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A Cost-Index Approach to Valuing Investment in “Far into the Future” Environmental Technology

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Abstract

Governments investing in long-lead technology development programs face considerable uncertainty as to whether the investment eventually will “pay off” for the taxpayer. This paper offers a framework to inform long-lead technology investment. We extend the theory of quality-adjusted cost indices to develop a conceptually rigorous, but data parsimonious, means of estimating consumer benefits from a new technology. We apply this model to a possible future electricity generation technology, space solar power (SSP). The United States, Japan, and other governments have begun investing in SSP but lack the benefit of a relevant economic context for informed decisions. We frame and analyze the economic relationship between SSP and competing electricity generation technologies with respect to direct costs, environmental externalities, and reliability. We also explicitly incorporate uncertainty and consider differences in the resource endowments available to electricity markets by considering four distinct world geographic regions.

Key Words: energy, environment, technological change, cost indices, space technology

JEL Classification Numbers: O3, Q2, Q4

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Contents

I. Introduction	1
II. Approach	2
IIA. Overview	2
IIB. Methodology.....	3
IIB1. Environmental Externalities	4
IIB2. The Power Reliability Module	7
IIB3. The Cost Indices Module.....	9
IIB4. Characterizing Uncertainty.....	15
IIB5. Adoption Rates	16
IIB6. Geographic Regions	17
III. Data.....	19
IV. Results.....	21
V. Summary and Conclusion	29
References.....	31
Appendix A: Model Parameters and Data Description	35
Appendix B: Estimates of Personal Consumption Expenditure	39

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I. Introduction

Governments investing in long-lead technology development programs face considerable uncertainty as to whether the investment eventually will “pay off” for the taxpayer. This paper offers a framework to inform long-lead technology investment. We extend the theory of quality-adjusted cost indices to develop a conceptually rigorous, but data parsimonious, means of estimating consumer benefits from a new technology. We apply this model to a possible future electricity generation technology, space solar power (SSP).

Space solar power, also referred to as “satellite solar power,” is a concept for generating electricity by collecting solar energy using space-based infrastructure and transmitting the energy to ground-based receivers. The power may then be transmitted and distributed by the electricity grid (although some configurations of SSP may involve different means for transmission and distribution). SSP originally was proposed some 40 years ago and recently has received funding for further technological development in the United States and other countries.

This paper involves detailed computer-based modeling of the possible economic value of SSP as a source of commercial power by the year 2020, including the explicit inclusion of environmental externalities and power supply reliability. These effects are defined and measured within a larger modeling framework in which the potential value of SSP is placed in economic context with conventional (terrestrial) fossil and renewable

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energy supplies in distinct geographic markets: two regions within the United States (the West Coast and the Midwest), Germany, and India. This detailed energy market and geographic modeling is intended to complement and facilitate further SSP engineering development and potential investment by providing an understanding of conditions under which SSP could flourish or fail.

Previous research largely has evaluated SSP by comparing it with fossil-fuel technologies based on highly aggregated U.S. national average data.¹ This research has not accounted for the role of terrestrial renewable electricity, technical innovation in electricity technology between now and the coming decades, and marked geographic differences in terrestrial renewable energy potential. For example, some regions lack geothermal and solar thermal capacity, but the availability of SSP is independent of terrestrial resource endowments. Importantly, prior research has treated environmental effects lightly in an integrated model, yet these effects can be wide-ranging and geographically different. No research consistently and rigorously has addressed the implications of SSP for power supply reliability, although this characteristic figures prominently among consumer concerns.

II. Approach

IIA. Overview

Satellite solar power generates electricity by collecting solar energy using space-based infrastructure and transmitting the energy to ground-based receivers. In this paper, we develop a conceptual framework, a computer-based model, and estimates of how much better off society at large could be by 2030 as renewable energy technologies, including SSP, continue to be improved and possibly gradually adopted for power production, compared to a counterfactual scenario that allows for continual improvement of conventional (terrestrial) power technology. The research proceeds from the position that the role and prospects of SSP can be assessed only within a market setting that considers competing energy technologies and sources. The model also allows for environmental effects and other characteristics, such as supply reliability. We evaluate

¹ NASA's Space Solar Power Exploratory Research and Technology Program (SERT) activities have included modeling SSP component, system, and integration costs (Feingold 2000 and Mullins 2000; see also a summary of these and other efforts in Moore 2000 and National Research Council 2001).

several renewable energy technologies, including SSP, solar photovoltaic, wind, biomass, and for some of the geographic areas considered here, solar thermal, geothermal, and nuclear power. For each, we assume an accelerated adoption rate due to technological advances and evaluate the benefits against baseline, conventional fossil-fuel technology.

Because there is wide geographic variation in the distribution of natural resource endowments for many renewable technologies (in this regard, the ubiquity of SSP is a notable advantage), we apply the model to four specific geographic regions: California, the U.S. Midwest, Germany, and India. The model explicitly and formally incorporates technological and market uncertainty with respect to energy supplies, power generation costs, environmental externalities, power reliability, and adoption rates.

IIB. Methodology

Figure 1 illustrates the model. The algorithm begins with detailed generation cost data for each power technology. These costs are then adjusted based on environmental effects and power reliability. Because many technologies meet or exceed the cost targets projected by engineers and other experts but can fail to meet a “market test,” adoption rates are specified based on a variety of market conditions. The rates generally take the form of an “s-shaped” curve that depicts somewhat slow initial adoption followed by somewhat faster adoption.

The conceptual linchpin of the model is development of quality-adjusted cost indices based on and analogous to consumer price indices. The advantage and intuitive appeal of the index-based approach is that it is fairly parsimonious in the amount of data required for estimation.

The final step uses the index to estimate the discounted present value of benefits through 2030. Engineers involved with SSP expect that it could be deployed by 2020 with adequate investment between now and then. We thus seek to capture innovation in conventional technologies from 2005–2030, as well as to estimate the potential benefits of SSP in relation to those of conventional technologies were SSP to be available beginning in 2020. This time period through 2030 is consistent with the time period for which data about conventional electricity are available (many of these data are from the U.S. Energy Information Administration and the International Energy Agency, and their latest projections extend to 2030). It is important to note that the model is not an optimization model designed to optimize the mix of power generation technologies by maximizing net present value over time. Rather, it represents a simpler problem—that of

identifying for decisionmakers involved in investing in long-lead technology the interplay of factors potentially influencing the value of the investment. To that end, the model incorporates uncertainty based on probabilities, “pioneering bias” adjustments, and Monte Carlo simulation.

IIB1. Environmental Externalities

Among the issues to consider in evaluating future electricity generation technologies from the perspective of social welfare are external effects, including those on the environment. Concern about these effects is manifested in increasingly stringent U.S. and foreign emissions regulations and taxation; large clean-fuel production and development subsidies; carbon trading proposals; foreign investment that is conditional on balancing energy demand, economic growth, and environmental concerns in developing countries; and in a host of other policies governing the environmental and health effects of power production. Historically the focus has been on undesirable air emissions of conventional fossil-based power. However, the effects on the environment of renewable energy resources are gaining attention as these resources attain wider markets. For instance, wind turbines’ effects on birds and bats (including endangered species and species protected under the migratory bird treaty) and the generation of noise, undesirable visual effects, electromagnetic interference, and possible leakages of hazardous lubricating oils and other fluids are externalities that are becoming prominent in discussions of wind power and have slowed or prevented siting of wind farms. A dedicated feedstock for biomass energy generation has neutral effects on the carbon cycle and soil erosion but can lead to potential problems of other types of air discharges and thermal effluent. Solar thermal and combined cycle gas turbines (CCGT) also raise concerns about thermal discharges, and even though CCGT releases less carbon than oil-fired plants, CCGT has other environmental and health effects.

The biosphere effects of SSP could include electromagnetic interference and possible microwave field effects, visual intrusion, and, in some engineering designs, extensive land requirements at rectenna locations. Other designs propose much less acreage (for instance, see Chapter 5 in Bekey et al. 2000), but in any case, the use of land may not constitute an “uncompensated” externality because landowners typically are compensated for the land. However, facility siting and public acceptance remain issues. As the SSP community has acknowledged, and as the history of the introduction of many new technologies demonstrates, the perception of adverse effects, even if they are not

“real,” can make or break public acceptance (for example, see National Research Council 2001; Bekey et al. 2000).

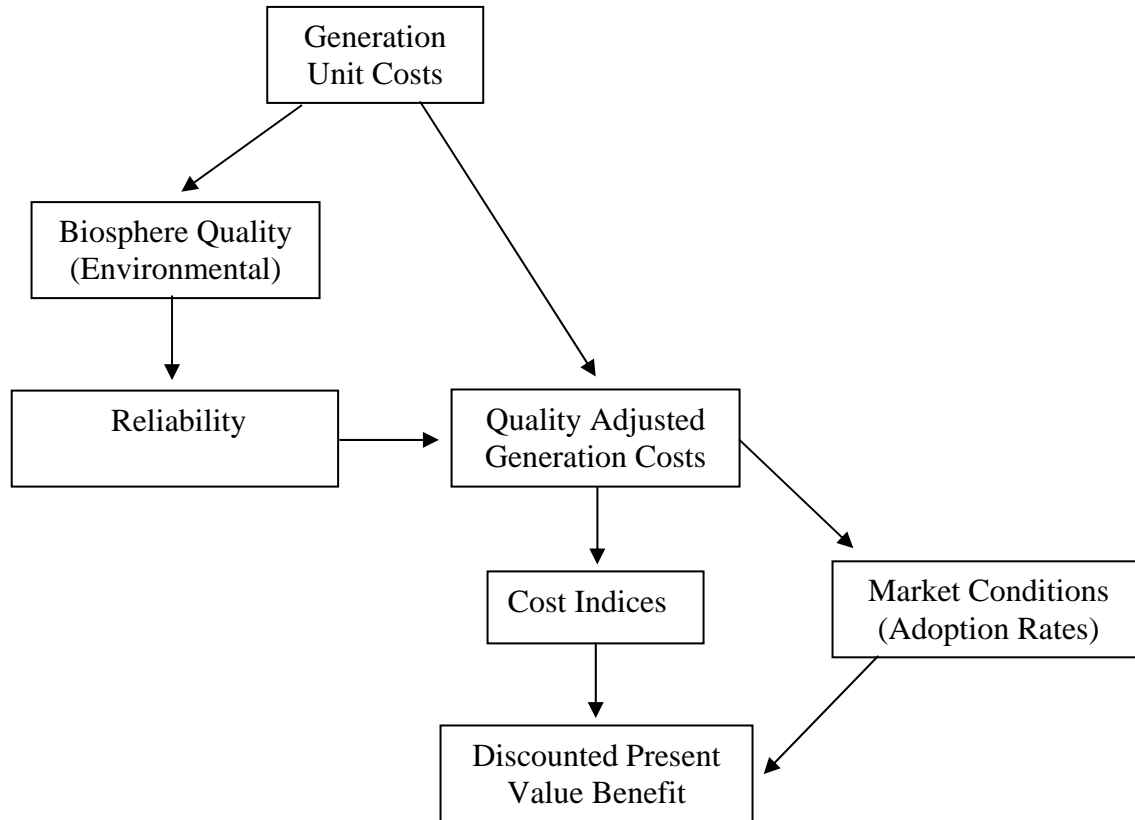


Figure 1. Model Structure (data parameterization is modeled subject to uncertainty as described in text)

