**Analysis of Multipollutant Policies for the U.S. Power Sector under Technology and Policy Uncertainty using MARKAL**

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**Abstract**

Investments in power generation, pollution controls, and electricity end-use equipment are made in the face of uncertainty. Unanticipated events can cause regret—commitments that in retrospect were the wrong choices. We analyze how three uncertainties—electricity demand growth, natural gas prices, and power sector greenhouse gas regulations—could affect electric power sector investment decisions and costs in the U.S. over the next four decades. The effect of multi-pollutant regulations such as the Clean Air Interstate Rule (CAIR) upon these decisions and costs is also considered.

We use decision trees to structure the problem, defining multiple futures for each uncertainty and then simulating how the U.S. energy market responds to them. A two-stage stochastic version of the energy-economy model MARKAL simulates the market. Relative importance of the uncertainties is assessed using two indices: expected cost of ignoring uncertainty (ECIU) and expected value of perfect information (EVPI). We also calculate the value of policy coordination (VPC), the cost saved by avoiding surprise changes in policy. An example shows how a stochastic program can be used to compute these indices. The analysis shows that the possibility of greenhouse gas regulation is the most important uncertainty by these measures.

**Keywords:**

Electricity; Greenhouse gas; Stochastic programming; Decision analysis; Value of information; MARKAL

## 1. Introduction

The purpose of multi-pollutant policies for the electric power industry is to lower compliance costs and make larger emissions reductions possible by coordinating the implementation of policies addressing $NO_x$, $SO_2$, hazardous

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air pollutants, and, in some cases, $CO_2$. For a summary of various multipollutant proposals, including the original Clear Skies legislation and proposed Clean Air Interstate Rule.[1] Because of the diverse health, material, visibility, and ecological effects of these emissions, and the uneven way in which the costs of control will impact different societal groups, explicit consideration of tradeoffs among objectives and interests is a critical part of the policy development process [2, 3]. The analysis builds upon previous multiobjective analyses of multipollutant policies for the electric sector that have been undertaken for the Office of Atmospheric Programs using the MARKAL energy-economy model [4]. The contribution of our analysis is the inclusion of crucial policy and economic uncertainties in the design of multi-pollutant policies that effectively address the full range of policy objectives, and the demonstration of methods for quantifying various indices of the comparative importance of uncertainties in market models. We address three questions:

- What is the value of considering policy and economic uncertainty in developing multipollutant policies?
- What is the value of better information about these uncertainties?
- What is the value of coordinating policies concerning multiple pollutants?

The questions are addressed by a decision tree-based analysis in which the energy-economy model MARKAL [5, 6] is used to assess the cost and emission tradeoffs associated with alternative policies addressing $SO_x$, $NO_x$, and greenhouse gas emissions of the U.S. power sector for the years 2000-2050. MARKAL is a linear program that has energy producing, conversion, and use activities and capacities as decision variables, and constraints representing energy balances, capacity limits, and various policy considerations. Demands for energy services, including both electric and non-electric energy, are fixed exogenously, and supply curves are defined for all fuels. The objective function is to minimize the cost of meeting those demands; this formulation simulates the operation of a competitive market with zero price elasticity for energy services. Five year increments through the year 2050 are considered (2000, 2005, …, 2050), and the values of decision variables in all years are solved simultaneously. The stochastic version of MARKAL is modified for the purposes of this study to force five year-lead times for power plants; that is, a commitment to build is made five years before generation capacity comes on line, and this commitment cannot be changed no matter what scenario occurs in the on-line year. This change reflects the reality that plant capacity cannot be added instantaneously; the change magnifies the effects of uncertainty, because it is more likely that decisions made in earlier years will be "regretted" under some future scenarios.

1See Burtraw et al. [1] for summaries of various Congressional proposals.

We adopt MARKAL because it is the most widely-applied energy-economy model in literature, it has a two-stage stochastic programming capability that facilities decision tree analyses, and a USEPA National MARKAL data base was available for the model. Such a stochastic model divides the time periods considered into at least two sets: "here and now" decisions that are made before it is known what scenario (e.g., demand growth) will occur, and "wait and see" decisions that are made after the scenario is known [7]. For instance, a model might consider three demand growth scenarios for the years 2015-2050: high, medium, and low. The model's decisions before 2015 would be of the "here and now" variety, and would necessarily be the same for all scenarios (the so-called "non-anticipativity constraint). Those after 2015 would be of the "wait and see" type, and would be modeled separately for each scenario so that a different set of, *e.g.*, prices and investments would occur after 2015 if demand growth is high than if it is low.

In order to limit the scope of the paper, the emphasis is upon demonstration of how such energy-economy models together with decision analytic techniques can provide useful answers to these questions. Therefore, the analyses address only a subset of the most important uncertainties in energy-environmental policy.[2]

For simplicity in this initial analysis, we consider a policy process involving initial choices of policy whose performance would be assessed under a range of scenarios concerning three major uncertainties:

- *Electric energy demand:* Future demand depend on many uncertain factors, such as economic growth and improvement of end-use technologies, so a range of growth rates are possible. We simulate these within MARKAL using different growth rates for electricity end use demands.[3]
- *Resource costs:* Oil, natural gas, and coal prices are uncertain, and their relative prices would affect the cost of achieving emission targets. Because of the importance of new gas-based generation in the last two decades, and the potential role of gas for complying with multipollutant regulations, we focus on uncertainty in gas prices.
- *Emission policies:* USEPA's Clean Air Interstate Rule (CAIR) tightens caps upon sulfur dioxide and nitrogen oxide emissions by power generators, while extending the reach of the SIP call $NO_x$ cap to more states and the entire year. These rules have been subject to court challenge and are currently being revised, so we consider, as sensitivity analyses, scenarios involving both implementation of CAIR and continuation of the previous, looser

2 To keep the scope of the analysis practical, we focus on three major uncertainties that have been identified in a number of other studies [8, 9, 10] as being highly influential: electricity demand growth, resource costs, and emission policy..

3 The distribution of the growth of electricity demands is based on a study by the California Independent System Operator of past errors in electricity demand forecasts. The growth of demand was expressed by percent ratios of high and low demand cases with respect to the base case, with these ratios being applied to the end use demand categories of MARKAL electricity sectors (see Section 5 for details).

caps that CAIR would supersede.[4] Proposed Congressional “three pollutant” bills also address these pollutants. However, greenhouse gases, especially carbon dioxide, may also be capped at some time in the future; consideration of this possibility could affect fuel and emissions control choices today. Indeed, northeastern states that are members of the Regional Greenhouse Gas Initiative have already imposed such caps on power generators. Hence, we undertake an analysis in which there is a nonzero probability—but not certainty—of having a national CO2 emissions cap imposed.[5]

Morgan and Henrion [12] present the framework that we use to evaluate the effects of alternative policies under uncertainty.[6] Electric sector investments in generation, energy efficiency, and pollution control are divided into two stages: "here-and-now" commitments (before the technological and economic uncertainties are resolved) and "wait-and-see" investments (made after further information is obtained on the uncertainties; e.g., ten years from now). The analysis searches for robust strategies that perform well under a range of possible conditions.

An upper bound for the value of information about those uncertainties is given by the EVPI (expected value of perfect information), calculated by considering what market equilibria would result under each of the individual technology and economic scenarios, if the market participants knew with certainty that the scenario would occur. The value of considering uncertainty (expected cost of ignoring uncertainty, ECIU [12]) will be estimated by comparing the market equilibrium that occurs when each market party optimizes its decisions under uncertainty with the expected performance of the equilibrium that results if parties naively considered only a single nominal or “base case” scenario. The “value of policy coordination” (VPC) is assessed as the cost savings that result from simultaneous commitments to caps on $NO_x$, $SO_2$, and $CO_2$ relative to the case in which industry first adapts to caps on the criterion pollutants $NO_x$ and $SO_2$,, and then later a $CO_2$ cap is imposed that industry did not plan for. In both cases, the $CO_2$ cap is implemented at the same time (2015 in our MARKAL runs); the difference is whether industry makes decisions before that time anticipating the implementation of that cap. Precise mathematical definitions of these concepts are given in Section 3 of this paper, with simple numerical examples in Section 4. Section 5 summarizes the MARKAL assumptions made in the analyses. The results are discussed in Section 6 and followed by conclusions in Section 7.

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4 Burtraw et al. [8] and Burtraw et al. [9] point out the importance of the interaction between CO2 and other air pollutants. The results showed that a $25 tax per metric ton of carbon save $12-$14 ancillary heath benefits. They concluded that greenhouse gases mitigation policies would yield NOx and SO2-related health benefits.

5 This framework resembles that used by Laitner et al. [11] in their analysis of the ability of different possible “scenarios of future worlds” for the U.S. energy economy to adapt to surprise developments, such as a sudden imposition of severe carbon taxes or limitations.

6 See Hobbs et al. [13] for illustrative applications of this framework to the adaptation of water resources policies to climate uncertainties.

## 2. Previous MARKAL analyses of pollution policies under uncertainty

Since MARKAL was developed in the late 1970s [5], analyses of greenhouse gas policies have been its most frequent reported application. Our work is most closely related to previous stochastic MARKAL analyses of greenhouse gas policies, and in the remainder of this subsection we contrast these with our approach.

Kanudia and Loulou [14] discuss the general advantages of a stochastic formulation of MARKAL. The basic advantage is that energy investments should be made recognizing their robustness to important uncertainties in economic growth, demand, prices, and policy. In most versions of stochastic MARKAL (including that implemented in this paper), "robustness" is operationalized as minimizing the probability-weighted sum of costs (present value) over a set of scenarios, simulating the actions of market parties who maximize their expected profit over those scenarios. A set of investments and market outcomes that are fine-tuned for one particular scenario might perform disastrously for others; in contrast, robust decisions perform reasonably well across a wide range of possibilities. Stochastic programs provide rich detail concerning not only investments and market results in early years in the face of uncertainties, but also the optimal future adaptations that would be made under each particular scenario.

