingredients in order to produce a given quantity of salad at a given price.

Radically different mixes can have nearly identical cost-risk characteristics, that is, they could be virtually co-located in the risk-cost space.

Figure 5. Feasible region and efficient frontier for multi-technology electricity portfolios



The blue curve (*PNSQ*) is the so-called efficient frontier (EF), the locus of all optimal mixes. There are no feasible mixes below the efficient frontier, and along it, only accepting greater risk can reduce cost. The blue-dot mixes in Figure 5 are sub-optimal or inefficient because it is still possible to reduce both cost and risk by finding mixes on the efficient frontier by moving below or to the left. As we will show below, the 2020 EU-BAU mix lies above the efficient frontier.

Although an infinite number of possible generating portfolios lie on the efficient frontier we focus on four typical optimal mixes *P, N, S, Q*. Taking the 2020 EU-BAU mix as the benchmark, they are defined as follows:

- Mix *P* is a high-cost/low-risk portfolio. It is usually the most diverse (see, for example, Stirling 1996 and Awerbuch *et al.* 2006).

- Mix *N* is an equal-cost/low-risk portfolio, that is, it is the mix with the lowest risk for costs equal to that of the 2020 EU-BAU mix.
- Mix *S* is an equal-risk/low-cost portfolio, that is, it is the mix with the lowest costs for a risk equal to that of the 2020 EU-BAU mix.
- Mix *Q* is a low-cost/high-risk portfolio. It is usually the least diverse portfolio.

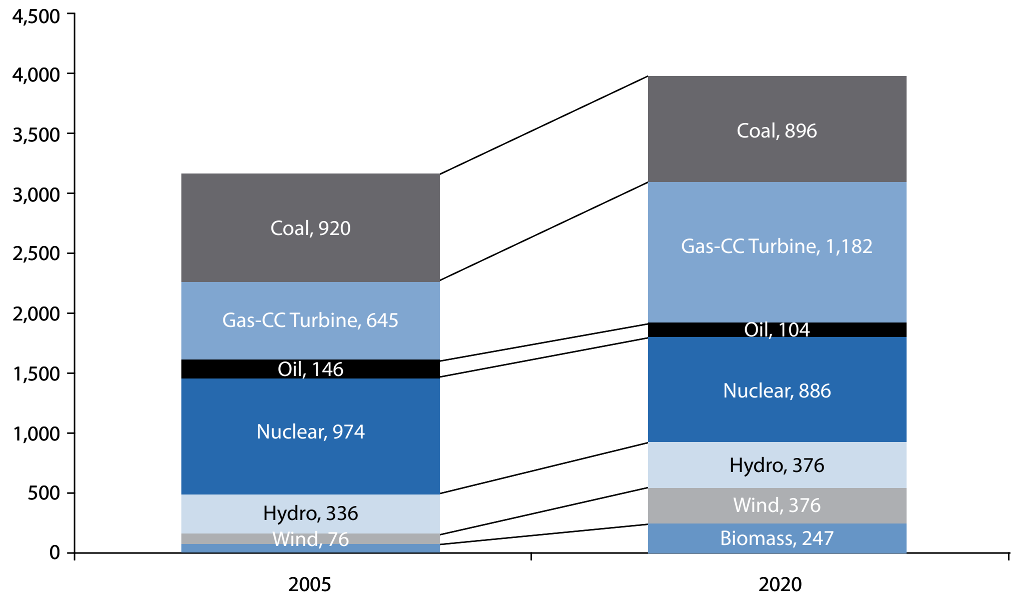
The portfolio analysis does not advocate any particular generating mixes, but rather displays the risk-cost trade-offs across many mixes. Although it may turn out that solutions in the region of the 2020 EU-BAU mix – for example, solutions between portfolios *N* and *S* – may be the most practical, we do not claim that our optimisation results help set technology targets for 2020. Rather, the idea is to highlight and quantify the trade-offs between generating mixes.

4.2 Efficient multi-technology electricity portfolios for 2020 – results

An aggressive technology deployment would likely be difficult to attain in practice …

The portfolio optimisation evaluates the 2020 EU-BAU mix shown in Figure 6 against two cases: 'Baseline' and 'Realisable' case. These cases differ in the extent to which future technology choices are constrained because of upper (and lower) bounds, representing either maximum attainable deployment levels for each technology or maximum resource limits, as in the case of renewables such as wind or hydro (see Awerbuch and Yang 2007 for a more detailed discussion). The Baseline represents aggressive technology deployment levels that would likely be difficult to attain in practice. Its purpose is to help explore practical policy limits and identify policies that may be worth pursuing. The Realisable case, however, represents a set of upper technology limits that could be attained in practice given sufficiently focused policies and accelerated resource deployments. Table 4 shows Baseline case and Realisable case lower and upper limits for the share of alternative technologies in the overall generation mix. For each set of constraints, we compute efficient electricity generation mixes and analyse the level of CO_2 emissions associated with them.

Figure 6. 2005 and 2020 EU-BAU generation mix (in TWh)



Source: European Commission (2005).

Table 4. Lower and upper technology limits (in % of electricity mix)

	Baseline case		Realisable case	
	Lower limit (%)	Upper limit (%)	Lower limit (%)	Upper limit (%)
Coal	3	52	5	35
Gas-CC Old	5	16	10	16
Gas-CC New	0	50	0	20
Oil	2	8	2	5
Nuclear	15	52	15	33
Hydro	8	13	8	11
Biomass	2	22	2	13
PV	0	5	0	1
Geo	0	½	0	0
Wind-onshore	2	32	2	7
Wind-offshore	0	40	0	7

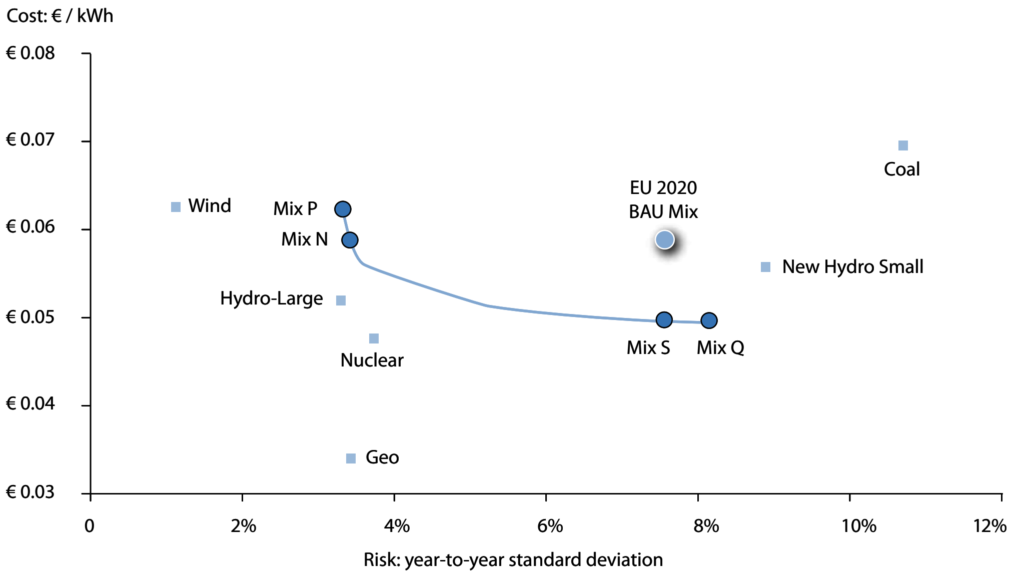
4.2.1 Efficient portfolios – Baseline case

