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Carbon Emissions Caps and the Impact of a Radical Change in Nuclear Electricity Costs

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ABSTRACT: In this study we analyze the impact of a radical change in nuclear electricity costs on the optimal electricity generation technology mix (EGTM) and constrain the value of information (VOI) on future nuclear costs. We consider three nuclear cost events and four carbon emissions caps. We develop a two-stage framework for energy-economic model MARKAL to eliminate foresight of future nuclear cost movements. We examine how the EGTM responds to these movements under alternative caps and analyze how these movements affect the cost of each cap. We define the expected savings from perfect foresight (ESPF), an upper bound on the VOI. We found that with current technologies, carbon mitigation that does not rely heavily on nuclear electricity is economically insensible. The Strong Cap is extremely costly because it restricts flexibility to respond to cost signals in choosing among technologies. The ESPF is highest under the Medium Cap by a substantial margin.

Keywords: MARKAL; nuclear electricity; value of information; foresight
JEL Classifications: C60; H23; O13; O33; Q40; Q50

1. Introduction

Research has suggested that the development of advanced technologies could reduce the cost of achieving carbon stabilization over the next century by more than 50%, resulting in global economic benefits in the hundreds of billions or trillions of dollars (Clarke et al., 2006). However, the timing and effect of radical technological change are difficult (or impossible) to predict (Bosetti and Tavoni, 2009). Future nuclear energy costs are particularly uncertain. On the one hand, a major breakthrough in an advanced nuclear technology such as nuclear fusion, small modular reactors, or pebble bed reactors could result in significantly lower nuclear costs (Lako et al., 1998); on the other hand, a large nuclear disaster or stricter safety regulations could result in significantly higher costs (Cooper, 2011).

The goals of this study are to (1) analyze the impact of a radical change in nuclear electricity costs on the optimal electricity generation technology mix (EGTM) for carbon reduction and (2) constrain the value of information (VOI) on future nuclear electricity costs. We use the energy-economic model MARKAL to conduct this analysis. The standard version of MARKAL assumes that economic actors have perfect foresight of future system parameters. To incorporate a lack of foresight of future cost changes, we build on a concept introduced by Keppo and Strubegger (2010) and run MARKAL in multiple stages. This framework allows the system to operate prior to the cost change as if it does not anticipate it, and then respond to the change after it occurs. To constrain the VOI we introduce a quantity called the expected savings from perfect foresight (ESPF) and define it as the difference between expected minimized discounted system costs (over a probability distribution of nuclear cost movements) in the multiple-stage framework and in the standard one-stage framework. The ESPF serves as an upper bound on the VOI on future nuclear costs. More specifically, we (1) define scenarios according to future nuclear electricity costs and carbon cap trajectories; (2) run the MARKAL model assuming both no foresight and perfect foresight of nuclear electricity cost changes in 2030; (3) analyze the response of the EGTM to these nuclear cost changes under the various carbon caps; (4) determine the economic cost of imposing each carbon cap with different future nuclear electricity costs; and (5) calculate the ESPF as a means of constraining the VOI on future nuclear costs.

This article is organized as follows. Section 2 briefly describes technological uncertainty, foresight, and VOI in the context of energy-economic models. In Section 3 we provide a brief overview of MARKAL and describe the extension to the two-stage framework. We introduce the ESPF upper bound on the VOI in Section 4. Section 5 describes the carbon targets and nuclear electricity cost events that combine to form the scenarios analyzed in this study. In Section 6, we examine how the EGTM varies across scenarios and draw conclusions about how electricity generation would respond to a radical change in nuclear costs. In Section 7, we report the cost of imposing each carbon cap assuming different future nuclear electricity costs as well as our ESPF calculations. Section 8 suggests some potentially interesting extensions to this study and related future research projects. We conclude in Section 9 with a summary of our most significant findings.

2. Technological Uncertainty, Foresight, and the Value of Information

2.1. Technological Uncertainty

A number of researchers have discussed technological change in the context of climate policy and energy-economic models (e.g., see Weyant and Olavson, 1999; Goulder and Schneider, 2000; Goulder and Mathai, 2000). Clarke and Weyant (2002) indicate that incorporating uncertainty into energy-economic models is extremely difficult, especially as it relates to technological change.

Van der Zwann and Seebregts (2004) provide an overview of modeling, methodological, and parameter uncertainties related to technology. Their comparison of the MARKAL and DEMETER models — with endogenous and exogenously-defined technological change — demonstrated that results (i.e., policy outcomes) may be particularly sensitive to these assumptions. Gillingham et al. (2007) also stress that modeling technological change is (1) a “critical determinant” in the estimation of results and (2) amenable to different approaches depending on the overall purpose of the analysis. Jaccard et al. (2003) discuss uncertainty surrounding technological innovation, implications for future financial costs, and how uncertainty increases as the time horizon is extended. Uncertainty in the cost assumptions of technologies can affect the optimal timing of abatement measures and EGTM. These effects often occur when an optimization program selects one technology to be deployed before another simply based on the technology that costs the least to deploy in order to achieve some energy/environmental policy goal. More specifically, if (1) a technology is initially deployed based on highly uncertain cost assumptions but usually higher costs than established technologies and (2) its capital costs in subsequent time periods decrease as a result of endogenous learning, then this technology may have a comparative advantage over other abatement technologies (a phenomenon known as “technological lock-in”). Zwaneveld (2008) analyzed how certain technologies might be considered relatively inferior during one time, but superior during a subsequent era, from a least-cost perspective.

Bosetti and Tavoni (2009) used the WITCH model to show how modeling innovation as an uncertain process in a stochastic framework leads to higher investment in research and development (R&D), and to lower policy costs. They noted, however, that “the rigidity of the energy sector — characterized by long-lasting investments with limited substitutability — is shown to constrain the contribution of a technology breakthrough solely in the electricity sector” (p. S25).

Smekens (2005) incorporated R&D shocks into the MARKAL model as an approximation of two-factor learning curves (TFLC). This analysis showed that R&D shocks have a limited impact on cost reduction. The author indicated that the role of technological assumptions in determining deployment is a subject that should be investigated in further detail.

2.2. Foresight

Perfect foresight, in the context of energy-economic modeling, is the assumption that the optimizing agent can predict the future values of parameters with total certainty. Some popular energy-economic models, including the standard variant of MARKAL used in this study[1], assume perfect foresight, and as a result, the agent has perfect information about future time periods (e.g., technology costs) and is able to make optimal decisions today based on this information. To fully incorporate uncertainty would require the use of a stochastic simulation model. However, some researchers note that solving sophisticated stochastic models is "currently beyond available computational resources" (e.g., see Babiker et al., 2009). Furthermore, the probabilities that define the stochastic processes are themselves difficult to estimate accurately.