However, probability-weighted (expected) costs are not the only way to define robust strategies. Loulou and Kanudia [15] proposed a "minimax regret" formulation of stochastic MARKAL. Such a model solves for a set of early year investments and market outcomes that minimize the worst "regret" across scenarios, without reference to probabilities. "Regret" for a particular solution and scenario is defined as the difference in cost between that solution under that scenario and a solution that is tuned (optimized under perfect foresight) for just that particular scenario. This model objective represents a type of risk aversion that weighs extreme scenarios most heavily. The minimax regret solutions differ in several ways from solutions using the expected (probability-weighted) cost objective. In particular, regret-based solutions will be more sensitive to the range of scenarios considered under the regret objective. However, most subsequent work with stochastic MARKAL (including ours) has continued to use the expected cost objective. In our case, expected cost is used because it lends itself to calculations of EVPI, VPC, and ECIU. Also, from a theoretical point of view, the minimax regret approach suffers from certain logical inconsistencies, including dependence upon irrelevant alternatives.[7]

Condevaux-Lanloy and Fragniere [16] focus on efficient specification and solution of stochastic MARKAL using a specialized solver for stochastic optimization problems. Such an approach is worth considering as stochastic

7 For example, by adding an unattractive alternative that performs very poorly in most scenarios, but is best in one scenario, the rank order of the most attractive solutions can be changed.

MARKAL models are large and challenging to solve—model size is roughly proportional to the number of scenarios. This is the infamous "curse of dimensionality."

Turning to analyses of policies using stochastic MARKAL, Kanudia and Shukla [17] use that model to simulate the response of the Indian energy economy to uncertainty concerning possible future global carbon taxes. The solutions show that it is prudent to reduce carbon emissions in anticipation of possible global restrictions in the future. Fragnierie and Haurie [18] undertake such an analysis for Switzerland, with a focus on demand-side management. Larsson [19] considered three sets of uncertainties in MARKAL for Sweden, including alternative rates of economic growth, three policies concerning shutdown of nuclear plants, and two carbon mitigation policies. The analysis concluded that a hedging strategy would be more valuable if economic growth was high, and that choice of strategy depends on the assessed likelihood of a carbon emissions cap.

Kanudia and Loulou [20] apply stochastic MARKAL to Quebec, and consider possible hedging strategies in the face of a 50% probability of implementing stringent carbon mitigation measures within 15 years. They compare these strategies to three sets of "perfect foresight" strategies developed assuming either that low, medium, or stringent carbon mitigation will eventually be required. They note that prior to resolution of the uncertainty, the hedging strategy's total emissions take a path similar to the medium mitigation strategy; however, the details differ by sector. Before resolution, electricity supply follows the medium path, natural gas and renewable energy are more similar to the low mitigation scenario, and oil supply resembles the high mitigation trajectory. The authors identify some specialized hedging technologies that are favored in the hedging strategy but in none of the perfect foresight ones.

The contribution of this paper is to include technology and policy uncertainties in the design of multi-pollutant policies. Our analyses differ from previous work by our focus on the electric sector in the U.S. in the context of multipollutant policies; by demonstrating how EVPI, ECIU, and VPC can be calculated from a stochastic energy market model; and finally by our use of EVPI and ECIU to assess the relative importance of three crucial uncertainties ($CO_2$ policy, natural gas prices, and electricity demand growth).

**3. Methodology**

The analysis includes the following tasks: selection of technology, economic, and policy scenarios and assumptions (described in Section 5); execution of stochastic MARKAL; and calculation of the outputs of the analysis (optimal strategies, EVPI, ECIU, and VPC). In this section, we define those outputs in mathematical terms.

*3.1. Solving for optimal strategies*

We consider a decision problem with two decision stages, involving one set of decisions ($\underline{X}_1$, the "here-and-now" decisions) that must be made before it is known which future state of the world ($\underline{\theta}$, different possible scenarios concerning demand, fuel prices, and $CO_2$ policy) will occur, and a second set ($\underline{X}_2$, the "wait-and-see" decisions) that are deferred until after $\underline{\theta}$ is known. We can term $\underline{X}_1^*$ the optimal first stage decision, and $\underline{X}_2^*(\underline{\theta}, \underline{X}_1^*)$ the optimal second stage decision, which depends on what first stage decisions are made and which scenario has been realized. The optimal strategy is the collection of optimal decisions in every decision stage for every possible scenario: $\{\underline{X}_1^*; \underline{X}_2^*(\underline{\theta}, \underline{X}_1^*), \forall\underline{\theta}\}$.

The simple example in the next section shows how decision trees can be "folded back" to solve for the optimal strategy for simple problems. Folding back is also termed "backwards dynamic programming." Mathematically, folding back proceeds as follows. Let:

$C_1(\underline{X}_1)$ = the present worth of the cost in the first stage of choosing $\underline{X}_1$. This does not depend on the scenario $\underline{\theta}$ because these are the costs that are incurred before a scenario occurs. For instance, if $\underline{\theta}$ represents different demand growth rates between 2010 and 2020, then $C_1$ includes only costs before 2010.

$C_2(\underline{X}_2 | \underline{\theta}, \underline{X}_1)$ = the present worth of cost of choosing $\underline{X}_2$ in the second stage under scenario $\underline{\theta}$ and given first stage decision $\underline{X}_1$.

$P(\underline{\theta})$ = the probability of scenario $\underline{\theta}$.

Note that the total cost of an arbitrary sequence of decisions $\{\underline{X}_1; \underline{X}_2\}$ under a given scenario $\underline{\theta}$ is the sum of the costs in the two stages $C_1(\underline{X}_1)+C_2(\underline{X}_2|\underline{\theta}, \underline{X}_1)$. The folding back procedure for a two stage problem has two steps:

1. Second Stage Optimization. For each value of $\underline{X}_1$ considered and each scenario $\underline{\theta}$ considered, obtain the optimal second stage decision:

$$\underline{X}_2^*(\underline{\theta},\underline{X}_1) = \arg \min_{\{\underline{X}_2\}} C_2(\underline{X}_2 | \underline{\theta}, \underline{X}_1) \qquad (1)$$

2. First Stage Optimization. Find the optimal first stage decision as follows:

$$\underline{X}_1^* = \arg \min_{\{\underline{X}_1\}} [C_1(\underline{X}_1) + \Sigma_{\underline{\theta}} P(\underline{\theta})C_2(\underline{X}_2^*(\underline{\theta},\underline{X}_1) | \underline{\theta}, \underline{X}_1)] \qquad (2)$$

In a stochastic programming model such as MARKAL, the "MIN" operations are the solution of an optimization model—in the case of MARKAL, a linear program. Two-stage stochastic programs solve (1) and (2) simultaneously in a single optimization model in which $\{X_1; X_2(\underline{\theta}), \forall\underline{\theta}\}$ are the decision variables.

*3.2. Expected cost of ignoring uncertainty and value of policy coordination*

We have just introduced one product of a decision analysis: the optimal decision strategy. Another product is the quantification of the expected penalty, if any, if uncertainty is disregarded. The expected cost of ignoring uncertainty (ECIU) compares the expected performance of two strategies: 1) a naïve strategy developed assuming that some nominal value for $\underline{\theta}$ (such as its expected value) will accrue with probability 1; and 2) an optimal strategy developed considering the full range of possibilities and their probabilities. This represents the expected loss of performance when a decision is made as if there is no risk. The procedure for calculating ECIU is as follows [12].[8]

1. Define a nominal (deterministic) value of $\underline{\theta}$, calling it $\underline{\theta}_{naïve}$. This may be some "base case" value of $\underline{\theta}$, (e.g., medium demand growth or no $CO_2$ cap) or, alternatively, its expected value.
2. Define the optimal two stage strategy $\underline{X}_{naïve} = \{\underline{X}_{naïve,1}, \underline{X}_{naïve,2}\}$ under the base case assuming that probabilities of every realization $\underline{\theta}$ are zero except $\underline{\theta}_{naïve}$:

$$\underline{X}_{naïve} = \arg \underset{\{\underline{X}\}}{\mathrm{MIN}}\, C(\underline{X} \mid \underline{\theta}_{naïve}) \tag{3}$$

where $C(\underline{X} \mid \underline{\theta}_{naïve})$ is the cost of $\underline{X}$ assuming that the naïve scenario will occur with certainty.

3. Calculate the expected cost of the naïve strategy from Step 2, considering the full probability distribution of $\underline{\theta}$:

$$E_{\underline{\theta}}\, [C(\underline{X}_{naïve,1} \mid \underline{\theta}))] = C_1(\underline{X}_{naïve,1}) + \Sigma_{\underline{\theta}}\, P(\underline{\theta}) C_2(\underline{X}_2^{*}(\underline{\theta},\underline{X}_{naïve,1}) \mid \underline{\theta}, \underline{X}_{naïve,1}) \tag{4}$$

   Notice that the naïve strategy is adapted after it becomes known which scenario $\underline{\theta}$ will be realized, and the optimal decision is made in stage 2, given the scenario and the (naïve) first stage decision. That is, it is not assumed that the second stage naïve strategy $\underline{X}_{naïve,2}$ is implemented, because at that point the decision makers in the market realize what scenario has actually occurred. In a sense, the "scales" have fallen from the eyes of the decision makers at that point, and they realize that the naïve assumptions that were made were misinformed.

4. Define the optimal strategy as in Section 3.1 and calculate its expected cost C*.
5. ECIU is defined as the improvement in the expected cost if the optimal first stage strategy is chosen instead of $\underline{X}_{naïve,1}$.

$$ECIU = E_{\underline{\theta}}\, [C(\underline{X}_{naïve,1} \mid \underline{\theta}))] - C^* \tag{5}$$

ECIU cannot be negative if decisions are made rationally (minimizing expected cost), and is usually positive if the naïve first stage strategy differs from the optimal first stage strategy.

8 Birge and Louveaux [7] call this the value of the stochastic solution (VSS), and describe how it can be calculated for mathematical programs with recourse, such as the MARKAL model solved here.

The value of policy coordination (VPC) is closely related to ECIU, but is calculated under certainty. It is the difference in cost between a naïve strategy that doesn't recognize that policies will change at some point in the future, and a strategy that foresees that policy modification because policy makers have announced the change early on and have adhered to that commitment. The calculation of the actual performance of the naïve strategy would then be interpreted as follows: the naïve strategy would consist of the first stage decisions being made assuming that the policy will not change, followed by a policy change, after which the decision makers and market adapt as best they can, given the naïve first stage commitments. Comparing this to the optimal strategy given that the policy will change shows the possible cost savings if policy modifications are committed to well in advance. The latter strategy is obtained by allowing the market to optimize over the entire time horizon, recognizing the changing policies.