This section discusses the 2020 Baseline optimisation results and compares their risk-return characteristics and CO_2 emissions to those of the projected 2020 EU-BAU mix. The results indicate that the optimal Baseline portfolios minimise cost and risk and reduce CO_2 emissions. This is shown in Figure 7, which illustrates the risk and return for the projected 2020 EU-BAU and for the typical optimised mixes under Baseline assumptions. The efficient frontier *PNSQ* shows the location of all optimal mixes.

… but if attained, it would minimise cost and risk and reduce CO_2 emissions.

The EU-BAU mix has an overall generating cost of 5.9 €-cents per kWh and a risk of 7.6 percent. By comparison, mix *N*, the equal-cost/low-risk mix, cuts risk nearly by half, to 3.4 percent. Alternatively, mix *S*, has the same risk as the BAU but reduces generating costs by 0.9 €-cents per kWh, which equates to an EU-wide cut in annual electricity outlays of €36 billion.[13]

Figure 7. Efficient frontier for 2020 electricity generation mix – Baseline case



Source: Own calculation.
Notes: For CO_2 cost of €35 per tonne.

13 Based on an annual consumption in 2020 of 4,006 TWh (€0.009/kWh × 4,006 × 10^9kWh = €36bn).

Mix *P*, the minimum-risk mix, reduces risk slightly relative to mix *N*. But this seems to represent an unattractive cost-risk trade-off over mix *N*. Similarly, mix *Q*, the minimum-cost mix, does hardly reduce cost relative to mix *S*, but comes with a noticeable increase in risk. It thus seems that in cost-risk terms, the practical range of policy interest generally runs from mix *N* down to mix *S*.

Policy makers tend to view climate change mitigation as an objective that is detrimental to low-cost electricity. But such beliefs are based on stand-alone cost concepts, not portfolio costs.

Policy makers tend to view climate change mitigation as an objective that competes with cost and, indeed, it is widely believed that low-carbon electricity generation will increase cost. But such beliefs are based on stand-alone cost concepts. The Baseline results, however, show that in addition to reducing cost and/or risk relative to the EU-BAU mix, the optimal mixes also reduce CO_2 emissions, in contradiction to widely held beliefs that climate change mitigation policies inevitably increase cost.[14] This is illustrated in Figure 8, which shows technology shares and portfolio risk on the left vertical axis, CO_2 emissions on the right axis, and portfolio generating cost along the top of the graph. The low-risk mixes, *P* and *N* reduce annual CO_2 to 199 million tonnes, which is 85 percent lower than emissions in the BAU mix (1,273 million tonnes of CO_2). They accomplish this primarily by substituting wind for gas and coal. Indeed, the share of onshore wind is 32 percent, its permissible upper limit (Table 5). Mixes *S* and *Q*, the low-cost mixes, reduce CO_2 emissions to 472 and 549 million tonnes, respectively, by incorporating larger shares of nuclear generation, which reaches its 52 percent upper limit in both mixes. This result – that is, that optimal low-risk mixes increase wind shares relative to the BAU while optimal low-cost mixes increase nuclear – tends to hold for the Realisable case, too, as we will see next.

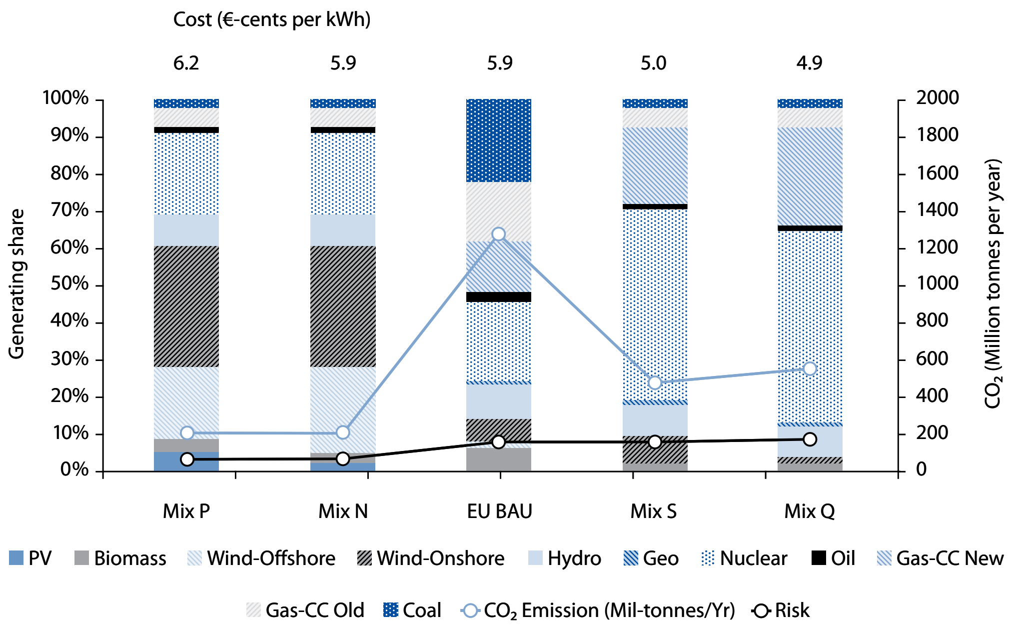
Table 5. Optimal portfolio shares and CO_2 emissions in 2020 – Baseline case

	EU-BAU	Mix P	Mix N	Mix S	Mix Q	Technology bounds	
	Share in electricity generating (%)					Lower (in %)	Upper (in %)
Coal	22	3 ^{L}	3 ^{L}	3 ^{L}	3 ^{L}	3	52
Gas-CC Old	16	5 ^{L}	5 ^{L}	5 ^{L}	5 ^{L}	5	16
Gas-CC New	13	0 ^{L}	0 ^{L}	19	27	0	50
Oil	3	2 ^{L}	2 ^{L}	2 ^{L}	2 ^{L}	2	8
Nuclear	22	22	22	52 ^{U}	52 ^{U}	15	52
Hydro	9	8 ^{L}	8 ^{L}	8 ^{L}	8 ^{L}	8	13
Biomass	6	4	3	2 ^{L}	2 ^{L}	2	22
PV	0	5 ^{U}	2	0 ^{L}	0 ^{L}	0	5
Geo	0	0	0	0	0	0	½
Wind-onshore	6	32 ^{U}	32 ^{U}	9	2 ^{L}	2	32
Wind-offshore	1	19	23	0 ^{L}	0 ^{L}	0	40
CO_2 emissions in million tonnes per year							
	1,273	199	199	472	549		

Source: Own calculation.
Notes: ^{L} and ^{U} indicate that technology share is at Lower or Upper bound; results for €35/t CO_2.

