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Effects of Carbon Policies and Technological Change on Consumer Surplus in Electricity Generation

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RESOURCES FOR THE FUTURE

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Abstract

We develop and estimate an index-based measure of expected consumer welfare under various carbon emissions control policies in the electricity generation sector. This approach estimates welfare effects by a somewhat less data intensive methodology than econometric approaches or more complex modeling. We include anticipated technological change in the production of renewable and nonrenewable power generation during the next two decades. We estimate welfare improvements from 2000 to 2020 as renewable energy technologies continue to be improved and gradually adopted, compared with a counterfactual scenario allowing for continual improvement of nonrenewable generation technology. We formally incorporate uncertainty. We evaluate the model under alternative carbon emissions control policies, including policies that create incentives through price mechanisms and policies that mandate the composition of the generation portfolio. We focus on three countries that differ widely in their power fuel mix: India, Germany, and the United States.

Keywords: carbon emissions control, electricity generation, technological change, consumer welfare

JEL Classification: Q40, Q42, O33

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Molly K. Macauley and Jhih-Shyang Shih[1]

1. Introduction

The electricity sector, primarily through the use of fossil fuel for power generation, is a major source of carbon dioxide emissions. Governments around the world are promoting increased nonfossil electricity production, but most analyses of the future of renewable energy predict that fossil fuels will continue to supply most of the world's power requirements during the coming decades.

Our model analyzes expected new additions to electricity generation capacity during the next two decades. We estimate the effects of adoption of different types of energy on consumer welfare, taking explicit account that renewable energy as well as conventional, fossil fuel technology (principally, combined cycle gas turbines) will continue to improve technologically. The model expressly accommodates differences among geographic regions in existing and projected electricity fuel mix. We use the model to measure the effects of public policy on changes in consumer surplus resulting from alterations in this mix. We consider two policies: carbon taxes and renewable portfolio mandates. Taxes and other forms of economic intervention on the carbon content of fossil fuels are among the most frequently discussed approaches to mitigating greenhouse gases. Another popular approach to energy policy requires minimum quantities of the fuel mix to be represented by renewable energy supplies —a renewable portfolio standard (RPS). We model the effect of several specifications of an RPS on surplus.

We focus on the fuel mix in India and Germany, and we also refer to results in previous research for the United States. Significant differences characterize the mix of

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conventional power fuels and renewable power sources among these regions (see Figures 1 and 2). By 2020, the mix evens out over fuel sources, although marked differences persist (see Figures 3 and 4). We intend this choice of countries to represent the regional diversity in patterns of electricity fuel use that can go far in explaining differences among countries in the effects of carbon taxes and RPS.

We find large differences in changes in consumer surplus among all of the countries under baseline parameters on rates of adoption of renewable energy and on the extent to which a host of environmental externalities are monetized in generation costs. These differences further increase when we model the effects of carbon taxes and RPS. These results illustrate challenges in domestic and international policy formulation; in suggesting a readily implemented model for estimating changes in consumer surplus, we hope the structure can prove useful in policy evaluation at many levels of governance.

We next describe the conceptual basis for the index, outline the simulation model we develop to evaluate the index under various scenarios, and give details about our data and assumptions. We then offer results under basic assumptions in baseline scenarios and under policy scenarios.

2. The Model

The basis of our model is a quality-adjusted cost index, which we use to estimate future consumer welfare gains under a variety of policy scenarios. The index is based on well-developed index number theory (a good overview is in National Research Council 2002, chapter 2) and its application in previous research to measuring realized gains from technological change (Bresnahan 1986; Austin and Macauley 2000, 2001; Macauley et al. 2002). The approach is similar to the methodology underlying the familiar consumer price index, which, to the extent possible, incorporates quality differences among goods and services. An advantage of an index-based approach is that, under certain general mathematical assumptions, the index is a function only of observed costs and the share of expenditure represented by the product in total expenditures. The index is also ideal for applying to derived demand rather than final demand for a product. For example, Bresnahan applies the index to consumer demand for new computer technologies as inputs into financial and other sectors of the economy. By analogy, we apply our index to derived demand for electricity generation.

Our approach, based on Austin and Macauley (1998), extends the conventional index in two directions. One extension makes the index prospective in order to be useful for evaluating the potential future gains from investment in new or improved technologies. We allow for gradual diffusion of renewable energy electricity generation technologies, and we express the model's parameters as probability distributions to reflect uncertainty over future or estimated parameter values for both the renewable technologies and the conventional, or defender, technology (combined cycle gas turbine). Another extension expands the index to account for externalities associated with the technologies, although data gaps somewhat limit the empirical application of this extension. This extension is similar to quality adjustments made in conventional applications of price indices. We also conduct sensitivity analyses, in which we shift parameter locations, to test the robustness of our assumptions about uncertain parameters.