The model is able to incorporate explicitly a wide range of environmental effects (see Box 1) and is limited only by the absence of quantifiable data about many of them.

Box 1. Environmental 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 (often lacking prices or other internalization mechanisms but influencing the generation technology):

- Atmospheric emissions (local, regional, global)
- Water discharges
- Soil contamination and geological disturbance
- Cultural and archaeological resource damage
- Biological resources and terrestrial ecosystems damages
- Recreational and wilderness values
- Visual intrusion
- Noise emissions
- Interference with electromagnetic communication systems
- Safety and microwave field effects

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 services (e.g., transportation, housing, employment)
- Land values
- 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).

Source: Adapted from Macauley et al. 2002.

Few if any external effects of biomass, solar thermal, and the other conventional renewable energy technologies have been evaluated in terms of damages, the costs to avoid damages, or other frameworks for estimating the value of these effects. However, some data are available (these are discussed below). For gaps in data, the model permits simulation of alternative values and sensitivity analyses (for instance, to answer “how

large would external biosphere effects have to be to undermine the competitive advantage of a given renewable”).

IIB2. The Power Reliability Module

Power reliability—ranging from vulnerability of the power system to natural disasters and domestic and international sabotage to import dependence on fuel supplies—is a long-standing concern in many countries. In newly revised guidelines for measuring the benefits of energy R&D and new technology investment, the White House Office of Management and Budget has specifically defined “national security” to include supply (fuel import) disruptions, infrastructure reliability, and price volatility as it affects investment decisions or retaining industrial capacity. Furthermore, environmental effects and reliability issues are related. For instance, a country that reduces fuel import dependence for power generation by relying more heavily on indigenous coal resources may not gain net environmental benefits.

Of the end-to-end components of power supply—generation, transmission and distribution—many experts traditionally have deemed transmission to be the most vulnerable to disruption in the event of disaster or sabotage (U.S. Congress 1990). However, utility managers and other experts, acknowledging the increasing susceptibility of power generation with respect to adequacy of fuel stocks and reliability of operations, now warn that the economic effects of electricity system disruption associated with generation problems potentially could be enormous.² Future concerns may diminish somewhat given the trend towards smaller, decentralized generation facilities resulting from the evolution of competitive electricity markets in the United States and other countries (U.S. Congress 1990; Stoft 2002). In fact, many experts identify distributed energy resources, such as small-scale generators (microturbines, fuel cells, micro-windmills) and local power storage facilities (flywheels, batteries, pumped storage units), as a future opportunity to enhance reliability (Brennan, Palmer, and Martinez 2002).

The potential merit of SSP in the context of reliability is thus several-fold: it offers an alternative generation source, possibly for base load capacity but also for on-demand and back-up supply; depending on its space- and ground-based technical

² For instance, the National Electricity Reliability Council noted that going into the summer of 2002, the “best estimate” was that a loss of 5 percent of capacity during 260 peak summer hours would have imposed costs of nearly \$6 billion in California (Gruenspecht 2002).

configuration, it may provide further capability for decentralized power; and, according to some engineers, suitably configured orbiting reflectors could be used instead of power lines (see Chapter 2 in Bekey 2000). Niche markets for SSP also have been discussed, including both geographic markets and time-of-day (peak period) demand (Macauley et al. 2000). All of these attributes contribute to the potential reliability benefits of SSP.

How best to measure the value of reliability is at the frontier of power economics and security research. Much of the focus is on the value of lost load, a measure of how much value customers place on maintaining their connection for both short- and long-run durations. As the literature emphasizes, value of lost load is extremely difficult to estimate accurately because most customers do not respond directly to real-time electricity pricing and values may vary dramatically among customers and for any given customer from one time to another. The range of estimates is large, but even the low end of this range is nearly 100 times the typical wholesale price of power (Gruenspecht 2002; Stoft 2002; Australian National Electricity Code Administrator 1999). Researchers also have developed an alternative measure using the implied prices for generation adequacy given an assumed reliability level and the investment and operating expenses required to sustain generation at that level (Stoft 2002). Finally, some estimates of the direct costs (product spoilage, lost sales, property damage, health and safety, and opportunity costs) and indirect costs (looting and vandalism, costs incurred by other households and firms) of outages of varying lengths and affecting residential customers; commercial, industrial, and agricultural firms; and infrastructure and public services also are available (U.S. Congress 1990).

The issue of national security as related to electricity markets also is relevant to consideration of SSP. While important, this concern is not modeled in this paper because we see security issues as a possible characteristic of SSP as well as of conventional power. Our justification for the omission is as follows. The concern in terms of conventional electricity supply includes the potential exercise of market power by international fuel exporters to raise fuel prices and macroeconomic disruptions from energy price instability when fuel supplies are curtailed for one reason or another (Toman [2002] summarizes these concerns). In the case of electricity, the feedstock supply is one of the largest possible security concerns. Only about 1/30 of primary energy used in the United States to generate electricity is oil, and neither Germany nor India relies on oil as

a major feedstock for power production.³ Germany is the third largest producer of natural gas in the European Union but imports about three-fourths of its requirements, largely from Norway, the Netherlands, and Russia. Sources of natural gas imports for India include Qatar and Australia.⁴ Because of tensions with countries through which pipelines pass, the national security benefits of SSP may be attractive for a country such as India. Given that the economic size of potential disruptions varies markedly among countries, the value of SSP in contributing to energy security in different countries also is likely to vary.

However, the contribution also will depend on other factors, such as who owns SSP assets (see discussion in Macauley et al. 2000). In fact, given the massive scale of an SSP system, its ownership and financing may well involve a consortium of governments or power companies representing a large number of countries. But in configuring such an institution, national security concerns may loom large—countries may not be willing to depend on international consortia for their power supply. Since we see strong arguments for security-related concerns with both conventional and SSP technologies, we do not model these in this paper. More detailed discussion of these, including hypothetical financing and ownership designs for SSP, are a topic for future research.

IIB3. The Cost Indices Module

As noted above, a cost index links the supply and demand components of the model. The index formulation is an extension of an approach pioneered by Bresnahan (1986), who developed an index for comparing 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 builds on consumer price indices in which, to the extent possible, quality differences among goods and services are incorporated. 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

³ The role of electricity as a substitute for oil in transportation in the United States and elsewhere could be radically enlarged if electric or hybrid electric cars enable significant oil savings, depending on the fuel source for the electricity power production (National Research Council 2001a).

⁴ Three new pipelines are under consideration for construction: from Iran through Pakistan, from Turkmenistan through Pakistan and Afghanistan, and from Burma through Bangladesh (BBC News 2005; Alexander's Gas & Oil Connections 2005).

differences, and the share of expenditures represented by the product in total expenditures. The index also is ideal for estimating 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, the model here is applied to demand for SSP as an input into the production of electricity.

We extend Bresnahan's approach in two directions. The first extension makes the index prospective to evaluate the potential future gains from investment in SSP. This adjustment allows for gradual diffusion of a new technology. A key feature in this extension is expressing the model's parameters as probability distributions to reflect uncertainty over future or estimated parameter values for both SSP and conventional, or "defender," technology.

The second extension adjusts for differences in environmental effects and reliability among all of the technologies to capture costs and benefits that are not fully reflected in capital and operating costs. Testing of the model includes sensitivity analyses by shifting parameter locations to assess the robustness of assumptions about uncertain parameters.

The result is a theoretically grounded economic model of future welfare gains. 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 the performance of prospective investment in new technologies. In this way, the index can be a useful tool for managers and engineers. The output also includes the discounted present value of expected benefits, an understandable and meaningful measure to communicate the potential value of SSP to decisionmakers.

Figure 2 illustrates the index. It shows the expected welfare gain from changes in electricity costs brought about by investment in new generation technology, called "renewable" here. The demand curve is given by D . Period 0 supply, S_0^{DT} , is the baseline, where only the defender technology, DT, is available. Investment in renewables shifts their supply curve to S_I^{RE} due to cost reductions (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_0^{DT} .