14 This is true only to the extent that the underlying generating costs shown in Figure 7 reflect all economic cost. However, since the costs shown in Figure 7 do not fully incorporate some economic costs such as investment grants that benefited some of these technologies (e.g., wind and nuclear), the resulting climate change mitigation may cost more than what Figure 7 suggests.

Figure 8. Technology shares, portfolio risk and cost, and CO_2 emissions – Baseline case



Source: Own calculation.
Notes: Results for €35/t CO_2.

4.2.2 Efficient portfolios – Realisable case

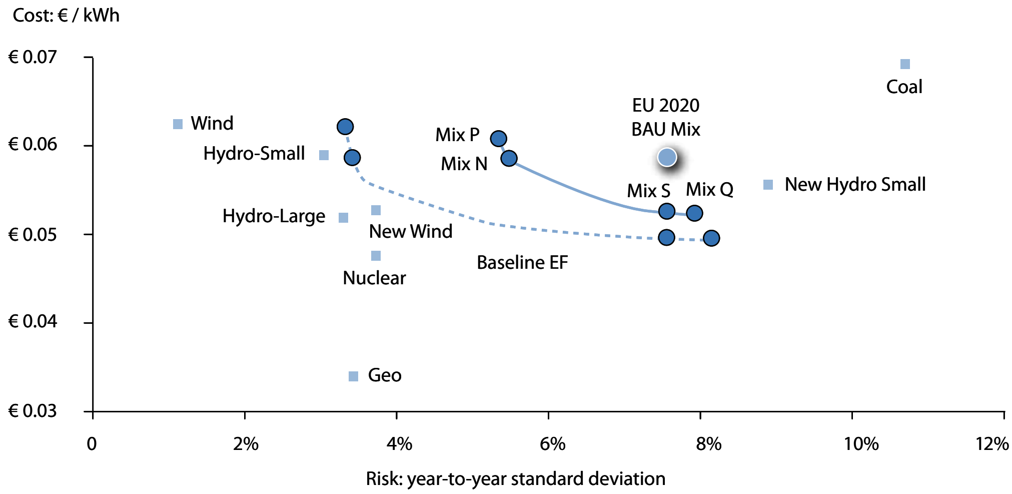
To recall, compared to the Baseline case, the Realisable case considers technology deployment levels that can be attained by 2020, assuming focused policy efforts. This case incorporates upper bounds for renewables based on the 'Realisable' scenarios developed by Ragwitz *et al.* (2005), who estimate the realisable market potential for renewable energy technologies as "the maximum achievable potential, assuming that all existing barriers can be overcome and all driving forces are active" (Ragwitz, personal communication 2006). Compared to the Baseline case, the Realisable case has less latitude to search for optimal solutions because it is limited to a smaller feasible region. As a consequence, optimal Realisable mixes are costlier and riskier, and they emit more CO_2 than optimal Baseline mixes.

From a portfolio perspective, a less aggressive but more realistic technology deployment is costlier and riskier.

Figure 9 shows the cost and risk results for the Realisable case (solid line). There are mixes on the efficient frontier that exhibit lower cost-risk than the projected EU-BAU mix. However, as the Realisable case is more constrained, the efficient frontier is shorter, riskier, and more costly relative to the Baseline. The tighter resource limits – particularly the penetration levels for onshore wind and nuclear – increase the cost of mixes *S* and *Q* and the risk of mixes *P* and *N*.

For example, the cost of mix *S* rises by 0.3 €-cents/kWh (6 percent) relative to the Baseline. This increase in cost equates to an increase in total annual outlays by EU electricity consumers of €12 billion. This figure represents about 0.1 percent of the current GDP of the EU. To illustrate the impact of tighter technology deployment limits on risk: with less wind resource available, the optimisation cannot reach the low risk levels of the Baseline. For example, in mix *N*, lower limits for wind (in particular) increase coal and nuclear shares, thereby raising risk by some 60 percent, from 3.3 percent in the Baseline case to 5.4 percent in the Realisable case.

Figure 9. Efficient frontier for 2020 electricity generation mix – Realisable case

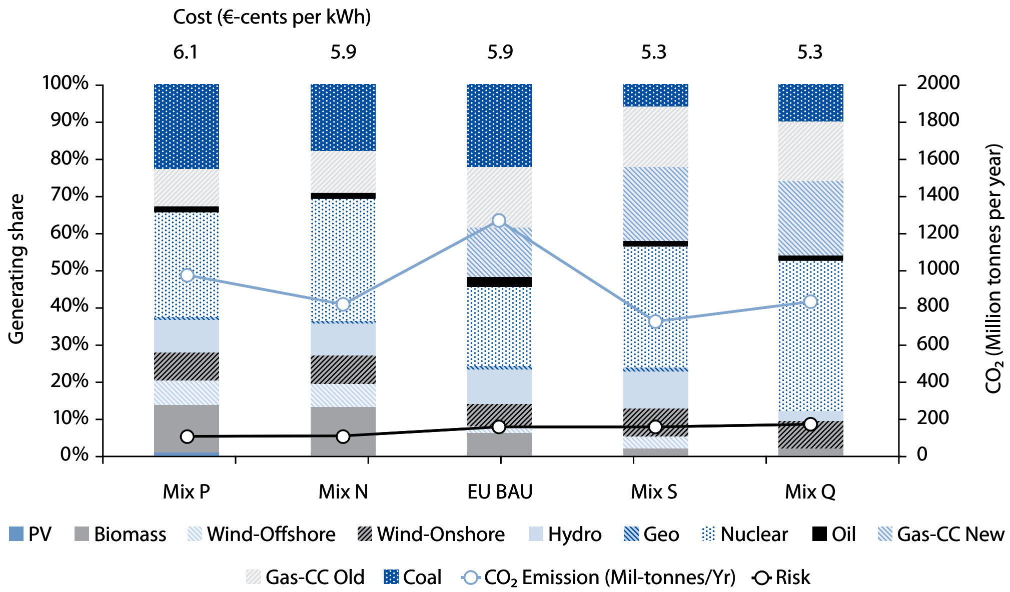


Source: Own calculation.
Notes: Results for €35/t CO_2.

Optimal shares of nuclear hit their upper limit in all optimal mixes except one.