*3.3. Expected value of perfect information*

EVPI is obtained by assuming that the decision makers in the market know the future state of the world $\underline{\theta}$ without error. This is represented by first randomly choosing $\underline{\theta}$ and then finding the optimal $\underline{X}_{p.i.}(\underline{\theta}) = \{\underline{X}_{p.i.1}(\underline{\theta}), \underline{X}_{p.i.2}(\underline{\theta})\}$ for each scenario. Because both the first and second stage decisions can be tailored to the scenario, costs cannot increase relative to the optimal stochastic decision from Section 3.1 $\{\underline{X}_1^*, \underline{X}_2^*(\underline{\theta},\underline{X}_1^*)\}$, in which the same first stage decision is imposed upon all scenarios. $X_{p.i.}(\theta)$ is found by solving the following program for each $\theta$:

$$\underline{X}_{p.i.}(\underline{\theta}) = \arg \min_{\{\underline{X}_1, \underline{X}_2\}} [C_1(\underline{X}_1) + C_2(\underline{X}_2 | \underline{\theta}, \underline{X}_1)] \tag{6}$$

In MARKAL, this is easily done by solving (3) with $P(\underline{\theta}) = 1$ for the relevant $\underline{\theta}$. The resulting cost is $C(\underline{X}_{p.i.}(\underline{\theta})|\underline{\theta})$. Then, the expected cost in Eq. (7) over all $\underline{\theta}$ is found by weighting each of those scenario-optimal costs by the probability of its scenario. EVPI in Eq. (8) is then defined as the improvement in expected cost resulting from knowing which scenario is going to occur before making any decisions:

$$C_{p.i.} = \Sigma_{\underline{\theta}} P(\underline{\theta}) C(\underline{X}_{p.i.}(\underline{\theta})| \underline{\theta}) \tag{7}$$

$$EVPI = C^* - C_{p.i.} \tag{8}$$

## 4. Hypothetical example of decision tree solutions

This section presents a tutorial example of a two decision stage problem in which capacity investment decisions are made now, followed by the possible (but not certain) implementation of a $CO_2$ emissions cap on the electric power industry, after which additional capacity decisions are made (Fig. 1(a)). This case provides an example to illustrate the concepts of optimal strategy, ECIU, EVPI, and VPC.

In a decision tree, time proceeds from left to right. The tree explicitly represents the earlier here-and-now (stage 1) decisions to the left, and the later wait-and-see (stage 2) decisions on the right. Decisions are indicated by a square node on the tree, with alternatives indicated by arcs leaving that node to the right. The stage 1 choices are to either have a balanced gas/coal mix for new capacity or to emphasize construction of coal-fired plants in, say, years 2000-2005. Meanwhile, there are three stage 2 choices, designated as A, B, and C in the tree: either build gas (A) or coal plants (B) to meet incremental energy demands (in, say, 2010 and afterwards), or build a large amount of gas-fired capacity (C) both to meet incremental demand and to allow some previously constructed coal capacity to be retired early, should demand, energy price, or policy developments render that capacity uneconomic. There is a chance node (designated by a circle) between the two decision stages, representing the probabilities of a greenhouse gas emissions cap being adopted. Arcs leaving a chance node to the right represent alternative possibilities, each with a probability. Finally, at the end of each branch of the tree is the present worth of cost; "INF" indicates that the capacity mix in stage 2 would not be feasible under the emissions cap. In MARKAL, this would mean that the particular combination of first and second stage decision variable values would result in violation of one or more constraints under that old scenario.

A decision tree is used to solve for the optimal strategy by folding back, as summarized in Section 3.1. Folding back proceeds from right to left—backwards through time—by calculating the expected cost at each chance node and choosing the least expected cost alternative at each decision node. This procedure is repeated until the left node is reached. Figure 1(a) shows the results of applying this process to a simple tree. The number on the top of a node is the expected cost from that point onwards. For decision nodes, an arrow indicates which choice is optimal.

The tree in Fig. 1(a) shows that if there is no cap, then emphasizing coal capacity in both stages is cheapest, but that if there is instead a cap, adding a mix of coal and gas plants early and then later adding some additional gas capacity would be best. Unfortunately, whether or not there will be a cap is unknown before stage 1 commitments must be made, so there is the possibility that a stage 1 choice will be made that would be regretted later (*e.g.*, build a lot of coal capacity early, but then have to retire some early later on in face of a cap). Folding back that tree finds that the coal / gas mix that has the lowest expected cost (47.5, vs. 50 for the coal strategy). The mix strategy is best because it avoids the high penalty that can occur if there is a large commitment to coal in stage 1 and then some of that capacity has to be retired prematurely in stage 2 ("Emphasize Coal" followed by "C" in the second stage, costing 60). That costly second stage decision is made because no other second stage decision is feasible.

In contrast, if the market naively assumed that there is no chance of a $CO_2$ cap, then the optimal solution would be to emphasize coal in both stages, resulting in a low cost of 40. However, this strategy would actually cost 50 in expected value terms, because in reality there is some possibility of such a policy being implemented. Of course, this expected cost depends on the assumed probability of such implementation. The ECIU is therefore the expected cost of the naïve strategy (50) minus the expected cost of the optimal strategy (47.5), or 2.5.

EVPI for the two-stage problem is obtained by solving a decision tree (Fig. 1(b)) in which the first node is a chance node for the uncertainty, representing the probabilities of different (perfect) forecasts. Solving that tree results in a decision to have a coal/gas mixture if a tight cap is forecast, whereas emphasizing coal is the optimal stage 1 decision if no cap is anticipated. With different decisions being made under different forecasts, the value of information can be positive. This is indeed the case, as a comparison of the optimal expected cost under perfect information (45) and the expected cost without that information (47.5) shows: EVPI = 47.5 – 45 = 2.5.

The value of policy coordination is calculated by comparing the naïve and optimal policies assuming that the probability of imposing the cap is 1. That is, if electric generation companies realized that they should be making decisions in Stage 1 recognizing both the in-place limits on $SO_2$ and $NO_x$ emissions as well as the real possibility of a $CO_2$ cap, they would choose a different capacity mix. VPC can be assessed by considering the "Tight $CO_2$ Cap" branch in Fig. 1(b), which shows that the coal/gas mix would be 10 cheaper than the naïve solution of emphasizing coal, assuming that the policy change would be implemented for certain. This is because the optimal strategy naïvely assuming no $CO_2$ policy (emphasize coal) has a cost of 60 if in reality such a cap is imposed, whereas the coordinated policy (the optimal policy anticipating the cap) costs only 50 in that case.

## 5. MARKAL-based analyses: Assumptions

The basis of the below analyses is the USEPA National MARKAL data base (version EPANMD07).[9] To avoid over-interpretation of the results, we report only cost and solution differences rather than totals in Section 6.

All dollar amounts are expressed in real \$1995. A discount rate of 5%/year is applied[10]. The base case set of technology efficiencies and costs is drawn from the USEPA National MARKAL data base. MARKAL minimizes cumulative costs for 2000-2050, present worthed to 2000. The model is a market simulation, not a central planning (social welfare maximization) model; thus, these costs are described from the firm's point of view, including emission taxes which from a social point of view are transfer payments. Energy firms are assumed to make an invest-

9 This version of data base was provided by Carol Shay of Air Pollution Prevention & Control Division, Office of Research and Development of USEPA.

10 The discount rate in USEPA national MARKAL database is consistent with other energy models such as the Integrated Planning Model [21] and National Energy Modeling System [22].USEPA

ment if the present worth of its expense is less than the present worth of its revenues from the market, rather than use some other criterion such as payback period. No distinction is drawn between private cost of capital (assumed to be 5% real per year) and social discount rates.

MARKAL is a linear programming model, so technological learning is exogenous. The USEPA national MARKAL database includes assumed rates of learning, in the form of decreased capital costs over time for energy supplies, energy conversion, end use demand, and emission reduction technologies.

Because MARKAL is alinear program, the elasticity of demand for energy services is assumed to be zero, although consumer decisions to invest in more efficient energy using equipment results in a nonzero elasticity for electricity. Macroeconomic feedbacks (energy prices change effective income, which changes economic activity, which can alter energy demand) are also not considered in this version of MARKAL. High costs of energy provision (due to higher demand, higher fuel prices, or regulation) either go to pay for factors of production (fuel and capital, mainly, possibly resulting in increased net income to owners of those factors) or to owners of generation firms whose revenue increases exceed the increases in their cost of inputs.

Some modifications were made for future scenarios to ensure realistic rates of additions of new technologies. For example, the database sometimes would add large amounts of hydro, geothermal, or nuclear capacity, which for our cases we considered to be unrealistic. Consequently, we added constraints to limit additions to realistic levels, which for some technologies were small, and for others were zero. In particular, we assume the new investment of hydro and geothermal will not be a significant proportion of future US generation capacity additions due to the paucity of suitable sites and, in the case of hydropower, likely public opposition to new dams. This is consistent with other national analyses; for similar reasons, the U.S. DOE Annual Energy Outlook(AEO) 2009 base case [22] projects additions of only 0.85 GW of hydropower and 0.47 GW of geothermal capacity in 2010-2030, with wind and biomass providing most renewable additions.. Nuclear power additions are limited to the rate (approximately 5 GW/decade, on average) projected by the AEO, which added 11.4GW nuclear in 2010-2030, in part reflecting construction capacity limitations. Thus, combined cycle, combustion turbine, coal (with and without CCS), biomass, wind, and, to some extent, nuclear investments are the major alternatives for meeting future load growth. We believe that this range of alternatives captures a wide range of possible high and low emissions technologies as well as baseload vs peaking facilities, which allows us to explore the possible impacts of different uncertainties upon generation choices.

The rest of this section details the assumptions made concerning scenarios of emissions caps, energy demand growth, and natural gas prices. The $NO_x$ and $SO_2$ caps in Table 1 are applied in the cases where we assume continuation of the existing Title IV and SIP call policies that the USEPA Clean Air Interstate Rule would supersede. Table 1 also shows the assumed caps for those criterion pollutants under the assumption that some variant of the CAIR or Congressional three pollutant ($NO_x$, $SO_2$, mercury) legislative proposals will be passed. We do not consider mercury limitations; however, this may be an important limitation because they would increase the cost of maintaining existing coal power plants and building new such capacity. Note that the $NO_x$ emissions limit is assumed to cover all $NO_x$ emissions, not just the summertime emissions in the eastern and Midwestern states to which the pre-CAIR SIP call actually applies. It should be noted that the present $NO_x$ limit was rarely binding in the solutions after 2010, and that the Title IV $SO_2$ constraint was rarely binding after 2025, as old dirtier capacity is retired and replaced by new plants that comply with tight New Source Performance Standards (NSPS) for air emissions. The possible $CO_2$ constraint was chosen to represent a level roughly equal to year 2000 emissions; without this constraint, $CO_2$ emission in 2030 would grow to as much as 50% over this value, depending on the scenario.

