Historical Case Studies of Energy Technology Innovation

CASE STUDY 16: TECHNOLOGY PORTFOLIOS.

TECHNOLOGY PORTFOLIOS: MODELING TECHNOLOGICAL UNCERTAINTY AND INNOVATION RISKS

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AUTHORS' SUMMARY

The case study reviews a range of methodologies and model-based applications that can assist policy decisions under irreducible technology innovation uncertainties. One approach uses scenario analysis. A scenario study that explored a range of salient future uncertainties identified energy efficiency and conservation as the single most important and also most robust technology option for climate mitigation. Another approach uses portfolio theory to quantify the benefits from diversified technology portfolios in the framework of risk-averse decision-making. Such studies suggest risk aversion leads to higher adoption rates of currently higher-cost energy technology options such as modern biomass, renewables, and also carbon capture and storage (CCS). Diversification not only reduces the mean of risk exposure but also drastically lowers the tails of extreme undesirable outcomes. Portfolio theory and scenario analysis can also be combined, as illustrated by a study of three different energy system objectives (energy security, air pollution, climate change) within a multi-criteria optimization framework. Scenarios in which objectives were met individually, and then all together, under a range of uncertainties again demonstrated the benefits of portfolio diversification with greater emphasis on energy efficiency and "general purpose" energy conversion technologies. These examples discussed in this case study show that formal tools and approaches, including scenario analysis, portfolio theory, and multi-criteria optimization, are increasingly available to move technology portfolio decisions onto a more rational ground.

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1 INTRODUCTION

Most large-scale, energy assessments rely on deterministic energy models. Technological uncertainty is either not represented at all (e.g.,IEA, 2008) or is described through a set of scenarios that vary the most important salient technological uncertainties such as availability, costs, resource constraints, as well as changing market environments like relative prices (e.g.,Nakicenovic et al., 2000; 1998).

Such approaches can offer only limited guidance for investments under technological uncertainty. Deterministic models tend to promote technologies which are least costly under the assumed parameterization and under a perfect-foresight decision making paradigm. Under slightly different circumstances, however, such choices can turn out to be considerably more expensive (e.g. if the technologies considered to be “optimal” do not develop at the projected rates) or even dangerous (e.g. if safety risks are ignored). It is therefore inherently important to include uncertainty into any energy system modeling and specifically in those applications, which are designed to guide policymaking. Fortunately, modeling techniques have greatly improved over the last years. This is in part due to increased computing power which allows for more complex models and analysis, but also due to advances on the theoretical side as well as the application of modeling tools from other fields including finance.

There are two main ways in which innovation uncertainty can be incorporated into energy systems modeling: scenario analysis and portfolio theory. Both approaches are reviewed and illustrated in this case study. A combination of both approaches using a multi-criterion optimization framework is also discussed. The case study concludes by drawing some generalizable insights for crafting technology portfolios.

2 SCENARIO ANALYSIS

Scenario analysis is a widely used technique to explore salient uncertainties of the future. As opposed to a (singular) deterministic forecast, a scenario is a set of conditional “what if…then” assumptions integrated into formal energy or climate policy models to explore the outcomes of exogenously assumed contingencies. Examples of such contingencies include for instance high or low energy or carbon prices, a moratorium on nuclear power, or its expansion. In order to investigate how the optimal energy mix changes under different assumptions and alternative developments, scenario analysis and model sensitivity analyses have proven to be useful and insightful tools. Relaxing certain assumptions (e.g. that prices remain stable in the long run) or imposing additional restrictions (e.g. due to the policy goal of achieving a less emission-intensive fuel mix) can lead to quite different strategies for energy technology investments over time.

Kann and Weyant (2000) present scenario analysis (along with sensitivity analysis) as a way to identify key uncertain parameters, which can then be modeled stochastically (see, e.g., Zapert et al., 1998) using simplified versions of integrated assessment models. The simplest procedure for propagating uncertainty through a model is by sampling from a joint distribution across input values (such as future technology costs derived from scenario studies), even though in practice such joint distributions are difficult to specify and also involve a large degree of subjectivity in deriving probabilistic uncertainty distributions from a wide range of scenarios whose probability of occurrence remains unknowable.

