Measuring the Contribution to the Economy of Investments in Renewable Energy: Estimates of Future Consumer Gains

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Abstract

In this paper we develop a cost index–based measure of the expected consumer welfare gains from innovation in electricity generation technologies. To illustrate our approach, we estimate how much better off consumers would be from 2000 to 2020 as renewable energy technologies continue to be improved and gradually adopted, compared with a counterfactual scenario that allows for continual improvement of conventional technology. We proceed from the position that the role and prospects of renewable energy are best assessed within a market setting that considers competing energy technologies and sources. We evaluate five renewable energy technologies used to generate electricity: solar photovoltaics, solar thermal, geothermal, wind, and biomass. For each, we assume an accelerated adoption rate due to technological advances, and we evaluate the benefits against a baseline technology, combined-cycle gas turbine, which experts cite as the conventional technology most likely to be installed as incremental capacity over the next decade. We evaluate benefits against both the conventional combined-cycle gas turbine prevalent at this time and a more advanced combined-cycle gas turbine expected to be employed during the coming decade. We estimate the model for two geographic regions of the nation for which renewable energy is, or can be expected to be, a somewhat sizable portion of the electricity market—California and the north central United States.

In present-value terms we find that median consumer welfare gains over 20 years vary markedly among the renewable technologies, ranging from large negative values (welfare losses) to large positive values (welfare gains). The effect of uncertainty can lead to estimates that are 20% to 40% larger or smaller than median predicted values. Our results suggest that portfolios that give equal weight to the use of each generation technology are likely to lead to consumer losses in our regions, regardless of the role of the externalities that we consider. However, when the portfolio is more heavily weighted toward certain renewables, consumer gains can be positive.

Key Words: energy economics, technical change

JEL Classification Numbers: Q4, O3

Contents

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Executive Summary

In the wake of calls for increased accountability in public sector investments, federal agencies are being asked to design and demonstrate performance results for their programs and policies. In addition to satisfying statutory reporting requirements, such as those set forth in the 1993 Government Performance and Results Act, measures of the effectiveness of federal investments can provide useful information for program managers and other decisionmakers in guiding the allocation of scarce resources.

In this paper we develop a cost index–based measure of the expected consumer welfare gains from innovation in electricity generation technologies. To illustrate our approach, we estimate how much better off consumers would be from 2000 to 2020 as renewable energy technologies continue to be improved and gradually adopted, compared with a counterfactual scenario that allows for continual improvement of conventional technology. We proceed from the position that the role and prospects of renewable energy are best assessed within a market setting that considers competing energy technologies and sources. We evaluate five renewable energy technologies used to generate electricity: solar photovoltaics, solar thermal, geothermal, wind, and biomass. For each, we assume an accelerated adoption rate due to technological advances, and we evaluate the benefits against a baseline technology, combined-cycle gas turbine, which experts cite as the conventional technology most likely to be installed as

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* Contact: macauley@rff.org. We thank the Department of Energy, under project DE-FG01-00EE10758, and Resources for the Future for their support of our project. Responsibility for errors and opinions rests exclusively with the authors. Macauley, Shih, Aronow, and Darmstadter are at Resources for the Future. Austin was at Resources for the Future during part of the project and is now at the Congressional Budget Office. None of the views in this paper represent those of the CBO. Bath is an independent consultant.

incremental capacity over the next decade. We evaluate benefits against both the conventional combined-cycle gas turbine prevalent at this time and a more advanced combined-cycle gas turbine expected to be employed during the coming decade. We estimate the model for two geographic regions of the nation for which renewable energy is, or can be expected to be, a somewhat sizable portion of the electricity market—California and the north central United States.

Among the most important issues to consider in comparing future electricity generation technologies from the perspective of social welfare are external effects, both negative and positive, on the environment, human health, and important attributes of society. For example, undesirable air emissions of conventional power produced by coal or even combined-cycle gas turbines are often cited by advocates of renewable energy as a major disadvantage of fossil-based technologies; wind turbines' effects on migrating birds or noise pollution for neighboring residents are externalities mentioned in discussions of wind power. Our model is able to explicitly incorporate a wide range of such externalities but for now is limited by the absence of quantifiable data about many of them. Few external effects of renewable energy technologies have been addressed systematically, and some gaps remain in the understanding and measurement of external effects associated with conventional power. Thus, we incorporate in our model two negative externalities that have been subjected to at least tentative empirical treatment: the effects of carbon dioxide on global warming and thermal pollution on water quality. We find that rigorous attention to a wider array of externalities constitutes a major area for further research in understanding the comparative economics of renewable and conventional energy.

Our model extends previous work by Bresnahan (1986). Using well-developed index number theory, he constructs an index for comparing realized welfare gains from past investment in new technologies. His index compares the price and performance of a new product against the price and performance of a best-available product had the technical advance not occurred. The approach is similar to the familiar consumer price index, which to the extent possible incorporates quality differences among goods and services. An advantage of an index-based approach is that under certain general mathematical assumptions, the index is a function only of observed costs, adjusted for quality differences, and the share of expenditure represented by the product in total expenditures. The index is also ideal for applying to derived demand rather than final demand for a product. For example, Bresnahan applies the index to consumer demand for new computer technologies as inputs into financial and other sectors of the economy. By analogy, we apply our index to derived demand for electricity generation.

We extend the model in two directions. The first extension makes the index prospective (Bresnahan's was retrospective) so that we can evaluate the potential future gains from new technologies. We allow for gradual diffusion of renewable energy electricity generation technologies, and we express the model's parameters as probability distributions to reflect uncertainty over future or estimated parameter values for both the renewables and the conventional, defender technology—combined-cycle gas turbine. We also extend the model to include externalities that may not be fully reflected in capital and operating costs. We conduct sensitivity analyses, in which we shift parameter locations, to test the robustness of our assumptions about uncertain parameters. The result is a theoretically grounded economic model of future welfare gains embedded within a cost-index simulation model. The output is a rigorous yet transparent measure that can be used to assemble research and development (R&D) portfolios from a selection of competing projects, or to indicate performance of prospective investment in new technologies. It is important to note that neither our approach, nor Bresnahan's original model, is representative of overall public *net* benefit, as we do not subtract public or private expenditures on energy R&D or other expenditures that represent the costs of obtaining these benefits. However, our results are a starting point toward measuring net benefit (a no doubt daunting task).

In present-value terms we find that median consumer welfare gains over 20 years vary markedly among the renewable technologies, ranging from large negative values (welfare losses) to large positive values (welfare gains). For example, wind power consistently leads to potential gains, and photovoltaics leads to potential losses. Although many observers would agree that wind power is the renewable technology most "likely to succeed" in the near term, the sizes of these effects, their sensitivity to adoption rates and inclusion of externalities, and their regional differences would be difficult to predict without the framework we offer. For example, our results show that including carbon and thermal water externalities can increase the relative benefits of some renewables on the order of 20% to 40% compared with combined-cycle gas turbines. Including a water externality but not a carbon externality increases the relative benefits of wind and geothermal technologies by 15% to 20% and worsens the relative performance of solar thermal and biomass compared with combined-cycle gas turbines, even though there is also a water externality associated with the turbines.

Our results also indicate the importance of considering technical innovation in the defending technology. Comparing advanced with conventional combined-cycle gas turbines and holding all other assumptions constant, we show that surplus values are overstated by around 5% when innovation in the defending technology is omitted.

The effect of uncertainty can lead to estimates that are 20% to 40% larger or smaller than median predicted values. These are rather large differences even though our uncertainty bounds are rather small (generally, plus or minus 10% of the reported data values). But the effects of uncertainty increase as the time period extends into the future. These results also suggest that comparing future scenarios without taking uncertainty into account could lead to misleading conclusions.

The 20-year, median discounted present value of potential consumer surplus for parameterizations of the model leading to welfare gains can range from about $111 to $556 per household in California and $300 to $600 per household in the north central region. For rough comparison, annual household expenditures on electricity are about $388 and $378 in each region, respectively. The discounted value of the largest potential surplus, then, is about 40% to 60% more than one year's household electricity expenditure.

The model also permits exogenous construction of hypothetical portfolios or combinations of energy generation technologies. Our results suggest that portfolios that give equal weight to the use of each generation technology are likely to lead to consumer losses in our regions, regardless of the role of the externalities that we consider. However, when the portfolio is more heavily weighted toward certain renewables that give positive surplus values in pairwise comparisons with the defending technology, consumer gains can be positive. The different allocations in the variable-weight portfolios for our regions illustrate the usefulness of models that can be separately evaluated on a geographic basis rather than nationally aggregated. In a future extension of our research, we would like to allow for an endogenous optimization of the portfolio.

I. Introduction

In the wake of calls for increased accountability in public sector investments, federal agencies are being asked to design and demonstrate performance results for their programs and policies. In addition to satisfying statutory reporting requirements, such as those set forth in the 1993 Government Performance and Results Act, measures of the effectiveness of federal investments can provide useful information for program managers and other decisionmakers in guiding the allocation of scarce resources.

In this paper we develop an index-based measure of the performance of research and development (R&D) investment in renewable energy technologies for the production of electricity. To illustrate our approach, we estimate how much better off consumers would be from 2000 to 2020 as renewable energy technologies continue to be improved and gradually adopted, compared with a counterfactual scenario that allows for continual improvement of conventional technology. Specifically, the application of our model in this paper singles out the use of renewables in electricity generation, the sector where an expanded role for renewables probably has greatest promise.[1] We proceed from the position that the role and prospects of renewable energy can be assessed only within a market setting that considers competing energy technologies and sources. We evaluate five renewable energy technologies used to generate electricity: solar photovoltaics, solar thermal, geothermal, wind, and biomass. For each, we assume an accelerated adoption rate due to technological advances, and we evaluate the benefits against a baseline technology, combined-cycle gas turbine, which experts cite as the conventional technology most likely to be installed as incremental capacity over the next decade. We evaluate benefits against both the conventional combined-cycle gas turbine prevalent at this time, and a more advanced combined-cycle gas turbine expected to be employed during the coming decade. We discuss and, where available data permit, adjust for several environmental externalities associated with these technologies. We estimate the model for two geographic

[1] The model can be generalized or extended to measure gains from investment in other technologies; for example, some of the authors have previously used it to consider gains from investments in new space technologies and new digital data storage devices.

regions of the nation for which data on production costs and social costs are available and for which renewable energy is, or can be expected to be, a somewhat sizable portion of the electricity market—California and the north central United States.

The model we develop is an index-based measure of the expected gains accruing to consumers, known formally as consumer welfare gains, from innovation in energy technologies. The framework (1) compares future welfare gains from renewable energy with those expected from conventional energy technology; (2) takes into account uncertainty surrounding anticipated future costs of producing renewable and conventional energy, including, importantly, cost reductions expected from technical innovation in both technologies; and (3) explicitly considers other social costs and benefits associated with energy technologies, such as environmental externalities. In addition, the model incorporates a spatial dimension that accounts for differences in the geographic distribution of renewable energy supplies, enabling the estimation of welfare gains for regions of the country or by the nation as a whole.

The approach goes beyond traditional measures of energy efficiency and energy balance (see discussion in Bath 1999) to combine these factors in a conceptually consistent and empirically estimable framework. The approach can balance investments in renewable energy on the basis of cost, performance, risk, and the potential contribution over time to energy and environmental goals. It is important to note that our approach is not representative of overall public net benefit, as we do not subtract public or private sector expenditures on energy R&D or other expenditures that represent the costs of obtaining these benefits. However, our results are a starting point toward measuring net benefit (a no doubt daunting task). We speculate further on net benefits in our conclusion.

The rest of the paper proceeds as follows. In section II we describe the model, our assumptions, and our incorporation of uncertainty. In section III we describe the specific energy generation technologies we address together with our data, their sources, and their limitations. Section IV gives results of numerous scenarios we construct for evaluating the model and testing its sensitivity to our assumptions. In this section, our scenarios include several "portfolios" that combine renewable technologies to estimate consumer surplus that might be associated with a portfolio approach to energy management. Section V presents our conclusions.

II. The Model

The model involves estimation of a quality-adjusted cost index that we use to calculate future consumer welfare gains. The index is based on well-developed index number theory and its application by previous researchers to measuring realized gains from technological change. We modify the framework to be forward looking, measuring prospective gains and, as a result, incorporating uncertainty. In our application, we also extend the framework such that the quality adjustments that are employed in traditional index measurement become adjustments to account for externalities associated with energy generation.

In this section we discuss the concept of the index and the simulation model we developed to estimate the index and calculate the value of consumer surplus. We also discuss our assumptions about adoption rates, the role of externalities, and the method by which we incorporate uncertainty about future generation costs and other data in the model.

Details about the Index

We extend an approach pioneered by Bresnahan (1986) to develop an index for comparing realized welfare gains from past investment in new technologies. Bresnahan's index compares the price and performance of a new product against the price and performance of a best-available product had the technical advance not occurred. The approach is similar to the familiar consumer price index, which to the extent possible incorporates quality differences among goods and services. An advantage of an index-based approach is that under certain general mathematical assumptions, the index is a function only of observed costs, adjusted for quality differences, and the share of expenditure represented by the product in total expenditures. The index is also ideal for applying to derived demand rather than final demand for a product. For example, Bresnahan applies the index to consumer demand for new computer technologies as inputs into financial and other sectors of the economy. By analogy, we apply our index to derived demand for electricity generation.

Our index, based on Austin and Macauley (2000 and 2001), extends Bresnahan's approach in two directions for applicability to the case of investment in renewable energy. The first extension is to make the index prospective (Bresnahan's was retrospective) so that we can evaluate the potential future gains from investment in the technologies. We allow for gradual diffusion of renewable energy electricity generation technologies, and we express the model's parameters as probability distributions to reflect uncertainty over future or estimated parameter values for both the renewables and the conventional, defender technology—combined-cycle gas turbine (CCGT). We also extend the model to account for externalities associated with the technologies, although data gaps somewhat limit the empirical application of this extension. We also conduct sensitivity analyses, in which we shift parameter locations to test the robustness of our assumptions about uncertain parameters. The result is a theoretically grounded economic model of future welfare gains embedded within a cost-index simulation model. The output is a rigorous yet transparent index that can be used to assemble R&D portfolios from a selection of competing projects, or to indicate performance of prospective investment in new technologies.

Figure 1 illustrates the index. It shows the expected welfare gain from changes in electricity costs (including externalities) brought about by investment in renewable energy. The demand curve is given by *D*. Period 0 supply, S_O^{DT}, is the baseline, where only the defender technology, DT, is available. Investment in renewables shifts their supply curve to S_I^{RE} because of a combination of cost reductions and net social benefits (see second panel). Meanwhile, continuous improvement in the defender technology means the baseline supply curve would shift to S_I^{DT}. The shaded area represents the welfare gain due to the investment in renewables. It is measured with respect to the future S_I^{DT} curve rather than the observed S_O^{DT}.

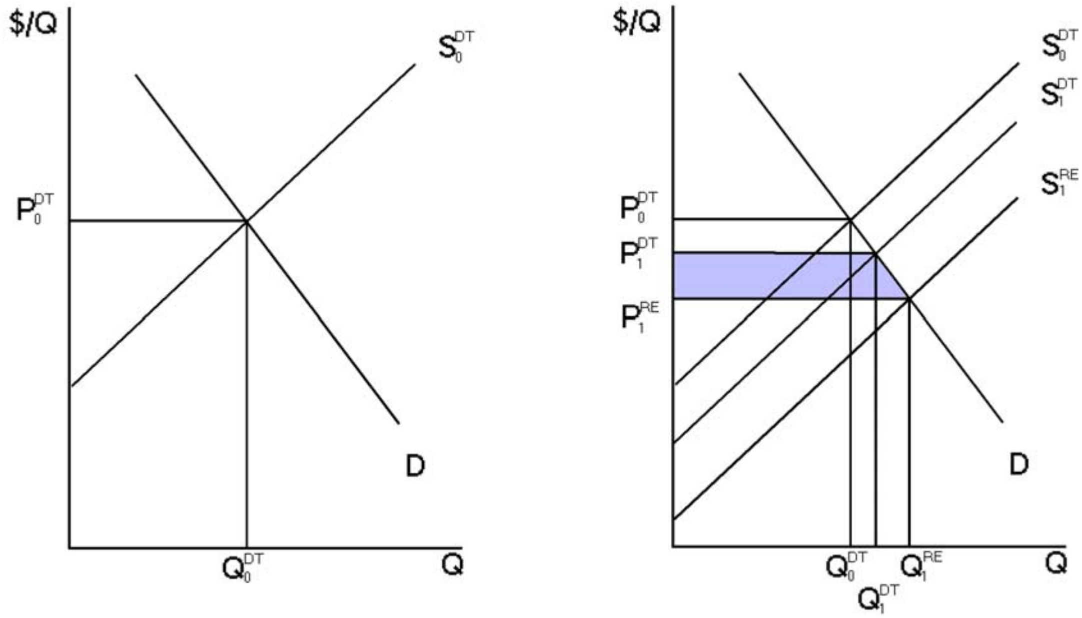

Figure 1. Derived demand for renewable energy technologies: Illustration of net surplus change

If S1RE lies to the right of S1DT, the investment offers an improvement over the defender technology. In this case, the index is greater than unity, meaning costs are higher under the baseline and consumers will be better off if the investment occurs.[2] In the absence of adjustments for social benefits and costs, the index may be less than unity (implying that investment in renewables does not appear to produce a welfare gain). However, these adjustments are likely to increase it significantly. Note that even if after adjusting for net social benefits the index is less than unity, the index permits useful comparisons across investments (favoring those that yield indexes as close to 1 as possible) and can indicate progress over time as continued investment results in innovation that nudges the index upward. This interpretation furthers the usefulness of the index for policymakers to measure performance over time.