Compared to the Baseline case, the Realisable case is characterised by significantly lower shares of nuclear, wind, and – in some cases – new and existing gas-fired power plants (see Table 6 and Figure 10). This is driven by the lower upper technology bounds for most technologies, as can be seen by comparing the right-hand column of Table 6 to that of Table 5. Further, as Table 6 indicates, wind hits its upper limit in all the optimal Realisable mixes, while offshore wind hits the upper limit in the low-risk mixes *P* and *N* where offshore wind is required to balance and complete the mix. Nuclear is at its upper limit in all except mix *P*. The results of Table 6 suggest that additional deployment of these technologies could lower cost, risk, and CO_2 emissions. As a comparison of the last row in Table 6 with the last row in Table 5 shows, the Realisable case reduces annual CO_2 emissions at best by 548 million tonnes (mix *S*) while they might fall by as much as 1,074 million tonnes under Baseline assumptions (mixes *P* and *N*).

Figure 10. Technology shares, portfolio risk and cost, and CO_2 emissions – Realisable case



Source: Own calculation.
Notes: Results for €35/t CO_2.

Table 6. Optimal portfolio shares and CO_2 emissions in 2020 – Realisable case

	EU-BAU	Mix P	Mix N	Mix S	Mix Q	Technology bounds	
	Share in electricity generating (%)					Lower (in %)	Upper (in %)
Coal	22	22	17	5 L	10	5	35
Gas-CC Old	16	10 L	11	15	16 U	10	16
Gas-CC New	13	0 L	0 L	20 U	20 U	0	20
Oil	3	2 L	2 L	2 L	2 L	2	5
Nuclear	22	29	33 U	33 U	33 U	15	33
Hydro	9	9	9	10	10	8	11
Biomass	6	13 U	13 U	2 L	2 L	2	13
PV	0	1 U	0 L	0 L	0 L	0	1
Geo	0	0 U	0 U	0 U	0 U	0	0
Wind-onshore	6	7 U	7 U	7 U	7 U	2	7
Wind-offshore	1	7 U	7 U	5	0 L	0	7
CO_2 emissions in million tonnes per year							
	1,273	981	825	725	836		

Source: Own calculation.
Notes: L and U indicate that technology share is at Lower or Upper bound; results for €35/t CO_2.

Table 7 summarises the changes in technology generating shares and CO_2 emissions for the typical optimal mixes relative to the 2020 EU-BAU. The low-risk mixes *P* and *N* show large percentage increases for nuclear, biomass, and wind, coupled with significant percentage reductions for gas, oil, and coal (in mix *N* only). The low-cost mixes *S* and *Q* show large percentage rises for gas, nuclear, and wind (in mix *S*), coupled with large reductions of coal, oil, and biomass.

The low-cost electricity mixes show large increases in the share of gas, nuclear, and wind, coupled with large reductions of coal, oil, and biomass.

Table 7. 2020 EU BAU electricity generation mix *vs*. optimal Realisable mixes

	Mix P	Mix N	EU-BAU	Mix S	Mix Q
Portfolio risk	5.3%	5.5%	7.6%	7.6%	7.9%
Portfolio cost in €/MWh	61	59	59	53	53
	% change from EU-BAU			% change from EU-BAU	
Annual CO_2	-22%	-35%	1,273m tonnes	-45%	-34%
Coal	0%	-22%	897 TWh	-78%	-57%
Gas-CC	-66%	-61%	1,182 TWh	+19%	+22%
Oil	-31%	-42%	104 TWh	-42%	-42%
Nuclear	+29%	+50%	886 TWh	+50%	+50%
Hydro	-4%	-4%	376 TWh	+12%	+8%
Biomass	+115%	+115%	247 TWh	-70%	-70%
Wind	+85%	+85%	303 TWh	+67%	+0%
Other	265%	-7%	12 TWh	-7%	-7%
Total			4,006 TWh		

Source: Own calculation.
Notes: Results for €35/t CO_2.

In practice, the move from the 2020 BAU mix to the Realisable mix *S* is probably the most attractive of the realisable possibilities. If new policies were to redirect investment so that mix *S* is achieved, this would have the highly desirable effect of cutting annual electricity costs by €24 billion[15] and CO_2 emissions by 548 million tonnes without changing risk.

However, other moves involving alternative risk choices are possible. For example, to the left of the 2020 BAU mix in Figure 9 lies mix *N*. Compared to the BAU mix, mix *N* cuts the portfolio risk by about one-third while simultaneously reducing annual CO_2 emission by 448 million tonnes, or 35 percent. This move produces no cost reductions and while CO_2 reductions are not as large as when moving from the BAU to mix *S*, risk is significantly reduced. Obviously, comparing the risk-cost and CO_2 combinations of *N* against *S* requires knowledge of societal preference functions.

Over the long run, further technology deployment may make it possible to move closer to Baseline mix *S* from the BAU mix (or the Realisable mix *S*). The decline in CO_2 emissions would be 46 percent higher (801 versus 548 million tonnes a year), accompanied by 33 percent greater cut in the EU's electricity bill (€36 compared to €24 billion).

4.3 A summary of key results

The results in this section highlight the importance of focused technology deployment policies designed to move the EU generating mix away from the BAU mix and closer to electricity generating portfolios such as the Realisable mix *S*. This mix would reduce annual EU electricity cost by around €24 billion and annual CO_2 emissions by more than 500 million tonnes. Taking annual electricity cost saving as perpetual and assuming an interest rate of 5-10 percent would justify investment today to the tune of €240-480 billion.

There seems to be a dichotomy between wind energy and nuclear energy that reinforces rather than solves the wide-ranging debate between pro-nuclear and pro-wind forces.

A key finding is that the low-risk mixes (*P* and *N*) generally reduce fossil shares and increase wind and other non-fossil shares relative to the BAU mix, while the higher-risk/lower-cost mixes (*S* and *Q*) increase primarily nuclear along with gas, wind, and hydro electricity at the expense of coal and oil. There thus seems to be a dichotomy between wind and nuclear, suggesting that our analysis reinforces rather than solves the wide-ranging debate between pro-nuclear and pro-wind forces. However, this debate incorporates numerous additional considerations that are not reflected in our optimisation, including highly uncertain waste disposal management costs. The next section tries to shed more light on the role of nuclear power and other factors influencing the results of our portfolio analysis.