The result is a theoretically grounded economic model of future welfare gains embedded within a cost-index simulation model. The output is a rigorous yet transparent index that can be used to evaluate a variety of policy scenarios, to assemble research and development (R&D) portfolios from a selection of competing projects, or to indicate the performance of prospective investment in new technologies.

Expression (1) defines the cost index. In (1), C^{*dt} is the minimum cost of achieving "utility" u^{dt}, or the socially optimal combination of conventional energy technology (for electricity) and other goods and services, expressed relative to the cost of u^{dt} given the investment in renewables that brings about reductions in their costs (or increases in their social benefits). Similarly, C^{*I} is the cost of achieving optimal utility u^I under the investment scenario with conventional energy costs, W^{dt}, relative to the cost of renewables with post-innovation costs, W^{RE}.

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

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

Figure 5 depicts the relationship among the expenditure functions (E^*), utility, and the two cost indexes represented by C^{*dt} and C^{*I}.[2,3] A welfare-enhancing innovation lowers consumers' costs of achieving a given level of utility, shifting the expenditure function downward from $E^*(u, W^{dt})$ to $E^*(u, W^{RE})$. The vertical distance between the two curves depends on the share of electricity generation costs in total consumption expenditures; their ratio is given by C^*. Given a welfare-enhancing innovation (I), consumers' optimal utility rises to $U^{*I} > U^{*dt}$. With separable utility and other prices unaffected, the relative cost to achieve u^{*I} with higher baseline prices (W^{dt}) versus reduced, post-innovation prices (W^{RE}) exceeds the relative cost to achieve U^{*dt}.

Simplification of (1) based on cost index theory (see Caves et al. 1982) and assuming, as is routine in expenditure theory, that the consumer expenditure function (E^*) can be represented by a translog functional form,[4] gives the index in (2):

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

The terms $s^{dt} + s^{I}$ give, respectively, electricity expenditures as a share of personal consumption expenditure (PCE) under the baseline and investment-in-renewables scenarios. These expenditure data serve as "weights" in the index. The monetary value to consumers of the investment is just the product of their predicted PCE times the exponent of the cost index.[5] Thus, interpretation of the index is "how much better off are we (that is, society in general) as a result of investment in renewables for

[2] 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, proportionality). The Tornqvist index satisfies many of the tests (see Diewert and Nakamura, 1993).

[3] To simplify figure labeling, prices (*P*) have been omitted from the expenditure functions.

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

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

the production of electricity, taking into account the alternative (conventional technology) and differences in the social benefits and costs between renewables and conventional technology?”[6]

From equation (2), the index is greater than one if the innovation is welfare-enhancing; it is less than one if the innovation is inferior to the defending technology; and it is closer to one the smaller the share of the total budget (or of total private consumption expenditures) spent on the technology. The illustration in Figure 5 assumes a welfare-enhancing technology. 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 can indicate progress over time as continued investment results in innovation that nudges the index upwards. This interpretation furthers the usefulness of the index to policymakers for measuring performance over time of investment in new technology or for considering the effects of policy on welfare.

2.1 The Simulation Model

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

Figure 6 illustrates the model. It begins with data on generation costs for each of the technologies. We add to these private costs the monetized costs of externalities to obtain the sum of private and social generation costs. We then use our assumptions about the rate at which new technologies will be used (which we label “adoption rates”) to estimate factor shares for the index, following equation (2). The cost index itself is the ratio of two alternative outcomes: generation costs weighted by the shares of PCE devoted to generation in the baseline, or defending technology scenario, compared with the innovating technology scenario (the former is combined cycle gas turbine technology and the latter is our renewable technologies). In the last step, we use the index to estimate the discounted present value of the stream of benefits to consumers over time.

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

We use the shares, together with the end use price of electricity and total PCE, to estimate consumer surplus[7] that would be expected from the innovating technologies (our renewables), measured in comparison with the baseline (the defending technology), given our assumptions and data. Surplus is expressed as the discounted present value of consumer benefits over the period 2000–2020. We use the same procedure to evaluate the effects of our carbon tax and RPS policy approaches.