Alternative electricity demand growth and natural gas price scenarios were based on a recent study by the California Independent System Operator [23] that analyzed the accuracy of past forecasts by the California Energy Commission regarding these important variables. Based on the standard deviations of forecast errors, three equiprobable scenarios were chosen for each year for demand and gas prices. The values for each scenario (expressed as a percentage of the base case) were chosen so that standard deviations of those ratios approximated the errors provided in that report. Table 2 shows the three demand scenarios considered for years 2015-2050, expressed as a percent ratio with respect to the base case. These ratios were applied to MARKAL end use demand categories for which electricity dominated. Table 3 provides the gas price ratios relative to the base case that we assumed.

## 6. Results

This section summarizes results for ECIU and EVPI for $CO_2$, demand growth, and natural gas uncertainties (Sections 6.1-6.3, respectively). We also consider how these results are affected by the presence of tighter conventional pollutant caps under CAIR-like rules. Moreover, in Section 6.1, value of policy coordination is quantified for $CO_2$ caps, as well as the effect of alternative policies upon prices and generation mixes. We also estimate the cost of the CAIR policies in that section. As sensitivity analyses, the joint ECIU and EVPI for $CO_2$ and demand growth uncertainties together is considered in Section 6.4, and the effect of a five year delay in the resolution of the $CO_2$ policy uncertainty (2020, as opposed to the original 2015) upon $CO_2$ ECIU and EVPI is analyzed in Section 6.5.

### *6.1. Carbon dioxide policy uncertainty*

*Optimal strategies and ECIU under alternative $SO_2$ and $NO_x$ cap assumptions.* Fig. 2(a) is a decision tree representation of the MARKAL market simulation in the face of uncertainty as to whether a tight $CO_2$ cap would be imposed on U.S. electric sector emissions starting in the year 2015. First, it is assumed that pre-CAIR caps on $SO_2$ and $NO_x$ emissions remain in place (Table 1). The figure portrays the range of feasible decisions for 2000-2010 as the first decision node, and 2015-2050 decisions as the second set of decision nodes. Each decision node represents a continuous range of possible decision variable values considered in the stochastic version of MARKAL. However, we highlight two particular first-stage solutions in the first stage, shown as separate branches:

- the naïve solution developed assuming that the future is known, and there is no $CO_2$ cap; and
- the optimal stochastic solution, in which market parties anticipate a 50:50 chance of a tight cap being imposed.

The values above each of their chance nodes give the expected cost of each of those two strategies compared to the naïve solution under the "No $CO_2$ Cap" scenario, expressed in billions of dollars ($B, present worth, in 1995 dollars). For instance, the naïve solution has a $797.7B higher cost[11] if the tight cap is imposed than if it is not, assuming pre-CAIR limits (Fig. 2(a)). Meanwhile, the optimal stochastic solution has a higher cost under the no cap scenario—as it must, since the naïve solution was optimized for that scenario.

The naïve solution's greater emphasis on pulverized coal steam generation (about 66 GW more added in 2000-2010, as indicated in Fig. 2(a)) results in lower overall costs by $35.8B (relative to the optimal stochastic solution), if there is no cap. However, under a $CO_2$ cap scenario, the naïve solution results in less (and thus inefficient) utilization of the pulverized coal steam capacity, but more construction (compared to the stochastic solution) after 2015 of efficient capacity such as integrated coal gasification combined cycle (IGCC) and natural gas. Under the cap, the naïve solution's costs are higher than the optimal solution's cost by $205.1B (= $797.7B - $592.6B). Consequently, compared to the optimal stochastic solution, the naïve solution's cost advantage in the no-cap scenario ($35.8B) is much less than its disadvantage when the cap is imposed ($205.1B). In contrast, the stochastic solution constructs more natural gas and IGCC capacity early on because it recognizes that there is 50% chance of $CO_2$ policy. In particular, it adds about 27 GW more IGCC and 24 GW more advanced natural gas combined cycle in 2015.

Taking expected values at the chance node, the stochastic solution has a (probability-weighted) average cost advantage (ECIU) of $84.6B (= $398.8B-$314.2B) over the naïve solution. This, as Fig. 2(a) shows, is the expected

11 At a 5% interest rate and a time horizon of 55 years, redistributing these costs as an end-of-year uniform series of annual payments for years 2000-2054 results in a cost of $42.8B/yr. This is calculated as (A|P, i=0.05, N=55)*797.7B = 0.0537*797.7B = $42.8B/yr, where the annual worth factor (A|P,i,N) = ((1+i)Ni)/((1+i)N-1).

cost of ignoring uncertainty in greenhouse gas policy. As some environmental groups have argued, energy companies ought to factor the possibility of greenhouse gas limitations into their investments. This risk can be hedged by diversifying investments, as done in the optimal stochastic solution, giving more emphasis to lower $CO_2$ emitting technologies. MARKAL simulates a market in which risk neutral producers choose and hedge physical investments in order to maximize expected profit.[12]

With imposition of tighter CAIR-like caps upon $SO_2$ and $NO_X$ emissions starting in 2010, the U.S. generation mix shifts. The analysis of the optimal stochastic strategy and ECIU is repeated in Fig. 2(b), but for the case of the tighter CAIR caps upon conventional pollutants. ECIU is $77.8B (= $428.5B - $350.8B) here, a slightly smaller amount because the CAIR caps slightly discourage the pulverized coal investment in the naïve solution that would be so heavily penalized if $CO_2$ caps are imposed.

*The cost of CAIR.* We briefly compare the optimal stochastic solutions for cases with and without the CAIR-like caps. Comparing the optimal stochastic solutions, the solution with CAIR-like cap has 5 GW more of efficient IGCC capacity installed in 2010 and 8 GW more natural gas capacity in 2010. The present worth of cost difference (1995$) between the two optimal stochastic solutions, assuming no carbon caps, is $41.1B (=76.9-35.8). Also, the naïve solution is $45.8B more expensive under CAIR caps than without those caps, assuming no CO2 limit. Thus, the expense of tightening conventional pollution limits alone is estimated as an annualized value of $2.5B/year (=0.0537*45.8).[13] However, the implementation of a carbon cap starting in 2015 drastically reduces the difference in cost between scenarios with or without CAIR-like caps; then the cost difference between the pre-CAIR caps and the CAIR-like caps falls to $32.0B for the optimal strategy. This occurs because less carbon-intensive technologies are chosen in later years for the $CO_2$ cap cases, and these technologies tend to have lower conventional pollution rates; as a result, the implementation of tighter CAIR-like caps on those pollutants makes less of a difference in that case.

MARKAL's simplified representation of residential and commercial consumer decisions relative to investments

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12 It is possible that the reactions of firms and the market to regulatory, demand, or gas price risk could differ from what an energy-economic model like MARKAL would yield. MARKAL, like other economy-wide engineering economic models, assumes that market actors are risk neutral (maximize expected present worth) and hold identical beliefs about the probabilities of the scenarios. Risk averse agents with a diversity of beliefs might make different investment decisions. Research has recently started on formulating energy market equilibrium models with risk-averse investors and diverse believes. For instance, Lin et al. [24] consider a two-stage equilibrium among risk averse gas and coal-fired plant investors in a simple electric economy; Cabero et al. [25] simulate generator operator decisions in a market in which plant owner risk aversion is represented by a CVaR formulation; Rocques et al. [26] analyze equilibrium capacity mixes when generator risk aversion is modeled using portfolio (mean-variance) methods; and Willems and Morsbee [27] consider equilibria among risk-averse investors in the presence of forward capacity markets.. However, the literature reports no formulations of technology-rich economy-wide models that represent the behavior of risk averse investors in the energy market. Such models would require both a multiple scenario formulation (as we have adopted) as well as representation of equilibrium behavior by risk-averse investors (for which only small research-scale models have been developed).

13 This is close to USEPA's conclusion using the IPM (Integrated Planning Model) solutions. (See www.epa.gov/airmarkets/progsregs/epa-ipm/index.html).

in efficient energy using equipment suggests that the cost of disregarding uncertainty may be understated. This is because anticipation of the future benefits of energy efficiency under a possible $CO_2$ cap should encourage earlier adoption of those technologies, yielding even more cost savings in the stochastic solution relative to the naïve solution. However, the amount of any understatement of ECIU can only be assessed by using a more sophisticated representation of consumer decision making.

*Expected value of perfect information.* We now turn to the value of information calculations for greenhouse gas policy uncertainty. Fig. 3(a) shows these for the case in which there is no change in $SO_2$ and $NO_x$ caps. As illustrated in Section 4 (Fig. 1(b)), EVPI is obtained by first assuming that the market learns what the future scenario will be, and then optimizing; this results in a tree in which the order of the decision and chance nodes is reversed. First, the market finds out in 1995 whether or not $CO_2$ limits will be imposed in 2015. Then, given each of those two scenarios, the subsequent decision node in Fig 3(a) shows one or two of the infinity of possible decisions for 2000-2010. One decision is the naïve solution, derived assuming no $CO_2$ cap. For the "No $CO_2$ Cap" scenario branch, this is the only solution shown, since by definition it is also the optimal decision for that particular scenario. This solution has a cost of \$0 under that scenario, because we have defined it as the basis of comparison for the other solutions. For the "$CO_2$ Cap" scenario, two different solutions are shown: the naïve decision (which in 2015-2050 adapts as best it can to the imposition of a cap) and a solution that is optimized for the cap. Just as in Fig. 2(a), the naïve solution then suffers a \$797.7B cost increase relative to the no cap scenario. In Fig. 3(a), this is \$215.2B (=\$797.7B-\$582.5B) higher than a solution optimized under the certain knowledge that a $CO_2$ cap is imposed. Such an optimized solution invests less in pulverized coal steam and more in clean capacity (IGCC and natural gas) in 2000-2010 compared to the naïve solution.