5. An eclectic view on factors influencing optimal electricity mixes

5.1 The role of nuclear power

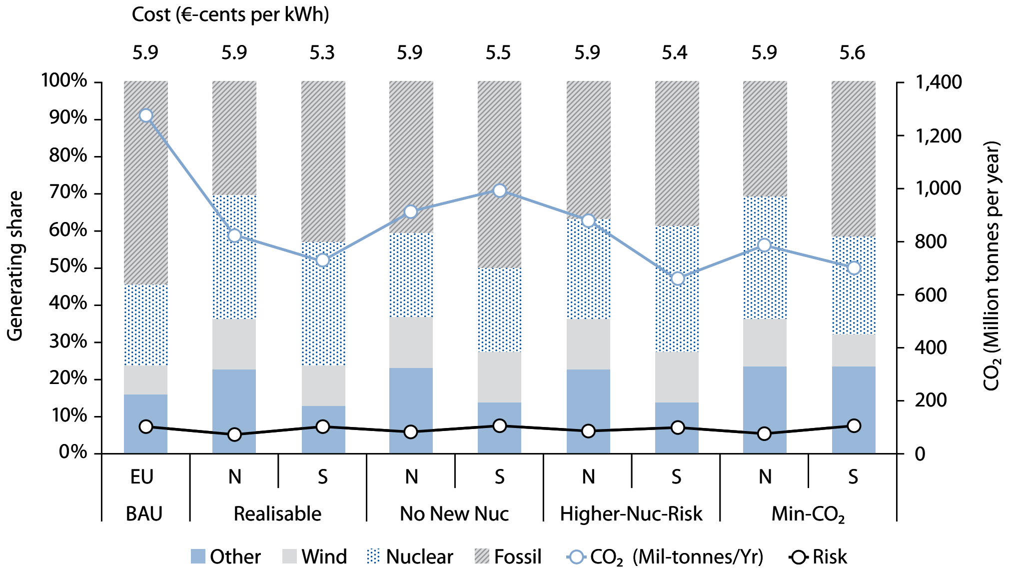
The nuclear cost estimates used for identifying efficient electricity portfolios do not account for the costs and risks of storing nuclear waste, which are essentially incalculable. CORWM (2006) recommends a lengthy, potentially decades-long process, involving interim waste storage in preparation for ultimate geological disposal. Although much of what is risky about nuclear seems to be a matter of expectations and is not necessarily always rational, countries may decide not to build new nuclear power stations – as is currently the case in Germany, for instance. Against this

15 (5.9-5.3) €-cents/kWh x 4,006TWh.

background, it is useful to test a policy of a nuclear moratorium – that is, no new nuclear – to see its effects on cost and risk of the EU portfolio mix. In principle, this can be done for the Baseline case and the Realisable case, but in what follows we will focus on the latter (for ease of comparison, we will call it the 'benchmark' Realisable case). In addition, we concentrate on generating mixes *N* that minimise portfolio risk for the cost of the 2020 EU-BAU mix and on mixes *S* that minimise portfolio cost for the risk of the 2020 EU-BAU mix.

As Figure 11 shows, for mix *S* cost rises from 5.3 €-cents to 5.5 €-cents per kWh. For Mix *N*, risk stays approximately unchanged. The big change is in terms of additional CO_2 emissions, where CO_2 emissions rise from 725 to 993 million tonnes (Mix *S*) and from 825 to 912 million tonnes (mix *N*). This is because for these portfolios, a good part (in mix *N* virtually all) of the drop in the share of nuclear is compensated for by fossil fuel-fired electricity generation.

Figure 11. Technology shares, portfolio risk and cost, and CO_2 emissions – sensitivity analyses



Source: Own calculation.
Notes: Results for €35/t CO_2.

In another sensitivity test, we have examined the impact of a change in risk of constructing and decommissioning nuclear power plants. To recall from Section 3, total generating costs of new nuclear power stations have been estimated at 4.1 €-cents/kWh, including decommissioning costs equivalent to 70 percent of the overnight plant construction cost of €1,710 per kW (see Figure 3). This makes nuclear attractive relative to other alternatives. It can be argued, however, that nuclear risk is understated because construction-period risk was arbitrarily set to the World Bank estimate for the construction-period risk of coal at 23 percent (Bacon *et al.* 1996). To account for this, we re-ran our scenarios several times, gradually increasing nuclear construction risk from 0.23 to 0.38. This raises total technology risk for nuclear from about 16 percent (see Figure 4) to 26 percent.

A higher level of construction cost risk for nuclear has a relatively small effect on the optimal cost-risk combination.

As can be seen from Figure 11, for the Realisable case ('Higher-Nuc-Risk'), a higher risk level for nuclear capital costs has a relatively small effect on the optimal cost-risk combination, that is, mix *N* comes with only a marginal increase in risk relative to the benchmark Realisable case, while mix *S* is associated with only a small increase in portfolio generating costs (5.4 €-cents/kWh instead of 5.3 €-cents/kWh). As expected, both portfolios have a lower share of nuclear – but the change is small because of the already tight upper and lower bounds for most technologies. It is interesting to observe that for the low-risk mix *N*, the share of renewables is virtually constant, with an increase in fossils making up for the drop in nuclear. As a result, CO_2 emissions rise. As for the low-cost mix *S*, the decline in nuclear is associated with a decline in fossils and an increase in renewables, all in all resulting in lower CO_2 emissions. The main reason why renewables become more important in mix *S*, but not in *N*, is that in the benchmark Realisable mix *S*, renewables – biomass in particular – are not as close to their technology upper bounds, whereas they are in the benchmark Realisable mix *N*.[16]

5.2 Efficient electricity portfolios that minimise CO_2 emissions

It is straightforward to illustrate that minimising CO_2 emissions is most likely to be economically inefficient.

We now turn to something that is not so much a sensitivity analysis, but – rather – a change in perspective: we want to identify the combinations of portfolio risk and portfolio generating cost (and the associated technology shares) that minimise CO_2 emissions. For the Realisable case, the results are shown on the very right-hand side of Figure 11. Comparing them to the benchmark Realisable case suggests only a moderate decline in CO_2 emissions: from 825 million tonnes per year to 782 million tonnes for mix *N* and from 725 million tonnes to 700 million tonnes for mix *S*. It is straightforward to illustrate that minimising CO_2 emissions is most likely to be economically inefficient. As Figure 11 shows, for mix *S*, portfolio generating cost increase by 0.3 €-cents/kWh, implying an increase in annual electricity cost of €12 billion and, thus, carbon reduction cost of €480/t CO_2 – a value way above current estimates of global warming damages.

Although not shown in Figure 11, results are very different when taking the Baseline case rather than the Realisable case as a benchmark. As shown in Awerbuch and Yang (2007), moving to the carbon-minimising mix *S* would cut CO_2 emissions by 273 million tonnes, implying carbon reduction cost of €44/t CO_2. Awerbuch and Yang (2007) also show that the risk-cost characteristics of the Baseline carbon-minimising portfolios are very similar to – in fact, slightly better than – those of the Realisable case shown in Figure 9 above. Though it is unlikely that Baseline technology penetration levels could be attained by 2020, this illustrates the significant benefits that could be achieved over a longer period by pursuing deeper penetrations of these technologies.

