Measuring the Potential of Renewable Energy

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Abstract

In this paper we measure the expected consumer welfare gains from innovation in electricity generation technologies. 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 evaluate renewable energy technologies used to generate electricity and for each, we assume an accelerated adoption rate due to technological advances. 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 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

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I. Introduction

In this paper we measure the performance of 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. 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 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 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 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 discuss 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 Simulation Model

We construct a computer-based model to estimate consumer surplus using Monte Carlo techniques. We use probability distributions, rather than point estimates, to characterize uncertainty. The model is implemented using Analytica, a software package optimized for conducting uncertainty analysis.

Figure 1 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 of the technologies in power generation. The measure itself is the ratio of two alternative outcomes: generation costs weighted by the shares of consumer expenditure 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 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 surplus 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.

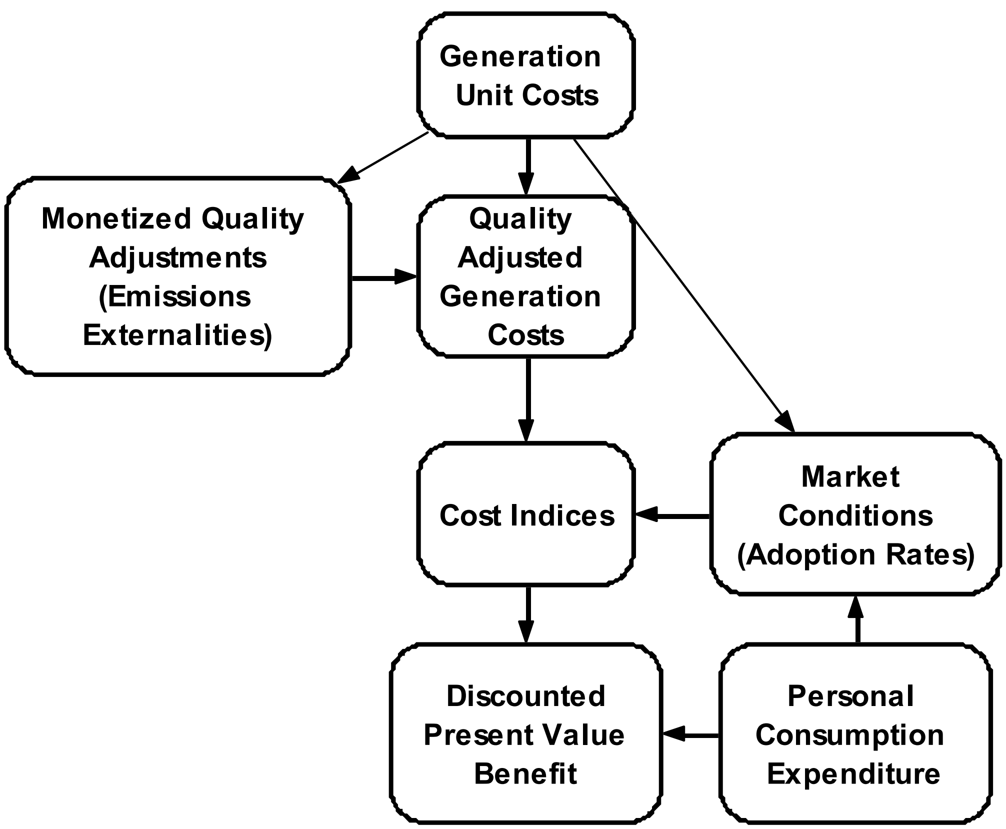

Figure 1. Structure of simulation model

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 typical Weibull process.

Accounting for Externalities

Our model is able to explicitly incorporate a wide range of environmental externalities in power production 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.[1] 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.

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—

[1] 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.

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).[2]
- 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

[2] 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).

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 2 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. Our data are defined in the longer version of our paper at http://www.rff.org (Macauley et al., 2002).