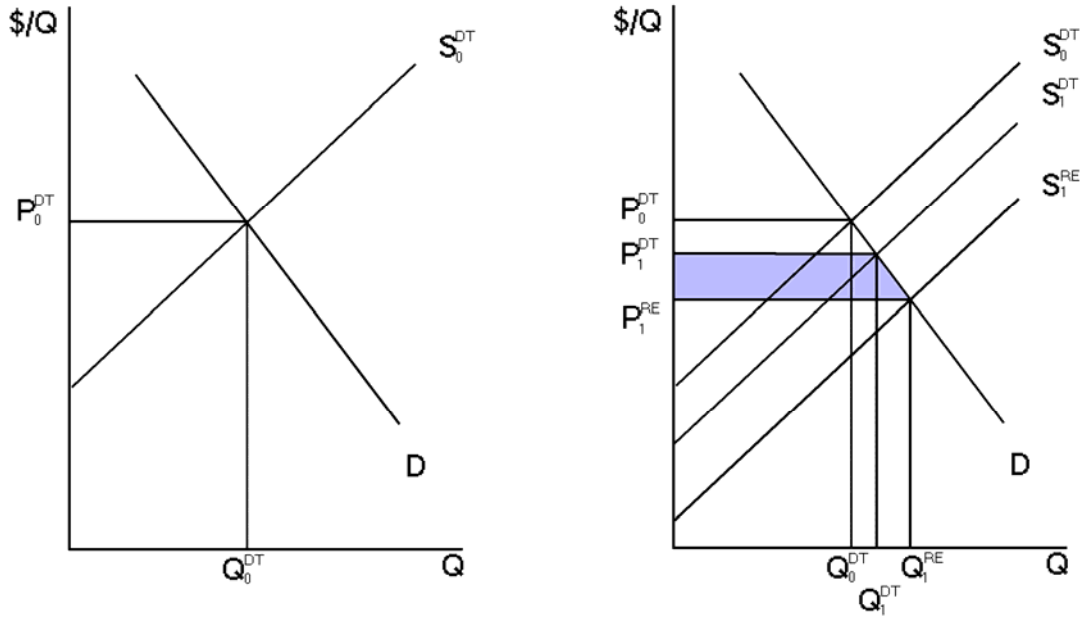


Figure 2. Derived Demand for a Renewable Energy Technology: Illustration of Net Surplus Change

If S_1^{RE} lies to the right of S_1^{DT} , 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 that consumers will be better off if the investment occurs.⁵ The index may be less than unity, implying that investment in the renewable technology under evaluation does not appear to produce a welfare gain. Note that even if the index is less than unity, the index permits useful comparisons across investments (favoring those that yield indexes as close to one as possible) and, importantly for evaluation of SSP, can indicate progress over time as continued investment results in innovation that nudges the index upwards. This interpretation furthers the usefulness of the index for program managers to measure performance over time.

⁵ The welfare gain is measured gross of the investment expenditure made in the technologies. For this reason, the results of the model would be used in conjunction with projected investment expenditures to ascertain net benefit.

To illustrate the underpinnings of the index, expression (1) below underlies the cost index given in (2). 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 a new technology (“RE”) that brings about reductions in its cost (or increases in its social benefits). Similarly, C^{*l} is the cost of achieving optimal utility u^l under the investment scenario with conventional energy costs W^{dt} relative to the cost of the renewable with post-innovation costs W^{RE} .

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

Because an innovation is assumed to be adopted gradually, the quality-adjusted cost of the renewable (that is, adjusted for biosphere and reliability effects) is a combination of use of the renewable and use of conventional technology, such that $W^{RE} = \rho W^l + (1 - \rho)W^{dt}$ where ρ is the adoption rate of the renewable and W^l is its cost if adopted. Prices P of other goods and services can change over time, but it is assumed that they are unaffected by the renewable: $P^{dt} = P^{RE}$ at all times. Manipulation of (1) based on cost index theory (see Caves et al. 1982) gives the index in (2):

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

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

Expression (2) corresponds to the area of the shaded rectangle in figure 3.⁶ Interpretation of the index is “how much better off is society in general as a result of investment in the new technology, taking into account the alternative (conventional technology) and differences in environmental impact and reliability between new and conventional technologies?”⁷

A diagrammatic exposition of the index showing the relationship among the expenditure functions E^* , utility, and the two cost indexes represented by C^{*dt} and C^{*l} is presented in figure 4.⁸ 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 $U^{*l} > U^{*dt}$. With separable utility and other prices unaffected, the relative cost to achieve u^{*l} with higher baseline prices W^{dt} versus reduced, post-innovation prices W^{RE} exceeds the relative cost to achieve U^{*dt} .

⁶ Because costs and expenditure shares of non-electricity consumption in personal consumption expenditures are assumed to be unchanged by the results of investment in renewables, routine assumptions in the theoretical literature allow these parameters to cancel in expression (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. These advantages make the index a sound approach that is parsimonious in the amount of data it requires.

⁷ Pecuniary externalities are a different class of externalities. Their effects are largely distributional and for this reason their effects in Figure 3 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 benefits and costs, the wins and losses cancel out, and the net effect to society 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 generally are thought to have no effect on economic efficiency. However, they can be important politically because of their wealth effects.

⁸ 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).

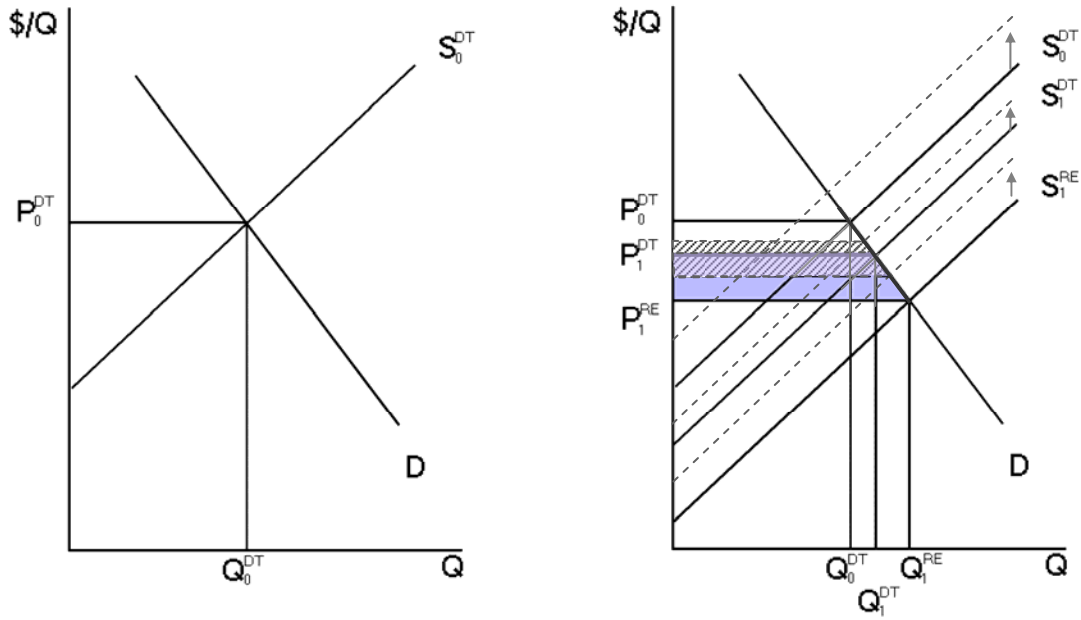


Figure 3. Derived Demand for a Renewable Energy Technology: Illustration of Net Surplus Change with External Costs

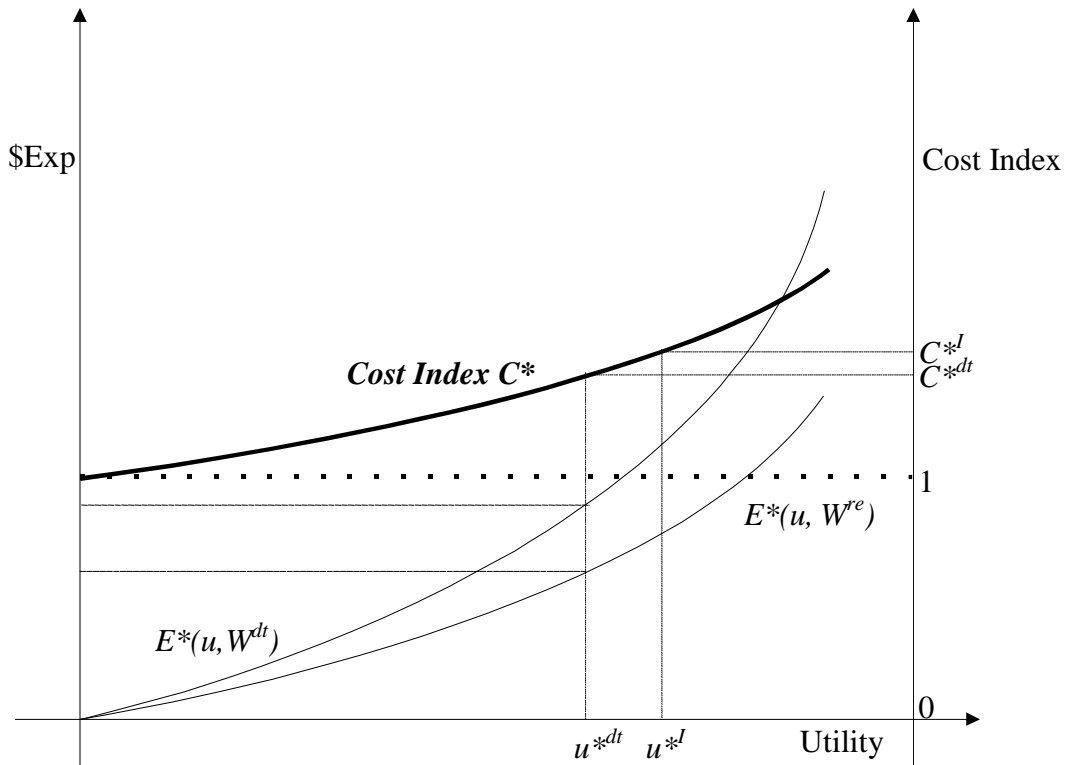


Figure 4. Relationship between Expenditures, Cost Index ⁹

⁹ To simplify figure labeling, prices P have been omitted from the expenditure functions.