5.3 The effect of upper limits on technology shares

In Awerbuch and Yang (2007) we investigate in a more rigorous way the economic cost of the constraints that prevent the share of wind, nuclear, and gas to be larger than the upper limit of the Realisable case. Using linear-programming techniques, we show that easing these constraints and, thus, allowing technology shares to move towards the Baseline case, has considerable economic value. More specifically, for the realisable mix *S* we find that increasing the upper limit for the share of nuclear energy by 1 percentage point would result in portfolio cost savings equivalent to 46 percent of the lifetime generating costs of additional nuclear power stations. The comparable results for wind and gas are 21 percent and 8 percent, respectively. The results for wind could significantly and positively impact the current debate regarding development of an EU offshore 'super-grid' to connect diverse offshore wind sites. They also impact on the nuclear debate in a similar fashion.

16 A word of caution is appropriate. The sensitivity of results to changes in underlying assumptions about nuclear energy do not, and are not intended to, resolve the nuclear-renewables debate. Rather, they are meant to quantify and highlight some of the important factors.

All in all, they indicate that failure to fully exploit the EU energy resource potentials needlessly raises generating cost and CO_2 emissions.

5.4 The effect of pricing CO_2 emissions

So far, our analysis assumed a charge of €35 per tonne of CO_2 emitted, which we interpreted as either a market price or a shadow price for carbon emissions. We will now investigate the effect of pricing CO_2 emissions on the cost-risk characteristics of the 2020 EU-BAU mix and of efficient generating portfolios. In addition, we discuss the impact of carbon pricing on CO_2 emissions. To keep things simple, we consider only the effect of moving from a carbon price of zero to one of €35/t CO_2 and we concentrate on the BAU mix and mixes *N* and *S* in the Realisable case.[17]

As Figure 12 illustrates, portfolio risks and costs rise with rising CO_2 prices. This is true for the BAU mix and the efficient electricity generating portfolios. For instance, the cost of the BAU mix increases by 23 percent or 1.1 €-cent per kWh (from 4.8 €-cents to 5.9 €-cents per kWh). The risk of that mix, however, rises a whopping 40 percent (from 5.4 percent to 7.6 percent), illustrating its considerable sensitivity to changing CO_2 (and fossil fuel) prices. By definition, the share of each technology in the BAU mix and, thus, CO_2 emissions do not change with a rise in CO_2 prices. Clearly, it makes little sense to keep technology shares constant when CO_2 prices rise.

On the contrary, with rising CO_2 prices it is optimal to reduce the share of fossil fuels in electricity generation – as indicated by the amount of CO_2 emissions, which is shown by parenthetical values next to the mixes in Figure 12. Since mixes *P* and *N* have lower shares of fossils than mixes *S* and *Q*, they have lower emissions at any given CO_2 price. Absent CO_2 charges, the Realisable mix *N* emits 1,358 million tonnes of CO_2 per year.[18] As the CO_2 price increases, optimal mixes are re-shuffled to minimise portfolios costs and risks. For a carbon price of €35/t CO_2, emissions fall by almost 40 percent to 825 million tonnes per year.

For a carbon price rise from €0 to €35/t CO_2, emissions fall by almost 40 percent to 825 million tonnes per year.

Let us take a closer look at the effect of carbon pricing by considering mix *S*. In general, the change in portfolio costs and CO_2 emissions is the result of two interrelated changes: a rise in CO_2 charges and the re-optimisation of portfolio mixes in response to this rise. Considered in isolation, the increase in the CO_2 price raises the cost of electricity from 4.4 €-cents/kWh (see Figure 12) by about 1.3 €-cents/kWh. This increase reflects the cost of carbon (€35/t CO_2 multiplied by 1,450 million tonnes of CO_2) for a total electricity production of around 4,000 TWh. But as pictured in Figure 12, portfolio generating cost increase only by around by 0.9 €-cents/kWh to a total of 5.3 €-cents/kWh. The cost savings of around 0.4 €-cents/kWh are due to the portfolio re-optimisation triggered by the pricing of carbon. But the associated decline in the share of fossil fuels in mix *S* not only offsets, in part, the increase in electricity costs resulting from the pricing of carbon, it also lowers CO_2 emissions from 1,450 million tonnes to 725 million tonnes.

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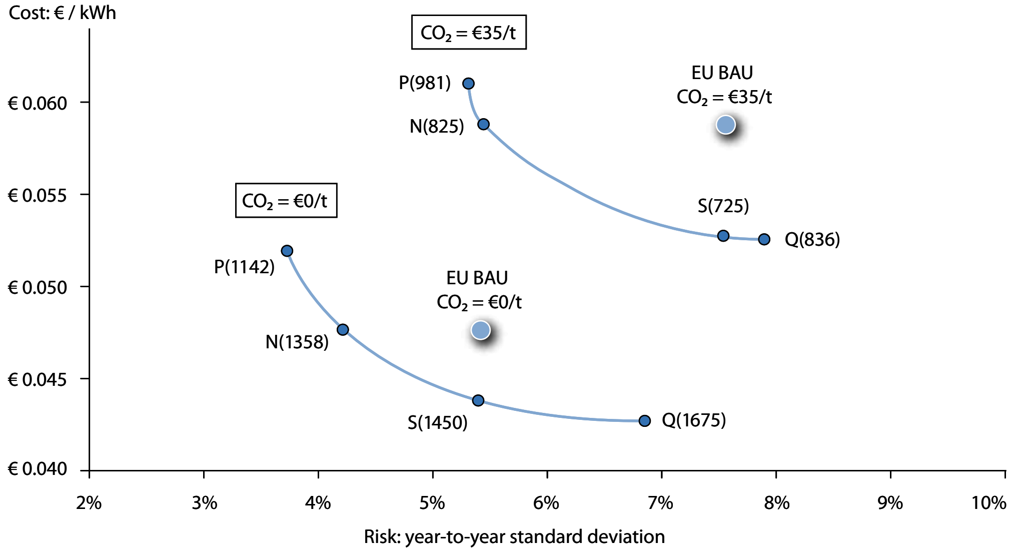
17 Results for carbon prices between zero and €35/t CO_2 and for other efficient generating mixes (in both the Realisable case and the Baseline case) are discussed in Awerbuch and Yang (2007).

18 It is worth pointing out that without carbon pricing, efficient portfolios that generate electricity at the same or lower cost than the BAU mix are more carbon intensive than the BAU mix (see the points that lie to the southeast of mix N on the 'CO_2 = €0' efficient frontier in Figure 12).

Figure 12. Efficient frontiers (€0/tCO_2 and €35/tCO_2) for 2020 electricity generation mix – Realisable case



Source: Own calculation.

Notes: Values in parentheses next to the mixes show annual CO_2 emissions in million tonnes. The 2020 EU-BAU emits 1,273 million-tonnes per year.

6. Summary and conclusions

Our analysis suggests that greater shares of non-fossil technologies, primarily nuclear or wind, can help reduce the cost and risk of the EU generating portfolio as well as its CO_2 emissions.