In Fig. 3(a), EVPI is calculated by taking the expected cost across $CO_2$ cap scenarios of the optimal decisions under each scenario (\$291.3B), and then subtracting that cost from that of the optimal stochastic solution in which decisions in 2000-2010 must be made *before* it is known whether or not a cap will be imposed (\$314.2B, Fig. 2(a)). The difference (\$22.9B) is the EVPI concerning $CO_2$ caps, assuming that the existing $NO_X$ and $SO_2$ limits remain in place. This is relatively small compared to ECIU (\$84.6B), which illustrates the following general point: that EVPI and ECIU have no necessary relationship with each other [12]. Either can be much larger than the other. That EVPI is relatively small here, meaning that having perfect information would not improve expected performance much compared to considering uncertainty optimally.

If instead tighter CAIR-like caps are imposed on $NO_X$ and $SO_2$ (Fig. 3(b)), then EVPI for $CO_2$ caps reduces to

$18.7B. This is the difference between $332.1B (the cost under perfect information) and $350.8B (the cost of the optimal stochastic solution). This occurs because less carbon-intensive technologies are chosen under CAIR-like caps in any event, so the with- and without $CO_2$ cap cases are less different.

*Value of policy coordination.* VPC describes the cost savings that could occur if the market was immediately informed that a $CO_2$ cap would definitely be imposed at some certain date (here, 2015) relative to the situation in which the market assumed wrongly that such a policy would not be imposed, but was then surprised when it was. An informed market would, in general, make different decisions in 2000-2010 in anticipation of the $CO_2$ cap than an uninformed market would. We calculate VPC for two cases: no change in $NO_x$ and $SO_2$ caps, and anticipated implementation of CAIR-like caps. In the naïve solution in latter case, the market anticipates in years 2000-2010 the tighter $NO_x$ and $SO_2$ caps, but the $CO_2$ cap still comes as a surprise.

If the pre-CAIR criterion pollutant caps remain in place, Fig. 3(a) shows that VPC is $215.2B. This is calculated as the cost of an optimal response to the $CO_2$ cap, when it is correctly anticipated ($582.5B), and the cost of a naïve strategy that disregards that possibility but then has to adjust when the cap is imposed ($797.7B). Thus, if the $CO_2$ cap is to be imposed, considerable cost savings can result from giving enough warning and coordinating responses to today's and tomorrow's pollution laws. If CAIR-like caps on $NO_X$ and $SO_2$ are to be imposed (Fig. 3(b)), the value of coordination is less ($192.9B = $811.3B - $618.4B), but still large compared to ECIU or EVPI. VPC is smaller in this case because some of the shifts in capacity mix from dirty technologies (pulverized coal steam) to clean ones (IGCC and natural gas) that would take place under a $CO_2$ cap would already be encouraged by the CAIR-like caps on criterion pollutants.

*Comparisons of decisions.* It is also of interest to compare the decisions that are made under perfect foresight with the naïve and stochastic decisions. First of all, under pre-CAIR limits on $NO_X$ and $SO_2$, the naïve solution would install almost 66 GW (14.0+51.6) more pulverized coal steam capacity by 2010 than a solution that results if instead there is a 100% certainty (perfect forecast) of a $CO_2$ cap. The latter solution has 29.7 GW more integrated coal gasification combined cycle (IGCC) and 30.8 GW (=170-139.2) more natural gas capacity in 2010. The incremental natural gas capacity additions between the perfect forecast ($CO_2$ cap) and the optimal stochastic solutions are 7.0 GW (170.0-163.0) for 2000-2010.

In contrast, under the CAIR-like tightened $NO_X$ and $SO_2$ caps, the optimal generation mix in the face of a $CO_2$ cap that would be implemented in 2010 would involve an increase of 46 GW (year 2010) in IGCC and 39.9 GW more natural gas capacity compared to the naïve solution. On the other hand, 65 GW (14+50.9) less pulverized coal capacity is put in place in the perfect forecast ($CO_2$ cap) solution compared to the naïve solution. Also, in the perfect forecast solution (in which the $CO_2$ cap is foreseen), 14 GW (=46-32) more of IGCC and 7.8 GW more natural gas capacity would be in place in 2010.

*Comparisons of prices.* An indicator of potential for energy efficiency as a means to mitigate the economic impacts of tighter $NO_x$, $SO_2$, and $CO_2$ caps is the difference between prices for electricity in the various scenarios with and without the caps. Differences in emissions prices also are indicators of the stringency of emissions caps.

The prices under pre-CAIR limits show the following general trends. $SO_2$ credit prices eventually fall to zero in all cases under pre-CAIR; these indicate that the model's assumed retirements of capacity and its replacement by NSPS-compliant capacity (which is willing to carry out the new source performance standards for emission) cause the caps to be nonbinding. Comparing $NO_X$ in the stochastic solutions with and without $CO_2$ cases, the imposition of a $CO_2$ cap causes prices for $NO_X$ to fall faster than without carbon cap case in 2015 and afterwards.

In contrast, the MARKAL runs with CAIR-like tightening of $SO_2$ caps yield positive prices for $SO_2$ emissions in 2010 and afterwards. This is because under the CAIR-like caps, sharp emission reductions of $SO_2$ caps are assumed to occur from 2010. Again, presence of the $CO_2$ cap from 2015 serves to lower $NO_X$ and $SO_2$ prices in the optimal stochastic solutions under the CAIR-like limits. Comparing the stochastic solutions under no carbon cap and with such a cap, imposing the cap motivates $NO_X$ and $SO_2$ reductions earlier, as might be expected. But in the naive solution (without carbon policy) and perfect solution (with carbon emission limit), however, $NO_X$ and $SO_2$ prices are sometimes lower under the cap, and sometimes higher.

Turning to $CO_2$ prices, under both the pre-CAIR and CAIR-like pollutant caps, the prices show high initial levels in 2015 and are then lower later on, even as demand grows, as the generation mix turns over. See Table 4 for prices of $CO_2$, $NO_x$, and $SO_2$ for the $CO_2$ uncertainty solutions under CAIR-like limits.[14] Again, this may be an artifact of the present MARKAL's relative lack of flexibility. It is of interest that the perfect solutions (with $CO_2$ cap) in both the pre-CAIR and CAIR-like cases have higher carbon prices than the stochastic solutions (with $CO_2$ cap), because the market's 100% anticipation of the tight limits upon $CO_2$ (perfect forecast) caused a earlier shift in generation mix than 50% anticipation (stochastic cases).

Differences in electricity prices reflect what is happening in the generation mixes. In 2010 and before, there is

14 Burtraw et al. [8] and Burtraw et al. [9] point out the importance of the interaction between $CO_2$ and other air pollutants. They conclude that greenhouse gases mitigation policies would yield $NO_x$ and $SO_2$-related health benefits. Their results indicate that a $25 tax per metric ton of carbon not only lowers $CO_2$ emissions, but could also provide $12-$14/ton of ancillary heath benefits due to reduced conventional pollutant emissions.

not any emission cap imposed so power prices (for the naïve, stochastic and perfect solutions) are almost the same. But the results show that in 2015 and afterwards, the presence of either $CO_2$ caps or CAIR-like $NO_X$ and $SO_2$ caps increases power prices. This is the result of adding cleaner capacity. The effect of the CAIR-like limits alone is modest compared to the $CO_2$ cap alone, with price increases typically on the order of less 10% after 2010 due to CAIR implementation, after an initial uptick in 2010. The price increases due to imposing a carbon limit are roughly an order of magnitude greater (50% to 100%). However, prices are not that much higher when both sets of caps (CAIR and $CO_2$) are imposed than when the $CO_2$ cap alone is present, indicating that the same types of generation are on the margin in both sets of the solutions.

We note that these are increases in generation prices (*i.e.*, wholesale prices), and not retail prices which also include transmission, distribution, and customer account costs. Nevertheless, such increases will translate into higher electric rates for consumers, and it should be expected that shifts in uses and increased investment in more energy-efficient end-use equipment would result. Again, MARKAL may exaggerate the price increases because it does not presently represent the full range of alternatives that are available to power generators and consumers to adapt to changing fuel, emissions, and energy prices.

*6.2. Demand growth uncertainty*

The costs associated with uncertainty regarding whether $CO_2$ caps will be imposed can be compared with costs stemming from other uncertainties to gauge their relative significance. In this section, we analyze cases in which demand growth in electricity is the major uncertainty, and quantify the associated ECIU and EVPI. Three possible post-2015 growth rates are considered: low, medium (base case), and high, which are assumed to be equiprobable (Table 2). The high and low scenarios are about 11% higher and lower, respectively, than the medium scenario in later years. Such uncertainty in demand imposes costs because power plants need to be built several years ahead of time (here, assumed to be 5 years for baseload power plants), and if demand growth for a particular year in MARKAL is uncertain, too much or too little capacity might be committed to. In this case, uncertainty in electricity demands for 2015 and afterwards means that decisions concerning investment in baseload plants in 2010 may be mistaken. The consequences of wrong decisions depend on the levels of demand growth. If all the demand growth scenarios involve generally high rates, then excess capacity from overconstruction will quickly be absorbed, but on the other hand, the cost of underconstruction might be greater.

The ECIU and EVPI analysis is done for two situations: preservation of the pre-CAIR caps on $SO_2$ and $NO_x$, and imposition of tighter CAIR-like caps. No $CO_2$ caps are considered. (In Section 6.4 below, we consider demand growth and $CO_2$ cap uncertainties simultaneously.)

Table 5 shows the optimal stochastic and naïve solutions for the case in which the pre-CAIR caps are maintained. The naïve solution is developed assuming that the medium growth rate occurs with 100% probability. It has a \$0.2B higher expected cost (ECIU) than the optimal stochastic strategy even though it is \$0.3B less expensive in the medium growth scenario because it performs worse in both the low and high growth scenarios than the more robust stochastic solution. The stochastic solution's main advantage is that it preserves some flexibility by making less of a commitment to capital-intensive coal capacity in 2000-2010. This hedging strategy is approximately the same as that adopted in Fig. 2(a) to deal with the $CO_2$ cap uncertainty; the stochastic solution has about 6 GW less pulverized coal capacity and 11 GW more natural gas capacity.

Table 5 also shows the optimal strategy and ECIU under demand uncertainty for the case of tighter (CAIR-like) $NO_x$ and $SO_2$ caps. At \$0.3B, the ECIU here is slightly but not appreciably higher than for the pre-CAIR regulation case (\$0.2B). Similarly, 5 GW less pulverized coal capacity and 10 GW more natural gas capacity are built for the stochastic solution in 2000-2010.