A large-scale scenario study (Riahi et al., 2007) addressed explicitly the question of how the portfolio of GHG mitigation technologies changes as a function of the representation of different salient uncertainties including energy demand, resource constraints, availability and costs of technologies and finally, the magnitude of GHG emissions constraints. All these uncertainties were varied together in 22 scenarios. The scenarios were quantified using the bottom-up, linear programming model MESSAGE that lends itself particularly to this type of analysis due to its detailed representation of energy technologies. For the quantification of the impact of scenario uncertainty the metric of cumulative future GHG emission reductions under alternative scenario specifications was adopted, deploying the concept of mitigation "wedges" (Pacala and Socolow, 2004). A mitigation wedge is simply the contribution to the cumulative emission reduction over the period 2000-2100 that a particular technological option provides compared to a baseline scenario.

First, three baseline scenarios without GHG emissions constraints were compared to corresponding hypothetical baselines that assume a "frozen" state of technology of the year 2000 (i.e. no technological change/improvements at all). Then for each baseline scenario a range of increasingly stringent GHG emissions constraint scenarios were calculated (constraints varied from as low as 480 ppm CO_2-equivalent GHG concentration by 2100 up to 670 ppmv-equivalent). Additional scenarios were performed to quantify the effects of innovation failures, i.e. assuming a particular technology (e.g. nuclear, or carbon capture and sequestration, CCS) would not be available. The concept of mitigation wedges is illustrated below in Figure 1 for an illustrative, high emissions scenario (A2r), its corresponding “frozen technology” baseline, and a GHG constraint resulting in 550 ppmv-equivalent concentration by 2100.

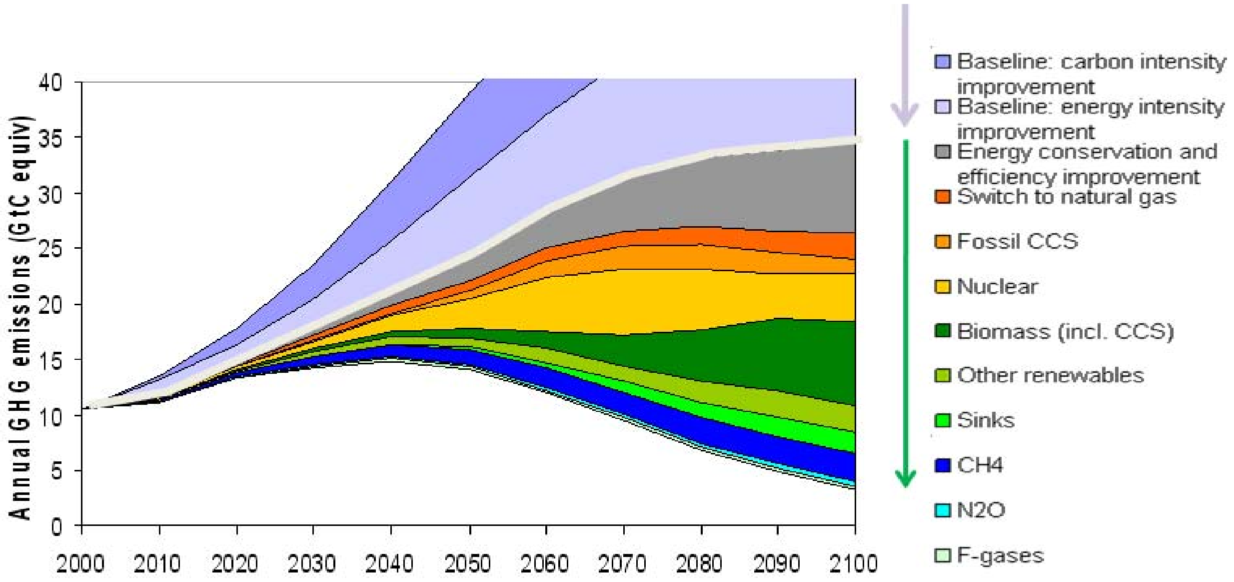

Figure 1. Greenhouse Gas Mitigation Wedges (GtC/Yr) For Climate Stabilisation. Notes: A wedge is the integral in terms of cumulative emissions reductions over the time period 2000-2100 compared to respective baseline scenarios. Wedges are calculated as the difference in emissions between a hypothetical baseline with frozen 2000 technology (top two ‘baseline’ wedges) or a scenario achieving atmospheric stabilization at 550 ppmv-equivalent by 2100 (all other wedges) compared to baseline scenario without GHG constraints.