This paper has presented a mean-variance portfolio optimisation analysis that develops and evaluates optimal (that is, efficient) EU electricity generating mixes for 2020. The results suggest that greater shares of non-fossil technologies, primarily nuclear or wind, can help reduce the cost and risk of the EU generating portfolio as well as its CO_2 emissions. To illustrate, an efficient generating mix that we consider to be achievable by 2020 is estimated to cut annual EU electricity generating cost by €24 billion and CO_2 emissions by 548 million tonnes. This mix thus produces perpetual annual benefits sufficient to justify current investments of up to €500 billion – which compares to an estimated EU investment of €900 billion in new electricity generation capacity needed by 2030. It is also shown that easing constraints on investment in nuclear and wind energy capacity would lower overall generating cost enough to offset 46 percent and 21 percent of the kWh costs of nuclear and wind generation. Against this background, policies designed to accelerate the deployment of key non-fossil technologies appear to be highly cost-effective.

Perhaps the single most important lesson of the portfolio optimisation analysis is that adding a fuel-less, fixed-cost technology (such as wind energy) to a risky generating mix lowers expected portfolio cost at any level of risk, even if the fuel-less technology costs more when assessed on a stand-alone basis. This underscores the importance of policy-making approaches grounded in portfolio concepts as opposed to stand-alone engineering concepts.

This is a tall order, since quantitative indicators in energy markets are primarily focused on stand-alone performance. In contrast, financial markets provide a *beta* measure to help investors think in terms of portfolio performance. The lack of a similar measure in energy markets prevents some from embracing the energy planning portfolio optimisation approach.

Ironically this issue is akin to the practical problems that initially confronted Harry Markowitz's portfolio approach. The new technique required massive analytic efforts (*sans* computers) to estimate the covariance of returns to each stock in the US market against every other stock. It was not until Sharpe and Lintner developed the Capital Asset Pricing Model (CAPM) to show that a single covariance with the market portfolio is sufficient (Varian 1993). Perhaps with further research, it may be possible to develop energy analogues that will enable a *beta* type measure to index the risk of particular generating technologies against a large generating mix such as the EU mix. This would provide a simple and expedient method for evaluating the costs and risks of individual technologies and their CO_2 emissions.

Today's dynamic and uncertain energy environment requires portfolio-based planning procedures that reflect market risk and de-emphasise stand-alone generating costs. Portfolio theory is well tested and ideally suited to evaluate electricity expansion strategies.[19] It identifies solutions that enhance energy diversity and security and are therefore considerably more robust than arbitrarily mixing technology alternatives. Portfolio analysis reflects the cost-risk relationship (covariances) among generating alternatives. Though crucial for correctly estimating overall cost, electricity-planning models universally ignore this fundamental statistical relationship and instead resort to sensitivity analysis and other ill-suited techniques to deal with risk. Sensitivity analysis cannot replicate the important cost inter-relationships that dramatically affect estimated portfolio costs and risks (Awerbuch 1993), and it is no substitute for portfolio-based approaches. The mean-variance portfolio framework offers solutions that enhance energy diversity and security and are therefore considerably more robust than arbitrarily mixing technology alternatives.

Today's dynamic and uncertain energy environment requires portfolio-based planning procedures that reflect market risk and de-emphasise stand-alone generating costs.

This being said, we must be clear about the purpose and the limitations of the portfolio approach to electricity sector planning. The portfolio optimisation presented in this paper does not point to a specific capacity-expansion plan. Such outputs would require considerably more detailed models. The results presented here are largely expositional, but they demonstrate the value of portfolio optimisation approaches and suggest that capacity planning made on the basis of stand-alone technology costs will likely lead to economically inefficient outcomes.

Moreover, in deregulated markets, individual power producers evaluate only their own direct costs and risks when taking investment decisions. These decisions do not reflect the effects the producers' technologies may have on overall generating portfolio performance. Wind investors, for example, cannot capture the risk-mitigation benefits they produce for the overall portfolio, which leads to under-investment in wind relative to levels that are optimal from society's perspective. Similarly, some investors may prefer the risk menu offered by fuel-intensive technologies such as combined-cycle gas turbines, which have low initial costs. Given sufficient market power, gas generators may be able to externalise fuel risks onto customers. In effect, these investors do not bear the full risk they impose onto the generating mix, which may lead to over-investment in gas relative to what is optimal from a total portfolio perspective (a quantitative treatment of this issue is given in Roques 2006). All this suggests a rationale for economic policies in favour of technologies that bring diversification benefits.

19 Other techniques have also been applied. For instance, Stirling (1996, 1994), develops maximum-diversity portfolios based on a considerably broader uncertainty spectrum. Though radically different in its approach, his diversity model yields qualitatively similar results.

Annex

Table A1. Fuel cost inputs and economic cost of CO_2.

Gas	€4.8/Mbtu
Oil	€41/bbl
Coal	€44/tonne
CO_2	€35/tonne
Uranium	€6/MWh
Biomass	€5.15/GJ

Table A2. O&M correlation coefficients

Technology	Coal	Gas	Nuclear	Oil	Hydro	Wind	Geo	Solar	Bio
Coal	1.00	0.25	0.00	-0.18	0.03	-0.22	0.14	-0.39	0.18
Gas	0.25	1.00	0.24	0.09	-0.04	0.00	-0.18	0.05	0.32
Nuclear	0.00	0.24	1.00	-0.17	-0.41	-0.07	0.12	0.35	0.65
Oil	-0.18	0.09	-0.17	1.00	-0.27	-0.58	-0.06	-0.04	0.01
Hydro	0.03	-0.04	-0.41	-0.27	1.00	0.29	-0.08	0.30	-0.18
Wind	-0.22	0.00	-0.07	-0.58	0.29	1.00	-0.28	0.05	-0.18
Geo	0.14	-0.18	0.12	-0.06	-0.08	-0.28	1.00	-0.48	-0.70
Solar	-0.39	0.05	0.35	-0.04	0.30	0.05	-0.48	1.00	0.25
Biomass	0.18	0.32	0.65	0.01	-0.18	-0.18	-0.70	0.25	1.00

References

Awerbuch, S. (1993). "The surprising role of risk and discount rates in utility integrated-resource planning". *The Electricity Journal*, (6:3), pp. 20-33.

Awerbuch, S. (1995). "New economic cost perspectives for valuing solar technologies", in Böer, K.W. (ed.), *Advances in solar energy: An annual review of research and development.* (10). ASES, Boulder, USA.

Awerbuch, S. (1995a). "Market-based IRP: It's easy!". *Electricity Journal*, (8:3), pp. 50-67.

Awerbuch, S. (1996). "Capital Budgeting, Technological Innovation and the Emerging Competitive Environment of the Electric Power Industry," (with J. Dillard, T. Mouck, and A. Preston), Energy Policy, Vol. 24, No. 2, 195-202.