The cost ratio indicates relative costs of the competing technologies, while 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 one, but, in any case, very close to one. Consumer surplus, or total benefits, can be very large, however.

As noted, we parameterize all of 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 feel its major limitation is data, which we discuss further below.

2.2 Adoption Rates

During 2000–2020, most experts agree that international demand for natural gas as a source of fuel for power generation will rise more strongly than demand for any other fossil fuel. And, the technology of choice will be combined cycle gas turbines, favored for a variety of reasons, including their high energy-conversion efficiency, low capital costs, and ease of operation. With this trend in mind, we assume that the adoption of new renewable technologies gradually displaces *some* adoption of new combined cycle gas turbine (CCGT) units, but does not force early retirements. The purpose is to carry the expected growth in CCGT capacity that could be displaced by growth in the adoption of new renewable technologies. (Our measurement and estimation of growth in CCGT

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[7] The end use price of electricity (that is, the price determined by generation, transmission, and distribution), rather than the fraction of the end use price represented by generation only, is the relevant measure for consumer surplus.

and renewables generation capacity are somewhat complex and we discuss them further in the data section.)

This assumption is somewhat weaker in the case of India because India has less access to cheap natural gas resources (and may be more likely to rely on coal-boiler and steam-turbine technology for additions to baseload capacity). But projections for the Indian fuel mix show reductions in coal and increases in gas for power generation. More stringent emissions control measures would also favor gas, as would further integration of gas markets, given the sizeable domestic natural gas resources in Bangladesh (International Energy Agency 2002a).

We include nuclear power as an alternative power technology in the cases of Germany and India, even though its future share of electricity generation is highly uncertain in these countries. As of 2000, some governments have expressed renewed interest in nuclear power as a means to reduce emissions and to improve the security of energy supply (see International Energy Agency 2002c).

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

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

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

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

Figure 7, on page 43, shows the renewable generation shares over time for these two adoption rates using Weibull functions.

2.3 Accounting for Externalities

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

From a conceptual perspective, the external effects that count for an "apples to apples" comparison— and with which we are largely concerned in this report—are *technological* externalities, or the uncompensated effects of one party's actions on another party. When these effects harm the other party, they increase the full cost to society, above and beyond the private resource costs, of the activity. External costs shift the expenditure functions in Figure 5 and alter the corresponding consumer surplus area

[8] In the case of thermal releases, all combustion involves heat rejection, the magnitude depending 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 a putative impact on aquatic integrity and activities, that merit treatment as an externality.

that we seek to measure. The surplus may increase or decrease depending on whether the external costs favor the defending or innovating technology.

For meeting environmental requirements, utilities may incur costs—for pollution control equipment, for example—that are considered internalized environmental costs because they are included in the electricity rates. However, there are other external costs that are not reflected in the rates—for example, mercury emissions not presently controlled.[9]

Externalities can arise at any stage of the electricity cycle, from development and extraction of a resource to transportation, processing, manufacturing, and assembly of materials and facilities, and generation, transmission, and disposal of all wastes or residuals from various activities and processes.[10] To keep our model tractable, and because fully accounting for these effects is outside the scope of our project in any case, we include only externalities arising during electricity generation.[11] Thus, we exclude any "upstream" externalities, such as leakages from gas transmission lines or "uninternalized" risks of energy disruptions. In addition, we focus on external costs, not the avoided external costs of nonpolluting systems. We note also that effects can vary by geographic region and over time. For instance, the extent of environmental and health effects depends on the affected population and may include both short- and long-term effects.

Our choice of external effects to include in our model is significantly restricted by a lack of empirical information. This is not a limit of the index, but one imposed by data. The technologies we consider have a variety of possible externalities:

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

[10] External effects—both technological and pecuniary—associated with energy generation range widely from effects on health and the environment (including climate change) to effects on occupational health in energy producing sectors, employment in energy sectors, fiscal effects in the form of government revenues affected by differential tax and subsidy treatment of energy technologies, and road damage from transportation of fuels, as well as a host of energy security implications (for example, the economic cost of oil supply disruptions; the cost of military expenditures to secure international trade). See discussion in Krupnick and Burtraw 1996; also Bohi and Toman 1992, and Green and Leiby 1993.

[11] Portney 1993–94 discusses the complexities of life-cycle approaches.

--For biomass energy generation: a feedstock that may have 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.

--For photovoltaics: potential occupational health effects arising during manufacturing 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 avian resources, including endangered species and species protected under the migratory bird treaty; noise; visual effects; electromagnetic interference; possible fluid leaks 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).