Keppo and Strubegger (2010) introduced a limited foresight method into an energy-economic model, MESSAGE. The authors provided an alternative decision framework, where "information for the full timeframe is not available immediately and sequential decision making under incomplete information is implied" (p. 2033). These authors evaluated possible consequences of limited foresight and estimated system-wide effects using three different assumptions concerning the decision horizon: (1) a model run where perfect foresight was assumed for the full timeframe of analysis (i.e., 2100); (2) a run where an unforeseen change occurred in the middle time period (i.e., 2050/2060); and (3) a run where decisions were made at each 10 year time step and always for a decision horizon of 30 years. Keppo and Strubegger (2010) concluded, among other things, that rapid consumption of oil and gas to achieve short-term cost reductions in their limited foresight cases led to under-investment in alternative energy sources such as nuclear.

2.3. Value of Information

A number of researchers have quantified the value of better (or perfect) information. Baker and Peng (2010) explored the value of better information on technological change. They estimated the expected value of better information (EVBI) obtained through expert elicitations about future technologies, including nuclear generation. They found that the EVBI is very large in comparison with the cost of performing expert elicitations and that the EVBI is higher for technologies with larger R&D budgets (e.g., nuclear).

Eppel and Winterfeldt (2008) conducted a VOI analysis for nuclear waste storage tanks, finding that VOI estimation approaches could be used to improve the collection of data about the composition of nuclear tank wastes and for subsequent decisions about tank-waste management.

Hu and Hobbs (2010) employed a two-stage stochastic version of MARKAL to estimate the relative importance of resolving uncertainties including (1) electricity demand growth, (2) natural gas prices, and (3) electricity sector greenhouse gas regulations. The authors estimated an expected value of perfect information (EVPI), expected cost of ignoring uncertainty, and the value of policy coordination (the cost saved by avoiding surprise changes in policy). This analysis found that system costs are most sensitive to greenhouse gas regulation uncertainty (i.e., reducing this policy uncertainty provides the greatest value to market participants).

Although perfect information rarely arises in practice, incorporating it in a model allows researchers to place an upper bound on the VOI. This suggests a maximum level of resources that should be allocated to obtaining more information about the uncertainty. In the context of a stochastic model, the EVPI serves as this upper bound. However, there is no such equivalent for a deterministic model run using a multiple-stage framework to incorporate a lack of foresight.

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[1] This study features the standard MARKAL variant in which parameters are deterministic and the agent has perfect foresight. For information on alternative MARKAL variants that incorporate near-sighted optimization or stochastic treatment of parameters, see the MARKAL documentation (Loulou et al., 2004).

3. MARKAL

3.1. Brief Overview of the MARKAL Model

MARKAL is a popular energy-economic model that minimizes the total discounted costs of the energy supply and demand system over an analysis period (usually to 2050). EPA (2006) used the MARKAL model to conduct scenario analyses of technology options for the U.S. electricity sector. Like other energy-economic models, a number of constraints must be satisfied including assumptions about future production growth, pollution, and resource availability. In this analysis, we parameterize the model using the EPA's 2008 MARKAL database (EPA, 2008), but eliminate future nuclear electricity capacity constraints.

The standard version of MARKAL does not incorporate technological change. A more sophisticated approach is to define technological change (cost and efficiency) trajectories exogenously according to pre-determined functional forms. An even higher level of sophistication is to incorporate endogenous technological change. This configuration allows costs to vary as a function of cumulative capacity according to performance curves. However, modeling technological change as a steady, gradual process involving only technologies that are currently operating or in development ignores a critical reality: radical technological change — such as a key technological breakthrough or major disaster — can dramatically alter the evolution of the energy sector (e.g., see Clarke et al., 2006).

3.2. One-Stage and Two-Stage MARKAL Frameworks

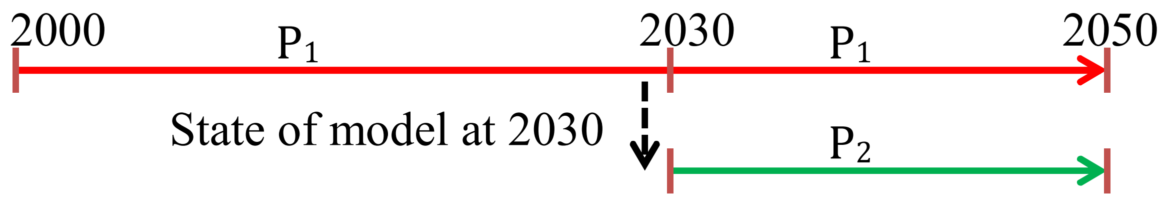
In this analysis, we considered the time horizon 2000 to 2050. We assumed that changes in nuclear electricity costs occur in 2030 and perform model runs using both one-stage (perfect foresight) and two-stage (no foresight) frameworks.

The standard one-stage MARKAL framework assumes perfect foresight. For the purposes of this study, this means that the optimizing agent minimizes discounted system costs from the perspective of year 2000 knowing exactly how nuclear costs will change in 2030. This change is reflected in the anticipated transition from parameters (i.e., costs) P_1 to parameters P_2 as illustrated in Figure 1.

Figure 1. One-stage MARKAL framework.

Alternatively, the two-stage framework assumes no foresight. In this case, the optimizing agent minimizes discounted system costs from the perspective of the year 2000 without anticipating the cost change in 2030, and then must suddenly react to any cost movement that occurs. The two-stage framework works as follows. First, we allow MARKAL to run over the entire time horizon without any change in costs in 2030 (base run). Next, we re-run MARKAL assuming a change in nuclear generation costs (holding all other parameter values constant) beginning in 2030 and using the state of the base run in that year as its initial state (see Figure 2).

Figure 2. Two-stage MARKAL framework.



4. Expected Savings from Perfect Foresight

We first clarify what is meant by the EVPI used with stochastic frameworks and then define the ESPF, a similar upper bound on the VOI that can be derived in the context of a deterministic cost-minimization model run in multiple stages to incorporate a lack of foresight.