IIB4. Characterizing Uncertainty

The time horizon of the study is 25 years, from 2005 to 2030, consistent with the time horizon for which many of the required data are available. Many of these data are from the U.S. Energy Information Administration (EIA) and the International Energy Agency (IEA), and 2030 is the extent of their projections at present. The EIA uses this time period for its modeling system and 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.” Of course, the actual extent to which costs are likely to change—either increasing or decreasing—over the next decades is highly uncertain. In the case of terrestrial renewable energy technologies during 1975 to 1995, McVeigh et al. (1999) find that actual reductions in generation costs met expected cost goals as forecast by a variety of experts. 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. 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, paradoxically, the diseconomies may 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.

Another source of significant uncertainty is developments in public policy governing electricity markets during the coming decades. The past few years have brought numerous initiatives at the federal and state level in the United States, as well as in other countries, including various forms of deregulation or liberalization in electricity markets, requirements to use renewable energy (typically referred to as renewable energy standards or portfolios), and production or other subsidies for renewable energy.¹⁰ Policies also recently have changed and may change yet again in coming decades regarding different types of energy, such as the phase-out of nuclear power in Germany. The German government and the German electricity industry agreed in June 2000 to a phase-out of existing nuclear stations (IEA 2004); most analysts anticipate the phase-out to conclude by 2020 or earlier. New and revised policies in the coming decades are likely

¹⁰ For example, see Growitsch and Musgens (2005) and the Organisation for Economic Cooperation and Development (2006).

among all of the regions in this study, and their effects on the parameters of our model could be profound.

Because future costs are uncertain, point estimates for the data are parameterized as location parameters of probability distributions. The approach is based on Bayesian probability, appropriate for non-repeatable events such as probable future costs or adoption rates. The data from engineering or technology expectations are not taken at face value, however. Instead, following the literature on expectations bias in “pioneering” technologies (Quirk and Terasawa 1986; Terasawa, Quirk, and Womer 1989) the probability distributions are skewed slightly to the left. In addition, uncertainty is modeled to increase over time, following a standard normal distribution with mean zero and standard deviation 0.01 (1%). The last step in the treatment of uncertainty is use of Monte Carlo techniques to predict values based on the data parameterizations. Although the use of some arbitrary assumptions is unavoidable given the data and their limitations, the resulting model is transparent and allows exploration of alternative assumptions.

IIB5. Adoption Rates

We assume that any adoption of (terrestrial) renewable and SSP technologies gradually displaces adoption of conventional, fossil-based technology but does not force early retirements. (Our measurement and estimation of growth in generation capacity are somewhat complex, and we discuss them further in the data section.) We assume that the generation shares of new technologies increase monotonically with time according to the following Weibull process:

$$F(t) = 1 - \exp(-\lambda t^\gamma) \quad (3)$$

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 the model.

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

Figure 5 shows the renewable generation shares over time for these rates using Weibull functions.

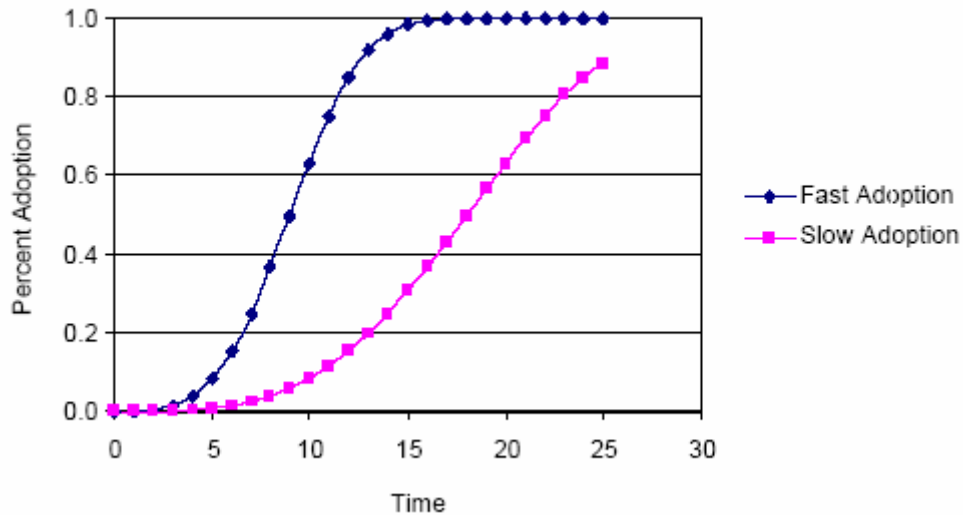


Figure 5. Weibull Adoption Rate Curves

IIB6. Geographic Regions

We select two regions in the United States—California and the Midwest—and India and Germany as our case study regions.¹¹ We chose these to illustrate the sensitivity of the value of SSP to geographic variation among these areas. They differ in their endowments of renewable resources, such as solar thermal, geothermal, and wind potential. In some regions, certain renewable technologies are not viable because the region lacks the resource base. For example, we do not include solar thermal technology

¹¹ Electricity data collection in the United States largely is based on geographic regions delineated by the North American Reliability Council, and we use the council's definitions. The Midwest (labeled the Mid-Continent Area Power Pool (MAPP) by the Council) includes Minnesota, Nebraska, North Dakota, and parts of South Dakota, Montana, Wisconsin, Iowa, Kansas, and Missouri.

as a possible choice for India and Germany.¹² In general, combined cycle gas turbine (CCGT) plants are expected by energy experts to be the preferred option for incremental growth in power demand because they have lower capital costs and typically faster construction times. Advanced CCGT plants also tend to have the lowest carbon dioxide emissions of all fossil fuel-based technologies because of the low carbon content of natural gas and the high efficiency of the plants themselves.

Initially in this project, CCGT using natural gas as the fuel stock was assumed for all areas. Between 2004 and 2006, however, the U.S. projections for expected prices of natural gas during the period 2005–2030 rose markedly, leading the EIA to anticipate that advanced (gasified) coal-based rather than natural gas-based CCGT would be the technology of choice for incremental capacity investment in the United States.¹³ In CCGT systems, feedstock costs represent the largest percentage (80 percent to 90 percent) of levelized costs; capital investment (due to the 40-year or longer lifetime of CCGT plants), operations, and maintenance are much smaller shares. The assumptions made about feedstock prices thus drive the cost trajectory over the time frame.

CCGT using natural gas is expected to represent an increasing share of generation in Organisation for Economic Cooperation and Development countries such as Germany as nuclear generators are phased out. In India, natural gas-based capacity and generation is expected to grow more than seven percent annually until 2030.¹⁴ But the price of natural gas has been unstable for several reasons, including uncertainty over prices of liquid natural gas imports and of total recoverable gas reserves deliverable via pipeline. Gas sales taxes and state regulatory authority over gas (struck down by the Indian Supreme Court) also have been sources of price uncertainty.

India's wind power capacity is among the highest in the world and is being actively promoted by government and industry, particularly for power in remote areas

¹² In the case of hydropower, declining availability of hydro sources and increasing environmental concerns make new hydro construction difficult in all of our areas.

¹³ Also see discussion in Darmstadter (2006). Over time, analysts expect increases in the capacity and share of natural gas-based CCGT in incremental generation in the United States until 2015 and then a small decline by 2030 (U.S. Department of Energy 2006a; U.S. Department of Energy, 2006b). More efficient plants come online but generation using natural gas declines and use of gasified coal increases as natural gas prices continue to rise.

¹⁴ Adoption of CCGT in India, however, has been hampered greatly by India's vast coal reserves. Most of India's power at present is coal-fired, with hydro and nuclear accounting for most of the remaining fuel mix. A number of new CCGT plants are under construction (for instance, see Gopalakrishnan 2000).

that cannot be connected through the transmission grid. Nuclear power generation is expected to increase from three percent to more than five percent as a share of electricity supply by 2030. We note, however, that even with development of new capacity to supply demand growth, 60 percent of the Indian population depended on traditional biomass (agricultural residue, firewood, and animal waste) for cooking and heating as of 2004, and by 2030, reliance on biomass and waste are expected to continue to represent a major source of household energy supply. As of 2002, Germany leads the world in the share of wind-based electricity generation (IEA 2004). We assume nuclear power will not be an option for addition to new generating capacity in Germany given the legislated phase-out.

III. Data

The cost index we estimate is a function of estimated total expenditures on electricity as a fraction of total personal consumption expenditures; the costs of power generation; differences in the environmental and reliability effects of the energy technologies; and expectations about the values of all of these inputs over the relevant time horizon. As noted, these also vary by geographic area. All of the parameters are drawn from probability distributions to reflect imperfectly observed data and uncertainty. For some parameters, the data are available in ranges of estimates and permit construction of distributions based on this information. In other cases, distributions are assumed.

Appendices A and B describe the data in detail. We estimate the model separately for the four geographic regions. We model the technological choice for additions to capacity required by demand growth during 2005–2030. We consider advanced gasified-coal-based and natural gas-based CCGT and terrestrial renewable energy in the form of photovoltaics, solar thermal systems, geothermal systems, wind systems, and biomass systems.¹⁵ These we refer to as “conventional technologies,” and of these, coal-based CCGT is our “defending technology” for the United States and gas-based CCGT is our defending technology for India and Germany given IEA forecasts. The defending technology is the technology seen by the experts as most likely to be used for new

¹⁵ The specific renewable power technologies are as characterized by the U.S. Department of Energy (1997), referenced there as parabolic trough solar thermal systems, hydrothermal binary geothermal systems, horizontal axis wind systems, and direct-fired dedicated-feedstock biomass.

incremental generating capacity through 2030. SSP is the “nonconventional” or “innovating” technology in the terminology of our model.