To illustrate the underpinnings of the index, expression (1) below underlies the concept of the cost index. In (1), C^{*dt} is the minimum cost of achieving "utility" u^{dt}, or the socially optimal combination of conventional energy technology (for electricity) and other goods and services, expressed relative to the cost of u^{dt} given the investment in renewables that brings

[2] An important note is that we measure the welfare gain *gross* of the investment expenditure made in renewables.

about reductions in their costs (or increases in their social benefits). Similarly, C^{*I} is the cost of achieving optimal utility uI under the investment scenario with conventional energy costs W^{dt} relative to the cost of renewables with postinnovation costs W^{RE}.

$$C^{*dt} = \frac{E^{*}(u^{dt}, P^{dt}, W^{dt})}{E^{*}(u^{dt}, P^{I}, W^{RE})} \text{ and } C^{*I} = \frac{E^{*}(u^{I}, P^{dt}, W^{dt})}{E^{*}(u^{I}, P^{I}, W^{RE})}. \tag{1}$$

Because we assume an innovation is adopted gradually, the quality-adjusted cost of renewables (i.e., adjusted for social benefits and costs) is a combination of use of renewables and use of conventional technology, such that $W^{RE} = \rho W^{I} + (1-\rho)W^{dt}$ where ρ is the adoption rate of the renewables and W^{I} is their cost if fully adopted. Prices P of other goods and services can change over time, but we assume they are unaffected by renewables: $P^{dt} = P^{RE}$ at all times.

Figure 2, which is counterpart to figure 1 on the basis of duality theory (linking demand curves to expenditure functions), depicts the relationship among the expenditure functions E^*, utility, and the two cost indexes represented by C^{*dt} and C^{*I}.[3] A welfare-enhancing innovation lowers consumers' costs of achieving a given level of utility, shifting the expenditure function downward from $E^*(u,W^{dt})$ to $E^*(u,W^{RE})$. The vertical distance between the two curves depends on the share of electricity generation costs in total consumption expenditures; their ratio is given by C^*. Given a welfare-enhancing innovation I, consumers' optimal utility rises to $U^{*I} > U^{*dt}$. With separable utility and other prices unaffected, the relative cost to achieve u^{*I} with higher baseline prices W^{dt} versus reduced, postinnovation prices W^{RE} exceeds the relative cost to achieve U^{*dt}.

[3] The indexes are a Laspeyres index, measuring consumer willingness to accept compensation to give up the gains from innovation, and a Paasche index, measuring their willingness to pay to receive gains from innovation. The Tornqvist index is an equally weighted average of the two. See Varian (1992) for details. As is well known from the theory of index numbers, no single index satisfies all "desirable" properties or tests (such as tests related to scalability, transitivity, symmetry, and proportionality). The Tornqvist index satisfies many of the tests (see Diewert and Nakamura 1993).

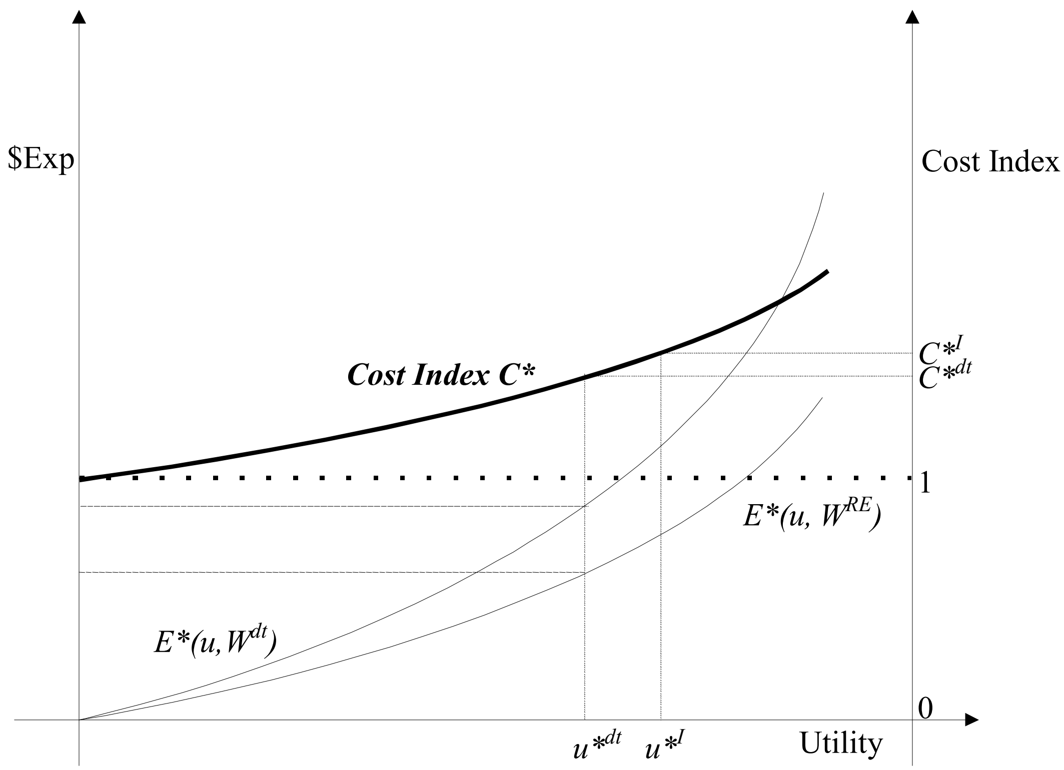

Figure 2. Relationship between expenditures, cost index[4]

Simplifying (1) based on cost index theory (see Caves et al. 1982) and assuming, as is routine in expenditure theory, that the consumer expenditure function E^* can be represented by a translog functional form,[5] we obtain the index in (2):

$$\tfrac{1}{2}\ln\left(C^{*dt} \times C^{*I}\right) = \left(\tfrac{1}{2}(s^{dt} + s^{I}) \cdot \ln\left(\frac{W^{dt}}{W^{RE}}\right)\right). \qquad (2)$$

The terms $s^{dt} + s^{I}$ give, respectively, electricity expenditures as a share of personal consumption expenditure (PCE) under the baseline and investment-in-renewables scenarios. These expenditure data serve as "weights" in the index. The monetary value to consumers of the investment is just the product of their predicted PCE times the exponent of the cost index. This

[4] To simplify figure labeling, prices P have been omitted from the expenditure functions.

[5] The translog well approximates many production and expenditure functions.

corresponds to the area of the shaded rectangle in figure 1.[6] Thus, the index lets us ask, "How much better off are we (i.e., society in general) as a result of investment in renewables for the production of electricity, taking into account the alternative (conventional technology) and differences in the social benefits and costs between renewables and conventional technology?"

To summarize, the index can be used as, first, a measure of performance, and second, a tool for allocating investment across different renewable energy technologies. The index allows an apples-to-apples comparison among renewables and between renewables and a conventional technology. It illustrates "how much better off" we are likely to be as a result of the investments, taking into account innovation in the conventional technology as well as in renewables.

The Simulation Model

We construct a computer-based model to estimate the index and consumer surplus. The model uses Monte Carlo techniques to predict values of the two measures based on data that we parameterize using probability distributions, rather than point estimates, to characterize uncertainty. The model is implemented using Analytica, a software package optimized for conducting uncertainty analysis.

Figure 3 illustrates the model. It begins with data on generation costs for each of our technologies. We add to these private costs the monetized costs of externalities to obtain the sum of private and social generation costs. We then use our assumptions about the rate at which new technologies will be used (which we label adoption rates) to estimate factor shares for the index, following equation (2). The cost index itself is the ratio of two alternative outcomes: generation costs weighted by the shares of PCE devoted to generation in the baseline, or defending technology scenario (combined-cycle gas turbine generation), compared with the innovating technology scenario (renewables). In the last step, we use the index to estimate the discounted present value of the stream of benefits to consumers over time. We use the shares together with the end use price of electricity and total personal consumption expenditures to estimate consumer

[6] Because costs and expenditure shares of nonelectricity consumption in personal consumption expenditure are assumed to be unchanged by the results of investment in renewables, separability assumes that these parameters cancel in (2). Also, changes in relative energy technology prices will affect the mix of inputs used in production of goods and services requiring electricity. However, it is not necessary to make any assumptions about input substitutions because the functional form of the cost function underlying the index places no restriction on technical substitution among inputs. Nor does the function restrict the income and price elasticities of demand for electricity-using services.

surplus[7] that would be expected from the innovating, renewable technologies, measured in comparison with the baseline, defending technology, given our assumptions and data. Surplus is expressed as the discounted present value of consumer benefits over the period 2000–2020.

The cost ratio indicates relative costs of the competing technologies, and the expenditure shares adjust for levels of demand. A superior new technology might generate a large quality-adjusted cost ratio, but since expenditures on electricity generation are small relative to PCE, consumers' cost of living will not be much affected. In other words, we expect our index numbers to be smaller or larger than 1, but in any case, very close to 1. Consumer surplus, or total benefits, can be very large, however.

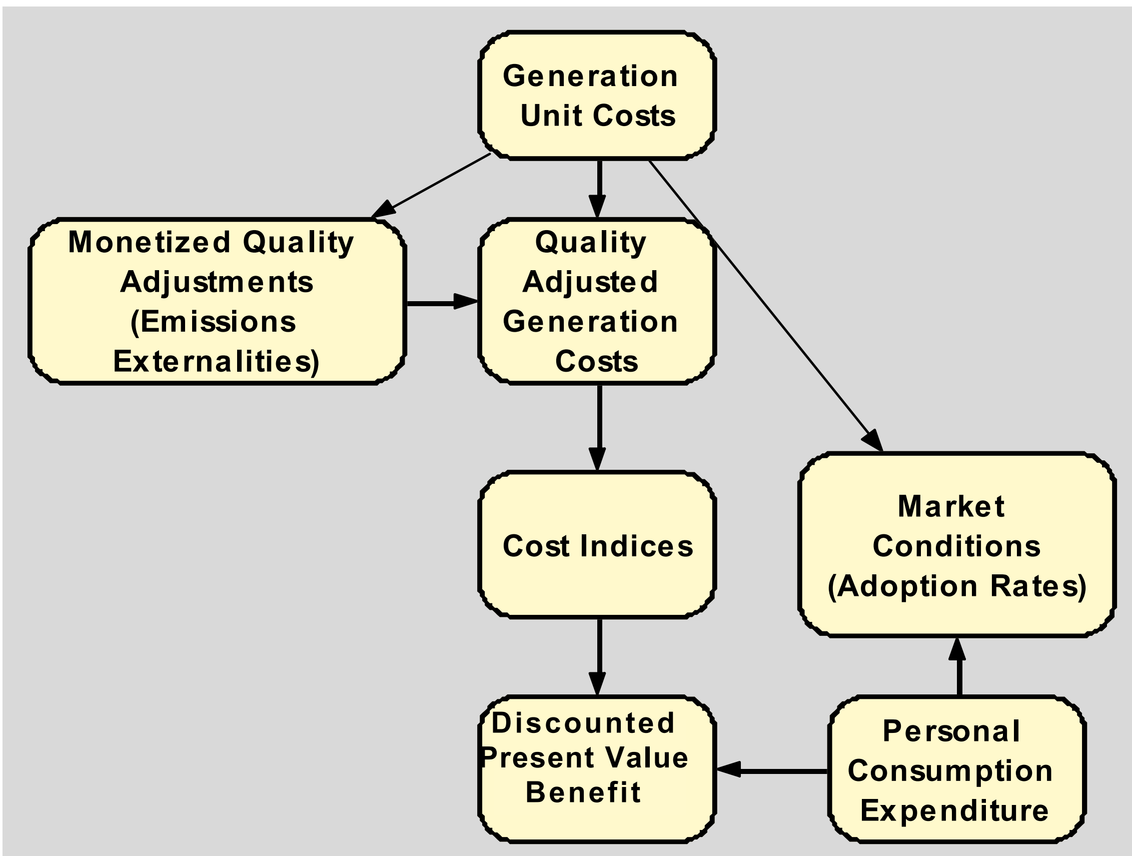

Figure 3. Structure of simulation model

[7] From figure 1 it can be seen that the end use price of electricity (i.e., the price determined by generation, transmission, and distribution) rather than the fraction of the end use price represented by generation only is the relevant measure for consumer surplus.

As noted, we parameterize all our data inputs using probability distributions to characterize uncertainty that may be present in imperfectly observed data as well as that which naturally surrounds expectations about the future. We discuss this parameterization below. In addition, we note that our modeling approach is independent of our choice of technologies and thus is useful for consideration of other technologies; it is also easily extended to include additional externalities and different assumptions about adoption rates and uncertainty. We believe its major limitation is data, which we discuss further below.

Adoption Rates

We assume that the adoption of new renewable technologies gradually displaces adoption of new combined-cycle gas turbine units but does not force early retirements. (Our measurement and estimation of growth in CCGT and renewables generation capacity are somewhat complex, and we discuss them further in the data section.)

In the model, the generation shares of renewable technologies, which replace the CCGT generation increments, increase monotonically with time according to the following Weibull process:

$$F(t) = 1 - \exp(-\lambda t^{\gamma}) \qquad (3)$$

Equation (3) describes the Weibull probability distribution that generates the S curve typically used to characterize the adoption of new technology. In (3), t is time in years; λ is a scale parameter, $0 < \lambda < 1$, having the interpretation of a hazard rate (which is therefore assumed to be constant); and $\gamma > 0$ is a shape parameter. Different pairs of λ and γ give differently shaped curves. In general, larger values of lambda imply a faster adoption rate. Larger values of gamma will delay the time at which the inflection point occurs. The box below gives the values we assume to characterize two adoption rates, "fast" and "slow," in our model.

Scenario	**Parameters**
Fast Adoption	$\lambda = 0.1$, γ=3.5
Slow Adoption	$\lambda = 0.05$, γ=3.5

Figure 4 shows the renewable generation shares over time for these two adoption rates using Weibull functions.

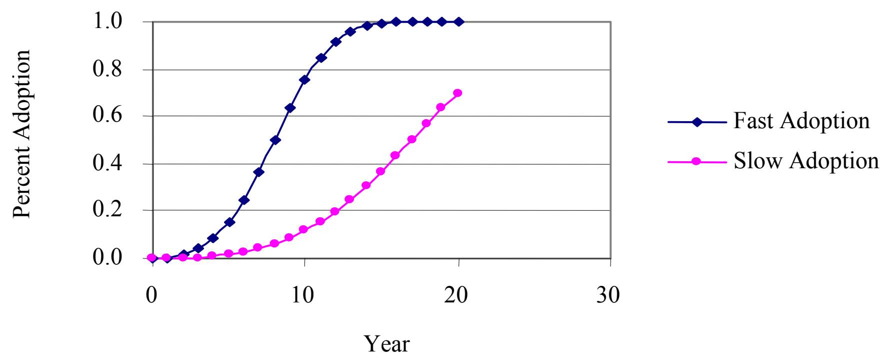

Figure 4. Weibull adoption rate curves

Accounting for Externalities

Among the most important issues to consider in comparing future electricity generation technologies from the perspective of social welfare are external effects, both negative and positive, on the environment, human health, and important attributes of society. To illustrate, undesirable air emissions produced by coal or even combined-cycle gas turbines are often cited by advocates of renewable energy as a major disadvantage of fossil-based technologies; wind turbines' effects on migrating birds or noise pollution for neighboring residents are externalities mentioned in discussions of wind power. Our model is able to explicitly incorporate a wide range of such externalities but for now is limited by the absence of quantifiable data about many of them. Few external effects of renewable energy have been addressed systematically, and some gaps remain in the understanding and measurement of external effects associated with conventional power. Thus, we incorporate in the quantification of our model two negative externalities that have been subjected to at least tentative empirical treatment: the effects of carbon dioxide on global warming and thermal pollution on water quality.[8] As we note later in the report, rigorous attention to a wider array of externalities constitutes a major area for further research in understanding the comparative economics of renewable and conventional energy.