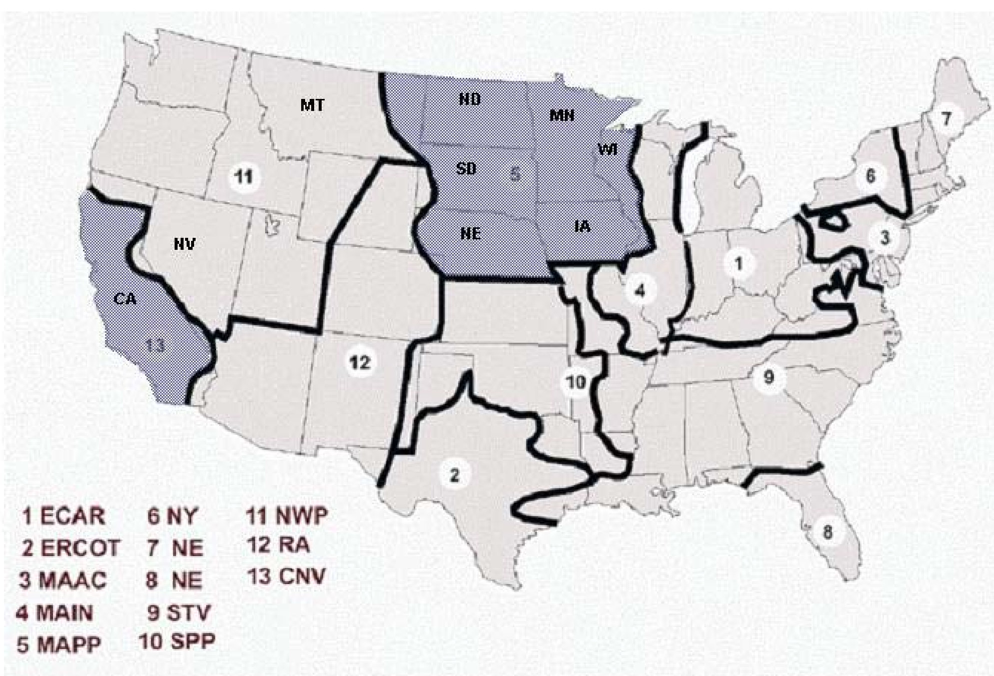

Figure 2. Electricity market module supply regions

Source: EIA

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 1995).[3] 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.

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 2000, 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

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

model with respect to learning by doing, returns to scale, and technological innovation.[4] 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.[5] 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 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.

IV. Results

In this section we discuss our estimates of 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

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[4] 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.

[5] 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.

different ways to create 10 scenarios for each of the two regions in our study. In all scenarios, we assume a 5% discount rate.

In each scenario, we compare each renewable technology with CCGT technology for the two regions. 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 illustrates several of our scenarios involving different combinations of assumptions about adoption rates and externalities.

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	
Portfolios: Equal weight **9-CNV** **9-MAPP** Variable weight **10-CNV** **10-MAPP**	8 models as in 1-CNV to 8-CNV 8 models as in 1-MAPP to 8-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.

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 3 and 4 further illustrate the time path and intervals for the cases of photovoltaics and wind class 6 for the discounted cumulative benefit for CNV. Figures 5 and 6 display the net benefits on five-year intervals and also show the confidence regions.

Table 2. Results: Scenarios 1–8

SCENARIO 1: *Weibull: .1, 3.5*
Externalities: Carbon, water
Base: EIA CCGT growth
Discounted present value, 2000–2020, $1999 billions

Defending technology / Innovating technology		
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
	(-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	
	(-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**	
	(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**	
	(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**	
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
	(-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**	
	(5%, median, 95%)	**(5%, median, 95%)**
	CNV	
	(-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		
	(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		
	(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)

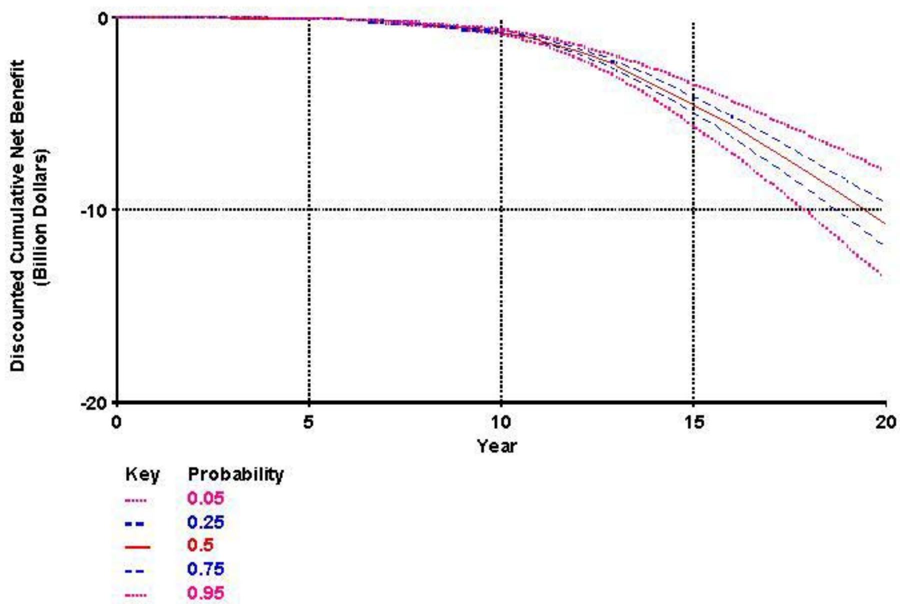

Figure 3. The present value of benefits from 2000 to 2020 for PV from scenario 1 for CNV