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The calculated technology-specific GHG mitigation wedges are summarized in **Error! Reference source not found.** showing mean as well as minima/maxima across all scenarios analyzed. The ranking of different mitigation options is quite robust across the scenarios explored (even including larger scenario samples than reported here) with energy efficiency and conservation being the single most important option with typically >50% contribution to cumulative 2000-2100 emission reduction.

Riahi et al. (2007) propose an additional "robustness" measure to describe different mitigation options, expressed as the dispersion between minima/maxima across all scenarios calculated. For instance, energy efficiency turns out to be very robust as all scenarios rely to a large degree on that option whereas nuclear exhibits low robustness as its deployment varies widely across the scenarios (*high* in scenarios of high demand, lack of technology progress in renewables, and stringent climate constraints; *low* in low demand scenarios with high shares of renewables and medium climate constraints).

Error! Reference source not found. also compares the calculated future mitigation potentials of technological options to cumulative past and current R&D expenditures, summarized for the total of all IEA countries (that account for the majority of global public energy R&D). This reveals a highly significant bias in past and current R&D portfolios in favor of nuclear and at the detriment of energy efficiency and conservation. The scenarios suggest that more than half of future GHG emission reductions rely on improvements in energy efficiency and conservation, compared to some 10 percent for nuclear. This compares to cumulative nuclear R&D expenditures well above 50% of the entire public energy R&D budget of all IEA countries over the period 1974-2008 and a share of less than 10% for energy efficiency and conservation. To put the latter numbers into an absolute perspective: IEA countries cumulative public R&D into energy efficiency totaled some 38 billion US$2008 in PPP-terms, which is lower than total cumulative expenditure into fusion energy (41 billion), a highly uncertain option having neither demonstrated technical feasibility yet, not to mention economic viability and social and environmental acceptability.

TABLE 1. TECHNOLOGIES NEEDED FOR FUTURE GHG MITIGATION VERSUS CUMULATIVE PUBLIC ENERGY R&D IN IEA COUNTRIES. NOTES: MITIGATION EXPRESSED AS CUMULATIVE 2000-2100 EMISSION REDUCTION (GTC-EQUIVALENT) WITH MEAN AND MIN/MAX ACROSS SCENARIOS DESCRIBING FUTURE UNCERTAINTIES (RIAHI ET AL., 2007); R&D IN BILLION US$2008 IN PPP-TERMS (IEA, 2009). SOURCE: GRUBLER AND RIAHI, 2010.

	cumulative emission reduction (2000-2100) (mean all scenarios)				cumulative R&D (1974-2008)	
	GtC	*%*	Min	Max	10e9 $2008	*%*
Energy efficiency	1695	*59.2*	666	3008	38	*9.1*
Fossil Fuels	177	*6.2*	19	415	54	*12.8*
Renewables	520	*18.2*	64	917	36	*8.7*
Nuclear	243	*8.5*	64	425	225	*53.8*
Others	229	*8.0*	72	361	65	*15.5*
Total	2864	*100.0*	885	5126	417	*100.0*

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Scenario analysis can thus help to reveal such apparent technology innovation biases and assist decision makers in crafting technology portfolios. It helps systematically understand the magnitudes of salient uncertainties and the corresponding risks involved across the range of possible outcomes. However, the choice of scenarios can never be fully comprehensive of all future uncertainties and contingencies. In addition, the scenario approach does not capture the full impact that uncertainty has on decisions of technology adoption. In a deterministic perfect foresight model formulation, scenarios describing technology investment trajectories represent cost minima in terms of discounted systems costs. Uncertainty and associated (e.g., financial investment) risks can have a significant influence on the behavioral patterns governing the composition of the energy mix (e.g. in delaying needed upfront investments).