Most of the data pertaining to the conventional technologies (levelized or busbar generation costs, quantities, and prices) are from the U.S. Department of Energy (DOE) (including DOE’s EIA and the National Renewable Energy Laboratory), the IEA, the Nuclear Energy Agency (2005), and the Organisation for Economic Cooperation and Development. For SSP, the data are from the National Research Council (2001) and NASA’s SERT program (Feingold 2000; Mullins 2000; and Moore 2000).¹⁶

During the coming decades (approaching 2020 and 2030 in our model), we assume the energy technologies will embody technological efficiency improvements and in most of our assumed technologies we project cost declines. As we noted above in the case of CCGT, however, any significant increase in the price of feedstocks that is not offset by cost-reducing innovation in CCGT plants or operations could cause CCGT generation cost to increase. In the cases of the renewable technologies, technological advance also is highly likely (U.S. National Renewable Energy Laboratory 2002). Wind power is expected to include improved turbine blades, hubs, generators, and electronics. In biomass, improvements are expected to include feedstock handling, gas processing and cleanup, and overall plant design.¹⁷ Photovoltaic cost reductions are likely to include higher solar cell efficiencies, increased reliability of photovoltaic systems, and improvements in cell manufacturing.

Externality costs for carbon dioxide emissions are from Krupnick and Burtraw (1996), including references cited therein (see also Oak Ridge National Laboratories and Resources for the Future 1998). These values are estimated mean monetary values of effects from environmental damages. The value for thermal effluent from solar thermal, biomass, and carbon-based power is estimated by determining how much it would cost the power plant to avoid the externality entirely. Thermal pollution occurs largely

¹⁶ Levelized or busbar costs do not include the effects of tax credits or production tax incentives; the costs for solar and geothermal assume the availability of high-quality resources (lower quality resources could as much as double the reported costs).

¹⁷ Examples of biomass include saw grass, forest harvest residue, agricultural residue, animal waste, and fermented liquids pressed from corn or sugar cane. Biopower technologies can include direct combustion, co-firing, gasification, pyrolysis and anaerobic digestion; the data in this study are costs for direct combustion.

through use and discharge of reject heat into streams and other water bodies.¹⁸ Because we do not have estimates of these effects by country, we assume identical values among the regions.¹⁹ A number of concerns have impeded significantly the development of wind sites, but to date no estimates have been made of the economic value associated with these effects.

Estimates of reliability vary widely depending on how long (a few minutes or days or longer), when (during peak or off-peak demand), and whether the interruption is anticipated or unexpected. The theoretical value is difficult to measure because in most markets around the world, usage is not metered in real time. Estimates of the value to customers range widely from \$1,000 to \$90,000 per MWh (Stoft 2002).²⁰ The power industry refers to reliability in financial terms as the value of lost load (VOLL), measuring the cost to the industry of building adequate reserve capacity to handle outages, while providing a high probability of reliability to customers. We assume that one percent of generation costs can be allocated to VOLL (the rest, to transmission and distribution). We also assume that this cost is associated only with the terrestrial technologies in our model. Even though generation interruption is possible with SSP, its cost to operators is unknown.

IV. Results

Our objective is to identify power market conditions under which SSP makes economic sense, as well as conditions under which SSP may not make sense, as 2030 approaches. We develop a large number of scenarios to characterize a variety of

¹⁸ Details of the estimation are in Macauley et al. (2002). Small amounts of thermoelectric water also come from groundwater aquifers, whose degradation can create an external cost. However, such groundwater is a negligible fraction of total thermoelectric water use.

¹⁹ These effects would vary depending on operating conditions and the vintage of the power supply infrastructure, the size and characteristics of affected populations, and differences in other baseline biosphere and health conditions. We also would expect differences in nations' reliability concerns, driven by energy demand, supply costs, import dependence, installed base and other existing infrastructure, and government policies, including environmental, tax, energy security, and other policies.

²⁰ The power industry invokes a proxy measure for VOLL based on the cost of involuntary load curtailment as borne by the system operator. In the event of an outage longer than a few minutes, the operator rations demand by shedding load. Systems are sized to withstand sudden disturbances, as well as to have enough capacity to remain in operation almost all of the time. Operators typically purchase operating reserves based on the expected likelihood of breakdown of some physical component of the power system. If generation capacity is lost for more than about 5 to 10 minutes, load must be shed to balance frequency and voltage (for more details see Stoft 2002).

conditions: a) adoption rates; b) biosphere effects of carbon emissions and thermal effluent; and c) reliability effects of VOLL. Table 1 lists eight scenarios varying (a) and (b). We model each of these with and without VOLL (for example, denoted scenario “1” and “1V” respectively, in the table) and under two assumptions about future SSP generation costs. We model all scenarios for each of the four regions, for a total of 128 scenarios. We assume that all of the technologies except SSP are available at 2005 and experience cost-reducing innovation (as forecast by our data sources) during 2005–2030. We assume that SSP is available beginning in 2020 and, thus, “competes” with the defending technology, which itself has experienced innovation since 2005. This is one of the fundamental objectives of the model—to provide the energy market context over the coming decades during which innovation in conventional terrestrial technologies will not stand still. SSP designers will need to “meet the future.”

In varying the adoption rates, we assume “fast” and “slow” adoption of new technologies to displace adoption of the defending technology, but we do not force early retirements. We use the Weibull probability distribution as described above and characterize fast adoption with the scale and shape parameters (λ, γ) valued at $(.1, 3.5)$ and slow adoption with $(0.05, 3.5)$. We include the economic value of damages associated with carbon emissions (associated with CCGT) and thermal effluent (associated with CCGT, biomass, and solar technologies) to characterize environmental effects. We use one percent of generating cost as the VOLL attributable to generation reliability for conventional (terrestrial) technologies. We assume SSP mean generation costs of 5.5 cents/kWh in one set of scenarios and a larger cost of 11 cents/kWh in another set. As discussed previously, the externality, reliability, and SSP cost parameters, as well as generation cost data for the other electricity generation technologies, are the means of probability distributions to capture the uncertainty inherent in these estimates.

The output of the model exercised for each scenario and region is the cost index and the discounted present value of the benefits it predicts over the period 2005–2030. In all of the present value calculations, we assume a five percent discount rate.

Appendix C, available as an Excel spreadsheet from the authors, contains detailed results for all of the scenarios. Table 2 highlights the set of results in which SSP is either most favorable or least favorable based on the discounted present value of its benefits over the time period. The table also indicates which technology among all of the options confers the largest discounted present value.

**Table 1. Definitions of Scenarios for Each of the Regions
(California, U.S. Midwest, Germany, India)**

Scenario	Weibull parameters		Environmental effects		Reliability effects
	Lambda	Gamma	Water	Carbon	VOLL
1	.1	3.5	Yes	Yes	Yes
1V					No
2	.1	3.5	Yes	No	Yes
2V					No
3	.1	3.5	No	Yes	Yes
3V					No
4	.1	3.5	No	No	Yes
4V					No
5	.05	3.5	Yes	Yes	Yes
5V					No
6	.05	3.5	Yes	No	Yes
6V					No
7	.05	3.5	No	Yes	Yes
7V					No
8	.05	3.5	No	No	Yes
8V					No

Table 2. Relative Economic Performance of SSP by Geographic Region
Discounted Present Value, 2005–2030

	Region	Discounted Present Value \$2005 million (5%, median, 95%)
	California (defending technology: advanced coal-based CCGT)	
Best	Environmental damages and reliability penalties; fast adoption; SSP low cost	(23, 97, 183)
Worst	No environmental damages or reliability penalties; fast adoption; SSP high cost	(-738, -441, -232)
Dominated by: Wind	Environmental damages and no reliability penalties; fast adoption	(1510, 2120, 2860)
	U.S. Midwest (defending technology: advanced coal-based CCGT)	
Best	Environmental damages and reliability penalties; fast adoption; SSP low cost	(1.6, 27, 66)
Worst	No environmental damages or reliability penalties; fast adoption; SSP high cost	(-242, -109, -13)
Dominated by: Wind	Environmental damages and no reliability penalties; fast adoption	(-35, 250, 549)
“Risk Averse” Wind	Environmental damages and no reliability penalties; slow adoption	(18, 155, 323)
	Germany (defending technology: natural gas-based CCGT)	
Best	Environmental damages and reliability penalties; fast adoption; SSP low cost	(-14, 39, 103)
“Risk Averse” Best	Environmental damages and no reliability penalties; slow adoption; SSP low cost	(-1, 0.3, 3)
Worst	No environmental damages or reliability penalties; fast adoption; SSP high cost	(-251, -100, 27)
Dominated by: Wind	Environmental damages and no reliability penalties; fast adoption	(22, 151, 312)
	India (defending technology: natural gas-based CCGT)	
Best	Environmental damages and reliability penalties; fast adoption; SSP low cost	(23, 62, 111)
Worst	No environmental damages or reliability penalties; fast adoption; SSP high cost	(-281, -147, -57)
Dominated by: Biomass	Carbon damages; no thermal damages or reliability penalties; fast adoption	(271, 401, 566)

California: Not surprisingly, the largest mean discounted present value of benefits associated with SSP in California occurs at the low mean SSP generation cost and under conditions that include the environmental effects and reliability penalty for conventional technologies. The estimated median value is about \$97 million. Even under these conditions, however, the total present value of the benefit from SSP is relatively small, in part because it is unavailable for adoption until 2020 and in the interim, cost-reducing innovation improves the attractiveness of other technologies. If the reliability penalty and the environmental carbon damages are omitted, the median benefits of wind and geothermal exceed those of SSP. Wind is the “all-around” best performing technology under these conditions, generating potential median benefits of about \$2 billion.

For California, the possible benefits of SSP are negative in any scenario at its higher mean generation cost of 11 cents. The worst performance of SSP is at this higher cost in the scenario in which there are no environmental damages or reliability penalties associated with conventional technologies and that involves fast adoption of these technologies.

The U.S. Midwest: In this region, the most favorable conditions for SSP are the same as in California: low SSP generation costs and environmental and reliability penalties for conventional technologies, together with fast adoption. Under these conditions, the median present value of benefits is about \$27 million. SSP performs least well at high generation costs and without penalties for conventional technologies under fast adoption. It has negative benefits under these conditions.

Wind confers the largest median value, but the adoption rate assumptions influence the range of the distribution. Under fast adoption, the lower tail at the five percent confidence interval is a negative value. Under slower adoption, the entire distribution falls within a range of positive values. Slower adoption allows expected innovation in wind technology to become realized in its generation costs.