From a conceptual perspective, the external effects that count for an apples-to-apples comparison—and with which we are largely concerned in this report—are technological externalities, or the uncompensated effects of one party's actions on another party. When these effects harm the other party, they increase the full cost to society, above and beyond the private resource costs, of the activity. External costs shift up the supply curves in figure 1 to the dashed lines in figure 5 and alter the corresponding consumer surplus area that we seek to measure. For meeting environmental requirements, utilities may incur costs—for pollution control equipment, for example—that are considered internalized environmental costs because they are included in the electricity rates.[9] However, there are other costs that are not reflected in the rates, such as mercury emissions, which are not currently controlled, and these are considered externalities.

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[8] Carbon dioxide releases, widely regarded as a major contributor to greenhouse warming and the ensuing damages from climate change, are a clear-cut instance of externalities. Even so, the fact that the carbon content of natural gas is the lowest of the fossil fuels, coupled with the high conversion efficiency of CCGT technology, makes these releases relatively modest. As for thermal releases, all combustion involves heat rejection, whose magnitude depends on the efficiency of the conversion process. The condensation and dispersal of such waste heat can take varying forms—different types of cooling towers, cooling ponds, or discharge into "common property" water bodies (such as rivers, lakes, or coastal water). It is such releases, with their putative impact on aquatic integrity and activities, that merit treatment as an externality.

[9] A good example is nitrogen oxide (NO_x) emissions from CCGT combustion. These are already capped under Clean Air Act statutes at exceedingly low levels. Releases below the permissible threshold are assumed not to represent an externality. Moreover, there is no empirical basis for estimating such residual damages, if any.

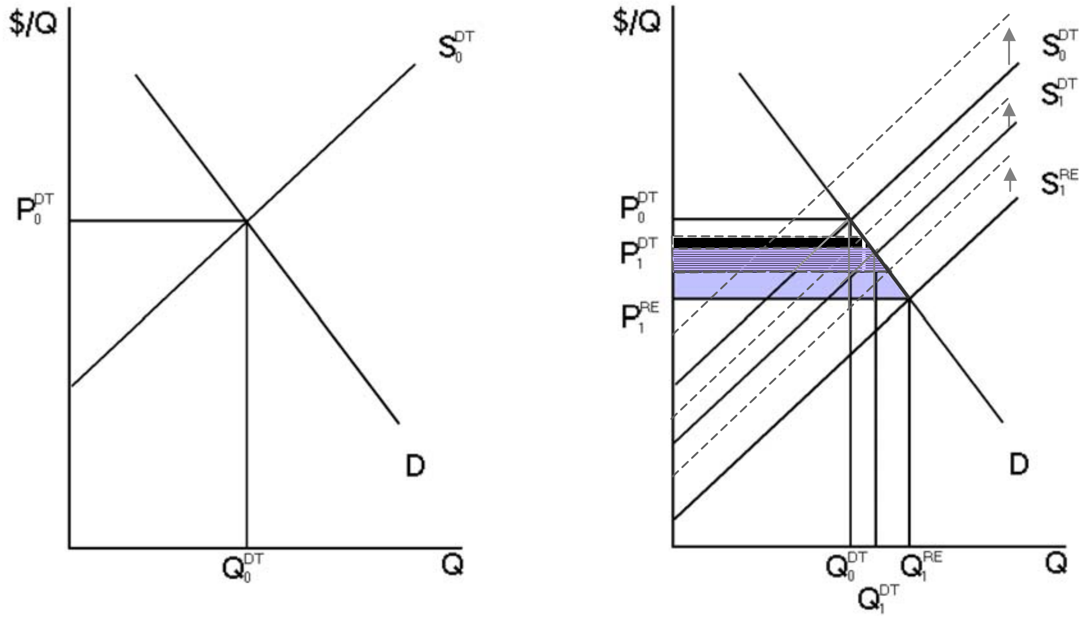

Figure 5. Derived demand for renewable energy technologies: Illustration of net surplus change with external costs

A different class of externalities is pecuniary externalities. Their effects are largely distributional, and for this reason their effects in figure 5 cancel out. The siting of a power plant can have a negative effect on neighborhood property values, for instance, but the full effect is a transfer of income in that it reallocates income to those who benefit by the new power capacity from those whose property values decline. From the perspective of the society-wide accounting ledger of benefit and costs, the wins and losses cancel out, and the net effect to society, the bottom line, is zero. Although the distinction between technological and pecuniary externalities can be blurred if households suffering reduced property values also benefit from use of power from the new plant, pecuniary externalities are generally thought to have no effect on economic efficiency. However, they can be politically important precisely because of their wealth effects.

Box 1 illustrates a gamut of external effects in the case of energy technologies. Externalities can arise at any stage of the electricity cycle, from development and extraction of a resource, to transportation, processing, manufacturing, and assembly of materials and facilities, to generation, transmission, and disposal of all wastes or residuals from various activities and processes. To keep our model tractable, and because fully accounting for these effects is outside the scope of our project in any case, we include only externalities arising during electricity generation.[10] Thus, we exclude any "upstream" externalities—say, leakages from gas transmission lines or "uninternalized" risks of energy disruptions. In addition, we focus on external costs, not the avoided external costs of nonpolluting systems. It is important to note, for example, that by accounting for the negative effects of carbon emissions from CCGT, we are implicitly adjusting for the external benefits of technologies that do not produce carbon emissions. In this relative sense, then, we implicitly account for some external benefits as well as external costs when we compare our technologies. We note also that effects can vary by geographic region and over time. For instance, the extent of environmental and health effects depends on the affected population and may include both short- and long-term effects.[11]

[10] Portney (1993—94) discusses the complexities of life-cycle approaches.

[11] In a 1995 study, the General Accounting Office (U.S. GAO 1995) reviewed approaches taken by states in considering externalities associated with electricity production. GAO found significant variation among approaches. As of the time of the survey, half of the states did not have requirements considering externalities; 16 states assigned a quantitative value to the externalities associated with coal-fired plants; and 9 states and the District of Columbia treated externalities qualitatively, by using, for example, a subjective ranking system for anticipated environmental impacts.

BOX 1. EXTERNALITIES AND THE ELECTRICITY CYCLE

The fuel cycle. The electricity cycle ranges from development and extraction of a resource and transportation, processing, manufacturing, and assembly of materials and facilities, to generation, transmission, consumption, and disposal of all wastes or residuals from various activities and processes.

The generation stage. The potential list of external effects is large. For example, in the generation of power, external effects include the following:

Technological *(lacking prices or other internalization mechanisms but influencing the generation technology):*

Atmospheric emissions (local, regional, global)
Water impacts
Geology and soils impacts (contamination, land disturbance)
Cultural resources impacts (archaeological resources)
Biological resources and terrestrial ecosystems impacts (plants, wildlife)
Recreational impacts (wilderness values)
Visual impacts (including light pollution)
Noise emissions (e.g., wind turbines)
Interference with electromagnetic communication systems

Pecuniary *(influencing generation technology but reflected in prices; may have significant income and other job-related distributional effects):*

Resource use (for resources for which "correct" market prices are in place)
Socioeconomic impacts (e.g., transportation, housing, employment)
Land value impacts
Tax revenues

Both direct costs and external effects can vary by geographic region (e.g., differences in resource endowments such as wind, geothermal), by time (season, time of day), and of course, by resource input (e.g., fuel type, solar).

As box 1 indicates, the external effects—both technological and pecuniary—associated with energy generation range widely and include effects on health and the environment (including climate change), effects on occupational health in energy-producing sectors, employment in energy sectors, fiscal effects in the form of government revenues affected by differential tax and subsidy treatment of energy technologies, road damage from transportation of fuels, and a host of energy security implications, such as the economic cost of oil supply disruptions and the cost of military expenditures to secure international trade.[12] Without entering into discussion about which effects are technological, which are pecuniary transfers, or which are sizable enough to matter, our choice of external effects to include in our model is significantly restricted by a lack of empirical information. That is, the limitation is imposed not by the index but by data.

Specifically in regard to the technologies we consider, the list below presents the externalities most often cited in the relevant engineering studies, environmental impact statements, and other public discussions. Of these, we have monetized values for two effects—carbon, in the case of combined-cycle gas turbines, and thermal effluent, in the cases of solar thermal, biomass, and combined-cycle gas turbines.

- For biomass energy generation: a dedicated feedstock and thus neutral effects on the carbon cycle, soil erosion, and other impacts; a potential problem of thermal discharges; and mitigation of emissions of particulates, ash, sulfur dioxide, and nitrogen oxide in compliance with environmental regulations.
- For photovoltaics: potential occupational health effects arising during manufacture of some types of materials, and possible leachate of harmful materials during disposal and recycling of cells.
- For geothermal energy production: waste heat, ejected gases, and sludge, depending on the specific production technique.
- For wind power production: the effects of turbines on birds, including endangered species and species protected under the migratory bird treaty, plus noise, visual effects, electromagnetic interference, possible leakage of potentially toxic or hazardous lubricating oils and hydraulic and insulating fluids, and the large amounts of land typically used for wind farms (although because landowners are typically compensated in the purchase of the land, the use of land can be a pecuniary effect).[13]

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[12] See discussion in Krupnick and Burtraw (1996); also Bohi and Toman (1992) and Green and Leiby (1993).

[13] Property owners near a new wind facility in Wisconsin recently accepted the facility's offer to buy their properties to settle a dispute over noise and other disamenities that the property owners claimed were caused by the facility. Bonseke, K. "WPS offers to buy land near wind turbines." *The Algoma-Record Herald* 16 May 2001. Online: http://www.algomarecordherald.com/page.html?article=100534 (accessed December 26, 2001).

- For solar thermal energy production: the possibility of spills or leaks from heat transfer fluids, wastewater, and thermal discharges.
- For combined-cycle gas turbines: thermal discharges and carbon releases, which are yet to be covered by environmental regulation of fossil-fuel generators.

The literature review and analysis in Lee et al. (1995), European Commission (1995), Hagler Bailly Consulting (1995), President's Committee of Advisors on Science and Technology (1997), Oak Ridge National Laboratories and Resources for the Future (1998), Hunt (2001), and RESOLVE (2001) contain in-depth discussions of the epidemiological and environmental effects. Krupnick and Burtraw (1996) summarize much of this literature, focusing on the effects for which researchers have developed monetized values.

We use estimates of the monetized values of the carbon and thermal discharge effects as median values and parameterize them using probability distributions (the estimates and the distributions are discussed in the next section). We use the Krupnick and Burtraw review for the estimate for carbon externalities and develop our own estimates for thermal discharges. We also note for our modeling effort that the Energy Information Administration's (EIA) *Annual Energy Outlook*, which is a source for our data on generation costs, indicates that new fossil units are required to meet the U.S. Environmental Protection Agency's NO_x emission standards. Because these standards are embodied in the model underlying the *Outlook* projections, the costs of compliance with the standards are internalized in generation costs for our combined-cycle gas turbine technologies.

III. Data

The data we use for our two regions over the period 2000–2020 are the generation costs for renewable and conventional energy technologies, the externalities associated with the energy technologies, total expenditures on electricity generation as a fraction of total personal consumption expenditures, and expectations about the values of all these inputs over the relevant time horizon. We estimate the model separately for two geographic regions as defined by the North American Electric Reliability Council: the Mid-Continent Area Power Pool (MAPP) and the California–Southern Nevada Power Pool (CNV). Figure 6 illustrates these regions. We chose these regions to highlight regional differences in resource endowments for power generation: CNV has resources for the production of all the renewable technologies in our study, and MAPP has resources for a subset of the technologies.

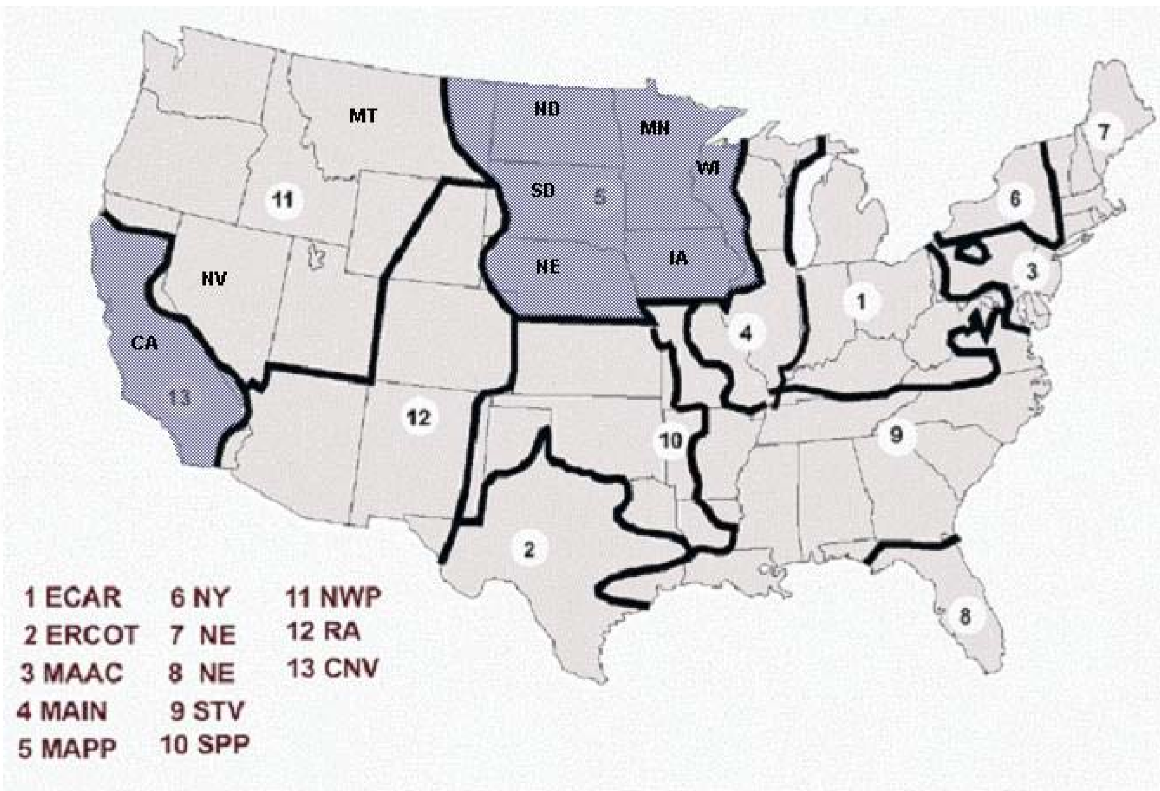

Figure 6. Electricity market module supply regions

Source: EIA

Description of the Technologies

We consider combined-cycle gas turbines and five renewable energy technologies: utility-owned residential photovoltaics, parabolic trough solar thermal, hydrothermal binary geothermal, horizontal axis wind farms, and direct-fired dedicated-feedstock biomass.[14] In this section, we briefly describe each and our rationale for selecting them. Most of the information about the technologies is from the U.S. Department of Energy (DOE) and Electric Power Research Institute's *Renewable Energy Technology Characterizations* (DOE/EPRI 1997) and the U.S. Department of Energy's *Annual Energy Outlook 2001* (DOE/EIA 2000a). We also highlight some information from the DOE forecast of future quantities of generation from each of the technologies, based on DOE's National Energy Modeling System (NEMS) in DOE/EIA (2001) and additional unpublished information provided to us for our specific regions of interest.[15] Appendix 1 contains more details from the DOE forecast of future generation.