The EVPI on an uncertainty is defined such that the value of the decision situation with perfect information and additional cost EVPI is equal to the value of the current decision situation. Assuming risk neutrality, the EVPI is just the difference between the value of a decision situation with perfect information and the value of the current decision situation. Referring specifically to a cost-minimization problem,

$$EVPI = min_x E[C(x,P;0,T)] - E[min_x C(x,P;0,T)] \tag{1}$$

where P is a random variable representing the values of all parameters, x represents a choice of actions, T is the time horizon, and $C(x,P;t_1,t_2)$ is the cost of taking actions x under parameter values P from time t_1 to time t_2. The first term is the expected cost of the current decision situation. In this case, P is unknown and x is chosen to minimize the expected cost over the probability distribution of P. The second term is the expected cost of the decision situation with perfect information. For each outcome P, the optimizing agent chooses the x that minimizes cost, so the expected value of these minimized costs is taken over the probability distribution of P. Note that the second term cannot be greater than the first term because acquiring perfect foresight cannot result in a higher minimized cost. Therefore, EVPI is non-negative.

The EVPI places an upper bound on VOI, but it is not well defined for deterministic optimization models such as MARKAL. The first term in (1), which corresponds to the current decision situation, describes a stochastic framework in which actions are declared before the uncertainty is resolved. Given that the standard version of MARKAL and many other optimization-based energy-economic models do not treat parameters stochastically, the EVPI is incompatible with these models and cannot be used to constrain the VOI.

For this reason, we define an upper bound on the VOI that can be derived in the context of a deterministic cost-minimization model run in multiple stages to incorporate a lack of foresight: the expected savings from perfect foresight (ESPF). The current decision situation is the two-stage framework with a lack of foresight. The optimizing agent selects actions x_1 to minimize cost over the entire time horizon [0,T] believing that the current parameter values P_1 will persist. When the parameter values change to P_2 unexpectedly at time τ, the agent selects new actions x_2 that minimize cost over the remainder of the time horizon under P_2. The decision situation with perfect information is the one-stage framework with perfect foresight. The optimizing agent selects actions x to minimize cost over the entire time horizon [0,T] knowing that the parameter values will change from P_1 to P_2 at time τ. In general,

$$\begin{aligned} ESPF = {} & E\left[C(x_1^*, P_1; 0, \tau) + min_{x_2 \in \chi(x_1)} C(x_2, P_2; \tau, T)\right] \\ & - E[min_x\{C(x, P_1; 0, \tau) + C(x, P_2; \tau, T)\}] \end{aligned} \tag{2}$$

where $x_1^* = argmin_{x_1} C(x_1, P_1; 0, T)$ and $\chi(x_1)$ is the restricted space of actions that can be taken between times τ and T — determined by inter-temporal constraints — given that actions x_1 were taken between times 0 and τ. Although (2) appears convoluted, the intuition for the ESPF is quite simple: it is the expected reduction in minimized cost that is achieved when the optimizing agent goes from having no foresight of a future parameter change to having perfect foresight of the change. Therefore, the ESPF places an upper bound on the VOI; as such, it is the maximum level of resources that should ever be allocated to obtaining knowledge of a future parameter change.

5. Scenarios

5.1. Carbon Caps

We evaluate the effect of four different carbon targets: No Cap, Weak Cap, Medium Cap, and Strong Cap (see Table 1). The Medium Cap is based on the trajectory outlined in the Waxman-Markey Bill (H.R. 2454, 2009). The Weak Cap and Strong Cap require a 20% lower and a 20% greater reduction in CO_2 emissions, respectively. The Waxman-Markey trajectory imposes progressively stricter carbon targets in 2020, 2030, and 2050. However, in this analysis, we chose to ignore the 2050 targets since they are too ambitious for MARKAL to meet using its available set of technologies. We delay the 2030 targets until 2040 so that the second strengthening of the carbon cap occurs after any change in nuclear costs.

Table 1. Carbon caps (as % of 2005 CO_2 emissions)

Carbon Target Scenario	2020	2040
No Cap	100.0%	100.0%
Weak Cap	86.4%	66.4%
Medium Cap	83.0%	58.0%
Strong Cap	79.6%	49.6%

5.2. Nuclear Electricity Costs

Nuclear plant construction costs have been extremely difficult to predict. EPA (2006) and EIA (1986) discussed how nuclear generation projects can cost nearly twice initial estimates. Nuclear energy is an example of a technology that could experience radical technological change in a positive or negative direction.

We consider three different cases for future nuclear electricity costs (see Table 2). The Base case represents the business-as-usual scenario in EPA's 2008 MARKAL database (i.e., there is no radical change in nuclear electricity generation costs). This scenario also serves as a point of comparison for the Cost Drop and Cost Rise cases. In the Cost Drop case, the investment cost for nuclear plants drops by 50% compared to the Base. This representation of nuclear technological improvement was chosen because capital investment represents approximately three-quarters of nuclear electricity costs (Cooper, 2009) and a breakthrough would likely entail a lower cost of installing new capacity. In the Cost Rise case, both the investment cost and variable costs rise by 50%. This reflects the fact that a nuclear disaster would result in more stringent safety regulations that would make it more expensive to both construct a new plant and operate existing plants.

Table 2. Future nuclear electricity cost scenarios (all changes occur in 2030)

2030 Nuclear Generation Cost Scenario	Change in Investment Cost (New Plants)	Change in Variable Costs (New and Existing Plants)
Cost Drop	- 50%	No Change
Base	No Change	No Change
Cost Rise	+ 50%	+ 50%

5.3. Scenarios and Model Runs

We evaluated the effects of 12 scenarios, which correspond to all possible combinations of our four carbon caps and three nuclear electricity cost events. For each scenario, we execute two model runs, one using the two-stage framework and another using the one-stage framework. Since the two-stage framework captures the unpredictable nature of radical cost change, the two-stage results are used to examine how the EGTM would respond to a radical change in nuclear costs in the system's attempt to meet an imposed carbon target. The one-stage results suggest how the EGTM might change if perfect foresight of future nuclear costs were available. The expected (over the probabilities of nuclear cost events) reduction in minimized discounted system costs when moving from the two-stage framework (no foresight) to the one-stage framework (perfect foresight) represents the ESPF on future nuclear electricity costs.