Awerbuch, S. (2000). "Investing in photovoltaics: Risk, accounting and the value of new technology". *Energy Policy*, Special Issue, (28:14), pp. 1023-1035.

Awerbuch, S. (2000a). "Getting it right: The real cost impacts of a renewables portfolio standard". *Public Utilities Fortnightly*, (February 15).

Awerbuch, S. (2004). "Restructuring our electricity networks to promote decarbonization: Decentralization, mass customization and intermittent renewables in the 21st century". Tyndall Centre Working Paper No. 49. www.tyndall.ac.uk/publications/working_papers/wp49.pdf

Awerbuch, S. (2005). "Portfolio-based electricity generation planning: Policy implications for renewables and energy security". *Mitigation and Adaptation Strategies for Global Change,* in-press.

Awerbuch, S. and Berger, M. (2003). "Energy security and diversity in the EU: A mean-variance portfolio approach". IEA Report Number EET/2003/03. http://library.iea.org/dbtw-wpd/textbase/papers/2003/port.pdf

Awerbuch, S., Beurskens, L., Drennen, T., and Jansen, J.C. (2005). "The cost of geothermal energy in the western US region: A portfolio-based approach: A mean-variance portfolio optimization of the region's generating mix to 2013". Sandia Report SAND 2005-5173.

Awerbuch, S. and Sauter, R. (2006). "Exploiting the oil-GDP effect to support renewables deployment". *Energy Policy* Volume 34, Issue 17, November 2006, pp. 2805-2819.

Awerbuch, S., Stirling, A., and Jansen, J. (2006). "Portfolio and diversity analysis of energy technologies using full-spectrum risk measures", in: Bodde, D. and Leggio, K. (eds.) *Understanding and managing business risk in the electric sector.* Elsevier, forthcoming.

Awerbuch, S. and Yang, S. (2007). "Efficient electricity generating portfolios for europe: Maximizing energy security and climate change mitigation," SPRU Working Paper, (forthcoming).

Bacon, R.H., Besant-Jones, J.F., and Heidurian, J. (1996). "Estimating construction costs and schedules: Experience with power generation projects in developing countries". World Bank Technical Paper No. 325.

Bar-Lev, D. and Katz, S. (1976). "A portfolio approach to fossil fuel procurement in the electric utility industry". *Journal of Finance*, (31:3), pp. 933-47.

Berger, M. (2003). *Portfolio analysis of EU electricity generating mixes and its implications for renewables*. *Ph.D. Dissertation*, Technische Universität Wien, Vienna.

Brealey, R.A. and Myers, S.C. (2004). *Principles of corporate finance*. McGraw Hill, New York, USA.

Committee On Radioactive Waste Management, CORWM. (2006). "Managing our Radioactive Waste Safely". July.

Dale, L., Milborrow, D., Slark, R., and Strbac, G. (2004). "Total cost estimates for large-scale wind scenarios in UK". *Energy Policy,* Volume 32, Issue 17, November 2004, pp. 1949-1956

European Commission. (2001). "Towards a European strategy for the security of energy supply". Green Paper.

European Commission, EREC. (2005). "European energy and transport: Trends to 2030 - update 2005. SHP Potential". http://www.erec-renewables.org/sources/hydro.htm

European Commission. (2006). "Commission Staff working Document". Annex to the 'Green Paper: A European strategy for sustainable, competitive and secure energy. What is at stake'. Background document SEC(2006) 317/2.

European Commission. (2007). "An energy policy for Europe". Communication from the Commission to the European Council and the European Parliament, Brussels, 10.1.2007. Com(2007) 1 Final {Sec(2007) 12}.

Fabozzi, F., Gupta, F., and Markowitz, H. (2002). "The legacy of modern portfolio theory". *The Journal of Investing,* (Fall), pp. 7-22.

Fox, B. and Flynn, D. (2005). "Managing intermittency of wind generation with heating load control", in collaboration with P. O'Kane. The Queen's University of Belfast.

German Energy Agency, DENA. (2005). "Grid Study" Presented in detail at the international 'Conference on the integration of wind energy into the German Electricity Supply', on May 10, 2005, in Berlin. http://www.ewea.org/fileadmin/ewea_documents/documents/publications/briefings/Dena_Study.pdf

Green, R. (2006). "Carbon tax or carbon permits: the impact on generators' risks". Institute for Energy Research and Policy, University of Birmingham.

Grubb, M., Butler, L., and Twomey, P. (2007). "Diversity and security in UK electricity generation: The influence of low carbon objectives". *Energy Policy*, in press.

Harlow, W.V. (1991). "Asset allocation in a downside-risk framework". *Financial Analysts Journal,* (47:5), pp. 29-40.

Huber C., Haas R., Faber T., Resch G., Green J., Twidell J., Ruijgrok W., and Erge T. (2001). "Final report of the project ElGreen". Energy Economics Group (EEG), Vienna University of Technology, Austria.

Humphreys, H.B. and McLain, K.T. (1998). "Reducing the impacts of energy price volatility through dynamic portfolio selection". *Energy Journal*, (19:3).

International Energy Agency, IEA. (2006). *World Energy Outlook 2006*. IEA, Paris, France.

Jansen, J.C., Beurskens, L.W.M., and van Tilburg, X. (2006). "Application of portfolio analysis to the Dutch generating mix: Reference case and two renewables cases: year 2030 - SE and GE scenario". Petten: ECN, February.

Mario Ragwitz, Gustav Resch, Claus Huber, and Thomas Faber (2005). "Potential of Renewable Energy Technologies". Fraunhofer Institute, Presented at Renewable Energy For Europe - Research In Action, Brussels, November 2005.

Roques, F.A. (2006). "The option value of diversity.", in Grubb M., Jamasb, T., and Pollitt, M. (eds), *Delivering a low carbon electricity system: Ttechnologies, economics and policy.* Cambridge University Press, Cambridge, UK.

Sinden, G. (2005). Wind power and the UK wind resource. Oxford, UK: Environmental Change Institute, http://www.eci.ox.ac.uk/publications/downloads/sinden05-dtiwindreport.pdf

Stirling, A.C. (1996). "On the economics and analysis of diversity". Science Policy Research Unit (SPRU) University of Sussex, Paper No. 28. www.sussex.ac.uk/spru.

Stirling, A.C. (1994). "Diversity and ignorance in electricity supply - Addressing the solution rather than the problem". *Energy Policy*, (22:3), pp. 195-216.

UK Energy Research Centre, UKERC. (2006). "The costs and impacts of intermittency: An assessment of the evidence". Imperial College of London.

Varian, H. (1993). "A Portfolio of Nobel Laureates: Markowitz, Miller and Sharpe". *The Journal of Economic Perspectives*, (7:1), pp. 159-169.