EVPI for demand uncertainties is also obtained for both criterion pollutant cap cases (pre-CAIR cap and CAIR-like cap) in Table 5. The EVPI for the pre-CAIR cap case is \$2.0B (\$5.4B minus \$3.4B), and equals \$1.9B for the CAIR-like cap (\$51.8B minus \$49.9B). In terms of changes in generation mix, low, medium, and high demand scenarios of pre-CAIR cap have 27 GW less, 11 GW less, and 19 GW more of natural gas generation capacity. Likewise, in CAIR-like case, 23 GW less, 10 GW less, and 19 GW more gas capacity is built. This ECIU and EVPI of the demand uncertainty are much smaller than the $CO_2$ cap uncertainty with both pre-CAIR and CAIR-like cap. The reason is that demand uncertainty causes fewer wrong decisions in 2000-2010 than $CO_2$ uncertainty (Section 6.1). Furthermore, unlike the $CO_2$ cap uncertainty case, the tightening of $NO_X$ and $SO_2$ caps to CAIR-like levels have similar ECIU and EVPI under demand uncertainty with pre-CAIR scenario. This makes sense, as a tightening of the caps means that the perfect information decisions with and without the $CO_2$ cap become more similar, as the CAIR-like caps push the solutions in the direction with or without $CO_2$ policy; the result is a smaller ECIU and EVPI under the CAIR-like caps. On the other hand, under demand uncertainties, imposition of tighter $NO_X$ and $SO_2$ caps does not impact the uncertainty or value of a perfect forecast of demand increases.

### *6.3. Natural gas cost uncertainty*

This is the third of the uncertainties considered. In 2015 and afterwards, three relative scenarios of natural gas prices are assumed to be low, medium, and high with equal probability (Table 3). In the later years, low and high gas prices are 40% below or above the medium levels. The presence of such fuel price uncertainty, together with the five-year lag time for plant construction, means that 2000-2010 commitments might be to the wrong type of generation capacity. For instance, if gas prices rise, then building a large amount of gas capacity early on may be suboptimal. If the wrong type of capacity is built in 2000-2010, but that capacity would eventually be built anyway under all scenarios, then the consequences of building capacity at wrong time would be less than if other types of capacity were always preferred. We calculate ECIU and EVPI for just the case of the pre-CAIR $NO_x$ and $SO_2$ caps.

We contrast the optimal stochastic and naïve solutions in Table 6, allowing calculation of ECIU for the natural gas uncertainties. The cost penalty of choosing the naïve solution is relatively low ($0.2B) for both cases of pre-CAIR and CAIR-like caps. Turning to generation capacity shift, for CAIR-like case, the stochastic solution has 0.5 GW more pulverized coal steam and 0.4 GW less natural gas capacity. This indicates that uncertainty in gas prices favors other fuels, especially coal.[15] However, the value to the market of considering this uncertainty explicitly is several times less than for uncertainties in $CO_2$ cap, at least for the USEPA National MARKAL data base.

The value of perfect information for natural gas uncertainty is obtained by comparing the expected cost of the optimal stochastic strategy with the optimal expected cost under perfect information (Table 6). The difference in cost ($1.5B = -$52.9B minus -$54.4B and $1.6B = -$6.7B minus -$8.3B) indicates the most that the market should be willing to pay for perfect forecasts. For the low, medium, and high gas costs scenarios, 5 GW more, 0.5 GW more, and 5 less gas capacity are built for CAIR-like case. Note that these values are similar to what we obtained for demand uncertainties, but are much less than the results for $CO_2$ uncertainty.

*6.4. Sensitivity analysis: Combined $CO_2$ cap and demand growth uncertainties*

In this section, both $CO_2$ cap and electric demand growth uncertainties are simultaneously considered, assuming that the pre-CAIR $NO_x$ and $SO_2$ caps remain in place. This allows us to consider whether these uncertainties interact so that their joint ECIU and EVPI are either less than or greater than the sum of their individual ECIU's and EVPIs (Sections 6.1, 6.2).

All six possible combinations of demand growth (low, medium, high) and $CO_2$ cap (none, cap imposed in 2015) are considered as separate scenarios in the decision tree. The probabilities of the cap and growth scenarios are assumed to be independent; for instance, the probability of the low demand-$CO_2$ cap scenario is then 1/3*1/2=1/6.

15 It is well known that increased volatility and risk in fuel prices actually can increase the attractiveness of a generation asset, so it is not necessarily the case that more uncertainty in natural gas prices would discourage additions of gas-fired capacity. This is most obvious for peaking facilities; the option of taking advantage of low prices can enhance the option value of the asset. On the other hand, fuel price risk in base loaded facilities is unlikely to increase their value, because their manner of operation probably would not be affected by the fuel cost.

The expected cost of the optimal stochastic strategy is \$319.7B (relative to the cost of the naïve strategy under the medium growth/no $CO_2$ cap case), while the naïve solution has an expected cost of \$405.1B. The cost of ignoring uncertainty in demand and the $CO_2$ cap when making decisions in 2000-2010 is therefore \$85.4B. Much of this comes from the very large advantage of the stochastic solution over the naïve solution if the $CO_2$ cap is imposed (\$167.8B, \$205.7B and \$250.4B less cost for low, medium and high demand growth, respectively), while the stochastic strategy has an \$37.0B, \$37.0B and \$36.5B disadvantage for the three without $CO_2$ cap scenarios of low, medium and high growth, respectively. This ECIU result is very similar to the $CO_2$ uncertainty only case (\$84.6B) in Fig. 2(a) in Section 6.1.

The ECIU for the two uncertainties combined (\$85.4B) is slightly larger than the sum of ECIU for $CO_2$ cap uncertainty alone (\$84.6B, Fig. 2(a)) and ECIU for demand growth uncertainty (\$0.2B, Table 5). Thus, adding the demand uncertainty to the $CO_2$ cap uncertainty is apparently superadditive. Comparing the stochastic solutions with naïve solutions, the impacts upon the 2000-2010 decisions are similar (for both $CO_2$ uncertainty case and two uncertainties case, a decrease of 60-70 GW in pulverized coal steam additions, with an approximately matching 20-30 GW increase in IGCC and natural gas additions). Thus, it might be inferred that the hedging strategy for demand and $CO_2$ cap uncertainties, separately or together, are approximately the same, and is a robust choice in the face of these uncertainties here.

The EVPI calculations yield a total value of \$25.6B for perfect forecasts of future demand growth rates and the presence of $CO_2$ caps. Again, this value is close to (and slightly larger than) the sum of the EVPI for $CO_2$ (\$22.9B, Fig. 3(a)) and demand uncertainty (\$2.0B, Table 5).

*6.5. Different dates for resolving $CO_2$ uncertainty*

The last analysis considers the effect of changing the date of the $CO_2$ cap chance node. In Section 6.1, we assumed that in 2015 a once-and-for-all decision would be made to impose a cap. Here, we postpone that decision to 2020. Unlike Section *6.1*, this means that commitments to build plants in 2015 (which would be on-line in 2020) would be made without knowing whether a cap would be in place. In reality, of course, imposing a cap can be considered in any year, and reconsidered later—either implementing a cap if one was not imposed earlier, or adjusting the level of the cap. But because stochastic MARKAL is limited to 10 scenarios (the feature of the software), its ability to consider multiple decision stages is limited.

Maintenance of the pre-CAIR $NO_X$ and $SO_2$ caps is assumed. The naïve solution's expected cost is \$104.7B greater in present worth terms than the optimal stochastic strategy under the 2020 date for a possible cap. This

ECIU value ($104.7B) is about a quarter higher than the case where the chance node was in 2015 instead ($84.6B, Fig. 2(a)). The reason for this is apparent from comparing the solutions. Assuming pre-CAIR cap, the naïve solution of 2020 case has about 1 GW more pulverized coal capacity in 2010 and 30 GW more coal in 2015 than the naïve solution of 2015 case which recognizes the $CO_2$ uncertainty in 2015. The naïve solution in the 2020 case has accumulated five years more of high $CO_2$ emitting coal capacity than the 2015 case. This high carbon emitting strategy increases the economic regret if a $CO_2$ cap is finally adopted.

For the same reason, the EVPI calculation for the 2020 $CO_2$ cap uncertainty yields a higher value than if the uncertainty is instead resolved in 2015. In the 2020 case, $27.7B is the expected value of a perfect forecast of whether a $CO_2$ cap will be imposed or not, exceeding the $22.9B (2015 case in Fig. 3(a)) for the 2015 uncertainty case.

**7. Conclusion**

The decision analysis framework presented in this paper includes two decision stages. These stages differentiate between “here and now” commitments that energy producers and consumers must make in the near term without knowing which of the possible futures will be realized, and later “wait and see” choices that are made after the market learns which scenario will occur. In most of the analyses, uncertainties concerning electricity demand, gas prices, and whether or not greenhouse gas limits will be imposed are assumed to be resolved in 2015, so optimal decisions before that time would likely involve some degree of hedging.

If an uncertainty is important, then investments made considering uncertainty will differ from decisions made naively assuming no uncertainty, and result in better (probability-weighted) performance (i.e., a positive ECIU). Furthermore, eliminating the uncertainty would improve strategies even further, meaning that improved forecasts of future conditions are valuable (i.e., a positive EVPI). Also, the value of policy coordination (VPC) is considered, equaling the difference between the cost of the strategy incorrectly based on the assumption of no carbon cap and the strategy that correctly anticipate pollutants and the carbon cap.

The calculation of optimal strategies under uncertainty as well as ECIU, EVPI, and VPC is illustrated using stochastic MARKAL and the USEPA National MARKAL data base. The carbon cap uncertainty is the economically most important uncertainty compared to the electric demand and natural gas uncertainties. In terms of the expected penalty if uncertainty is disregarded, the ECIU with respect to the possibility of carbon trading is $84.6B (present worth, 1995 dollars), while the expected value of knowing for certain whether or not such a cap will be imposed (EVPI) is calculated as $22.9B. This assumes that both the probability of a cap being imposed in 2015 is 50:50, and that market parties in the naïve scenario assume that there is a 100% chance of no cap. The optimal strategy in the face of the carbon cap uncertainty involves more investment in more efficient IGCC and cleaner natural gas-fired power generation capacity compared to the naïve solution, which results in the most significant ECIU.