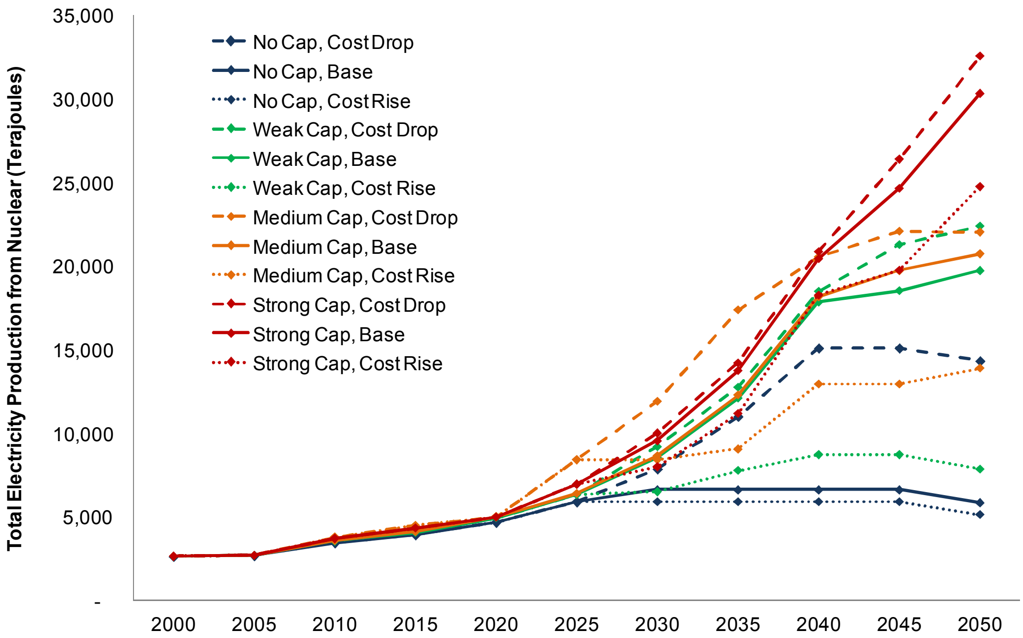
6. Results and Discussion: Electricity Generation Technology Mix

In this section, we discuss results for the two-stage framework model runs, in which technological breakthroughs and plant disasters cannot be anticipated. We show how future nuclear electricity production might change due to two effects and evaluate the role of two other important generation technologies: (1) coal with carbon capture and sequestration (CCS) and (2) wind.

6.1. Nuclear Electricity Production

Figure 3 shows total nuclear electricity production in each period for all 12 scenarios. We can distinguish two effects on the share of nuclear in the EGTM: (1) the Cap Effect and (2) the Cost Effect. The Cap Effect describes the increase in nuclear share as the cap becomes stricter. It is clear that for any given nuclear cost case, the nuclear share increases with the strength of the cap. This effect makes sense, because nuclear electricity is virtually carbon-free and relative to other low-carbon technologies is feasible and cost-effective on a large scale. The Cost Effect describes the decrease in nuclear share as nuclear electricity costs rise. It is clear that for any given carbon cap, the nuclear share decreases with nuclear electricity costs. This effect is intuitive, because when nuclear costs rise, other competing technologies will be relatively more cost-effective. With less stringent carbon caps in place, the Cost Effect largely dominates the Cap Effect. For example, the nuclear share in 2050 is higher with No Cap and a Cost Drop than with the Medium Cap and a Cost Rise. However, with more stringent carbon caps in place, the Cap Effect largely dominates the Cost Effect. As an example, the three highest nuclear shares in 2050 are in the scenarios featuring the Strong Cap; even the Strong Cap and Cost Rise scenario features more nuclear generation than any scenario featuring a weaker cap. Taken together, the results shown in Figure 3 suggest that moving from weaker to more stringent caps inhibits the ability of nuclear generation — and electricity generation in general — to respond to cost signals.

Figure 3. Nuclear electricity production for all scenarios.



More generally, these results show that nuclear electricity must play an increasingly important role in achieving emissions reductions. Even when the cost of nuclear generation rises, the nuclear share must expand, often significantly, in order to reduce emissions to desired levels. This suggests that with the current set of technologies, any carbon emissions reduction program that does not rely heavily on nuclear generation cannot be justified economically and could only be justified on political or public safety grounds.

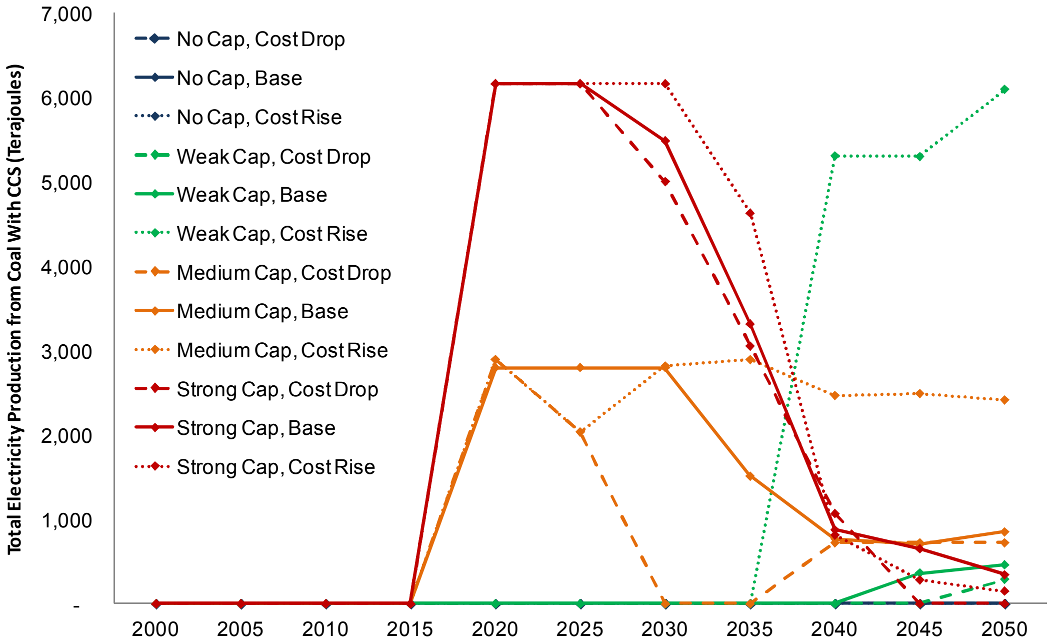
6.2. Coal with Carbon Capture and Sequestration (CCS) Electricity Production

Figure 4 shows coal with CCS electricity production in each period for all scenarios. In general, we found that substituting coal with CCS production for conventional coal production is a significant system response to a mid-range cap but does not reduce carbon emissions sufficiently to meet the strongest caps.

The No Cap scenarios are the only scenarios in which there is still a significant amount of conventional coal in the EGTM at the end of the time horizon. Without a carbon reduction requirement, there is neither a carbon nor cost incentive to switch conventional coal production to coal with CCS, so this transformation of the coal-fired generation subsector does not occur.