Germany: A low SSP median generation cost and environmental and reliability penalties for conventional technologies, together with fast adoption, result in the largest present value of benefits associated with SSP in Germany. At the lower tail of the distribution, however, the benefit measure is negative. Under slow adoption, the negative value in the lower tail is smallest (in absolute value). The guidance for decisionmakers seeking to minimize the “downside” as reflected in the lower tail would be slow adoption. SSP at a higher generation cost and without damages or reliability penalties results in the lowest median value of benefits which, although negative, has a positive

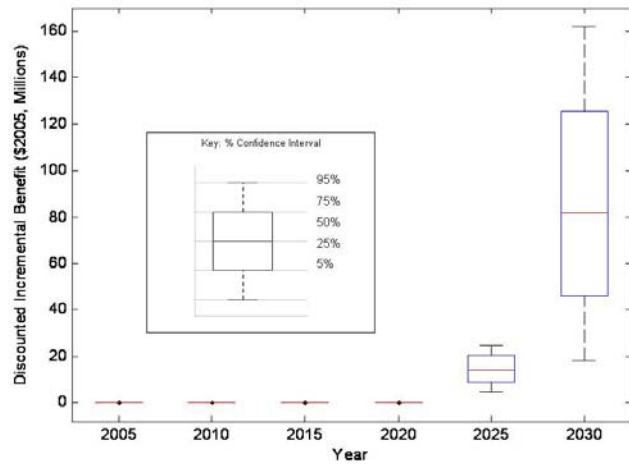
value at the upper tail (95% confidence interval). Germany is the only region in the study for which the “worst” case for SSP can nonetheless result in positive benefit. The best performing technology in Germany is wind when environmental damages are included, giving a discounted present value of median benefits of about \$151 million.

India: India is a fourth example confirming that the relative benefits that may be realizable from SSP are most likely when environmental damages and reliability penalties are applied to other power technologies and when SSP has a low generation cost. As in the two U.S. regions, but not in Germany, the “worst” case for SSP results in negative values even at the upper tail of the distribution. In India, biomass is the power technology most likely to confer the largest discounted value of benefits, and these are largest when carbon damages are included for CCGT but no thermal damages are included for biomass power. The estimated median present value of benefits in this case is \$401 million.

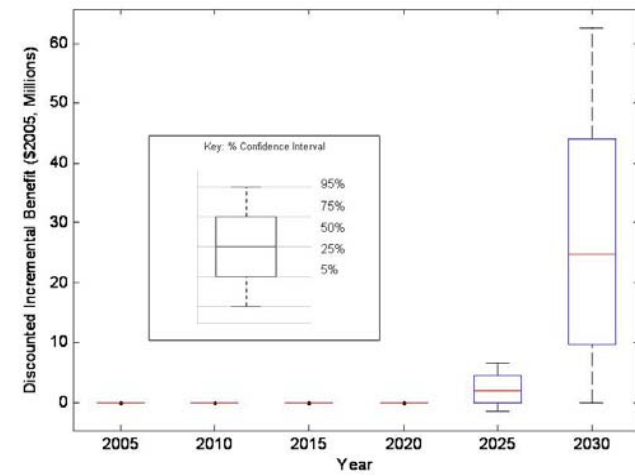
The results illustrate the potential benefit, in terms of discounted present value, of the adoption of new technology to meet the incremental growth in electricity requirements in the coming decades. The results demonstrate the influence of the value of environmental effects and power generation reliability, as well as differences in the relative value of different power technologies among geographic regions. We also explicitly incorporate uncertainty about future generation costs, adoption rates of new technology, and the size of environmental and reliability effects.

We have “stacked the cards” to favor SSP insofar as environmental damages and potential reliability losses are attributable only to the conventional (terrestrial) technologies. We take at their word the view of SSP engineers that SSP could be available by 2020 or so at somewhere around 5 cents to 11 cents per kWh and that SSP generation would be “plugged into” the conventional power grid’s transmission and distribution systems. We realize that research is underway to improve understanding of any potential environmental effects of SSP, as well as other operating characteristics. The model can readily incorporate this information as it becomes known.

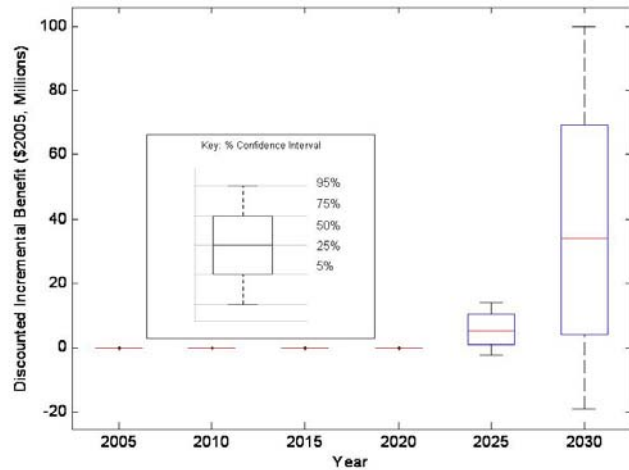
A great deal of additional uncertainty is inherent in investing in such long-lead technology as SSP. We build numerous sources of uncertainty into the model and accordingly, the probability distributions of the results are quite wide. Figure 6 demonstrates the wide bands of the confidence intervals for the scenarios in which SSP confers the largest median benefits. These are shown five (2025) and ten years (2030) after projected availability of SSP.



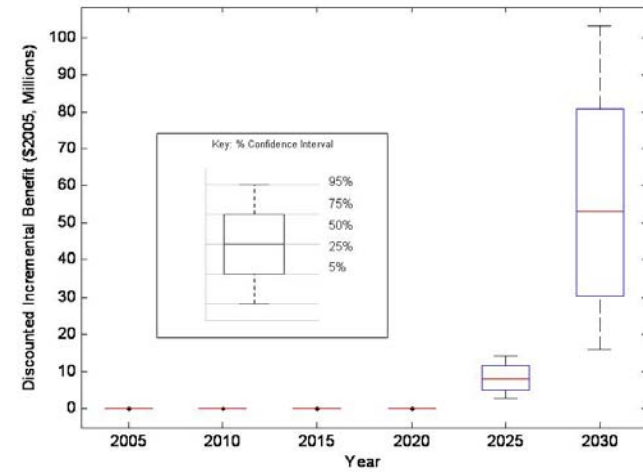
Discounted incremental benefit from 2020 to 2030 for SSP from Scenario 1 for CA



Discounted incremental benefit from 2020 to 2030 for SSP from Scenario 1 for MAPP



Discounted incremental benefit from 2020 to 2030 for SSP from Scenario 1 for Germany



Discounted incremental benefit from 2020 to 2030 for SSP from Scenario 1 for India

Figure 6. Discounted Present Value of Benefits Associated with SSP: Confidence Intervals

We think this feature of the results is appropriate for characterizing explicitly the factors associated with long-lead investment, as its return will depend on:

- The success of SSP technology development in meeting its expectations with respect to cost and operating attributes.
- Cost-reducing innovation in competing power technologies; based on our results, particularly in wind and biomass.
- Continued advances in the efficiency and environmental safeguards associated with CCGT.
- Relative costs of CCGT fuels, including coal and natural gas.
- Public policy governing commercial nuclear power, electricity market deregulation, responses to concerns about environmental effects of energy on climate, subsidies and other financial incentives for energy development, as well as taxes, carbon trading, and other financial interventions affecting power markets.

Does this long list—and the wide bands in Figure 6—undermine the usefulness of the results? We do not believe so. Rather, we see these as factors essential to long-run planning and indicative of influences that need recognition and, when possible, quantification in technology investment decisions. Toward this end, uncertainty is transparent and prominent in the model and its results.

As noted earlier, it is important to note that the model is not an optimization model designed to optimize the mix of power generation technologies by maximizing net present value over time. Rather, the model represents a simpler problem: that of identifying for decisionmakers involved in investing in long-lead technology the interplay of factors potentially influencing the value of the investment. Use of the expenditure-weighted cost index reflects the demand side in a parsimonious but conceptually consistent approach and enables measurement of public benefits accruing from the investment. The major limitations of the results largely are the lack of data about values of other environmental effects, such as those associated with wind power, the future costs of natural gas and coal as components of CCGT, and the relative performance expected from SSP with regard to its cost, its environmental effects, and its reliability. The results presented here assume that SSP cost targets will be met and that SSP will involve no untoward environmental and (un)reliability effects.

V. Summary and Conclusion

This study models and analyzes the relationship of SSP, the environment, and electricity reliability. It seeks to promote an understanding of the costs and opportunities, and how to address them in a systematic and quantitative framework, for characterizing the possible contribution of SSP to electricity markets. The detailed computer-based model developed here estimates the potential economic value of SSP as a source of commercial power by the year 2030. The model explicitly incorporates environmental effects and reliability concerns associated with conventional (terrestrial) power technologies. These effects are defined and measured within a larger modeling framework in which the potential value of SSP is placed in economic context with electricity supplies in distinct geographic markets: two regions within the United States (California and the Midwest), Germany, and India. Previous SSP research has largely evaluated SSP by comparing it with fossil-fuel technologies based on highly aggregated U.S. national average data. This research, therefore, has not accounted explicitly for the role of terrestrial renewable energy, technical innovation in other technology between now and the coming decades, and marked geographic differences in terrestrial renewable energy potential (for example, some regions lack geothermal and solar thermal capacity, but the availability of SSP is independent of terrestrial resource endowments). Importantly, prior research has also not included environmental effects in an integrated model.