In effect, decisions depend critically on the risk preferences of a decision-maker whether or not he or she will trade more risk for a higher expected return on his/her investment and vice versa. For instance a decision maker might decide to bet the entire energy strategy on the breakthrough of a *potentially* low-cost, clean energy technology (e.g. fusion), which constitutes a considerable risk in cases when the anticipated technology promise does not materialize (e.g. fusion turns out to be either infeasible or far too expensive). Diversifying the technology innovation and investment portfolio is therefore a useful strategy to hedge against risks, but the extent of diversification and thus the composition of the resulting portfolio depends on both risk attitudes (premiums) of the decision maker as well as on a correct representation of the risks associated with technological (innovation) uncertainty (e.g. failure, or cost overruns of new technologies).

3 PORTFOLIO THEORY

Addressing these issues associated with decision making is at the heart of portfolio theory (Markowitz, 1952; Markowitz, 1959). Originally designed to find the optimal mix of financial assets to keep the risk at a pre-specified level, or to minimize risk for a fixed rate of return, portfolio theory has recently also been applied to energy sector investment in a number of applications (see the review in Bazilian and Roques, 2008). Earlier work includes Bar-Lev and Katz (1976), Awerbuch and Berger (2003), Awerbuch (2006), van Zon and Fuss (2006), Krey and Zweifel (2006), and Roques et al. (2008), among others). (Real options theory is another tool adapted from finance - see Box).

BOX. REAL OPTIONS THEORY.

Another decision-making tool adapted from finance is real options theory (Dixit and Pindyck, 1994). Real options analysis values an investment opportunity as an option, which will only be exercised when the immediate benefits of doing so exceed the value of waiting and making a decision later. With sufficiently large uncertainty, this continuation value can be so large that the adoption of a new technology might be postponed until information becomes available that enables the investor to make a better decision. Note that, while portfolio theory allows for a top-down view of the energy mix, the real options approach is more suited to represent decision-making at the plant and investment project level. Recent applications to energy investment include Madlener et al. (2005), Fleten et al. (2007), Laurikka and Koljonen (2006), Szolgayová et al. (2008), Yang et al. (2008), Fuss and Szolgayová (2009). The focus of the review here is on large-scale energy systems modeling, however, for which the use of real options approaches is practically limited by issues of computational practicality. See also Kann and Weyant (2000) on this topic.

Core to both scenario analysis and portfolio theory is the required representation of salient uncertainties. Relevant references here are Messner et al. (1996), Krey et al. (2007), Grubler and Gritsevskyi (2002), and Gritsevskyi and Nakicenovic (2000). These studies not only focus on stochastic energy prices, but also on technological uncertainties, in particular uncertain future technology costs and how these respond to alternative innovation and investment strategies (i.e. uncertain increasing returns to technology adoption).

Portfolio theory has the advantage of explicitly capturing the benefits from diversification in the framework of risk-averse decision-making. Krey and Riahi (2009), for example, address a very important problem in current large-scale energy systems modeling: conventional analysis suggests that optimal investments should focus on those technologies projected to have the least cost in the future. However, this ignores the potential of currently high-cost alternatives providing a more favorable risk profile. Krey and Riahi (2009) implement an endogenous risk (premium) formulation into a stochastic variant of the technology-explicit MESSAGE model of the global energy system in which all salient model variables are treated as uncertain. Their model runs show that optimal investment strategies based on conventional modeling (ignoring uncertainty) can be very costly. Risk aversion leads to higher adoption rates of currently higher cost technology options such as modern biomass and renewables and also carbon capture and storage (CCS) in order to hedge against inevitable innovation uncertainty (Figure 2). Thus, the model suggests higher short-to-medium term investments into advanced (but currently costlier) technologies under risk aversion.

Krey and Riahi (2009) also conduct sensitivity analysis to identify risk hedging strategies, which lead to improved robustness of energy investment decisions across a wide range of future uncertainties, including future carbon prices. Energy end-use and efficiency improvements were not modeled in the study so the results describe optimal technology portfolio diversification of energy supply options as a function of the willingness to pay to hedge against technological uncertainty (represented by the “risk premium” expressed as a percentage of total discounted energy systems costs). CO_2 emission reductions prove to be larger under optimal risk management of technological uncertainty.