Replacing conventional coal with coal with CCS is a significant system response to a mid-range carbon target. The large surges in coal with CCS production visible in Figure 4 occur with the Weak Cap 2040 target and Medium and Strong Cap 2020 targets. However, with the strongest carbon targets – the Medium and Strong Cap 2040 targets – coal with CCS does not reduce emissions enough to be an attractive alternative to conventional coal, so production declines. Under the strongest carbon targets, the electricity sector is constrained to virtually zero CO_2 emissions because the other sectors in the MARKAL model (transportation, industrial, etc.) have comparatively lower potential for significant CO_2 reductions. In this situation, the only electricity generation technologies feasible on a large scale are nuclear and renewables.

Figure 4. Coal with CCS electricity production for all scenarios.



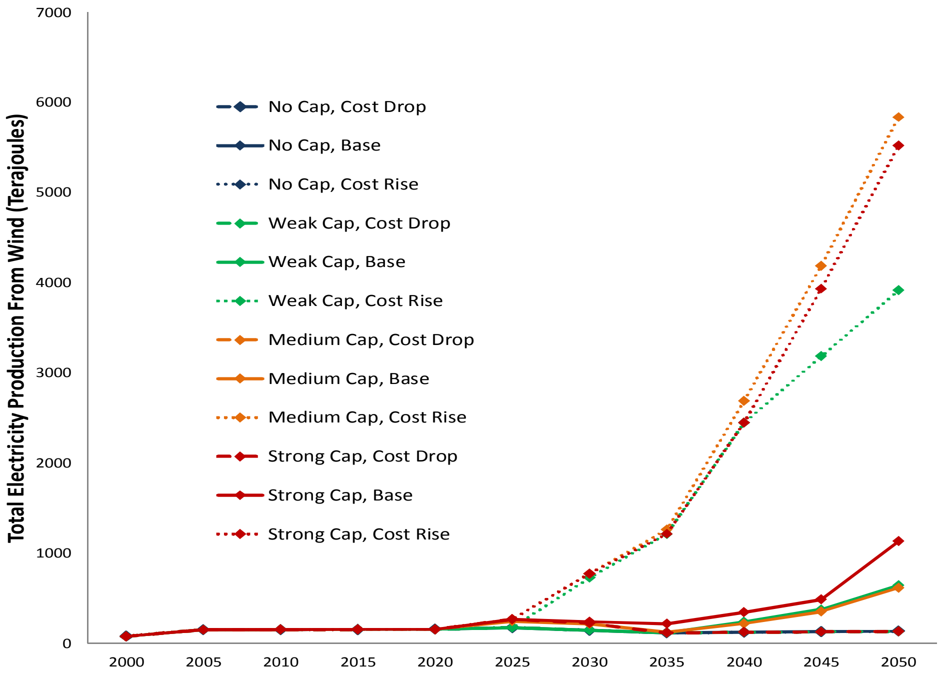
We found that the stronger the carbon cap, the less sensitive coal with CCS production is to nuclear costs. With the Weak Cap, the expansion of coal with CCS after 2040 is far more dramatic in the Cost Rise case than in the Base or Cost Drop cases. This is an intuitive response to a change in relative costs. With the Medium Cap, the persistence of coal with CCS in the later periods demonstrates some dependence on nuclear cost. Coal with CCS production declines from its peak only slightly in the later periods when nuclear costs rise and declines most rapidly when nuclear costs drop. Under the Strong Cap, the coals with CCS trajectories are nearly identical to one another, indicating very limited responsiveness to nuclear costs. Again, results suggest that the stronger carbon caps inhibit the ability of the EGTM to respond to cost signals.

6.3. Wind Electricity Production

We found that stringent caps make wind the dominant alternative to nuclear and that wind generation replaces nuclear generation more as nuclear costs rise. Figure 5 shows wind electricity production in each period for all scenarios.

Wind electricity production only expands when a carbon cap is imposed. However, once a carbon cap is in place, wind generation is determined far more by nuclear costs than by the strength of the carbon cap. In Figure 5, aside from the No Cap scenarios in which wind production does not expand, the trajectories are clustered by nuclear cost case. The three greatest wind shares are observed in the three scenarios featuring a nuclear cost rise. These results suggest that under a carbon cap, nuclear and wind are, in economic terms, substitute electricity generation technologies. However, given that wind is an intermittent electricity source, as its share grows it should cease to become a substitute for more conventional base load electricity technologies. While its generation share is never high enough in any of these model runs for its intermittency to be a significant concern, at some larger share wind installations would need to be accompanied by complementary additions of base load capacity to ensure ability to meet demand during times when wind resources are scarce.

Figure 5. Wind electricity production for all scenarios.

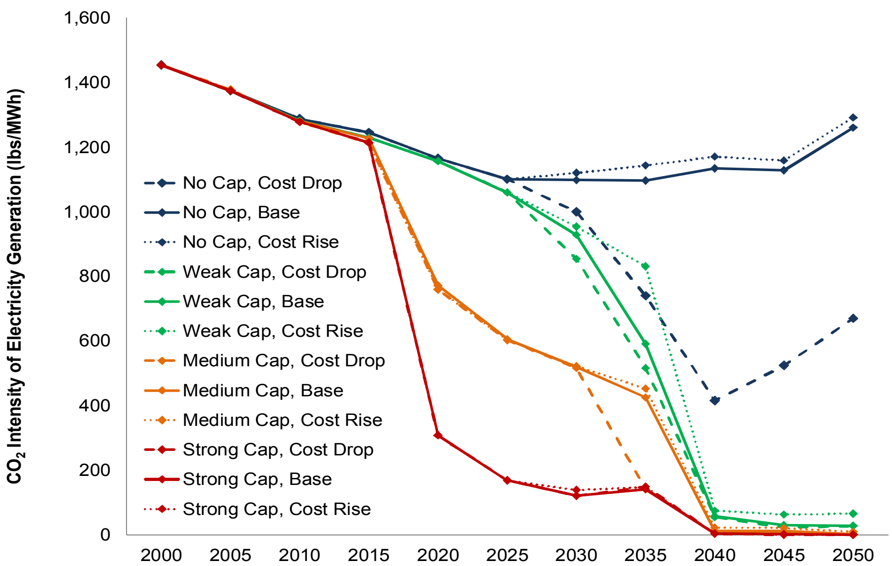


Wind generation increases most in later periods when the carbon caps are most stringent. Given that coal with CCS is no longer a valid option under the strongest carbon caps, wind is the dominant alternative to nuclear when the carbon cap is severe. In general, what we observe is that the imposition of a mid-range carbon target leads to replacement of conventional coal with coal with CCS and some expansion of nuclear. The imposition of a very strict carbon target leads to a drastic expansion of nuclear and a late expansion of wind, with wind displacing nuclear from the EGTM more as nuclear costs rise.