By using cost indices, the model has conceptual rigor but is parsimonious in some of its data requirements. We also incorporate formal statistical measures of uncertainty with respect to the cost performance of power technologies in the future, as well as public policy likely to govern or influence future electricity markets. The output of the model is the discounted present value of the putative economic benefits of SSP compared with conventional electricity generation as the year 2030 approaches and additions to power generation capacity are required to meet growing demand. We find that conditions under which SSP is more likely to be competitive in meeting growth in demand include electricity markets in which carbon emissions and thermal effluent associated with some conventional power generation technologies are assessed financially (through fees or taxes). Another discriminating factor is the extent to which the reliability of conventional generation technologies is less than that which is expected from SSP. We find that the benefits of SSP vary markedly among geographic regions due to differences in resource endowments, power generation costs (including fuelstock costs), and public policy. This detailed energy market and geographic modeling is intended to complement and facilitate

significantly further SSP engineering development and related investment decisions by providing an understanding of the conditions under which SSP could be successful.

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Appendix A: Model Parameters and Data Description

<i>Variables (units)</i>	<i>Technology/Year</i>	<i>Parameterization (CA)</i>	<i>Parameterization (MAPP)</i>	<i>Technology/Year</i>	<i>Parameterization (Germany)</i>	<i>Parameterization (India)</i>
Gencosts05 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(22.69,25.22,27.74) Tri(9.38,10.43,11.47) Tri(3.15,3.50,3.85) Tri(3.60,4.00,4.40) Tri(2.86,3.18,3.50) Tri(7.06,7.86,8.64) Tri(4.43,4.92,5.41) Tri(4.34,4.83,5.31) NA Tri(4.38,4.86,5.35)	Tri(35.22,39.14,43.05) NA NA Tri(3.6,4,4.4) Tri(2.86,3.18,3.50) Tri(7.06,7.85,8.63) Tri(4.58,5.08,5.59) Tri(4.49,4.99,5.49) NA Tri(4.53,5.04,5.54)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(47.709,53.01,58.311) NA Tri(14.319,15.91,17.501) Tri(6.3,7,7.7) Tri(7.038,7.82,8.602) NA NA Tri(4.842,5.38,5.918)	Tri(28.359,31.51,34.661) Tri(0,0,0) Tri(5.112,5.68,6.248) Tri(6.543,7.27,7.997) Tri(4.779,5.31,5.841) Tri(5.625,6.25,6.875) Tri(0,0,0) Tri(4.842,5.38,5.918)
Gencosts10 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(19.97,22.19,24.40) Tri(7.32,8.13,8.95) Tri(2.78,3.09,3.40) Tri(3.01,3.34,3.68) Tri(2.43,2.70,2.97) Tri(6.80,7.56,8.32) Tri(4.52,5.03,5.53) Tri(4.44,4.93,5.42) NA Tri(4.50,5.00,5.50)	Tri(30.996,34.44,37.884) NA NA Tri(3.0123,3.347,3.6817) Tri(2.4345,2.705,2.9755) Tri(6.8085,7.565,8.3215) Tri(4.6836,5.204,5.7244) Tri(4.5909,5.101,5.6111) NA Tri(4.6728,5.192,5.7112)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(46.053,51.17,56.287) NA Tri(15.21,16.9,18.59) Tri(5.796,6.44,7.084) Tri(6.795,7.55,8.305) NA NA Tri(4.941,5.49,6.039)	Tri(27.333,30.37,33.407) Tri(0,0,0) Tri(5.283,5.87,6.457) Tri(6.327,7.03,7.733) Tri(4.608,5.12,5.632) Tri(5.49,6.1,6.71) Tri(0,0,0) Tri(4.941,5.49,6.039)
Gencosts15 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(17.26,19.18,21.09) Tri(7.01,7.79,8.57) Tri(2.63,2.92,3.21) Tri(2.81,3.12,3.44) Tri(2.33,2.59,2.84) Tri(5.64,6.27,6.89) Tri(4.62,5.13,5.64) Tri(4.53,5.03,5.54) NA Tri(4.62,5.14,5.65)	Tri(26.766,29.74,32.714) NA NA Tri(2.8161,3.129,3.4419) Tri(2.331,2.59,2.849) Tri(5.643,6.27,6.897) Tri(4.7763,5.307,5.8377) Tri(4.6836,5.204,5.7244) NA Tri(4.797,5.33,5.863)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(44.388,49.32,54.252) NA Tri(16.11,17.9,19.69) Tri(5.328,5.92,6.512) Tri(6.561,7.29,8.019) NA NA Tri(5.04,5.6,6.16)	Tri(26.307,29.23,32.153) Tri(0,0,0) Tri(5.454,6.06,6.666) Tri(6.111,6.79,7.469) Tri(4.446,4.94,5.434) Tri(5.355,5.95,6.545) Tri(0,0,0) Tri(5.04,5.6,6.16)
Gencosts20 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass	Tri(14.54,16.16,17.77) Tri(6.60,7.33,8.06) Tri(2.43,2.70,2.97) Tri(2.72,3.02,3.32) Tri(2.23,2.48,2.73) Tri(5.64,6.27,6.89)	Tri(22.554,25.06,27.566) Tri(0,0,0) Tri(0,0,0) Tri(2.7234,3.026,3.3286) Tri(2.2383,2.487,2.7357) Tri(5.643,6.27,6.897)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear	Tri(42.732,47.48,52.228) NA Tri(17.001,18.89,20.779) Tri(4.761,5.29,5.819) Tri(6.327,7.03,7.733) NA	Tri(25.281,28.09,30.899) Tri(0,0,0) Tri(5.625,6.25,6.875) Tri(5.895,6.55,7.205) Tri(4.275,4.75,5.225) Tri(5.22,5.8,6.38)

Resources for the Future

Macaulay and Shih

	CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(4.71,5.24,5.76) Tri(4.62,5.14,5.65) Tri(5.67,6.30,6.93) Tri(4.56,5.07,5.57)	Tri(4.869,5.41,5.951) Tri(4.7763,5.307,5.8377) Tri(11.349,12.61,13.871) Tri(4.7349,5.261,5.7871)	SSP CCGT	Tri(11.349,12.61,13.871) Tri(5.139,5.71,6.281)	Tri(11.349,12.61,13.871) Tri(5.139,5.71,6.281)
Gencosts25 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(11.82,13.14,14.45) Tri(6.41,7.12,7.84) Tri(2.34,2.60,2.86) Tri(2.67,2.96,3.26) Tri(2.18,2.43,2.67) Tri(5.64,6.27,6.89) Tri(4.81,5.34,5.88) Tri(4.71,5.24,5.76) Tri(5.67,6.30,6.93) Tri(4.50,5.00,5.50)	Tri(18.324,20.36,22.396) NA NA Tri(2.6721,2.969,3.2659) Tri(2.187,2.43,2.673) Tri(5.643,6.27,6.897) Tri(4.9725,5.525,6.0775) Tri(4.8798,5.422,5.9642) Tri(11.349,12.61,13.871) Tri(4.6728,5.192,5.7112)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(41.067,45.63,50.193) NA Tri(17.892,19.88,21.868) Tri(4.383,4.87,5.357) Tri(6.093,6.77,7.447) NA Tri(11.349,12.61,13.871) Tri(5.238,5.82,6.402)	Tri(24.255,26.95,29.645) Tri(0,0,0) Tri(5.787,6.43,7.073) Tri(5.67,6.3,6.93) Tri(4.104,4.56,5.016) Tri(5.085,5.65,6.215) Tri(11.349,12.61,13.871) Tri(5.247,5.83,6.413)
Gencosts30 (c/kWh \$2005)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(9.10,10.12,11.13) Tri(6.23,6.92,7.61) Tri(2.25,2.51,2.76) Tri(2.63,2.92,3.21) Tri(2.14,2.38,2.62) Tri(5.64,6.27,6.89) Tri(4.90,5.45,5.99) Tri(4.81,5.34,5.88) Tri(5.67,6.30,6.93) Tri(4.44,4.93,5.42)	Tri(14.094,15.66,17.226) NA NA Tri(2.6307,2.923,3.2153) Tri(2.1456,2.384,2.6224) Tri(5.643,6.27,6.897) Tri(5.0652,5.628,6.1908) Tri(4.9725,5.525,6.0775) Tri(11.349,12.61,13.871) Tri(4.6008,5.112,5.6232)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(39.402,43.78,48.158) Tri(0,0,0) Tri(18.783,20.87,22.957) Tri(4.05,4.5,4.95) Tri(5.859,6.51,7.161) NA Tri(11.349,12.61,13.871) Tri(5.337,5.93,6.523)	Tri(23.229,25.81,28.391) Tri(0,0,0) Tri(5.958,6.62,7.282) Tri(5.454,6.06,6.666) Tri(3.942,4.38,4.818) Tri(4.95,5.5,6.05) Tri(11.349,12.61,13.871) Tri(5.346,5.94,6.534)
Tfactor (% per year)		Normal(0.0,0.01)	Normal(0.0,0.01)		Normal(0.0,0.01)	Normal(0.0,0.01)
Water externality (%)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	0.00 (Tri(2,3,4)/100) 0.00 0.00 0.00 (Tri(2,3,4)/100) (Tri(1.5,2.25,3)/100) (Tri(1.5,2.25,3)/100) 0.00 (Tri(1.5,2.25,3)/100)	0.00 (Tri(2,3,4)/100) 0.00 0.00 0.00 (Tri(2,3,4)/100) (Tri(1.5,2.25,3)/100) (Tri(1.5,2.25,3)/100) 0.00 (Tri(1.5,2.25,3)/100)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	0.00 (Tri(2,3,4)/100) 0.00 0.00 (Tri(2,3,4)/100) 0.00 0.00 (Tri(1.5,2.25,3)/100)	0.00 (Tri(2,3,4)/100) 0.00 0.00 (Tri(2,3,4)/100) 0.00 0.00 (Tri(1.5,2.25,3)/100)
Fossil emissions cost (mills/kWh , 2005\$)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional)	0.00 0.00 0.00 0.00 0.00 0.00 Tri(2.7,3,3.3)	0.00 0.00 0.00 0.00 0.00 0.00 Tri(2.7,3,3.3)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP	0.00 0.00 0.00 0.00 0.00 0.00 0.00	0.00 0.00 0.00 0.00 0.00 0.00 0.00