Combined-cycle gas turbines (CCGT). In a conventional combined-cycle gas turbine, gas is injected into a chamber containing compressed air, which causes the gas to burn. The hot gases rise, turning a turbine wheel to generate electricity. The waste heat is pumped to a boiler to generate steam, which turns a second turbine. An advanced combined-cycle turbine is expected to be more efficient, have lower NO_x emissions, and produce cheaper electricity than conventional CCGT technology. The Department of Energy's program goals for advanced CCGT are for the technology to exceed 60% efficiency with NO_x emissions of less than 9 parts per million, and to achieve a 10% reduction in the cost of electricity. The agency expects plants with these specifications to be deployed in 2002.[16]

We chose natural gas CCGT as our defender technology because the majority of new generating capacity is expected to use this technology. According to DOE forecasts, natural gas is the fastest-growing energy source for electricity generation; 86% of the new generating capacity brought online between now and 2020 is expected to be natural gas. Currently, natural

[14] Although the cost-of-energy data used in our model reflect the cost of these particular technologies, the data on quantity of generation in this report reflect the generation by fuel source rather than by technology. For example, the natural gas generation data include generation by combined-cycle gas plants as well as conventional gas plants. Likewise, the biomass data reflect generation from cofired biomass as well as dedicated biomass plants. It is the opinion of our coauthor and technology expert that most of the new generation capacity in each of these categories will be in the form of the technology we have selected.

[15] The unpublished information is from our conversation with Namovicz (2001). We are aware that NEMS has been criticized for its assumptions about market penetration, transmission constraints, costs, and other characteristics of its modeling and forecasting approach (e.g., see Osborn et al. 2001). However, we feel that the NEMS estimates are a good starting point for our model because our purpose is, in part, to illustrate its transparency to a wide variety of assumptions about market penetration and costs.

[16] "Tomorrow's Turbines." Available at http://www.fe.doe.gov/coal_power/turbines/index.shtml.

gas fuels about 12% of net U.S. electricity generation,[17] including 1% of electricity generation in the MAPP region and 31% of electricity generation in CNV. DOE forecasts that natural gas will generate 33% of the nation's electricity in 2020 and will represent 67% and 78% of new generation in 2001–2020 for CNV and MAPP, respectively.

Photovoltaics (PV). The basic photovoltaic configuration consists of a DC photovoltaic panel, an AC converter, and connecting wires. We assume a configuration described in DOE/EPRI as consisting of many PV units on numerous residential rooftops and owned by a utility company.[18] The net energy generated by the photovoltaic units would be transmitted back to the grid. The technology for the crystalline-silicon cells is not expected to improve dramatically, although thin-plate films in development could dramatically reduce costs through improved conversion efficiency and lower cost of fabrication. The DC-AC conversion efficiency is also expected to improve. DOE/EPRI expect the majority of cost reduction to come from improvements in standardization, lower installation costs, and improved manufacturing processes resulting from experience gained as the market grows. As of 2001, photovoltaics is used for 2 thousandths of 1% of power in the nation, and 0.02% of power in CNV. By 2020, it is expected to grow to 0.03% of power nationally, and 0.13% in CNV.

Solar thermal (ST). In a parabolic trough solar thermal system, rows of parabolic solar collectors heat a heat transfer fluid, which generates steam. The steam turns a conventional turbine to produce electricity. These plants are expected to operate as solar-fossil hybrids through 2005 and then switch to all-solar plants when thermal storage is added. Currently, solar thermal is used for 0.03% of power in the nation and is expected to remain at the same level through 2020. In CNV, this technology is expected to shrink from 0.42% of generation today to 0.30% in 2020. Solar thermal is not used in MAPP, nor is it expected for the future in this region.

Geothermal (GT). In a hydrothermal geothermal binary plant, high-temperature geothermal water is pumped from wells into the plant and used to heat another fluid—the "working fluid"—that has a lower boiling temperature. Steam from the boiling working fluid turns a turbine that generates electricity. Binary plants can use medium-temperature geothermal resources, which are the most available. Several technological improvements are expected in the

[17] We use "generation" to mean electricity produced by dedicated power plants only, and exclude power produced by cogenerators, which produce both electricity and usable heat.

[18] We acknowledge the "form value" applications of photovoltaics but do not consider them in this paper; however, our model can incorporate these applications.

coming years. The cost of well drilling is expected to decrease by 20% in 10 years because of drill bit improvement. Other improvements over the next 20 years will be conversion cycle design changes, operation and maintenance reductions, and streamlining of complex instrumentation.

Geothermal is expected to grow nationally from 0.39% of current generation to 0.53% in 2020. Its share of CNV generation will shrink, from 4.5% today to 2.7% in 2020. Geothermal is not forecasted to develop in MAPP, which lacks economical GT resources.

Wind. A wind farm consists of any number of individual wind turbines and transmission lines sending the turbine power to a central station. The power-producing capability of wind varies by "wind class," a designation relating wind speed at various heights to electricity production; our study addresses classes 4 and 6. Class 4 is a low-to-moderate power class (an average wind speed of 5.6 to 6.0 meters per second at a 10-meter height, producing about 1.14 Gwh per year under standard loss assumptions), and class 6 is a higher power class (an average wind speed of 6.4 to 7.0 meters per second at a 10-meter height, producing 1.56 Gwh per year under standard assumptions). Future reductions in cost will be due to higher volume, advances in manufacturing resulting from R&D efforts, and other technology advances. R&D is expected to account for a 10% to 20% cost reduction by 2030, and production volume is anticipated to account for a 20% to 30% cost reduction. In 2001, wind generated 0.2% of power in the nation, 0.7% of power in MAPP, and almost 2% of power in CNV. By 2020, it is expected to grow to 0.3% of power nationally; in CNV and MAPP it will grow slightly but decline as a percentage of overall regional electricity generation.

Biomass. In a direct-fired biomass plant, biomass feedstock is burned in a furnace to create heat, which generates steam in the boiler. The steam turns a turbine to generate electricity. Biomass plants require systems to store the feedstock and feed it through a screen into the furnace-boiler. Although today's feedstock is mainly agricultural or forest product waste, we follow DOE/EPRI in assuming that the main fuel source in the future will be "dedicated" feedstock grown expressly for fuel.

Biomass plant cost reductions are expected mainly from realization of economies of scale. Plant efficiency is expected to increase by 20% from 2000 to 2020 as larger-scale plants permit more severe turbine operating conditions. Advances in power station performance involve the incorporation of available commercial technology. R&D is expected to focus on developing fuel additives and boiler modifications.

Biomass is used for 0.4% of power in the nation, 0.3% of power in MAPP, and 1.1% of power in CNV. By 2020 it is expected to grow to 0.5% of power nationally, 0.4% in MAPP, and 0.7% in CNV.

Cost and Other Data

Our data requirements and sources include the following:

Generation costs, renewable energy technologies. We base our cost data on the levelized cost of energy reported in DOE/EPRI (1997), which describes the technical and economic status of renewable energy options for electricity supply through the year 2030. DOE/EPRI reports, in $1997, discounted after-tax cash flows levelized to an annual payment and divided by the annual energy output to yield a cost per kilowatt hour (kWh). The costs reflect DOE/EPRI assumptions about debt, equity, taxes, inflation, and a rate of return under their definition of a generating company ownership structure. Tax credits factored in include the 10% investment tax credit for solar and geothermal, but not the production tax credits for wind or closed-loop biomass that (at the time of the publication of the estimates) were set to expire in mid-1999.

We use these data to represent the CNV region. We adjust the cost given for photovoltaics to reflect the lower solar flux in the MAPP region based on the national map of solar intensity in DOE/EPRI.[19] In addition, we do not include solar thermal and geothermal technologies for the MAPP region, since it is generally agreed that this region lacks economic resources for these technologies. We also adjust the generation cost data from $1997 to $1999 using the chained price index from the Bureau of Economic Analysis.

Generation costs, conventional and advanced CCGT. We derive the costs of capital, operation and maintenance, and fuel from the *Annual Energy Outlook 2001* (DOE/EIA 2000a). We adjust the capital and fuel costs for regional differences based on additional data given in the *Outlook.* The tax treatment of data on generation costs is comparable to that for renewable costs,

[19] We use the isomorphs in the national map to estimate the ratio of average annual flux and power produced in the MAPP region. We assume that the costs given for photovoltaics are for the best solar resources, such as CNV, and then use this ratio as a multiplier to increase the costs for MAPP in direct proportion to the reduction of intensity of solar resources for MAPP.

and upstream tax provisions affecting fuel costs are assumed to be included in generation costs.[20] Appendix 2 describes our calculations in detail. The *Outlook* also includes projections of natural gas prices. For conventional CCGT, generation costs inclusive of fuel costs based on these low, reference, and high gas prices range from 4.38 to 4.44 cents/kWh in 2005 and from 3.33 to 4.84 cents/kWh in 2020; for advanced CCGT these range from 4.16 to 4.23 cents/kWh in 2005 and from 3.27 to 4.63 cents/kWh in 2020. We compared these ranges with the parameterization of uncertainty in CCGT generation costs in the model. Our bounds for conventional CCGT in 2005 range from 4.08 to 5.03 cents/kWh, and in 2020, from 2.56 to 5.08 cents/kWh. For advanced CCGT, the bounds range from 3.98 to 4.95 cents/kWh in 2005 to 2.51 to 4.97 cents/kWh in 2020.[21] In particular, we tested whether our assumed distribution covers this range to capture uncertainty about projected fuel costs, and we found that the bounds we assume indeed bracket the *Outlook* forecasts. We thus capture the range of uncertainty reflected in the forecasts.

Externality costs. The value for the externality for carbon dioxide emissions from CCGT is from Krupnik and Burtraw (1996). The amount reflects estimated mean monetary values of impacts from environmental damages. Krupnick and Burtraw survey and assess monetary estimates from other authors' large-scale models of the health and environmental damages from electricity in the United States and Europe. Their paper represents the most recent rigorous assessment of these studies.

We estimate the value for thermal effluent from solar thermal, biomass, and CCGT by determining how much it would cost the power plant to avoid the externality entirely. Thermal pollution occurs largely through use and discharge of reject heat into streams and other water bodies. Small amounts of thermoelectric water also come from groundwater aquifers, whose degradation can therefore create an external cost. However, such groundwater is a negligible fraction of total thermoelectric water use in both our study regions and nationally (0.4% in

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[20] Scott Sitzer, Energy Information Administration, telephone call November 20, 2001. Upstream provisions include, for example, expensing of exploration and development costs for gas; exemption from passive loss limitation for working interests in gas properties; and the excess percentage depletion over cost deductions for oil and gas producers.

[21] More precisely, our bounds represent the 5% and 95% intervals from our probability distributions for characterizing uncertainty; thus, the actual bounds are somewhat lower and higher at the lower and upper ends, respectively, of the distribution.

1995).[22] Thus, we do not here consider aquifer drawdown for thermoelectric generation as a consequential externality phenomenon.

A closed-loop, dry cooling tower would avoid water use and thermal discharge. However, it increases the cost of generation in a CCGT plant by 1.5% to 3%, based on an annualized capital cost increase. Advanced CCGT, with higher conversion efficiency, may translate into reduced cooling requirements and therefore less negative thermal effects than conventional CCGT. We do not have data to make this adjustment, but in effect, it would improve the performance of advanced CCGT in our model simulations for which we include this externality.

Biomass and solar thermal are less efficient than CCGT and thus require more cooling per kWh produced. Data on the use of consumables and cooling water from DOE/EPRI indicate that solar thermal and biomass generation costs would increase by about 2% to 4% with the addition of a dry cooling system.

Generation quantity for the period 2000 to 2020. Our data on generation quantities (in kWh) for total generation, CCGT generation, and renewables generation are from DOE/EIA (2000a, reference case forecast, supplemental data). In 2010 and 2015 we subtract nuclear generation (given in DOE/EIA) from total generation. Between these years, the retirement of nuclear plants affects the total generation data. No adjustments were made to the data on CCGT generation; for these data, we generally use new gas generation as inputs in our model. Renewable generation includes conventional hydropower, geothermal, municipal solid waste, biomass, solar thermal, solar photovoltaics, and wind.[23] The generation data for individual renewable technologies are from personal communication with Christopher Namovicz (2001).[24]

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[22] See Solley et al. (1998, 51).

[23] CCGT generation and renewable generation do not sum to total generation because total generation also includes generation by coal, petroleum, nuclear except between 2010 and 2015, and other small-in-quantity fuel sources.

[24] As we were completing our research, the data for 2002 were published on-line on the EIA website. The generation forecasts were significantly revised; the national natural gas generation forecast is smaller and renewables, nuclear, and coal generation are higher because of overall increases in electricity demand, a projected decrease in natural gas generation, and improvements in the cost and performance of nuclear energy. For CNV, the 2002 forecasts more than double the 2001 forecast of that region's wind capacity by 2020 and also forecast a larger increase in geothermal capacity. MAPP generation forecasts change very little. We use the DOE/EIA data for 2001 largely as a starting point for our adoption scenarios, but we note that part of the usefulness of our model in addressing forecast variation is its formal incorporation of uncertainty.

To be consistent with the time period of our other data, we use changes in total generation for CCGT and our renewables in intervals (2000–2005, 2005–2010, 2010–2015, and 2015–2020) as the base amount to which we apply adoption rates. Specifically, we construct two such base quantities. One is the DOE/EIA (2000a) forecast for CCGT. Our rationale in using this base is to investigate the consumer surplus that might arise from switching from CCGT to our renewable technologies for the quantities indicated by our assumed adoption rates. In other words, we create additional renewable generation by applying our adoption rate to each period's new natural gas generation. Even after this quantity has been allocated to renewable generation, most new capacity still represents natural gas generation. In separate runs of the model, we also use a different base constructed as the sum of the DOE/EIA forecasts for new gas generation and new renewables generation. Because the latter is so small, our results differ very little with respect to our choice of base.

For both of the base quantities, we test the model's predictions of the fraction of renewable energy technology divided by total generation capability to see whether the ratio exceeds 15%. This 15% rule-of-thumb is consistent with the general assumption that incremental renewable energy use from photovoltaics, wind, and solar thermal will consist of intermittent rather than dispatchable, base load capacity. The 15% rule is never violated in our model runs.

A final note on our data is that we use quantities that are generated in the region. That is, we include electricity generated that will be exported, but not electricity generated that is imported and consumed in the region. Imports and exports are often seasonal in nature, and the net electricity exchange for a region can be relatively small. For example, in MAPP in 1999, imports and exports were roughly the same (13% of generation). In CNV, however, electricity imports in 1999 amounted to about 1/3 of what was produced within the region, but exports were only 1/16 of within-region production. Both regions' imports and exports decrease over time because of EIA's expectation that natural gas plants, which make up most of the new capacity, will be built closer to consumers than coal and other large plants. MAPP imports decrease to 2% of regional generation in 2020, and exports decrease to 4%. CNV imports decrease to 7% of regional generation, and exports decrease to 1%.

Personal consumption expenditure for 2000 to 2020. We created a historical (annual 1989 to 1999) PCE dataset for each region. We forecast PCE to 2020 by regressing past PCE against time (1989 to 1999). Appendix 3 contains the calculations and the regression results. National and state personal income data and national personal consumption data are from the Bureau of Economic Analysis. We combine population data from the National Association of Counties with the NEMS map from the Energy Information Administration because our electricity data are given by the NEMS electricity market module region, but there is no source for data on the corresponding populations of those regions. We used the chained price index from the Bureau of Economic Analysis to inflate the historical PCE to $1999.

Expected market price of electricity for 2000 to 2020. The price data are from the *Annual Energy Outlook 200*1 (DOE/EIA 2000a, reference case forecast) in $1999.

Data summary. Appendix 4 summarizes the data, including the median values and the probability distributions (described below).

Uncertainty

The time horizon of our study is 20 years, consistent with the time horizon in the Department of Energy modeling system. The NEMS documentation describes this duration as "the midterm period in which the structure of the economy and the nature of energy markets are sufficiently understood that it is possible to represent considerable structural and regional detail" (see DOE/EIA 2000a, assumptions to the Annual Energy Outlook 2001). DOE's reported generation costs for all of our technologies decline over time, reflecting assumptions in the DOE model with respect to learning by doing, returns to scale, and technological innovation.[25] Thus our costs decline over time, as forecast by DOE.

Even with these explicit representations of technological change in our model, the actual extent to which costs are likely to change—either increasing or decreasing—over the next 20 years is uncertain. In the case of renewable energy technologies from 1975 to 1995, McVeigh et al. (1999) find that cost declines indeed met expected goals. Additional recent research by Isoard and Soria (2001) on these costs over time in the case of photovoltaics and wind finds that future costs are likely to be highly sensitive to scale effects.[26] They find evidence of learning effects that reduce costs, but these are offset at small scales of production by diseconomies of scale. They suggest that the diseconomies may, paradoxically, indicate that marginal costs could

[25] Learning by doing represents learning effects of workers, managers, and their use of physical capital and production processes—improvements that tend to lower generation costs. Some researchers also include learning by adopters – the demand side—as a learning curve effect. Returns to scale may be increasing, constant, or decreasing, and may vary with the scale of production.