6.4. Carbon Intensity of Electricity Production

Figure 6 shows the aggregate CO_2 intensity of electricity production for all scenarios. With a carbon cap in place, the CO_2 intensity is for the most part dictated exogenously by the cap trajectory. However, several features of Figure 6 are worth analyzing.

Figure 6. Aggregate CO_2 intensity of electricity production for all scenarios.



First, the No Cap results suggest that the reduction in carbon emissions that would naturally occur if nuclear costs drop is immense (i.e., the CO_2 intensity of electricity production following a nuclear cost drop would fall to roughly half its value in the Base Case). This dramatic decrease in carbon intensity is achieved in less than two decades. These findings by themselves imply that it may be worth investing significant resources in efforts to decrease the cost of installing nuclear electricity capacity. Second, it is possible to see the effects of nuclear cost changes on carbon intensity in the period between the two cap introductions, 2020 to 2040. In this period, the Weak Cap and Medium Cap trajectories lie lowest with a nuclear cost drop and highest with a nuclear cost rise. This means that the decline in carbon intensity that takes place prior to the introduction of the stricter 2040 caps is more gradual with lower nuclear costs and more sudden with higher nuclear costs.

7. Results and Discussion: Cap Costs and Expected Savings from Perfect Foresight

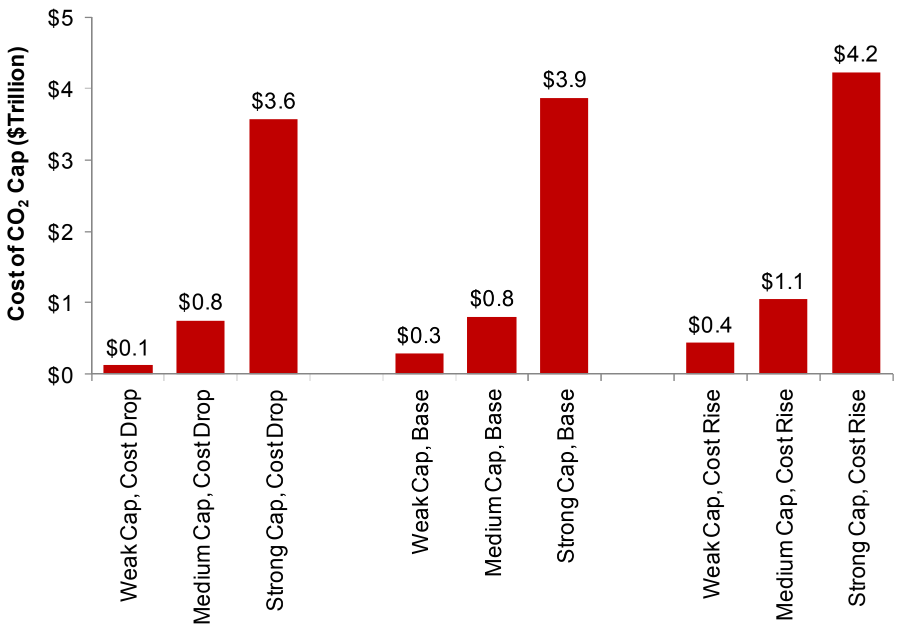
In this section, we discuss the costs of imposing carbon caps as well as the ESPF on future nuclear electricity costs.

7.1. Cost of Carbon Caps

For a given nuclear electricity cost case, the economic cost of imposing a particular carbon cap can be calculated by taking the difference between the minimized discounted system costs with that cap and with No Cap. Figure VII displays the additional economic cost that is incurred to meet each carbon cap under the alternative nuclear electricity cost cases.

The most striking feature of Figure VII is that under all nuclear electricity cost cases, the Strong Cap is significantly more costly than the Weak and Medium Caps. Achieving the last 20% of additional emissions reduction is far more costly than achieving all prior emissions reduction, suggesting that emissions reduction is characterized by sharply rising marginal costs. The dramatically higher cost of the Strong Cap is due to the fact that, under the Strong Cap, there is a lack of flexibility to choose among technologies based on cost signals. The emissions reduction requirements are so stringent that technology choices are almost entirely governed by the push toward zero-carbon electricity production.

Figure 7. Cost of imposing CO_2 caps under the three nuclear electricity cost cases ($ year 2000).



Another notable trend is that the cap costs increase with nuclear electricity costs, which is expected. The cost of the Strong Cap is heavily dependent on future nuclear generation costs. For example, a Cost Drop would make meeting the Strong Cap roughly $300 billion cheaper, whereas a Cost Rise would make meeting the Strong Cap roughly $300 billion more expensive. Therefore, imposing the Strong Cap increases the relative sensitivity of the system to future nuclear electricity costs. The greater sensitivity of the Strong Cap cost to nuclear costs is reasonable, because under this scenario the system has the least ability to deviate from an EGTM that is dominated by nuclear generation. The extremely stringent emissions reduction requirements mean that the only valid alternatives to nuclear are renewables like wind and solar. These technologies tend to be relatively more expensive (EPA, 2008) and only substitute for nuclear in significant quantities when nuclear costs are very high.

7.2. Expected Savings from Perfect Foresight

We calculated the ESPF by first assuming that the carbon cap is fixed. Applying equation (2), the ESPF on future nuclear electricity costs is calculated according to equation (3).

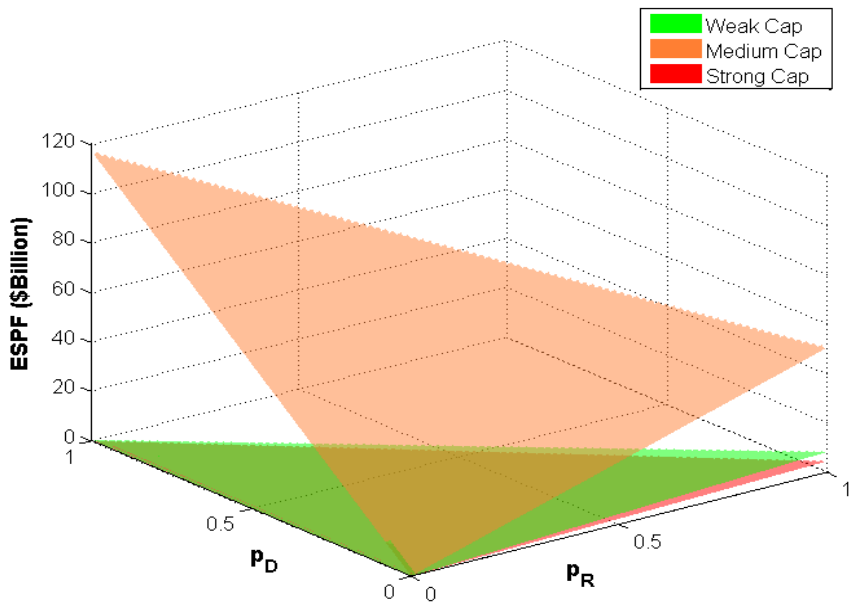
$$\begin{aligned} ESPF &= \left(p_D C_{2,D} + p_B C_{2,B} + p_R C_{2,R}\right) - \left(p_D C_{1,D} + p_B C_{1,B} + p_R C_{1,R}\right) \\ &= p_D\left(C_{2,D} - C_{1,D}\right) + p_B\left(C_{2,B} - C_{1,B}\right) + p_R\left(C_{2,R} - C_{1,R}\right) \\ &= p_D\left(C_{2,D} - C_{1,D}\right) + p_R\left(C_{2,R} - C_{1,R}\right) \end{aligned} \tag{3}$$