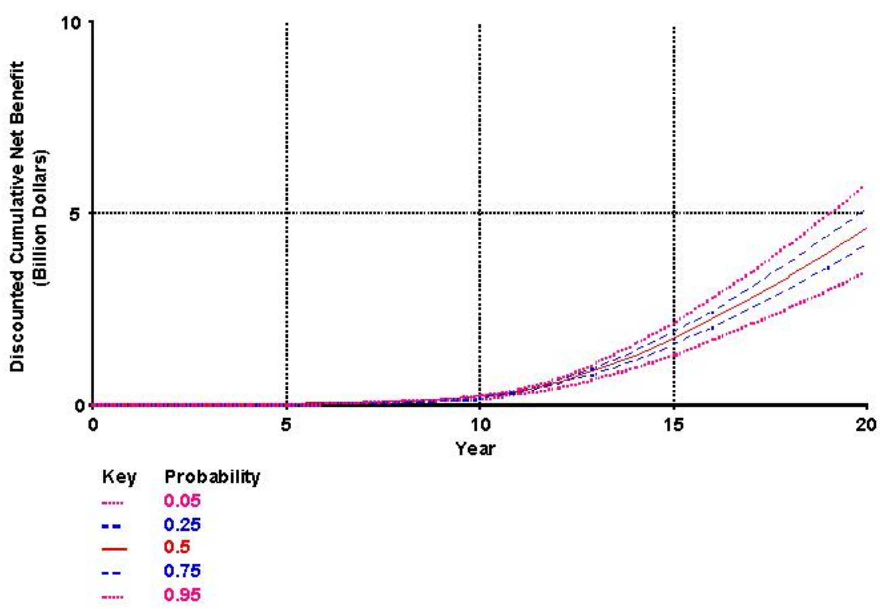

Figure 4. The present value of benefits from 2000 to 2020 for Wind Class 6 from scenario 1 for CNV

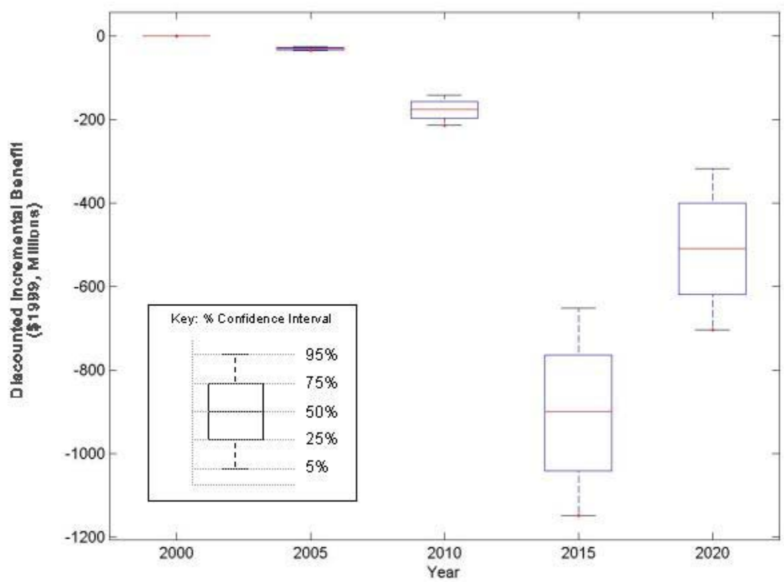

Figure 5. Discounted incremental benefits from 2000 to 2020 for PV from scenario 1 for CNV

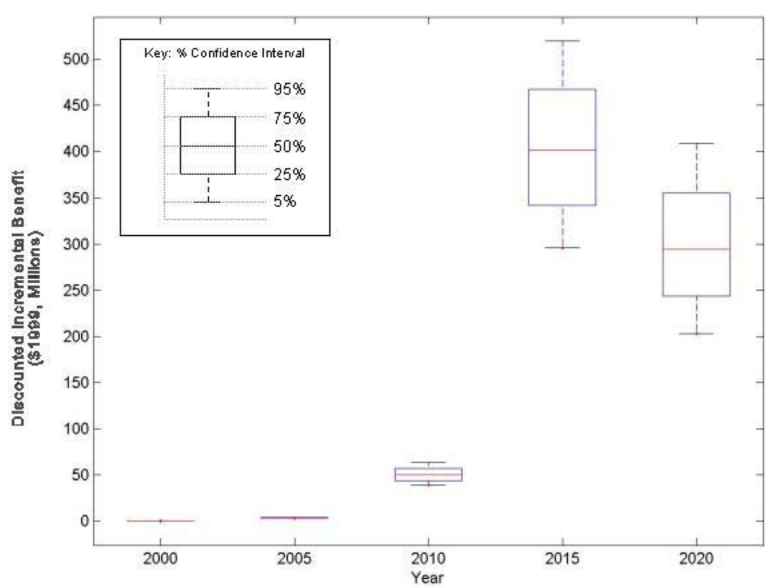

Figure 6. Discounted incremental net benefits from 2000 to 2020 for wind class 6 from scenario 1 for CNV

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 9-10. In another exercise of the model we construct hypothetical renewable "portfolios." We ask, "What surplus values are predicted by combining renewable technologies?" In scenarios 9-CNV and 9-MAPP we assume that an equal fraction of expected new generation will be supplied by each of the renewables. In scenarios 10-CNV and 10-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 the earlier scenarios, generating additional sets of results for both regions. Table 3 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 3. 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.

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 a simulation model to estimate consumer surplus 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.

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.

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