The authors do not only consider variance as a risk measure, but also take into account the risk of high impact tail events. For example, a risk premium of only about 1% of total energy expenditures is found to decrease the value of the 99th-percentile of economic risk by more than a factor of 2. A “risk ignorant” investment strategy thus imposes extremely high energy system costs if anticipated future cost reductions do not materialize. Diversification thus not only reduces the mean of risk exposure but especially drastically lowers the tails (and economic consequences) of extreme events (undesirable innovation outcomes).

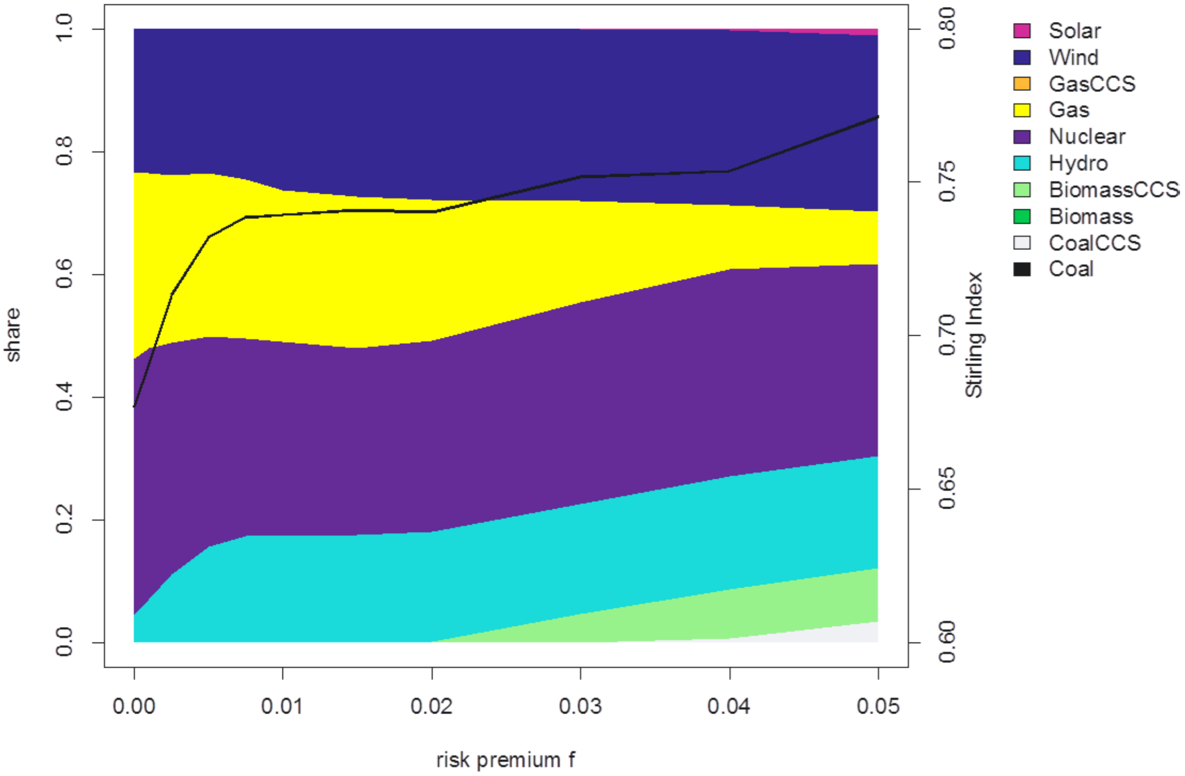

FIGURE 2. TECHNOLOGY SHARES (COLORED BLOCKS, LEFT AXIS) IN 2050 FOR A GLOBAL ENERGY SYSTEM AND CORRESPONDING STIRLING DIVERSIFICATION INDEX (LINE, RIGHT AXIS) VERSUS INCREASING RISK PREMIUM (FRACTION OF TOTAL DISCOUNTED SYSTEMS COSTS). NOTES: A ZERO RISK PREMIUM CORRESPONDS TO A DETERMINISTIC MODEL SOLUTION WITH ALL UNCERTAIN VARIABLES SET AT MEAN VALUES. POSITIVE RISK PREMIUMS (MAXIMUM OF 5% IN ABOVE FIGURE) REFLECT THE DECISION MAKERS' WILLINGNESS TO PAY FOR PORTFOLIO DIVERSIFICATION TO HEDGE AGAINST RISKS ARISING FROM UNCERTAINTY REPRESENTED AS LOGNORMAL DISTRIBUTIONS AROUND MEAN VALUES. MODELED UNCERTAINTIES INCLUDE FUTURE TECHNOLOGY AVAILABILITY AND COSTS AS WELL AS UNCERTAIN CARBON PRICES. HIGHER RISK AVERSION LEADS TO A MORE DIVERSIFIED TECHNOLOGY PORTFOLIO (AS REPRESENTED BY THE HIGHER STIRLING DIVERSIFICATION INDEX AND CHANGING SHARES IN TECHNOLOGIES DEPLOYED). SOURCE: KREY AND RIAHI, 2009.

Portfolio theory and scenario analysis are evidently not two mutually exclusive ways to incorporate uncertainty into energy and climate policy modeling and the ensuing crafting of technology strategies. In particular, portfolios can be designed to be robust across scenarios, so that scenario analysis can provide the basis for better-informed portfolio optimization. In this context, it is also important to consider different measures of risk. The choice of the risk metric depends on whether the underlying distributions have fat tails or not and whether the decision maker is averse to the amount that can potentially be lost in the tails rather than against the variance of his/her costs (e.g., variance versus "conditional value-at-risk" - see Fortin et al. (2008) for an application).

Another important question relates to the cost and risk associated with strategies that are robust across a wider set of scenarios, so that the optimal portfolio would perform best even if the worst scenario materialized. This has for instance been implemented by Fuss et al. (2009) using mini-max criteria in the objective function. This method also benefits from being essentially distribution-free insofar as all scenarios are treated equally likely (avoiding the problem of assigning inherently subjective scenario probabilities).