In Section 6.1, we analyze the effect of carbon policy uncertainty with and without the tighter CAIR NOX and SO2 caps. The results show that generation technologies with fewer carbon emissions are chosen for the CO2 cap cases, and that they also emit fewer conventional air pollutants. This descreases the cost of complying with conventional pollutant caps, especially in the more stringent CAIR cases. Accordingly, the implementation of $CO_2$ emission policies reduces the cost difference between the scenarios with and without CAIR $NO_x$ and $SO_2$ caps. The annualized cost of the tighter caps is about $2.5B/yr starting in 2015; but the incremental cost of the tighter $NO_x$ and $SO_2$ caps is about halved (corresponding to a CAIR-like scenario) than if instead a $CO_2$ cap is also imposed at the time (see also Burtraw et al. [8, 9]). The major difference is the amount of IGCC and natural gas capacity that is added (more is added in the 2000-2010 period under the higher $NO_X$ and $SO_2$ caps). Marginal generation prices are higher in the presence of the CAIR-like caps, suggesting that there may be economic opportunities for investments in energy efficiency in the demand side of the market.

The analysis in Section 6.4 jointly considers carbon policy and demand growth uncertainties; the ECIU and EVPI are roughly close to the sum of ECIU and EVPI for two uncertainties alone (carbon policy and demand growth uncertainty). Future research should examine these results further to understand the interactions between these uncertainties. The sensitivity analysis in Section 6.5 calculates the ECIU and EVPI for a carbon policy uncertainty resolved in 2020 rather than 2015. The present worths of ECIU and EVPI of the 2020 case are similar in magnitude but slightly higher than the values of the 2015 case. This shows that the estimates are robust with respect to the year of implementation of the $CO_2$ policy.

It would be of interest to compare the gas price, demand, and policy uncertainties with uncertainties in other categories of parameters. Future work should consider, for example, uncertainties concerning the feasible amount of nuclear build or technological improvements in renewable energy, penetration of electric vehicles or of hydrogen fuel cell vehicles, and new emission mitigation technologies. Also, the sensitivity of MARKAL results to the discount rate and other major parameters should be addressed in future work. Given the capital intensity of the power industry, the discount rate might significantly affect results by changing the relative attractiveness of capital-intensive versus high fuel cost technologies. (As one example, we lowered the interest rate for coal plants with carbon sequestration and storage relative to normal coal plants, and the share of former plants significantly increased.)

In conclusion, this research shows that uncertainties in pollution emission laws, demand growth rates and fuel prices can result in economic regret. The advantage of our methodology is its ability to quantify the potentially high cost from wrong decisions using stochastic MARKAL. Additionally, it suggests that investments should be made recognizing a range of possible economic and regulatory developments. “Good” or “robust” decision strategies under uncertainty are those that will perform relatively satisfactorily across a range of possible scenarios. “Brittle” decisions, in contrast, are choices that might be finely tuned for a particular scenario, but perform poorly under others. Robust decisions tend to hedge risks by investing in a diversity of technologies, or in technologies that are more flexible either in their fuel use and emissions, or which have short lead times.

The advantage of MARKAL for identifying robust energy market solutions is that it is widely used, has a non-proprietary database for our region of interest, can be run on a PC, and contains a built-in stochastic programming capability. Furthermore, we could adapt it to calculate EVPI, ECIU, and VPC, and include the feature of construction commitments having to be made before the future scenario is revealed. Other models (such as USEPA’s IPM [21]) have more detail on electric utilities, but are proprietary, very large, and/or lack stochastic capabilities. This is not to say that MARKAL is without limitations; presently, it is limited to 10 scenarios, and it was necessary to overcome some software and database difficulties in order to use it for our purposes. Nevertheless, MARKAL enabled us to meet the goals of our analysis better than other energy market models.

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Table 1
Assumed emission limits (thousand tonnes)

| Case | Emission | 2000 | 2005 | 2010 | 2015-2050 |
|---|---|---|---|---|---|
| Pre-CAIR caps | $NO_x$ SIP Call | 4,750 | 4,000 | 3,500 | 3,600* |
| | $SO_2$ Title IV | 10,630 | 10,540 | 9,900 | 8,950 |
| CAIR-Like Caps | $NO_x$ | 4,750 | 4,000 | 1,510 | 1,510 |
| | $SO_2$ | 10,630 | 10,540 | 2,250 | 2,250 |
| Possible $CO_2$ Cap | | - | - | - | 560,000 |

*Slight increases allowed in later years

Table 2
Demand scenarios: ratios compared to base case (in %)

| Scenario | 2015 | 2020 | 2025 | 2030-2050 |
|---|---|---|---|---|
| Low | 95 | 93.1 | 89.4 | 89.4 |
| Medium (Base) | 100 | 100 | 100 | 100 |
| High | 105 | 106.9 | 110.6 | 110.6 |

Table 3
Gas price scenarios: ratios compared to base case (in %)

| Scenario | 2015 | 2020 | 2025 | 2030-2050 |
|---|---|---|---|---|
| Low | 70 | 60 | 60 | 60 |
| Medium (Base) | 100 | 100 | 100 | 100 |
| High | 130 | 140 | 140 | 140 |

Table 4

Prices of $CO_2$, $NO_X$, $SO_2$ (1995 U.S. thousand dollars/tonne) for $CO_2$ uncertainty cases under CAIR-like limits

| Price | 2000 | 2005 | 2010 | 2015 | 2020 | 2025 | 2030 | 2035 | 2040 | 2045 | 2050 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Naïve solution (no $CO_2$ cap) | | | | | | | | | | | |
| $CO_2$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $NO_x$ | 0.24 | 0.28 | 0.56 | 2.24 | 2.24 | 2.24 | 2.24 | 7.88 | 5.03 | 11.96 | 2.75 |
| $SO_2$ | 0 | 0 | 1.33 | 1.33 | 2.56 | 2.71 | 2.75 | 3.58 | 2.56 | 1.33 | 1.27 |
| Perfect information solution ($CO_2$ cap in year 2015 and afterwards) | | | | | | | | | | | |
| $CO_2$ | 0 | 0 | 0 | 0.20 | 0.27 | 0.28 | 0.16 | 0.20 | 0.19 | 0.21 | 0.37 |
| $NO_x$ | 0.24 | 0.28 | 0.56 | 2.82 | 0.99 | 2.24 | 2.24 | 3.62 | 5.19 | 9.10 | 11.79 |
| $SO_2$ | 0 | 0 | 1.33 | 0.23 | 0.20 | 0 | 2.21 | 2.56 | 4.47 | 2.56 | 0.15 |
| Stochastic solution (no $CO_2$ cap in year 2015 and afterwards) | | | | | | | | | | | |
| $CO_2$ | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $NO_x$ | 0.24 | 0.28 | 0.52 | 2.24 | 2.24 | 2.24 | 2.24 | 3.62 | 2.33 | 13.69 | 15.32 |
| $SO_2$ | 0 | 0 | 1.33 | 1.38 | 2.56 | 3.2 | 2.93 | 3.37 | 2.39 | 1.63 | 1.27 |
| Stochastic solution ($CO_2$ cap in year 2015 and afterwards) | | | | | | | | | | | |
| $CO_2$ | 0 | 0 | 0 | 0.21 | 0.27 | 0.32 | 0.16 | 0.21 | 0.19 | 0.22 | 0.36 |
| $NO_x$ | 0.24 | 0.28 | 0.52 | 2.08 | 0.59 | 2.24 | 2.24 | 2.59 | 5.10 | 7.97 | 11.44 |
| $SO_2$ | 0 | 0 | 1.33 | 0.33 | 0.24 | 0 | 2.39 | 2.82 | 3.83 | 2.56 | 0.05 |

Table 5

Optimal stochastic, naïve solutions, ECIU, and EVPI under demand growth uncertainty (1995 U.S. Billion dollars)

| Demand Uncertainty | | Low | Med | High | Expected | Indices |
|---|---|---|---|---|---|---|
| Pre-CAIR | Optimal | -324.0 | 0.3 | 339.8 | 5.4 | |
| | Naïve | -324.6 | 0 | 341.5 | 5.6 | 0.2 (ECIU) |
| | Perfect Inf | -326.8 | 0 | 337.0 | 3.4 | 2.0 (EVPI) |
| CAIR-like | Optimal | -280.6 | 46.1 | 389.9 | 51.8 | |
| | Naïve | -281.1 | 45.8 | 391.4 | 52.0 | 0.3 (ECIU) |
| | Perfect Inf | -283.2 | 45.8 | 387.1 | 49.9 | 1.9 (EVPI) |

Table 6

Optimal stochastic, naïve solutions, ECIU, and EVPI under natural gas cost uncertainty (1995 U.S. Billion dollars)

| Natural Gas Price Uncertainty | | Low | Med | High | Expected | Indices |
|---|---|---|---|---|---|---|
| | Optimal | -731.1 | 0.3 | 572.0 | -52.9 | |
| Pre-CAIR | Naïve | -730.6 | 0 | 572.4 | -52.7 | 0.2 (ECIU) |
| | Perfect Inf | -732.5 | 0 | 569.2 | -54.4 | 1.5 (EVPI) |
| | Optimal | -687.6 | 46.0 | 621.6 | -6.7 | |
| CAIR-like | Naïve | -687.4 | 45.8 | 622.1 | -6.5 | 0.2 (ECIU) |
| | Perfect Inf | -689.2 | 45.8 | 618.5 | -8.3 | 1.6 (EVPI) |

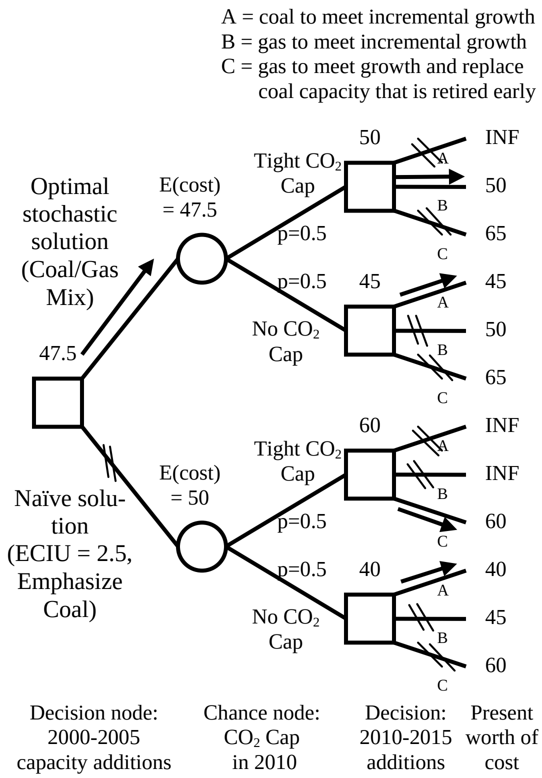
**Figure Captions**

Fig. 1. Simple hypothetical example of two stage optimization under $CO_2$ policy uncertainty: (a) Naïve and optimal stochastic solutions. (b) EVPI calculation.