[26] See Isoard and Soria (2001) for recent research on these effects in renewable energy generation technology. For photovoltaics and wind, they find evidence of learning effects, which decrease costs, and diseconomies of scale at small scales of production, which increase costs.

increase if R&D activities lead to discovery of new applications that require further technical sophistication, increasing the unit cost of new technologies. At larger levels of output, they find economies of scale.

Because future costs in any case are uncertain, we add uncertainty bounds to the cost data. We also note, however, that our assumed adoption rates could be interpreted as learning effects of adopters, and thus we acknowledge that sorting out the relative contribution of adoption effects that are implicit in the DOE estimates (and explicit in our model) is a subject for future research.

We parameterize the point estimates for our data as location parameters of probability distributions. Because we do not have empirical bases for choosing one family of distributions over another, we use triangular distributions, which we believe appropriately characterize uncertainty and have a straightforward interpretation. We arbitrarily assign 10% of the location parameter as upper and lower bounds. In addition, we assume that uncertainty increases over time, following a standard normal distribution with mean zero and standard deviation 0.01 (1%). Uncertainty grows at about 1% each year. To illustrate some of the distributions, figure 7 shows the probability distribution we assume for CCGT and wind. Although the use of some arbitrary assumptions is unavoidable given the data and their limitations, the resulting model is very transparent, and alternative assumptions can easily be explored.

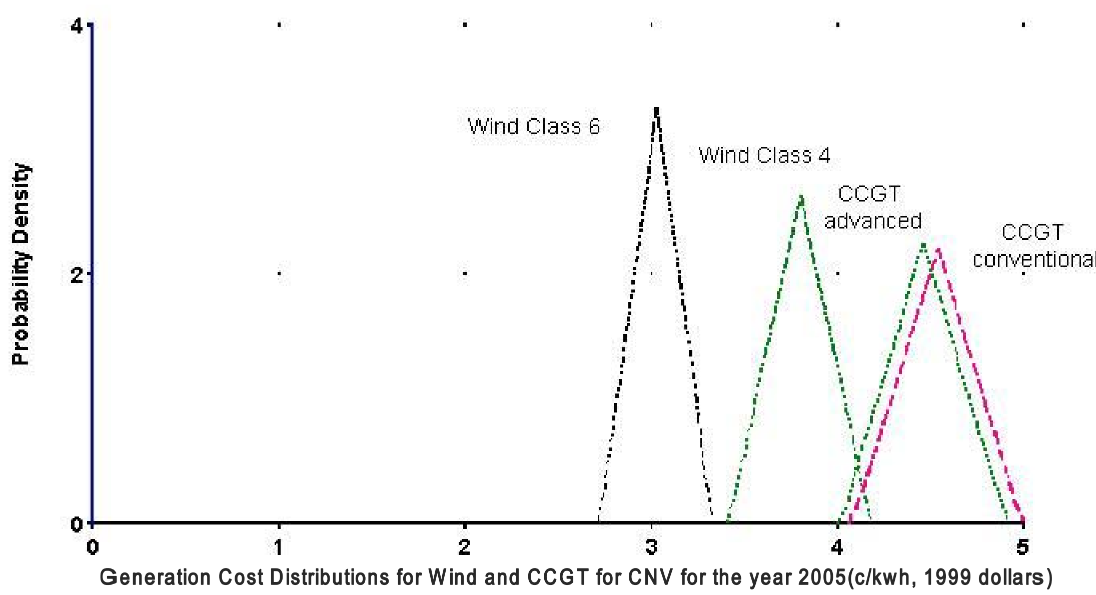

Figure 7. Wind and CCGT generation costs

Market Assumptions

Our data also reflect a specific market financial structure—that identified as a generating company, or GenCo. DOE describes this and various other financial structures, including independent power producer, municipal utility, and regulated investor-owned utility. The GenCo seems to us to be most representative of the future electricity market. According to DOE (DOE/EPRI 1997, 7-1 to 7-2),

> The GenCo takes a market-based rate of return approach to building, owning, and operating a power plant. The company uses balance-sheet or corporate finance, where debt and equity investors hold claim to a diversified pool of corporate assets. For this reason, GenCo debt and equity are less risky than for an independent power producer and therefore GenCos pay lower returns.

Our choice is based on our assumption that over the next decade, economic regulation in the electricity industry will continue to evolve toward greater competition. By 2001, roughly half the states had committed to move from traditional cost-of-service based regulation, with prices set by a regulator, toward prices determined more by market forces. The summer 2001 experience in California and its effects on deregulation are still being studied and debated, but many scholars have thus far concluded that it involved factors somewhat specific to California, such as retail price controls, and may not be a harbinger of a return to regulation (see, e.g., Brennan 2001 and Joskow and Kahn 2001).

State and Local Regulatory Practices

States and localities can implement regulations and policies that may markedly influence renewables use in the next 20 years. We did not include individual state and local effects on energy generation or use in our model (even though it can include such effects). For example, a major Minnesota utility is required, under a state statute, to commit around 550 megawatts (MW) of renewable generating capacity (425 MW of which is wind power) in the next few years. This obligation represents a *quid pro quo* under which the company's continued accumulation of radioactive waste at its nuclear power plant (beyond a mandated state deadline) will be allowed. Though it seems doubtful that Minnesota—or other states contemplating obligatory renewables commitments—would impose technology whose cost is excessive, it may also be the case that economic analysis (with or without externality considerations) may play a secondary role in the setting of mandated renewables targets. Thus, projections and eventual *ex post* evidence of a growing renewables market share might point to a policy-driven outcome not necessarily or entirely governed by comparative cost calculations. Notwithstanding the trend toward deregulation and competitive electricity markets noted in the preceding paragraph, this point serves as a qualifier to that assumption.

IV. Results

In this section we discuss our estimates of the cost index and the discounted present value of the benefits it predicts over the period 2000–2020. We make several assumptions about the rate of adoption of the technologies, whether external effects of carbon and water are included in generation costs, and the growth in electricity generation during this period. We combine these assumptions in different ways to create 17 scenarios for each of the two regions in our study. In all scenarios, we assume a 5% discount rate.

Our goal in specifying and evaluating these scenarios is twofold. One aim is to demonstrate the use of the index, together with its capability in transparently incorporating assumptions and uncertainty, as a tool with which to evaluate the performance of competing technologies. A separate but related aim from a policy perspective is using existing data to estimate the present value of the future benefits from the availability of new technologies while also taking into account continued technical progress in the defending technology.

In each scenario, we calculate indexes to compare each renewable technology with CCGT technology for the two regions. Since electricity generation costs constitute a small fraction of total personal consumption expenditures, the indexes are only slightly different from 1. On a discounted present value basis for each of our regions, however, differences in the size of consumer benefits are quite large.

Our Scenarios

Table 1 defines our scenarios. The first eight scenarios (labeled 1-CNV to 8-CNV, and 1-MAPP to 8-MAPP) involve different combinations of assumptions about adoption rates and externalities and use as a base for the quantity of new generation the DOE/EIA forecasts of CCGT generation, as described in our data section. The next four scenarios (9-CNV to 12-CNV) use a different base for the quantity of new generation, the DOE/EIA forecasts of CCGT plus renewables generation (again, see the data section). We carry out these scenarios only for the CNV region since the results suggest very little change compared with the scenarios that use the alternative base quantity (we could also carry out these scenarios for the MAPP region).

Those 12 scenarios each consist of pairwise comparisons of a renewable technology with the two variations of defending technology (conventional and advanced CCGT). In two additional scenarios (13-CNV and 13-MAPP, plus 14-CNV and 14-MAPP) we illustrate the possible use of the model to evaluate portfolios of technologies. We experiment by constructing different "renewable portfolios" that allocate some amount of future electricity generation among all the renewable technologies.

Table 1. Definitions of Scenarios

Scenario and region	*Weibull parameters* Lambda	Gamma	*External effects* Water	Carbon	Base quantity
1-CNV **1-MAPP**	.1	3.5	Yes	Yes	CCGT generation
2-CNV **2-MAPP**	.1	3.5	Yes	No	
3-CNV **3-MAPP**	.1	3.5	No	Yes	
4-CNV **4-MAPP**	.1	3.5	No	No	
5-CNV **5-MAPP**	.05	3.5	Yes	Yes	
6-CNV **6-MAPP**	.05	3.5	Yes	No	
7-CNV **7-MAPP**	.05	3.5	No	Yes	
8-CNV **8-MAPP**	.05	3.5	No	No	
9-CNV **10-CNV** **11-CNV** **12-CNV**	.1 .1 .1 .1	3.5 3.5 3.5 3.5	Yes Yes No No	Yes No Yes No	CCGT and renewables generation
Portfolios: Equal weight **13-CNV** **13-MAPP** Variable weight **14-CNV** **14-MAPP**	12 models as in 1-CNV to 12-CNV 12 models as in 1-MAPP to 12-MAPP 1 model as in 1-CNV 1 model as in 1-MAPP				CCGT generation

Scenario 1: Here, we parameterize the Weibull distribution to describe a fast adoption rate. We also include both the carbon and the water externalities. We use the EIA forecast of future electricity generation by CCGT as the base for estimating the relative shares of generation by each renewable technology and CCGT. The results for this scenario are in table 2 for scenario 1-CNV and 1-MAPP.

Table 2. Results: Scenarios 1–12

SCENARIO 1:	*Weibull: .1, 3.5* *Externalities: Carbon, water* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-13.6, -10.8, -8.04)	(-13.7, -10.9, -8.08)
Solar thermal	(-7.02, -5.38, -3.86)	(-7.17, -5.57, -3.96)
Geothermal	(2.62, 3.47, 4.45)	(2.51, 3.31, 4.26)
Wind class 4	(2.10, 2.90, 3.77)	(2.00, 2.73, 3.61)
Wind class 6	(3.50, 4.60 ,5.80)	(3.35, 4.44, 5.59)
Biomass	(-5.37, -3.99, -2.74)	(-5.46, -4.17, -2.88)
	MAPP	
Photovoltaics	(-6.40, -4.62, -2.92)	(-6.51, -4.70, -2.97)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.79, 1.18, 1.65)	(0.74, 1.09, 1.56)
Wind class 6	(1.14, 1.75, 2.41)	(1.13, 1.67, 2.31)
Biomass	(-1.61, -1.10, -0.64)	(-1.75, -1.17, -0.69)

SCENARIO 2:	*Weibull: .1, 3.5* *Externalities: Water* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology		
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-14.3, -11.5, -8.69)	(-14.5, -11.6, -8.73)
Solar thermal	(-7.71, -6.06, -4.51)	(-7.88, -6.25, -4.62)
Geothermal	(2.01, 2.86, 3.82)	(1.85, 2.67, 3.62)
Wind class 4	(1.47, 2.26, 3.16)	(1.35, 2.08, 2.98)
Wind class 6	(2.88, 3.98, 5.18)	(2.69, 3.81, 4.98)
Biomass	(-6.05, -4.65, -3.37)	(-6.17, -4.84, -3.53)
	MAPP	
Photovoltaics	(-6.61, -4.81, -3.13)	(-6.71, -4.91, -3.17)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.60, 0.99, 1.46)	(0.54, 0.90, 1.36)
Wind class 6	(0.95, 1.56, 2.21)	(0.93, 1.48, 2.11)
Biomass	(-1.82, -1.29, -0.84)	(-1.96, -1.38, -0.88)

SCENARIO 3	*Weibull: .1, 3.5* *Externalities: Carbon* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-13.9, -11.0, -8.16)	(-14.0, -11.1, -8.22)
Solar thermal	(-6.96, -5.32, -3.78)	(-7.09, -5.50, -3.90)
Geothermal	(2.50, 3.30, 4.23)	(2.35, 3.14, 4.06)
Wind class 4	(1.97, 2.72, 3.56)	(1.86, 2.55, 3.39)
Wind class 6	(3.33, 4.43, 5.57)	(3.20, 4.27, 5.39)
Biomass	(-5.28, -3.90, -2.67)	(-5.36, -4.09, -2.84)
	MAPP	
Photovoltaics	(-6.47, -4.68, -2.96)	(-6.60, -4.77, -3.00)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.75, 1.12, 1.56)	(0.69, 1.03, 1.47)
Wind class 6	(1.10, 1.70, 2.33)	(1.08, 1.61, 2.23)
Biomass	(-1.59, -1.07, -0.62)	(-1.72, -1.15, -0.66)

SCENARIO 4	*Weibull: .1, 3.5* *Externalities: None* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-14.6, -11.7, -8.87)	(-14.7, -11.9, -8.91)
Solar thermal	(-7.65, -5.99, -4.45)	(-7.79, -6.18, -4.57)
Geothermal	(1.86, 2.66, 3.59)	(1.70, 2.48, 3.39)
Wind class 4	(1.31, 2.08, 2.93)	(1.20, 1.89, 2.76)
Wind class 6	(2.74, 3.79, 4.94)	(2.57, 3.62, 4.76)
Biomass	(-5.96, -4.58, -3.32)	(-6.09, -4.78, -3.49)
	MAPP	
Photovoltaics	(-6.70, -4.88, -3.17)	(-6.82, -4.98, -3.22)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.56, 0.93, 1.38)	(0.49, 0.83, 1.28)
Wind class 6	(0.91, 1.50, 2.13)	(0.88, 1.42, 2.03)
Biomass	(-1.80, -1.27, -0.82)	(-1.93, -1.36, -0.87)

SCENARIO 5	*Weibull: .05, 3.5* *Externalities: Carbon, water* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-6.07, -4.69, -3.35)	(-6.21, -4.80, -3.39)
Solar thermal	(-2.93, -2.18, -1.49)	(-2.99, -2.24, -1.56)
Geothermal	(0.82, 1.10, 1.41)	(0.78, 1.06, 1.36)
Wind class 4	(0.68, 0.93, 1.21)	(0.64, 0.89, 1.16)
Wind class 6	(1.04, 1.40, 1.78)	(1.01, 1.35, 1.72)
Biomass	(-2.08, -1.50, -0.99)	(-2.16, -1.58, -1.05)
	MAPP	
Photovoltaics	(-3.39, -2.40, -1.47)	(-3.49, -2.47, -1.50)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.26, 0.40, 0.57)	(0.25, 0.38, 0.54)
Wind class 6	(0.35, 0.56, 0.77)	(0.34, 0.54, 0.76)
Biomass	(-0.66, -0.43, -0.23)	(-0.71, -0.47, -0.25)

SCENARIO 6	*Weibull: .05, 3.5* *Externalities: Water* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-6.46, -5.09, -3.73)	(-6.61, -5.20, -3.80)
Solar thermal	(-3.26, -2.49, -1.79)	(-3.32, -2.57, -1.86)
Geothermal	(0.65, 0.92, 1.24)	(0.60, 0.87, 1.18)
Wind class 4	(0.49, 0.75, 1.03)	(0.44, 0.69, 0.97)
Wind class 6	(0.88, 1.24, 1.62)	(0.83, 1.18, 1.55)
Biomass	(-2.41, -1.78, -1.26)	(-2.49, -1.88, -1.33)
	MAPP	
Photovoltaics	(-3.54, -2.54, -1.62)	(-3.66, -2.62, -1.64)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.20, 0.35, 0.51)	(0.19, 0.32, 0.48)
Wind class 6	(0.30, 0.51, 0.72)	(0.29, 0.49, 0.71)
Biomass	(-0.75, -0.52, -0.31)	(-0.81, -0.56, -0.34)

SCENARIO 7	*Weibull: .05, 3.5* *Externalities: Carbon* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-6.19, -4.79, -3.42)	(-6.33, -4.90, -3.49)
Solar thermal	(-2.90, -2.14, -1.46)	(-2.95, -2.22, -1.51)
Geothermal	(0.79, 1.05, 1.35)	(0.74, 1.01, 1.29)
Wind class 4	(0.63, 0.88, 1.15)	(0.60, 0.83, 1.09)
Wind class 6	(1.00, 1.35, 1.72)	(0.97, 1.31, 1.66)
Biomass	(-2.06, -1.46, -0.95)	(-2.11, -1.54, -1.03)
	MAPP	
Photovoltaics	(-3.47, -2.45, -1.50)	(-3.57, -2.51, -1.52)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.25, 0.39, 0.54)	(0.24, 0.36, 0.51)
Wind class 6	(0.34, 0.55, 0.75)	(0.33, 0.52, 0.74)
Biomass	(-0.65, -0.42, -0.22)	(-0.70, -0.45, -0.24)