4 MULTI-CRITERIA OPTIMIZATION

These illustrative modeling applications discussed above provide important insights and policy guidance under conditions of uncertainty, but nonetheless are restricted by the use of a single policy (and hence mathematical optimization) criterion, be it minimizing future GHG emissions, or minimizing financial risks (costs) associated with insufficient technology portfolio diversification. In reality, however, both public policy as well as energy sector investments should consider a range of different policy objectives that need be factored in when designing technology portfolios. As well as climate change mitigation, energy security, affordability, and the health impacts of energy systems are among the examples of such a range of sometimes conflicting policy objectives and decision criteria. In this context, multi-criteria optimization approaches can shed additional insights into technology portfolio strategies (for reviews see, e.g., Stewart, 1992; Wierzbicki et al., 2000; Figueira et al., 2005).

A recent modeling study by McCollum et al. (2011) explored the implications of pursuing three alternative policy objectives (improving energy security, lessening traditional air pollution and ensuing health impacts of energy systems, as well as meeting climate change targets) first individually, and then in an integrated fashion. The study combines the scenario technique for describing the future uncertainties that lead to a wide range of technology deployment scenarios within a multi-criteria optimization framework. In this case, future uncertainties are represented by the varying degrees of stringency of adhering to the three policy objectives modeled, from weak, to intermediate and stringent.

A significant finding from the modeling study is that optimizing energy systems for the policy objectives of energy security, and traditional air pollutants yields limited co-benefits ("policy spillovers") on the climate change policy objective. Conversely, using climate change mitigation as a policy entry point yields significant co-benefits on the other two policy objectives of energy security and air pollution/health.

Another important finding was that the additional costs of meeting all three policy objectives simultaneously are comparatively modest compared to the costs of meeting any policy objective alone, and that the aggregate costs of an integrated policy approach (optimizing all three criteria simultaneously) are significantly below the sum of the costs that would have to be incurred when pursuing each policy objective individually (McCollum et al. 2011).