$C_{1,D}$, $C_{1,B}$, and $C_{1,R}$ denote the minimized discounted system costs in the one-stage model runs with the Cost Drop, Base Case, and Cost Rise, respectively; and where $C_{2,D}$, $C_{2,B}$, and $C_{2,R}$ denote the analogous quantities for the two-stage model runs. p_D, p_B, and p_R represent the probabilities of the Cost Drop, Base Case, and Cost Rise events, respectively. For the final manipulation in equation (3) we note that in the Base Case there is no difference between the minimized discounted system costs in the one-stage and two-stage model runs.

We know that the probabilities p_D and p_R are highly uncertain (Lako et al., 1998). One approach to estimating p_R would be to examine the frequency of past nuclear plant disasters and adjust for changes in the number of operating nuclear reactors. However, this approach relies on a relatively short track record of nuclear plant operation and assumes that future nuclear reactors will have the same susceptibility to disasters as reactors in the past. Furthermore, there are other potential reasons why there would be a future rise in nuclear electricity costs including challenges in the disposal of nuclear waste or legislation that preemptively imposes stricter safety regulations. It is even harder to estimate p_D, since major technological breakthroughs are inherently unpredictable as noted by Bosetti and Tavoni (2009).

Therefore, rather than estimate p_D and p_R, we plot the ESPF for all possible combinations of p_D and p_R under each cap (see Figure 8). The feasible domain is characterized by $p_D + p_R \leq 1$ (it follows that $p_B = 1 - p_D - p_R$).

Figure 8. ESPF on future nuclear electricity costs ($ year 2000) under each cap and over various beliefs about the probabilities of nuclear cost movements.

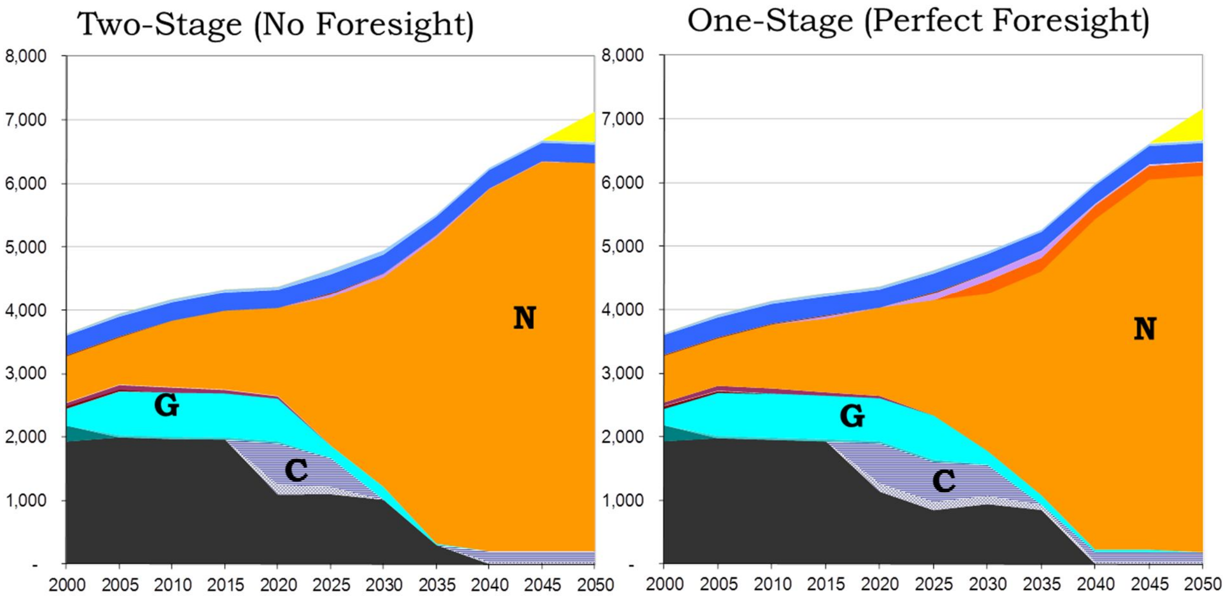


Under the Weak Cap, the ESPF is relatively low because the incremental emissions reduction requirements are small enough that the system can adjust to them quickly. There is little advantage to be gained from knowing future nuclear electricity costs in advance, since the system can wait and react without much economic penalty. In other words, the Weak Cap is not strict enough to make knowledge of future nuclear electricity costs particularly valuable.

Under the Medium Cap, the ESPF is at its highest because (1) emissions reductions are significant enough to make knowledge of future nuclear electricity costs valuable, yet (2) relaxed enough to allow the system to modify the EGTM based on cost information. As discussed earlier, the largest component of nuclear electricity cost is capital cost. Accordingly, the system responds to an anticipated cost rise by investing in more nuclear capacity before 2030 when it is relatively cheaper, and less after 2030 when it is relatively more expensive. Although variable costs will be higher in the later periods, meeting the Medium Cap 2040 target requires a larger share of nuclear and it is more cost-effective to build any new plants before the cost rise.

The system responds to an anticipated cost drop by delaying some investment in nuclear capacity until after the cost drop occurs in 2030 (see Figure 9). If agents have perfect foresight about the future cost decrease, more nuclear capacity expansion occurs later to take advantage of lower costs after 2030. Greater persistence of natural gas and coal with CCS in the EGTM makes it possible to delay investment in new nuclear generation capacity.

Figure 9. EGTM (Thousand GWh) in the Medium Cap, Cost Drop scenario. While there are many other technologies in the mix, attention is focused on nuclear (N), natural gas (G), and coal with CCS (C).