SCENARIO 8	*Weibull: .05, 3.5* *Externalities: None* *Base: EIA CCGT growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-6.62, -5.22, -3.82)	(-6.76, -5.32, -3.90)
Solar thermal	(-3.23, -2.46, -1.77)	(-3.28, -2.55, -1.83)
Geothermal	(0.60, 0.87, 1.17)	(0.55, 0.81, 1.11)
Wind class 4	(0.44, 0.69, 0.96)	(0.40, 0.63, 0.90)
Wind class 6	(0.84, 1.18, 1.55)	(0.79, 1.13, 1.48)
Biomass	(-2.38, -1.76, -1.24)	(-2.44, -1.85, -1.32)
	MAPP	
Photovoltaics	(-3.62, -2.59, -1.65)	(-3.72, -2.67, -1.67)
Solar thermal	N/A	N/A
Geothermal	N/A	N/A
Wind class 4	(0.19, 0.33, 0.48)	(0.17, 0.30, 0.45)
Wind class 6	(0.29, 0.49, 0.70)	(0.28, 0.47, 0.68)
Biomass	(-0.75, -0.51, -0.31)	(-0.80, -0.55, -0.34)

SCENARIO 9	*Weibull: .1, 3.5* *Externalities: Carbon, water* *Base: EIA aggregate growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-14.6, -11.6, -8.68)	(-14.9, -11.8, -8.90)
Solar thermal	(-7.39, -5.66, -4.10)	(-7.57, -5.83, -4.28)
Geothermal	(2.72, 3.58, 4.53)	(2.59, 3.40, 4.35)
Wind class 4	(2.16, 2.97, 3.87)	(2.04, 2.80, 3.69)
Wind class 6	(3.58, 4.74, 5.94)	(3.44, 4.57, 5.78)
Biomass	(-5.55, -4.16, -2.88)	(-5.73, -4.33, -3.05)

SCENARIO 10	*Weibull: .1, 3.5* *Externalities: Water* *Base: EIA aggregate growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-15.3, -12.4, -9.39)	(-15.7, -12.6, -9.67)
Solar thermal	(-8.11, -6.35, -4.79)	(-8.32, -6.55, -4.97)
Geothermal	(2.07, 2.93, 3.90)	(1.91, 2.76, 3.69)
Wind class 4	(1.53, 2.32, 3.23)	(1.38, 2.13, 3.06)
Wind class 6	(2.98, 4.10, 5.33)	(2.79, 3.94, 5.14)
Biomass	(-6.26, -4.84, -3.55)	(-6.42, -5.04, -3.74)

SCENARIO 11	*Weibull: .1, 3.5* *Externalities: Carbon* *Base: EIA aggregate growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-14.9, -11.8, -8.84)	(-15.2, -12.0, -9.07)
Solar thermal	(-7.29, -5.58, -4.04)	(-7.48, -5.76, -4.18)
Geothermal	(2.58, 3.39, 4.30)	(2.44, 3.22, 4.13)
Wind class 4	(2.02, 2.79, 3.65)	(1.90, 2.61, 3.46)
Wind class 6	(3.47, 4.55, 5.72)	(3.30, 4.39, 5.58)
Biomass	(-5.49, -4.08, -2.80)	(-5.59, -4.25, -3.00)

SCENARIO 12	*Weibull: .1, 3.5* *Externalities: None* *Base: EIA aggregate growth* **Discounted present value, 2000–2020, $1999 billions**	
Defending technology / Innovating technology	**Conventional CCGT**	**Advanced CCGT**
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
Photovoltaics	(-15.6, -12.6, -9.57)	(-16.0, -12.8, -9.88)
Solar thermal	(-8.03, -6.29, -4.74)	(-8.21, -6.49, -4.91)
Geothermal	(1.91, 2.74, 3.64)	(1.75, 2.55, 3.47)
Wind class 4	(1.36, 2.13, 3.00)	(1.23, 1.94, 2.84)
Wind class 6	(2.83, 3.90, 5.07)	(2.66, 3.73, 4.92)
Biomass	(-6.20, -4.78, -3.49)	(-6.34, -4.96, -3.68)

For CNV, the largest of the median discounted present values of benefits are $2.9 billion for wind class 4, $3.5 billion for geothermal, and $4.6 billion for wind class 6 when these technologies are compared with conventional CCGT. The median values are slightly smaller, ranging from $2.7 billion to $4.4 billion, compared with advanced CCGT. For the other renewable technologies—photovoltaics, solar thermal, and biomass—the median values range from –$4 billion to –$10.8 billion compared with conventional CCGT and are slightly larger (and still negative) compared with advanced CCGT, ranging from –$4.2 billion to –$10.9 billion. In the case of MAPP, the median values range from $1.2 billion for wind class 4 and $1.8 billion for wind class 6, to –$1.1 billion for biomass and –$4.6 billion for photovoltaics compared with conventional CCGT. Compared with advanced CCGT, the median values for MAPP range from $1.1 billion for wind class 4 and $1.7 billion for wind class 6 to –$1.2 billion for biomass and –$4.7 billion for photovoltaics.

The influence of the distributions we have specified to characterize uncertainty in our data is indicated by the 5% and 95% interval estimates. In the scenario for CNV, the benefits could be as large as $5.8 billion for wind class 6 compared with conventional CCGT (see the 95% interval), and fall to –$13.7 billion for photovoltaics compared with advanced CCGT (see the 5% interval). For MAPP, the benefits could be as large as $2.4 billion for wind class 6 compared with conventional CCGT (see the 95% interval), and losses could increase to –$6.5 billion for photovoltaics compared with advanced CCGT (see the 5% interval). Figures 8 and 9 further illustrate the time path and intervals for the cases of photovoltaics and wind class 6 for the discounted cumulative benefit for CNV. Figures 10 and 11 display the net benefits on five-year intervals and also show the confidence regions.

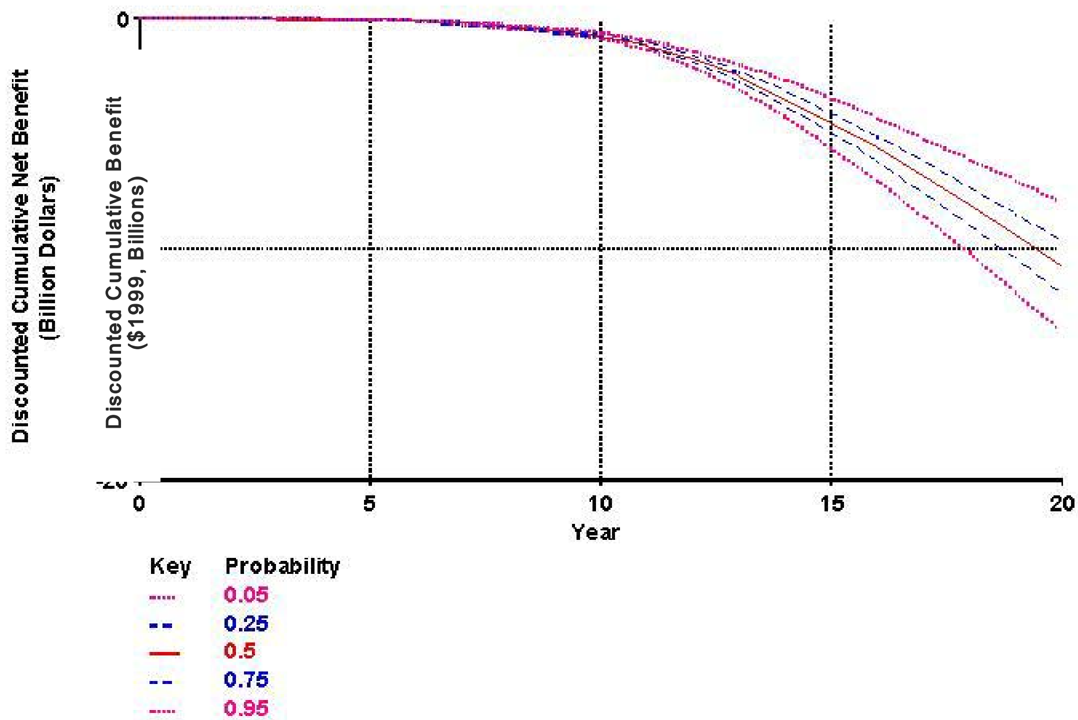

Figure 8. The present value of benefits from 2000 to 2020 for PV from scenario 1 for CNV

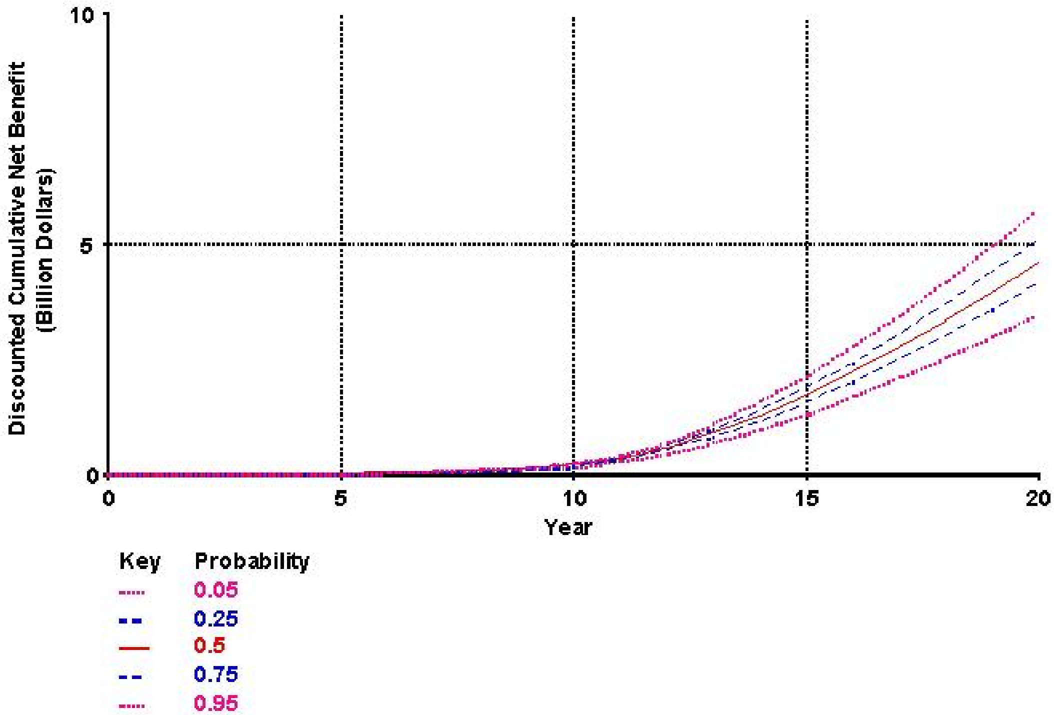

Figure 9. The present value of benefits from 2000 to 2020 for Wind Class 6 from scenario 1 for CNV

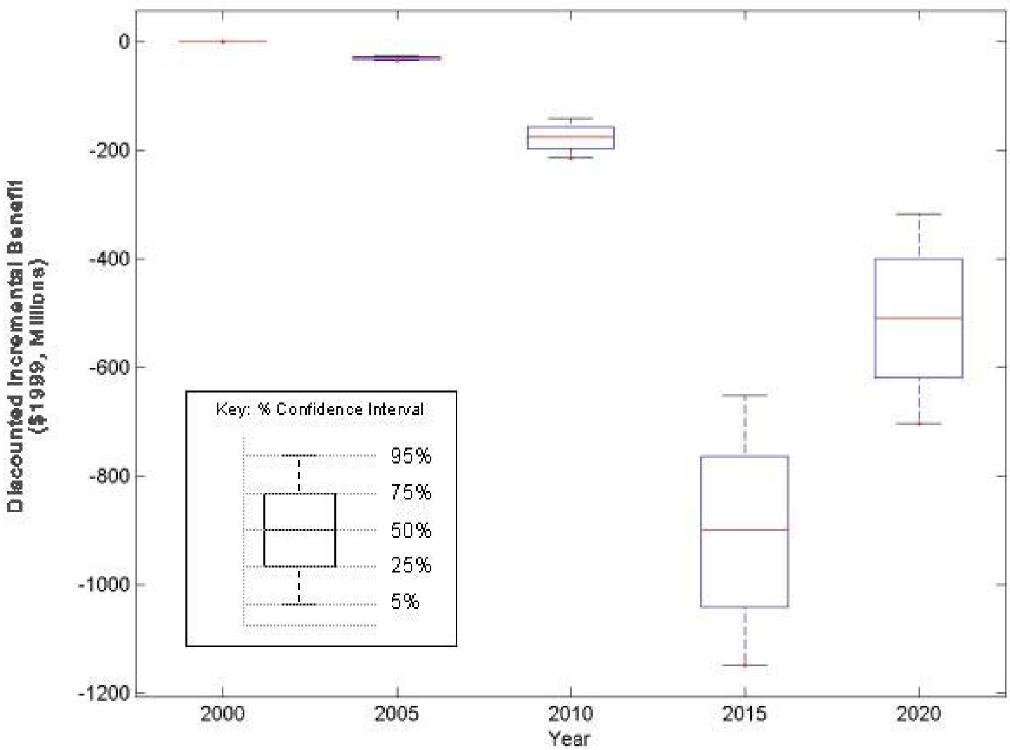

Figure 10. Discounted incremental benefits from 2000 to 2020 for PV from scenario 1 for CNV

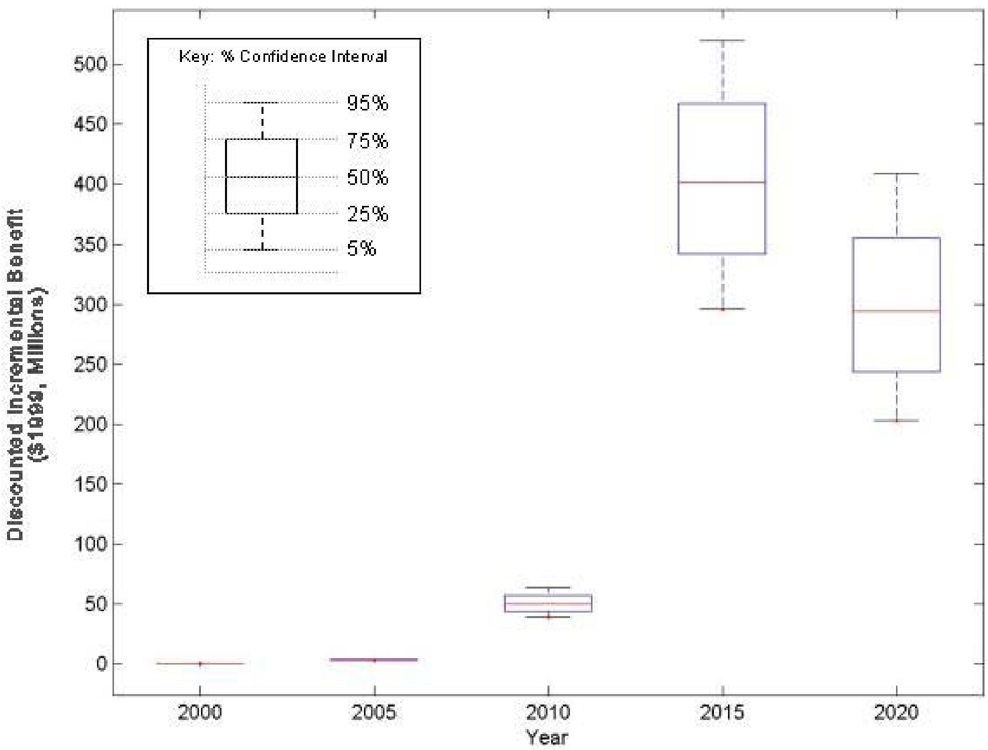

Figure 11. Discounted incremental net benefits from 2000 to 2020 for wind class 6 from scenario 1 for CNV

Scenarios 2 and 3: In these scenarios we test the sensitivity of our results to assumptions about the carbon and water externalities. In scenario 2, we omit the carbon externality, and in scenario 3, we omit the water externality. The rest of our assumptions remain as in the first scenario.

The results for these scenarios are in table 2 under scenario 2-CNV, scenario 3-CNV, scenario 2-MAPP, and scenario 3-MAPP. Because the omission of the carbon externality causes the social generation cost of CCGT to be less expensive, the estimated relative benefits from renewables decline in scenario 2 compared with scenario 1. For CNV, the largest median discounted present values of benefits are $2.3 billion for wind class 4, $2.9 billion for geothermal, and $3.9 billion for wind class 6 compared with conventional CCGT. The median values are slightly smaller when this set of renewables is compared with advanced CCGT. The values range from $2.1 billion to $3.8 billion. For the other renewable technologies the median values range from –$4.7 billion to –$11.5 billion compared with conventional CCGT and –$4.8 billion to –$11.6 billion compared with advanced CCGT. In the case of MAPP, the median values (in absolute value) follow a similar pattern with CNV in that they are smaller than in scenario 1, and smaller when the defending technology is conventional CCGT. The values range from $1 billion for wind class 4 and $1.6 billion for wind class 6 to –$1.3 billion for biomass and –$4.8 billion for photovoltaics compared with conventional CCGT. Compared with advanced CCGT, the median values for MAPP range from $0.9 billion for wind class 4 and $1.5 billion for wind class 6 to –$1.4 billion for biomass and –$4.9 billion for photovoltaics.