The results from the study can also be examined with respect to its implications for technology portfolios using cumulative (2010-2050) energy sector investments as a metric (which links to the potential for new business models, jobs, and overall macro-economic multiplier effects). Figure 3 shows illustrative results for the policy scenarios modeled that meet each criteria individually at the "stringent" policy fulfillment levels, as well as their combined multi-objective optimization (with all three policy objectives at their "stringent" policy fulfillment level).

The dominance of energy end-use in total energy system investments and the only modestly higher investments needed to achieve all three policy objectives simultaneously are both striking. In the original study, only price/policy induced investments into energy efficiency were modeled (i.e. excluding current and future baseline investments without additional policies). To account for energy investments comprehensively, a range of current energy end-use investments from 300 to 3,5000 billion US$ per year was added based on empirical estimates developed for the Global Energy Assessment (Grubler et al., 2012). This number is (conservatively) considered to remain constant over the modeling time horizon 2010-2050. The range in energy end-use investments reflects the different system boundaries that can be drawn to define the end-use technology (broadly) or just its energy-using component (narrowly). See Wilson and Grubler (2011), and the case study on end-use investments for more details.

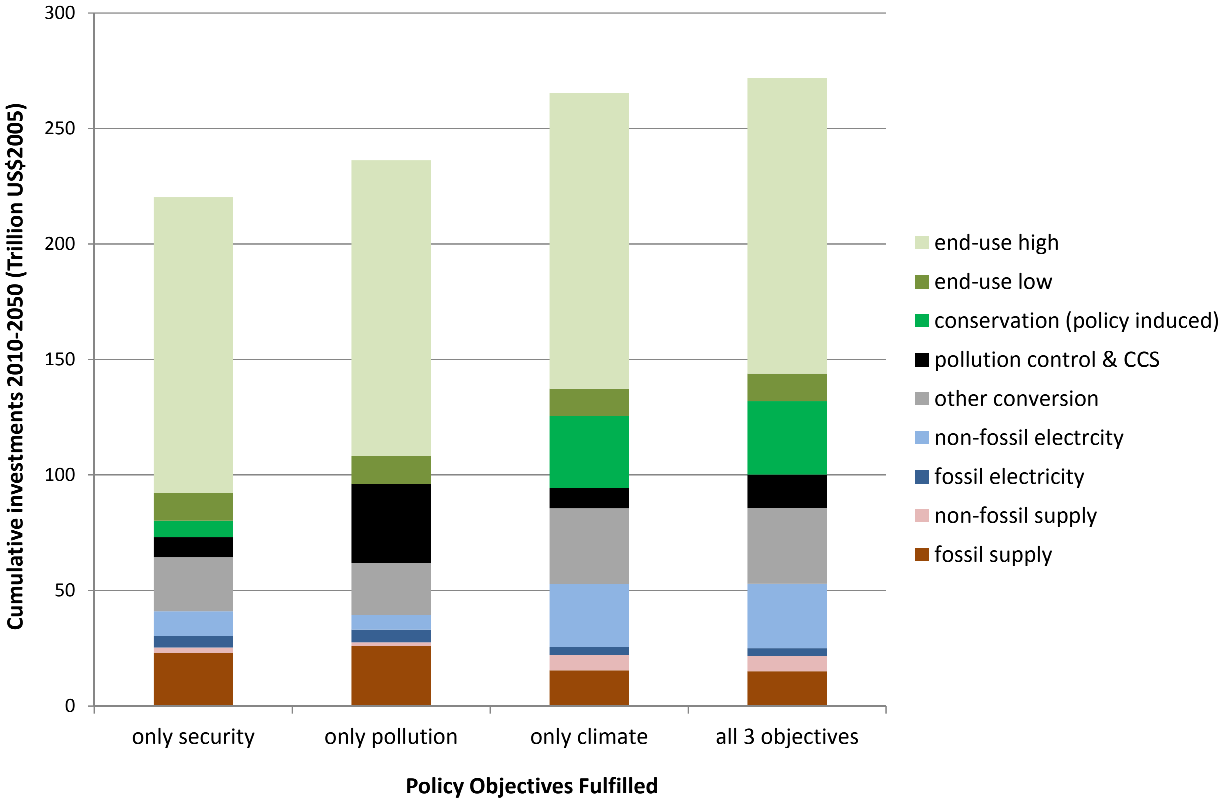

FIGURE 3. CUMULATIVE GLOBAL ENERGY TECHNOLOGY INVESTMENTS IN THREE ALTERNATIVE POLICY OBJECTIVES, AND A FOURTH POLICY INTEGRATION SCENARIO USING MULTI-CRITERIA OPTIMIZATION. NOTES: INVESTMENTS SHOWN IN TRILLION US$2005 DURING 2010-2050. SOURCE: MCCOLLUM ET AL., 2011.