Resources for the Future

Macaulay and Shih

	CCGT (advanced) SSP Advanced Coal	Tri(2.7,3,3.3) 0.00 0.00	Tri(2.7,3,3.3) 0.00 0.00	CCGT	Tri(2.7,3,3.3)	Tri(2.7,3,3.3)
Carbon Tax (c/kWh, 2005\$)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.15 0.15 0.00 0.25	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.15 0.15 0.00 0.25	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.15	0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.00 0.15
Value of Loss Load (c/kWh, 2005\$)	Photovoltaic Solar Thermal Hydro/Geothermal (Binary) Wind Class 4 Wind Class 6 Direct-fired Biomass CCGT (conventional) CCGT (advanced) SSP Advanced Coal	Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) 0 Tri(1,3,5)	Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) 0 Tri(1,3,5)	Photovoltaic Solar Thermal Hydro/ Geothermal Wind Biomass Nuclear SSP CCGT	Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) 0 Tri(1,3,5)	Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) Tri(1,3,5) 0 Tri(1,3,5)
Pricetime (c/kWh, 2005\$)	2005 2010 2015 2020 2025 2030	12.54*(1+Tfactor*time) 11.10*(1+Tfactor*time) 10.07*(1+Tfactor*time) 9.76*(1+Tfactor*time) 9.45*(1+Tfactor*time) 9.45*(1+Tfactor*time)	6.37*(1+Tfactor*time) 6.58*(1+Tfactor*time) 6.17*(1+Tfactor*time) 6.17*(1+Tfactor*time) 6.07*(1+Tfactor*time) 6.17*(1+Tfactor*time)	2005 2010 2015 2020 2025 2030	15.24*(1+Tfactor*time) 13.35*(1+Tfactor*time) 13.02*(1+Tfactor*time) 13.24*(1+Tfactor*time) 13.52*(1+Tfactor*time) 13.71*(1+Tfactor*time)	3.88*(1+Tfactor*time) 3.4*(1+Tfactor*time) 3.31*(1+Tfactor*time) 3.37*(1+Tfactor*time) 3.44*(1+Tfactor*time) 3.49*(1+Tfactor*time)
Totgencap4 cast (Billion kWh)	2005 2010 2015 2020 2025 2030	Tri((201.6*0.9),201.6,(201.6*1.1)) Tri((232.7*0.9),232.7,(232.7*1.1)) Tri((260.4*0.9),260.4,(260.4*1.1)) Tri((299.8*0.9),299.9,(299.8*1.1)) Tri((334.9*0.9),334.9,(334.9*1.1)) Tri((370.8*0.9),370.8,(370.8*1.1))	Tri((170.8*0.9),170.8,(170.8*1.1)) Tri((186.9*0.9),186.9,(186.9*1.1)) Tri((189.9*0.9),189.9,(189.9*1.1)) Tri((192.4*0.9),192.4,(192.4*1.1)) Tri((200.3*0.9),200.3,(200.3*1.1)) Tri((215.4*0.9),215.4,(215.4*1.1))	2005 2010 2015 2020 2025 2030	Triangular((574.9*0.9),574.9,(574.9*1.1)) Triangular((598*0.9),598,(598*1.1)) Triangular((617.3*0.9),617.3,(617.3*1.1)) Triangular((636.6*0.9),636.6,(636.6*1.1)) Triangular((656*0.9),656,(656*1.1)) Triangular((675*0.9),675,(675*1.1))	Triangular((695*0.9),695,(695*1.1)) Triangular((848*0.9),848,(848*1.1)) Triangular((1058*0.9),1058,(1058*1.1)) Triangular((1267*0.9),1267,(1267*1.1)) Triangular((1536*0.9),1536,(1536*1.1)) Triangular((1804*0.9),1804,(1804*1.1))
Renewbase 4cast (Billion kWh)	2005 2010 2015 2020 2025 2030	Tri((53.18*0.9),53.18,(53.18*1.1)) Tri((71.41*0.9),71.41,(71.41*1.1)) Tri((72.53*0.9),72.53,(72.53*1.1)) Tri((79.07*0.9),79.07,(79.07*1.1)) Tri((85.38*0.9),85.38,(85.38*1.1)) Tri((88*0.9),88,(88*1.1))	Tri((18.3*0.9),18.3,(18.3*1.1)) Tri((22.1*0.9),22.1,(22.1*1.1)) Tri((22.04*0.9),22.04,(22.04*1.1)) Tri((22.23*0.9),22.23,(22.23*1.1)) Tri((22.25*0.9),22.25,(22.25*1.1)) Tri((21.84*0.9),21.84,(21.84*1.1))	2005 2010 2015 2020 2025 2030	Triangular((46.1*0.9),46.1,(46.1*1.1)) Triangular((54.7*0.9),54.7,(54.7*1.1)) Triangular((62.9*0.9),62.9,(62.9*1.1)) Triangular((71.2*0.9),71.2,(71.2*1.1)) Triangular((79.5*0.9),79.5,(79.5*1.1)) Triangular((87.8*0.9),87.8,(87.8*1.1))	Triangular((106.5*0.9),106.5,(106.5*1.1)) Triangular((138*0.9),138,(138*1.1)) Triangular((163.5*0.9),163.5,(163.5*1.1)) Triangular((189*0.9),189,(189*1.1)) Triangular((214*0.9),214,(214*1.1)) Triangular((239*0.9),239,(239*1.1))
Advcoalbas e4cast (Billion kWh)	2005 2010 2015 2020 2025	Tri((30.8*0.9),30.8,(30.8*1.1)) Tri((56.98*0.9),56.98,(56.98*1.1)) Tri((67.76*0.9),67.76,(67.76*1.1)) Tri((114.8*0.9),114.8,(114.8*1.1)) Tri((151.2*0.9),151.2,(151.2*1.1))	Tri((124.9*0.9),124.9,(124.9*1.1)) Tri((137.3*0.9),137.3,(137.3*1.1)) Tri((138.7*0.9),138.7,(138.7*1.1)) Tri((139.5*0.9),139.5,(139.5*1.1)) Tri((147.5*0.9),147.5,(147.5*1.1))	2005 2010 2015 2020 2025		

Resources for the Future

Macaulay and Shih

	2030	Tri((186.7*0.9),186.7,(186.7*1.1))	Tri((163.4*0.9),163.4,(163.4*1.1))	2030		
Ccgtbase4cast (Billion kWh)	2005			2005	Triangular((56.5*0.9),56.5,(56.5*1.1))	Triangular((73.5*0.9),73.5,(73.5*1.1))
	2010			2010	Triangular((86.5*0.9),86.5,(86.5*1.1))	Triangular((122*0.9),122,(122*1.1))
	2015			2015	Triangular((93.6*0.9),93.6,(93.6*1.1))	Triangular((179.5*0.9),179.5,(179.5*1.1))
	2020			2020	Triangular((100.8*0.9),100.8,(100.8*1.1))	Triangular((237*0.9),237,(237*1.1))
	2025			2025	Triangular((108*0.9),108,(108*1.1))	Triangular((279*0.9),279,(279*1.1))
	2030			2030	Triangular((115.2*0.9),115.2,(115.2*1.1))	Triangular((321*0.9),321,(321*1.1))
Basepce1 (Billion \$2005)	2005	Normal(8.17e+011,6.65e+010)	Normal(2.86e+011,1.90e+010)	2005	Normal(1.88e+012,1.09e+011)	Normal(3.67e+011,2.7e+010)
	2010	Normal(8.98e+011,1.18e+011)	Normal(3.21e+011,3.80e+010)	2010	Normal(2.04e+012,2.19e+011)	Normal(4.22e+011,5.2e+010)
	2015	Normal(9.78e+011,1.77e+011)	Normal(3.57e+011,6.00e+010)	2015	Normal(2.19e+012,3.44e+011)	Normal(4.77e+011,8.2e+010)
	2020	Normal(1.06e+012,2.45e+011)	Normal(3.92e+011,8.50e+010)	2020	Normal(2.34e+012,4.86e+011)	Normal(5.32e+011,1.18e+011)
	2025	Normal(1.14e+012,3.20e+011)	Normal(4.27e+011,1.14e+011)	2025	Normal(2.49e+012,6.42e+011)	Normal(5.86e+011,1.59e+011)
	2030	Normal(1.22e+012,4.04e+011)	Normal(4.62e+011,1.47e+011)	2030	Normal(2.64e+012,8.13e+011)	Normal(6.41e+011,2.06e+011)

Appendix B: Estimates of Personal Consumption Expenditure

For each year, for California and the Mid-Continent Area Power Pool, we calculate the product of per capita personal income by the midyear population in that region and the ratio of national personal consumption expenditures (PCE) to national personal income for that year. Then we add each region's contribution to obtain a regional PCE for each year between 1989 and 1999. Using the historical datasets, we first regress annual PCE against time using the following equation:

$$PCE_t = a + bt$$

We then use estimation results to forecast PCE to 2030 (PCE is in 1999 billions of dollars).

We repeat this for Germany and India. Using an historical data set (1995 to 2001 for Germany and 1989 to 1999 for India), we regress annual PCE against time. We then forecast PCE to 2030 using the regression results. The Germany historical PCE data are from the German Federal Statistics Office. The India historical PCE data are from the Reserve Bank of India. The data were converted to year 2000 dollars using the Bureau of Labor Statistics consumer price index and exchange rates from the Federal Reserve Bank of New York, the International Monetary Fund, and the Reserve Bank of India.

In the following table, we summarize regression results:

Variable	CA	MAPP	Germany	India
<i>A</i>	474.4 (13.0)	145.0 (2.5)	1381.7 (10.3)	161.8 (4.1)
<i>B</i>	14.0 (1.9)	6.1 (0.4)	27.0 (2.3)	9.7 (0.6)
Adj R-Sq	0.84	0.96	0.96	0.96
Years of Obs.	1989-1999	1989-1999	1995-2001	1989-1999
Dollar	1999	1999	2000	2000
Standard errors in parentheses				