Fig. 2.  Naïve and optimal stochastic solutions under $CO_2$ policy uncertainty: (a) pre-CAIR limits on $SO_2$ and $NO_x$; (b) CAIR-like limits (1995 U.S. Billion dollars).

Fig. 3. EVPI under $CO_2$ policy uncertainty: (a) pre-CAIR limits on $SO_2$ and $NO_x$; (b) CAIR-Like limits (1995 U.S. Billion dollars).

Fig. 1.
(a)


A = coal to meet incremental growth
B = gas to meet incremental growth
C = gas to meet growth and replace coal capacity that is retired early
Optimal stochastic solution (Coal/Gas Mix)
47.5
E(cost) = 47.5
Tight $CO_2$ Cap
p=0.5
p=0.5
No $CO_2$ Cap
50
45
INF
50
65
45
50
65
Naïve solution (ECIU = 2.5, Emphasize Coal)
E(cost) = 50
Tight $CO_2$ Cap
p=0.5
p=0.5
No $CO_2$ Cap
60
40
INF
INF
60
40
45
60
A
B
C
Decision node: 2000-2005 capacity additions
Chance node: $CO_2$ Cap in 2010
Decision: 2010-2015 additions
Present worth of cost

(b)

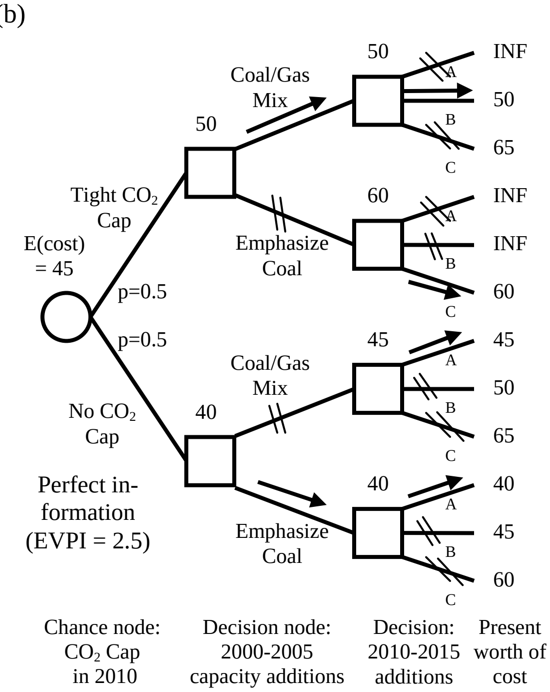
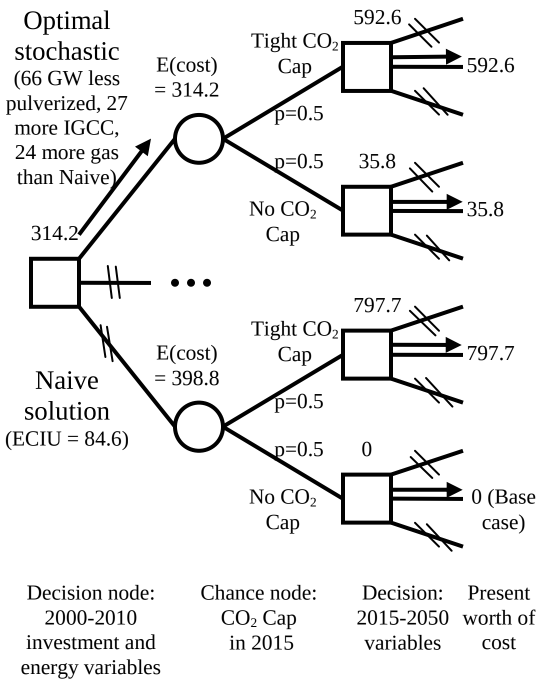

E(cost) = 45
Tight $CO_2$ Cap
p=0.5
p=0.5
No $CO_2$ Cap
Perfect information (EVPI = 2.5)
50
40
Coal/Gas Mix
Emphasize Coal
Coal/Gas Mix
Emphasize Coal
50
60
45
40
INF
50
65
INF
INF
60
45
50
65
40
45
60
A
B
C
Chance node: $CO_2$ Cap in 2010
Decision node: 2000-2005 capacity additions
Decision: 2010-2015 additions
Present worth of cost

Fig. 2.
(a)


Optimal stochastic (66 GW less pulverized, 27 more IGCC, 24 more gas than Naive)
314.2
E(cost) = 314.2
Tight CO2 Cap
p=0.5
592.6
592.6
p=0.5
35.8
No CO2 Cap
35.8
Naive solution (ECIU = 84.6)
E(cost) = 398.8
Tight CO2 Cap
797.7
797.7
p=0.5
p=0.5
0
No CO2 Cap
0 (Base case)
Decision node: 2000-2010 investment and energy variables
Chance node: CO2 Cap in 2015
Decision: 2015-2050 variables
Present worth of cost

(b)

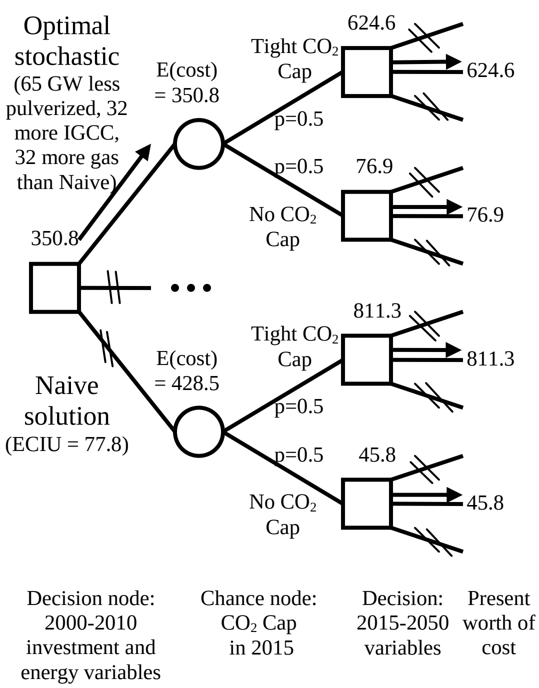
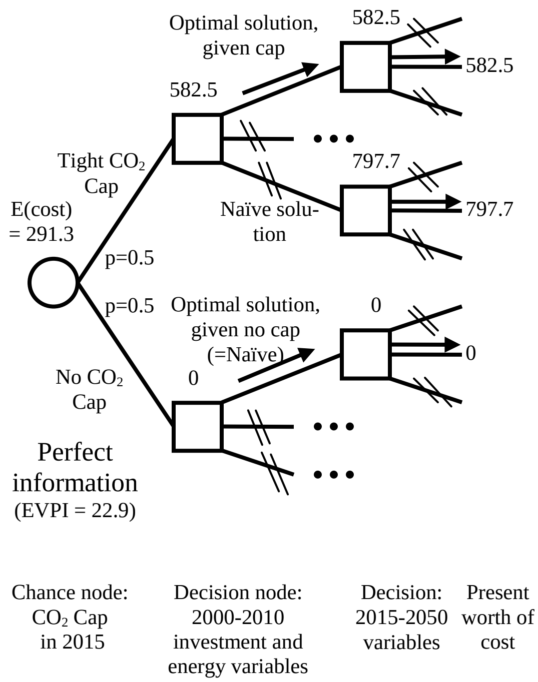

Optimal stochastic (65 GW less pulverized, 32 more IGCC, 32 more gas than Naive)
350.8
E(cost) = 350.8
Tight CO2 Cap
p=0.5
624.6
624.6
p=0.5
76.9
No CO2 Cap
76.9
Naive solution (ECIU = 77.8)
E(cost) = 428.5
Tight CO2 Cap
811.3
811.3
p=0.5
p=0.5
45.8
No CO2 Cap
45.8
Decision node: 2000-2010 investment and energy variables
Chance node: CO2 Cap in 2015
Decision: 2015-2050 variables
Present worth of cost

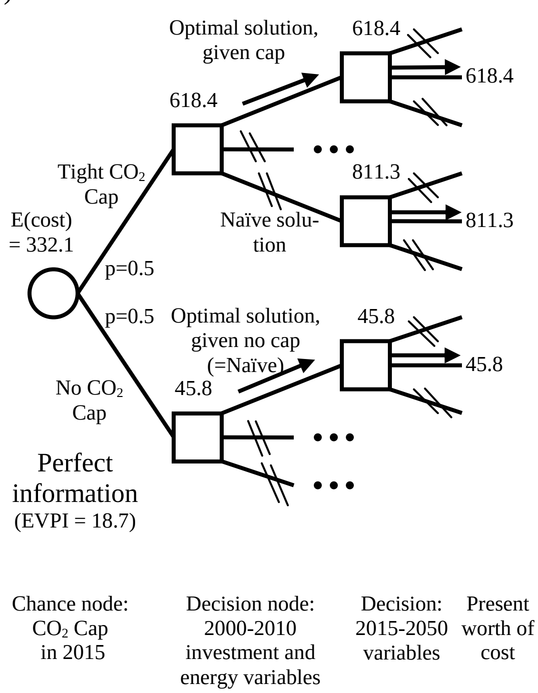
Fig. 3.

(a)



Optimal solution, given cap
582.5
582.5
582.5
Tight $CO_2$ Cap
797.7
797.7
E(cost) = 291.3
Naïve solu-tion
p=0.5
p=0.5
Optimal solution, given no cap (=Naïve)
0
0
0
No $CO_2$ Cap
Perfect information
(EVPI = 22.9)
Chance node: $CO_2$ Cap in 2015
Decision node: 2000-2010 investment and energy variables
Decision: 2015-2050 variables
Present worth of cost


(b)



Optimal solution, given cap
618.4
618.4
618.4
Tight $CO_2$ Cap
811.3
811.3
E(cost) = 332.1
Naïve solu-tion
p=0.5
p=0.5
Optimal solution, given no cap (=Naïve)
45.8
45.8
45.8
No $CO_2$ Cap
Perfect information
(EVPI = 18.7)
Chance node: $CO_2$ Cap in 2015
Decision node: 2000-2010 investment and energy variables
Decision: 2015-2050 variables
Present worth of cost