To interpret Figure 3, it is important to realize the magnitude of the “baseline” energy sector investments (i.e. excluding policy-induced investments) estimated to be about 200 trillion US$2005 over the period 2010 to 2050, or of some 5 trillion US$2005 per year on average. Meeting various policy objectives requires additional investments that increase across the three policy objectives modeled, from energy security and air pollution, to climate change mitigation. More important is to realize the very small extra investments required to meet all three policy objectives simultaneously, compared to a scenario in which only one objective is met. For instance the integrated policy scenario entails cumulative investments of some 260 trillion US$2005, compared to the “climate protection only” policy scenario with some 253 trillion US$2005, i.e. a difference of some 3% only.

It is also instructive to examine the different implications for technology portfolios among the alternative policy formulations. Singular policy objectives also tend to increase investments into single-purpose technologies (e.g., high investments into end-of-pipe pollution control technologies in the "air pollution only" policy scenario). Conversely, under an integrated policy paradigm, investments into "general purpose" technologies, most notably increased energy efficiency, increase significantly. End-use investments account for up to 61% of all energy sector investments in such a policy integration scenario.

Equally noteworthy is the increasing diversification of energy supply and infrastructure investments with more non-fossil fuel supply and electricity generation investments, in addition to stepped up investments into "general purpose" energy conversion technologies and infrastructures such as syngases and hydrogen that can be supplied from a variety of fossil and non-fossil sources. These changes in long-term technology portfolios under a changed paradigm of an integrated policy framework provides useful guidance for innovation policies which have to date insufficiently supported energy end-use and efficiency as well as general purpose energy conversion technologies.

5 CONCLUSIONS

This case study provided a brief summary of methods and examples of modeling applications available to assist policy makers in crafting better technology innovation portfolios. The main conclusion is that formal tools in the form of scenario analysis, portfolio theory, and multi-criteria optimization, are increasingly available to move technology policy decisions onto a more rational footing. The choice of a particular tool will evidently depend on the policy question at hand and is of secondary importance compared to the need to arrive at technology portfolio decisions in a reproducible and transparent fashion. Formal tools and public disclosure are good instruments to assure transparency and reproducibility, and to date technology policy decisions have been falling short on these criteria.

Modeling studies in the field of energy technologies reveal a general pattern of portfolio diversification and of enhanced experimentation and earlier niche market investments under technological and innovation uncertainty, the extent of which depends on the (user specified) degree of risk aversion in addition to the underlying innovation uncertainty distributions. A second robust finding from the modeling studies is a much greater emphasis on energy end-use efficiency in technology portfolios responding to a range of risks and policy objectives. Greater energy end-use efficiency provides multiple benefits and also reduces risks and increases flexibility in supply-side energy technology portfolios.

These qualitative findings are in stark contrast to what appears to be a systemic energy technology innovation bias (Wilson et al., 2012) extending from public and private sector R&D, technology programs and roadmaps, analysis and modeling, through to private venture capital and niche market deployment incentives. Invariably, few selected energy supply technologies (nuclear in public R&D, solar and wind electricity in niche market incentives) obtain the lion share of funding and policy attention, with energy end-use and efficiency falling significantly short. And yet, improved energy efficiency has been shown to dominate the desired outcomes of innovation efforts from outputs from mitigation portfolios, social rates of return, or learning and cost reduction potentials. Technology portfolio analyses can reveal such innovation biases and misalignments in policies and incentives and thus help in starting to address them through changed innovation policies.

6 FURTHER READING

Fuss et al. (2009) provide a useful application of portfolio theory in relation to climate change mitigation. Awerbuch (2006) is another interesting and detailed demonstration of portfolio design in an energy context.

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