Under our assumed distributions to characterize uncertainty in the data, the benefits in CNV under scenario 2 could be as large as $5.2 billion for wind class 6 compared with conventional CCGT and fall to –$14.5 billion for photovoltaics compared with advanced CCGT. For MAPP, the benefits could be as large as $2.2 billion for wind class 6 compared with conventional CCGT and losses as large as –$6.7 billion for photovoltaics compared with advanced CCGT.

In scenario 3, the omission of the water externality associated with solar thermal, biomass, and both conventional and advanced CCGT technologies reduces the social generation costs of these technologies. Because this scenario does include the carbon externality associated with both CCGT technologies, however, the benefits conferred by renewables tend to increase compared with the benefits of CCGT. For CNV, the largest median discounted present values of benefits are $2.7 billion for wind class 4, $3.3 billion for geothermal, and $4.4 billion for wind class 6. These benefits are larger than those in scenario 2. The losses associated with other renewables are smaller than in scenario 2, ranging from –$3.9 billion for biomass to –$11 billion for photovoltaics. For MAPP, benefits range from $1.1 billion to $1.7 billion for the classes of wind and are around –$1.1 billion and –$4.7 billion for biomass and photovoltaics, respectively.

Given our assumptions about uncertainty, the benefits in CNV in scenario 3 could be as large as $5.6 billion for wind class 6 compared with conventional CCGT and losses on the order of –$14 billion for photovoltaics compared with advanced CCGT. For MAPP, the benefits could be as large as $2.2 billion for wind class 6 compared with conventional CCGT and losses on the order of –$6.6 billion for photovoltaics compared with advanced CCGT.

Scenario 4: Here we omit externalities in generation costs. External costs "penalize" both the defending technologies and several of the renewable technologies under our assumptions, but they penalize the defending technologies by a larger amount. For this reason, in the absence of external costs, consumer losses are likely to be larger and consumer gains are likely to be smaller than in scenario 1 (where externalities are included). From table 2 for scenario 4-CNV, the median discounted present value for photovoltaics is on the order of –$11.7 billion to –$11.9 billion. The values for wind are about $2 billion for wind class 4 and $3.6 billion to $3.8 billion for wind class 6. Losses are about –$6 billion for solar thermal and –$4.6 billion to –$4.8 billion for biomass. For scenario 4-MAPP, the value for photovoltaics is around –$4.9 billion. The values for wind are about $1.5 billion for wind class 6 and $0.9 billion for wind class 4. The value for biomass is about –$1.3 billion. The uncertainty bounds indicate that losses could be as large as –$6.8 billion for photovoltaics and benefits as large as $2.1 billion for wind class 6 in MAPP, with losses of –$14.7 billion for photovoltaics or benefits as large as $4.9 billion for wind class 6 in CNV.

External costs differ among renewables and in turn affect their relative performance. For example, comparing the results of this scenario with those of scenario 1 demonstrates that the losses under photovoltaics narrow relative to those of solar thermal when external costs associated with the latter technology are excluded. The relative difference is not large, however—on the order of 2% to 3%.

Scenarios 5–8: In these scenarios we use a slower adoption rate than in the four preceding scenarios but maintain our other assumptions. For scenario 5, the other assumptions are identical to those in scenario 1; scenario 6 corresponds to scenario 2; scenario 7 corresponds to scenario 3; and scenario 8 corresponds to scenario 4.

The overall effect of a slower adoption rate is to reduce substantially both the gains and the losses associated with renewables (see table 2, scenarios 5–8-CNV). The changes reduce the gains and losses by 50% to 70% in CNV and 40% to 65% in MAPP. In both regions, the reductions are slightly larger compared with conventional CGGT than with advanced CCGT, and are slightly larger for wind and biomass than for the other renewables. The relative differences in the value of the estimates at the median and 5% and 95% intervals are also smaller under slower adoption rates because uncertainty grows over time in the model.

Scenarios 9–12: In these scenarios, which we model only for CNV, we change our measure of expected growth in generation capacity. We use the DOE (DOE/EIA 2000a) total forecasted increase in generation capacity for both CCGT and renewables as the basis to which we apply the adoption rate. Our other assumptions are as in scenarios 1–4. Because we assume that no individual renewable energy technology will comprise more than 15% of total new generation capacity, we checked the quantities that are forecasted using this alternative basis to make sure the capacity assumption was not violated. We use data in DOE/EIA (2000a) for generation capacity from 2000 to 2020 for each region. The largest percentage share of renewables occurs in 2015, when the share is about 6% (see table 3).

In these scenarios, because the quantity of renewable capacity that is added to the base is so small, the overall effect of the alternative base is to increase both the gains and the losses by less than 10% (largest in the case of photovoltaics) and typically on the order of 1% to 2% (see table 2, scenarios 9–12-CNV).

Table 3. Percentage Share of Renewable Energy in Total Generation Capacity

Base		**2000–05**	**2005–10**	**2010–15**	**2015–20**
CCGT					
	CNV	.04	.7	6.0	5.0
	MAPP	.0005	.8	6.0	3.0
CCGT + Renew					
	CNV	.1	.8	6.0	5.0
	MAPP	.008	.8	6.0	3.0

Scenarios 13–14. In another exercise of the model we construct hypothetical renewable "portfolios." We ask, "What surplus values are predicted by combining renewable technologies?" In scenarios 13-CNV and 13-MAPP we assume that an equal fraction of expected new generation will be supplied by each of the renewables. In scenarios 14-CNV and 14-MAPP we assign different fractions to the share of each renewable to obtain a positive consumer surplus. In the equal-weight renewable portfolio (EQWTRP), the fraction is 1/6. In the variable-weight case (VARWTRP), the fractions for CNV and MAPP are as follows:

	PV	**ST**	**GT**	**Wind 4**	**Wind 6**	**Biomass**
CNV:	.034	.083	.25	.25	.3	.083
MAPP:	.025	N/A	N/A	.475	.475	.025

We use equal-weighted portfolios under each set of assumptions as in scenarios 1–12, generating 24 additional sets of results for both regions. Table 4 shows the results that give the largest surplus for both the equal- and variable-weight portfolios. Under equal weights, the surplus values are negative under all sets of assumptions. The negative values are smallest when adoption rates are slow and both externalities are included. In this case, the discounted surplus is about –$ 1.1 billion to –$1.2 billion for CNV and –$.7 billion to –$.8 billion for MAPP. It is smallest (in absolute value) in comparison with conventional CCGT. It might be expected that the more expensive renewables in the portfolio offset the cost advantages of less expensive renewables to generate the negative value. It is less easy to predict, however, that the offset would be smaller when the adoption rate is slower since the same adoption rate applies to all renewables (even those that are less expensive than CCGT). The offset is also smaller when all externalities are included, even though some of the externalities increase the costs of some renewables relative to others and relative to CCGT.

Under the variable weights that favor some renewables, a portfolio can generate positive surplus values. The largest surplus values under our assumptions are $0.68 billion to $0.84 billion for CNV and $0.8 billion to $0.9 billion for MAPP. The assumptions that lead to these results requiring weighting wind heavily, fast adoption, and inclusion of both externalities.

Our approach to applying the model to a portfolio of renewables is, at this stage in our research, limited to exogenous specifications of the weights in the portfolio. In future research we would like to make the allocation of the portfolio an endogenously specified solution to an optimization problem that maximizes consumer benefit.

Table 4. Largest Surplus Gains under an Exogenously Specified "Portfolio"

Discounted present value 2000–2020, $1999 billions

Base: EIA CCGT growth

	CNV (5%, median, 95%)	**MAPP (5%, median, 95%)**	**Assumptions**
EQWTRP			Weibull: .05, 3.5 External effects: Carbon, water
C-CCGT	(-1.54, -1.11, -0.72)	(-1.07, -0.72, -0.42)	
A-CCGT	(-1.63, -1.20, -0.77)	(-1.13, -0.79, -0.78)	
VARWTRP			Weibull: .1, 3.5 External effects: Carbon, water
C-CCGT	(0.41, 0.84, 1.28)	(0.59, 0.92, 1.25)	
A-CCGT	(0.22, 0.68, 1.11)	(0.56, 0.83, 1.17)	

Overview of Results

In present-value terms we find that median consumer welfare gains over 20 years vary markedly among the renewable technologies, ranging from large negative values (welfare losses) for some of the technologies to large positive values (welfare gains). The sizes of these effects, their sensitivity to adoption rates and inclusion of externalities, and their regional differences would be difficult to predict without the framework offered by our model. Our modeling assumptions, limits, and data, as described earlier, are an important context for our results, and these factors also serve as caveats in discussion of our results.

In scenarios 1 through 8, the largest gains for both regions occur under scenario 1, under our assumptions of fast adoption and inclusion of external effects. For CNV, wind class 6 gives the largest gains, followed by geothermal and then wind class 4. For MAPP, the largest gains are wind class 6, and then wind class 4. Photovoltaics, solar thermal, and biomass technologies generate welfare losses under all assumptions, with the largest losses from scenario 4 in the case of photovoltaics, with fast adoption and no external costs. Losses are also large in scenario 2, which assumes fast adoption and adds no carbon externality to the generation costs of CCGT.

Although the ranking of the renewable technologies based on our measure of consumer surplus might be consistent with what we would expect based on the sizes of their private and social generation costs, it is less easy to predict *a priori* the relative ranking of performance under different assumptions about externalities. For example, our results show that including a carbon and water externality can improve the relative performance of renewables; including a water externality but not a carbon externality gives results very similar to no externality at all; and including water but not carbon worsens the relative performance of solar thermal and biomass compared with CCGT, even though there is also a water externality associated with CCGT. We find this pattern of results whether we use estimates of new CCGT generation as a base from which to forecast renewables adoption, or whether we use estimates of new CCGT plus renewables generation as a base.

Our results for portfolios of renewables suggest that equal portfolio weights (represented as adopted quantities) are likely to lead to consumer losses in our regions, regardless of the role of externalities. However, when the portfolio is weighted toward renewables that give positive surplus values in pairwise comparisons with conventional and advanced CCGT, consumer gains can be positive. But these portfolio gains are substantially smaller than under scenarios involving adoption only of renewable technologies that confer positive surpluses in pairwise comparisons with CCGT. The different allocations in the variable-weight portfolios for CNV and MAPP illustrate the usefulness of models that can be separately evaluated on a regional basis rather than nationally aggregated.

Our results also indicate the importance of considering technical innovation in the defending technology. Holding all other assumptions constant, we find that surplus values are overstated by around 5% when renewables do not contend with innovation in CCGT.

The effect of uncertainty can lead to estimates that are 20% to 40% larger or smaller than median predicted values. These are rather large differences, even though our uncertainty bounds are rather small (plus or minus 10% of the reported data values). But the effects of uncertainty increase as the time period extends into the future. The importance of allowing for uncertainty suggests that frequently updated or improved data could improve understanding of the future relative performance of the technologies, particularly when uncertainty may arise because of data gaps (for example, in measures of the externalities). These results also suggest that comparing future scenarios without taking uncertainty into account could lead to misleading conclusions.

On a per capita basis for the two regions, the discounted median present value of consumer surplus resulting in the largest potential gains is about $139 for CNV and $150 for MAPP (from scenario 1 in the case of wind class 6). Multiplying our per capita surplus by 4 (assuming four persons per household) gives a surplus per household of $556 in CNV and $600 in MAPP. For rough comparison, annual household expenditures on electricity are about $388 in CNV and $378 in MAPP. The discounted, 20-year value of the surplus, then, is about 40% to 50% more than one year's electricity expenditure by a household. Or, as an alternative comparison, these amounts are roughly the average "tax rebate" given to U.S. households during summer 2001. For the small positive surplus under the variable-weight portfolio, the savings per household is about $111 in CNV and $300 in MAPP.

V. Conclusions

We seek to offer a conceptually sound but readily implemented approach to considering a dimension of evaluating public investment in energy generation innovation—that of measuring consumer surplus. We develop our approach using a cost index that is well grounded in demand theory and develop a simulation model to estimate the value of the index and the consumer surplus it predicts over the period 2000–2020, for two regions of the country. Where data are available, we explicitly incorporate the value of externalities that may be associated with our technologies. Because we forecast future consumer benefits, we also include model uncertainty by parameterizing inputs with probability distributions and using standard procedures for drawing randomly from these distributions in running the model. Although the usual demand elasticities are explicit in the cost index, we use hypothesized adoption rates, described by the

Weibull function, to characterize how future market demand will evolve during the 20-year period.

Our approach has several limitations. From a conceptual perspective, the model does not allow power companies to optimize their choice of power generation technologies by choosing a mix of technologies based on costs or other factors (consumers' desire to purchase green power, say); then allow consumers to respond to this mix; and then further adjust supply and demand to obtain a market equilibrium. Rather than this general equilibrium approach, our model involves more modest pairwise comparisons of conventional and new technologies. It has the virtue, by way of the cost index, of incorporating the elasticity parameters that are the key to a general equilibrium approach, but it does not allow iteration between demand and supply in endogenously reaching equilibrium. Our model's structure does allow us exogenously to construct hypothetical portfolios of combinations of energy generation technologies (either proposed by government or reached by hypothesizing a general equilibrium) and then evaluate future consumer benefits. In this regard, the approach could also be a useful tool for informing discussion about energy portfolios. In a future extension of the model, we would like to allow for endogenous optimization of the portfolio.

We would also like to extend the model to forecast other types of benefits, including those singled out in a recent National Research Council report (2001) on the costs and benefits of energy research. These other benefits include the extent to which research projects have commercialization potential (a benefit we have considered in previous applications of our model to other technological innovation (see Austin and Macauley 2000 and 2001) or lead to improvements in knowledge that in turn contribute to new products or services "spun off" from the original innovation. As the National Research Council study emphasizes, a broad array of benefits, taken together, can serve as a tool for measuring returns to a portfolio of individual energy R&D initiatives. In such a portfolio (used here in an investment sense, and thus with a different meaning than in the paragraph above), some projects may perform better than others, but collectively the portfolio may confer positive benefit.

Our model is also limited by data about external effects associated with energy generation. The literature has advanced furthest in quantifying the social costs of carbon emissions from fossil-fuel electricity generation, and we rely heavily on this literature. The literature is less developed in discussion of other effects, such as thermal discharges associated with fossil-fuel and some renewable technologies. We make our best guess about the cost of this effect in our study. The literature is even less advanced in assessing the social costs of other externalities associated with renewables, although there is ample discussion of the possible physical effects of, say, wind turbines on bird populations, including in some cases scientific studies of the magnitude of these physical effects.

With those caveats in mind, we believe that the model provides useful guidance for decisionmakers and researchers alike. Our results illustrate the usefulness of the framework to test assumptions and evaluate scenarios with respect to their implications for consumer surplus and indicate the extent to which different renewable technologies may be more or less promising in their contribution to surplus. In addition, the model complements proposals for assessing the "energy contribution potential" of renewable energy technologies by offering an assessment approach somewhat analogous to that taken for conventional energy supplies (i.e., the assessment of energy resources, accessible resources, and reserves; see Bath 1999). By adding the external effects of technologies, our model allows a more complete evaluation of overall welfare results of improving renewable technology performance.

Finally, even though we measure only gross surplus, our estimates do shed some light on overall public net benefits. We do not subtract the cost of public R&D energy expenditures to date, nor do we include future public expenditures that could be necessary to bring about the adoption rates we posit. Over the 20 years 1978–98, in 1999 dollars, federal R&D spending on renewable energy (predominantly in electricity generation applications) totaled around $13 billion, the largest proportion of which was allocated to solar photovoltaics (roughly $2.5 billion) and wind power ($1.5 billion).[27] However, if our gross benefit estimates are in the ballpark, at least part of this spending could be recouped over the next 20 years by consumer surplus accruing to the regions we study. Whether that level of government expenditure was too much, too little, or just about right is a matter that deserves a close look but is well beyond the scope of this paper.

[27]U.S. General Accounting Office (1999). The numbers in the GAO report are in current dollars, converted here to constant dollars using the relationship of current-dollar and constant-dollar gross domestic product for the 20-year period. The GDP numbers appear in the *Economic Report of the President 2001*.