There are several possible explanations for why the Medium Cap ESPF increases as the relative likelihood of a cost drop compared to a cost rise increases. First, the increase in variable nuclear electricity costs in the Cost Rise case diminishes the gains achieved by investing in new capacity before the cost rise because those plants are then more expensive to operate in later periods. Second, it is possible that there is an asymmetry in the cost-effectiveness gap between nuclear and the next least or most expensive technology.

Under the Strong Cap, the ESPF is at its lowest because emissions reduction requirements are so stringent that there is essentially no flexibility to choose among electricity generation technologies based on cost signals. For example, even if the system anticipates a nuclear electricity cost drop that would make it cheaper to invest in nuclear capacity starting in 2030, waiting to invest in nuclear capacity is not an option because the 2020 Strong Cap target requires an early expansion of low-carbon technologies. In short, the Strong Cap inhibits the ability of the electric power sector to respond to cost signals to such a degree that information about future costs has little value.

Our analysis of the ESPF on future nuclear electricity costs has important implications for policymakers and the broader research community. First, this analysis illustrates how much more demanding the Strong Cap is than the other caps. The Strong Cap significantly limits the ability of the electricity sector to respond to cost signals, making it difficult for planners to exploit better information about future costs as it arises. Perhaps more importantly, this analysis suggests that policymakers should assess the likelihoods of different carbon emissions targets before allocating resources to expert elicitations about future nuclear electricity costs. This finding is consistent with results reported earlier noting that the possibility of greenhouse gas regulation is the most valuable uncertainty (Hu and Hobbs, 2010). We found that a carbon cap similar to the one proposed in the Waxman-Markey Bill (the basis for our Medium Cap) may justify a significant investment to develop more accurate estimates of future costs. With such a cap, the ESPF is very high across a wide range of assumptions about the relative likelihood of future nuclear cost scenarios.

8. Future Research

We believe that this study constitutes a step forward in understanding how a radical change in nuclear electricity costs might influence efforts to meet various carbon caps. There are a number of potentially interesting extensions to this study and a myriad of future research questions to explore in the area of radical technological change.

8.1. Timing of Cost Change

In this study, we assumed that future changes in nuclear electricity costs occur in 2030. This date was selected because it is close to the midpoint of the time horizon and is surrounded symmetrically by the carbon target introduction dates in 2020 and 2040. It would be interesting to examine the effects of varying the timing of nuclear electricity cost changes. For example, one could evaluate how much cumulative CO_2 emissions and minimized discounted system costs might fall if nuclear electricity costs drop in 2020 instead of 2030. Results could influence the relative merit of policies that promote rapid investment in technologies compared to policies that advocate waiting for more information to arise.

8.2. Sensitivity Analysis of Cost Change Assumptions

Given that it is impossible to predict with certainty how much nuclear electricity costs would change as a result of some future technological breakthrough or plant disaster, our representations of radical cost change were somewhat arbitrary. For that reason, we conducted a preliminary sensitivity analysis in which the Cost Rise assumes a doubling of investment cost and variable cost (100% change). We found that the trends we observed and conclusions we drew continue to hold with a doubling of costs. Having said that, we believe that future work should be devoted to a formal sensitivity analysis of these cost change assumptions. For example, it would be useful to assess whether our conclusions are robust over the range of future cost changes one might potentially see following a technological breakthrough or plant disaster.

8.3. Incorporation of Demand-Side Effects

Energy demand in the standard version of MARKAL used in this study is extremely inelastic. As a result, the responses of electricity production and system costs to changes in electricity costs are possibly inflated. It is likely that demand-side effects (e.g., energy efficiency, demand response) will play an important role in determining the future EGTM, especially with more stringent CO_2 targets. Clearly, more work should be devoted to incorporating demand-side effects in the MARKAL model.

8.4. Other Technologies

We focused on nuclear electricity because it is already widespread and will likely play a significant role in meeting carbon targets in the near future. However, it would be interesting to analyze the impact of radical cost changes in other technologies, including coal with CCS or renewables. Different technologies have very different capital and variable costs. Nuclear, for one, is distinguished by the dominant role of capital costs (i.e., plant construction costs) in the overall cost of electricity production. Perhaps technologies with different cost structures will behave differently and lead to fundamentally different results.

8.5. Cost Changes in Multiple Technologies

It is likely that the costs of other technologies will change over the time horizon either independently or as a result of changes in nuclear costs. Therefore, future research could be devoted to evaluating the effects of simultaneous cost changes across multiple technologies.

9. Conclusion

In this analysis, we considered four carbon caps and three nuclear electricity cost events. We developed a two-stage MARKAL framework to reflect the unpredictable nature of radical cost changes and evaluated the response of the electricity generation sector to these changes under the alternative carbon caps. Finally, we determined the cost of imposing each carbon cap with different nuclear cost scenarios and calculated the ESPF as a means of constraining the VOI on future nuclear electricity costs.

We found that, regardless of what happens to its costs, nuclear electricity production must expand in order to significantly reduce CO_2 emissions. This suggests that any ambitious carbon emissions reduction program that does not rely heavily on nuclear electricity cannot be justified economically and can only be justified on political or public safety grounds. The Cost Effect describes the decrease in the nuclear share as its costs rise. The Cap Effect describes the increase in nuclear share as the carbon cap gets more stringent. Under weaker carbon caps, the Cost Effect dominates and the nuclear share is more responsive to costs. Under stronger carbon caps, the Cap Effect dominates and the nuclear share is less responsive to costs. Replacing conventional coal with coal with CCS is a valid and relatively cost-effective alternative to nuclear under mid-range carbon caps, but under the strongest variants of the cap even coal with CCS is too carbon-intensive to meet emissions reduction requirements. Under the strongest caps, the only valid large-scale alternative to nuclear is wind. The share of wind generation is more sensitive to nuclear costs than to the severity of the carbon cap. Wind displaces nuclear from the EGTM more as nuclear costs rise; in economic terms, wind and nuclear electricity generation are substitute technologies in the presence of a carbon cap. The Strong Cap is significantly more costly than the Weak and Medium Caps. The cost of imposing the Strong Cap is very high because its emissions reduction requirements are so stringent that the feasible set of EGTMs is constrained to such a degree that there is virtually no flexibility to respond to cost signals in choosing among technologies. The ESPF on future nuclear electricity costs is greatest under the Medium Cap. The Weak Cap is not stringent enough to make information on future costs particularly valuable and the Strong Cap is so restrictive that it makes it nearly impossible to exploit better information on future costs. The Medium Cap strikes a balance between strength and flexibility, which results in a high ESPF across a wide range of probability distributions describing the likelihoods of nuclear cost events. These findings suggest that policymakers should consider the likelihoods of carbon targets before allocating financial resources to expert elicitations about future nuclear electricity costs.

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