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Appendix 1. Forecast Information from the Department of Energy

Electricity generation from natural gas

Natural gas	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of region's new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	412	1587	12%	33%	86%	285%
CNV	62	161	31%	47%	67%	159%
MAPP	1.8	39	1%	18%	78%	2102%

Electricity generation from photovoltaics

PV	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of region's new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	0.05	1.36	0.002%	0.03%	0.1%	2476%
CNV	0.04	0.45	0.02%	0.13%	0.3%	974%
MAPP	0	0	0	0	0	0

Electricity generation from solar thermal

ST	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of region's new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	0.89	1.37	0.03%	0.03%	0.04%	53%
CNV	0.89	1.06	0.5%	0.3%	0.12%	19%
MAPP	0	0	0	0	0	0

Electricity generation from geothermal

GT	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of region's new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	13.6	25.8	0.39%	0.53%	0.9%	90%
CNV	8.97	9.08	4.5%	2.7%	0.06%	1%
MAPP	0	0	0	0	0	0

Electricity generation from wind

Wind	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	6.6	13.1	0.2%	0.3%	0.5%	98%
CNV	3.5	3.7	1.8%	1.1%	0.1%	5.6%
MAPP	1.1	1.4	0.7%	0.6%	0.5%	22%

Electricity generation from biomass

Biomass	*Generation, billion kWh*		*Percentage of region's electricity*		*Percentage of region's new electricity*	*Growth*
	2001	*2020*	*2001*	*2020*	*2001–2020*	*2001–2020*
U.S.	13.6	22.1	0.4%	0.5%	0.6%	63%
CNV	2.25	2.25	1.1%	0.7%	0%	0%
MAPP	0.43	0.92	0.3%	0.4%	1%	114%

Appendix 2. Derivation of CCGT Generation Costs

Our calculations are as follows:

1. Capital costs. By working back from DOE/EIA (2000, *Annual Energy Outlook 2001,* advanced reference case numbers for 2005 and 2020, 78), we estimate a capital recovery factor of around 15% and an annual load factor of around 80%. For example, for conventional CCGT in 2005, the assumptions are a cost of (\$440/kw)(15%)/6950 hours = 0.95 cents/kWh. Other estimates are similarly derived. We multiply the capital costs by 1.004 for MAPP and 1.058 for CNV, which are the regional construction cost adjustments (for power plant construction labor and other cost differences) given in DOE/EIA (2000).

2. Operation and maintenance (O&M) costs. For advanced CCGT, the reference case numbers published in DOE/EIA (2000, 75) of 0.19 cents/kWh are applied across all years. Conventional CCGT O&M is derived from DOE/EIA assumptions data (2000, 69), which indicate no difference between conventional and advanced CCGT with respect to the variable component of O&M costs but show a slightly higher fixed cost for the conventional version. Fixed O&M represent approximately 73% of total O&M in the advanced case. Assuming the same ratio for conventional, we multiply the percentage increase (from advanced to conventional) in fixed O&M, by the percentage of fixed O&M to total O&M, by the 0.19 cents/kWh. This resulted in a 0.20 cent/kWh estimate of conventional CCGT O&M.

3. Fuel costs. We use the DOE/EIA (2000) advanced CCGT reference case numbers for 2005 and 2020 (\$0.0279/kWh and \$0.0252/kWh, respectively). Intermediate years were interpolated linearly. We multiply the fuel costs by the regional natural gas price multipliers given in the DOE/EIA (2000) supplement to adjust for regional fuel cost differences. Note that the gas multipliers are given by census region. We matched census region WNC to EMM region MAPP and likewise Pacific to CNV.

Appendix 3. Estimates of Personal Consumption Expenditure

For each year, for each state in a region, we calculate the product of state per capita personal income by the midyear population in that state, the percentage of the state's population that lives within the regional boundaries, and the ratio of national personal consumption expenditures to national personal income for that year (which ranged from .65 to .67). Then we add each state's contribution to obtain a regional PCE for each year. To forecast PCE for future years, we use the following regression results:

Personal consumption expenditure regression results

$PCE_t = a + bt$

t = 1989 to 1999

CNV REGION:

The REG Procedure
Model: MODEL1
Dependent Variable: PCE

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	21695	21695	53.36	<.0001
Error	9	3659.03964	406.55996		
Corrected Total	10	25354			

Root MSE	20.16333	R-Square	0.8557
Dependent Mean	558.70909	Adj R-Sq	0.8396
Coeff Var	3.60891		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	474.44727	13.03902	36.39	<.0001
year	1	14.04364	1.92250	7.30	<.0001

MAPP region

The REG Procedure
Model: MODEL1
Dependent Variable: pce

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	4158.62290	4158.62290	275.60	<.0001
Error	9	135.80365	15.08929		
Corrected Total	10	4294.42655			

Root MSE	3.88449	R-Square	0.9684
Dependent Mean	181.91872	Adj R-Sq	0.9649
Coeff Var	2.13529		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	145.02694	2.51198	57.73	<.0001
year	1	6.14863	0.37037	16.60	<.0001

Appendix 4. Data Description

Model Parameters

Variables (units)	*Parameterization (CNV)*		*Parameterization (MAPP)*	
Gencosts00 (c/kWh, $1999)	Photovoltaic	Triangular(27.47,30.52,33.57)	Photovoltaic	Triangular(42.58,47.31,52.04)
	Solar Thermal	Triangular(10.91,12.13,13.34)	Solar Thermal	NA
	Hydro/Geothermal (Binary)	Triangular(3.33,3.7,4.07)	Hydro/Geothermal (Binary)	NA
	Wind Class 4	Triangular(3.98,4.42,4.86)	Wind Class 4	Triangular(3.98,4.42,4.86)
	Wind Class 6	Triangular(3.14,3.49,3.84)	Wind Class 6	Triangular(3.14,3.49,3.84)
	Direct-fired Biomass	Triangular(6.94,7.71,8.48)	Direct-fired Biomass	Triangular(6.94,7.71,8.48)
	CCGT (conventional)	Triangular(4.17,4.63,5.09)	CCGT (conventional)	Triangular(3.78,4.2,4.62)
	CCGT (advanced)	Triangular(4.12,4.58,5.03)	CCGT (advanced)	Triangular(3.75,4.16,4.58)
Gencosts05 (c/kWh, $1999)	Photovoltaic	Triangular(21.6,24,26.4)	Photovoltaic	Triangular(33.47,37.19,40.91)
	Solar Thermal	Triangular(8.97,9.97,10.97)	Solar Thermal	NA
	Hydro/Geothermal (Binary)	Triangular(3.01,3.34,3.67)	Hydro/Geothermal (Binary)	NA
	Wind Class 4	Triangular(3.42,3.8,4.18)	Wind Class 4	Triangular(3.42,3.8,4.18)
	Wind Class 6	Triangular(2.73,3.03,3.33)	Wind Class 6	Triangular(2.73,3.03,3.33)
	Direct-fired Biomass	Triangular(6.71,7.45,8.2)	Direct-fired Biomass	Triangular(6.71,7.45,8.2)
	CCGT (conventional)	Triangular(4.08,4.54,4.99)	CCGT (conventional)	Triangular(3.82,4.24,4.66)
	CCGT (advanced)	Triangular(4.02,4.46,4.91)	CCGT (advanced)	Triangular(3.76,4.17,4.59)
Gencosts10 (c/kWh, $1999)	Photovoltaic	Triangular(15.72,17.47,19.22)	Photovoltaic	Triangular(24.37,27.08,29.79)
	Solar Thermal	Triangular(7.03,7.81,8.59)	Solar Thermal	NA
	Hydro/Geothermal (Binary)	Triangular(2.68,2.98,3.28)	Hydro/Geothermal (Binary)	NA
	Wind Class 4	Triangular(2.87,3.19,3.5)	Wind Class 4	Triangular(2.87,3.19,3.5)
	Wind Class 6	Triangular(2.31,2.57,2.83)	Wind Class 6	Triangular(2.31,2.57,2.83)
	Direct-fired Biomass	Triangular(6.47,7.19,7.91)	Direct-fired Biomass	Triangular(6.47,7.19,7.91)
	CCGT (conventional)	Triangular(3.6,4,4.4)	CCGT (conventional)	Triangular(3.71,4.12,4.54)
	CCGT (advanced)	Triangular(3.55,3.94,4.34)	CCGT (advanced)	Triangular(3.64,4.04,4.45)
Gencosts15 (c/kWh, $1999)	Photovoltaic	Triangular(12.58,13.98,15.37)	Photovoltaic	Triangular(19.5,21.66,23.83)
	Solar Thermal	Triangular(6.84,7.60,8.37)	Solar Thermal	NA
	Hydro/Geothermal (Binary)	Triangular(2.59,2.88,3.17)	Hydro/Geothermal (Binary)	NA
	Wind Class 4	Triangular(2.77,3.08,3.39)	Wind Class 4	Triangular(2.77,3.08,3.39)
	Wind Class 6	Triangular(2.27,2.52,2.77)	Wind Class 6	Triangular(2.27,2.52,2.77)
	Direct-fired Biomass	Triangular(5.92,6.58,7.23)	Direct-fired Biomass	Triangular(5.92,6.58,7.23)
	CCGT (conventional)	Triangular(3.52,3.91,4.31)	CCGT (conventional)	Triangular(3.87,4.3,4.73)
	CCGT (advanced)	Triangular(3.45,3.84,4.22)	CCGT (advanced)	Triangular(3.75,4.17,4.59)
Gencosts20 (c/kWh, $1999)	Photovoltaic	Triangular(9.43,10.48,11.53)	Photovoltaic	Triangular(14.62,16.25,17.87)
	Solar Thermal	Triangular(6.66,7.4,8.14)	Solar Thermal	NA
	Hydro/Geothermal (Binary)	Triangular(2.5,2.77,3.05)	Hydro/Geothermal (Binary)	NA
	Wind Class 4	Triangular(2.68,2.98,3.28)	Wind Class 4	Triangular(2.68,2.98,3.28)
	Wind Class 6	Triangular(2.22,2.47,2.71)	Wind Class 6	Triangular(2.22,2.47,2.71)
	Direct-fired Biomass	Triangular(5.36,5.96,6.56)	Direct-fired Biomass	Triangular(5.36,5.96,6.56)
	CCGT (conventional)	Triangular(3.45,3.83,4.21)	CCGT (conventional)	Triangular(3.78,4.2,4.62)
	CCGT (advanced)	Triangular(3.36,3.73,4.1)	CCGT (advanced)	Triangular(3.65,4.05,4.46)
Tfactor (% per year)	Normal(0.0, 0.01)		Normal(0.0, 0.01)	
Water externality (%)	Photovoltaic	0.00	Photovoltaic	0.00
	Solar Thermal	Triangular(2,3,4)/100	Solar Thermal	Triangular(2,3,4)/100
	Hydro/Geothermal (Binary)	0.00	Hydro/Geothermal (Binary)	0.00
	Wind Class 4	0.00	Wind Class 4	0.00
	Wind Class 6	0.00	Wind Class 6	0.00
	Direct-fired Biomass	Triangular(2,3,4)/100	Direct-fired Biomass	Triangular(2,3,4)/100
	CCGT (conventional)	Triangular(1.5,2.25,3)/100	CCGT (conventional)	Triangular(1.5,2.25,3)/100
	CCGT (advanced)	Triangular(1.5,2.25,3)/100	CCGT (advanced)	Triangular(1.5,2.25,3)/100
Fossil emissions cost (mills/kWH)	Photovoltaic	0.00	Photovoltaic	0.00
	Solar Thermal	0.00	Solar Thermal	0.00
	Hydro/Geothermal (Binary)	0.00	Hydro/Geothermal (Binary)	0.00
	Wind Class 4	0.00	Wind Class 4	0.00
	Wind Class 6	0.00	Wind Class 6	0.00
	Direct-fired Biomass	0.00	Direct-fired Biomass	0.00

	CCGT (conventional)	Triangular(2.7,3,3.3)	CCGT (conventional)	Triangular(2.7,3,3.3)
	CCGT (advanced)	Triangular(2.7,3,3.3)	CCGT (advanced)	Triangular(2.7,3,3.3)
Pricetime (cents/kWh)	2000	10.36 *(1+Tfactor*time)	2000	5.60 *(1+Tfactor*time)
	2005	8.35 *(1+Tfactor*time)	2005	5.22 *(1+Tfactor*time)
	2010	6.91 *(1+Tfactor*time)	2010	5.22 *(1+Tfactor*time)
	2015	6.99 *(1+Tfactor*time)	2015	5.21 *(1+Tfactor*time)
	2020	7.16 *(1+Tfactor*time)	2020	5.13 *(1+Tfactor*time)
Ccgtgenincr (billion kWh)	2000	0	2000	0
	2005	Triangular(((65.52-62.25)*0.9),(65.52-62.25),((65.52-62.25)*1.1))	2005	Triangular(((1.81-1.8)*0.9),(1.81-1.8),((1.81-1.8)*1.1))
	2010	Triangular(((73.39-65.52)*0.9),(73.39-65.52),((73.39-65.52)*1.1))	2010	Triangular(((5.52-1.81)*0.9),(5.52-1.81),((5.52-1.81)*1.1))
	2015	Triangular(((119.5-73.39)*0.9),(119.5-73.39),((119.5-73.39)*1.1))	2015	Triangular(((27.31-5.52)*0.9),(27.31-5.52),((27.31-5.52)*1.1))
	2020	Triangular(((161-119.5)*0.9),(161-119.5),((161-119.5)*1.1))	2020	Triangular(((39.46-27.31)*0.9),(39.46-27.31),((39.46-27.31)*1.1))
Totgencap4cast (billion kWh)	2000	Triangular((197.6*0.9),197.6,(197.6*1.1))	2000	Triangular((162.9*0.9),162.9,(162.9*1.1))
	2005	Triangular((208.3*0.9),208.3,(208.3*1.1))	2005	Triangular((185*0.9),185,(185*1.1))
	2010	Triangular((254.5*0.9),254.5,(254.5*1.1))	2010	Triangular((193.8*0.9),193.8,(193.8*1.1))
	2015	Triangular((300.7*0.9),300.7,(300.7*1.1))	2015	Triangular((219.0*0.9),219.0,(219.0*1.1))**
	2020	Triangular((342.6*0.9),342.6,(342.6*1.1))	2020	Triangular((231.5*0.9),231.5,(231.5*1.1))**
Renewbase4cast (billion kWh)	2000	Triangular((53.64*0.9),53.64,(53.64*1.1))	2000	Triangular((17.18*0.9),17.18,(17.18*1.1))
	2005	Triangular((59.42*0.9),59.42,(59.42*1.1))	2005	Triangular((18.77*0.9),18.77,(18.77*1.1))
	2010	Triangular((59.87*0.9),59.87,(59.87*1.1))	2010	Triangular((18.73*0.9),18.73,(18.73*1.1))
	2015	Triangular((59.96*0.9),59.96,(59.96*1.1))	2015	Triangular((18.7*0.9),18.7,(18.7*1.1))
	2020	Triangular((60.1*0.9),60.1,(60.1*1.1))	2020	Triangular((18.67*0.9),18.67,(18.67*1.1))
Ccgtbase4cast (billion kWh)	2000	Triangular((62.25*0.9),62.25,(62.25*1.1))	2000	Triangular((1.8*0.9),1.8,(1.8*1.1))
	2005	Triangular((65.52*0.9),65.52,(65.52*1.1))	2005	Triangular((1.81*0.9),1.81,(1.81*1.1))
	2010	Triangular((73.39*0.9),73.39,(73.39*1.1))	2010	Triangular((5.52*0.9),5.52,(5.52*1.1))
	2015	Triangular((119.5*0.9),119.5,(119.5*1.1))	2015	Triangular((27.31*0.9),27.31,(27.31*1.1))
	2020	Triangular((161*0.9),161,(161*1.1))	2020	Triangular((39.46*0.9),39.46,(39.46*1.1))
Basepce1 (billion $1999)	2000	Normal(6.429e+011,2.017e+010)	2000	Normal(2.188e+011,3.880e+009)
	2005	Normal(7.131e+011,5.803e+010)	2005	Normal(2.496e+011,1.691e+010)
	2010	Normal(7.833e+011,1.029e+011)	2010	Normal(2.803e+011,3.301e+010)
	2015	Normal(8.535e+011,1.548e+011)	2015	Normal(3.111e+011,5.218e+010)
	2020	Normal(9.237e+011,2.137e+011)	2020	Normal(3.418e+011,7.443e+010)