--For solar thermal energy production: the possibility of spills or leaks from heat transfer fluids, wastewater, and thermal discharges.

-- For nuclear power: a host of concerns, including operation and maintenance safety, and handling and disposal of wastes.

--For combined cycle gas turbines: thermal discharges and other releases not yet 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; Oak Ridge National Laboratories and Resources for the Future 1998; Hunt 2001; and RESOLVE Inc. 2001 contain in-depth discussion of the epidemiological and environmental effects for a small subset of externalities. Krupnick and Burtraw summarize much of this literature, focusing on the effects for which researchers have developed monetized values.

Due to data limitations, we have monetized values only for a few of these possible effects. In addition, we assume that the external costs in our model take identical values across the countries in our study.

2.4 Data

A context for our data and for ensuing results comes from differences in the electricity fuel mix among the countries we study.

Germany

Germany is Europe's largest electricity market. In 1999, about two-thirds of Germany's power came from fossil fuels (mainly coal), one-third came from nuclear power (Germany ranks fourth worldwide in installed nuclear capacity, behind the United States, France, and Japan), and small amounts came from hydropower and other renewable sources. During the 1990s, Germany increased its wind capacity, largely in small projects owned by individuals and private operating pools rather than by utilities (see U.S. Department of Energy, undated). Nuclear power has become controversial in Germany since the 1998 elections; the government formally signed an agreement with utility companies in 2001 to gradually phase out nuclear power, with the result that by 2021 nuclear power would be eliminated (see U.S. Department of Energy 2001). Some representatives of the commercial power sector have claimed that the 2001 agreement is reversible, and that an electricity shortage or a change in political parties could lead to a renewal of nuclear energy (see U.S. Department of Energy 2001). The country ranks third in total carbon emissions within the Group of Seven industrialized nations (after the United States and Japan). Germany signed the United Nations Framework Convention on Climate Change in Rio de Janeiro in June 1992 and ratified it on December 9 1993. Signers of the agreement pledged to stabilize per capita carbon dioxide emissions in 2000 and beyond at 1990 levels. Under the Kyoto Protocol of December 1997, Germany would have to further reduce emissions some 8% by 2008–2012.

India

India has the third-largest coal reserves in the world, and the bulk of its existing electric power supply is coal-fired. The International Energy Agency (IEA) predicts a three-fold increase in India's generation capacity by 2020, at an annual yearly growth rate of 5.2%. While renewable energy represents only a small share of generation capacity (about 2.5%, including hydropower, in 1997), the share of renewables is growing and India has been called a world leader in the diffusion and development of some renewable technologies, according to the IEA (see International Energy Agency 2002a and Gosh et al. 2001). A "Policy Statement on Renewable Energy," issued by the government in 2000, calls for increased capacity from renewables. India has more installed wind capacity than any other developing country (as of 1999) and ranks fourth in the world (after Germany, the United States, and Denmark). Most of this capacity was added with significant government support in the mid 1990s. Most of the wind power is concentrated in three states (Tamil Nadu, which had 75% of India's total in 1996; Gujarat; and Andra Pradesh). Investment in wind has slowed in recent years with a slowing economy and a change in government. Various state electric boards have agreed to purchase wind power at guaranteed prices (see U.S. Department of Energy, undated). India's solar potential is also large (see International Energy Agency 2002a; Gosh et al. 2001).

Much of the power system in India is hindered by transmission and distribution (T&D) losses that account for about 20% of generated electricity, and experts see a large potential for improvement in T&D (see extensive discussion in Gosh et al. 2001).

The United States

Coal will remain the most important fuel in power generation during the coming decades, but the share of coal in total generation is expected to decline because of fast growth in gas-fired generation. Most of the new generation capacity brought on line will be natural gas-fired. Nuclear generation will decline as existing plants are retired and few new plants are licensed. The share of renewable energy in the power mix is expected to increase, largely due to federal and state incentives to promote a large increase in investment in new wind and biomass capacity, but the share of renewables in total generation will continue to be small. The carbon intensity of U.S. emissions is projected to decline due to a reduction in the energy intensity of the economy and because natural gas is less carbon intensive than coal and oil.

The data we use for the period 2000–2020 are the generation costs for conventional and renewable energy technologies, the externalities associated with these technologies, total expenditures on electricity generation as a fraction of total personal consumption expenditures, and expectations about the values of these inputs over the relevant time horizon.

We use national averages for India and Germany for electricity generation costs and expenditures. We realize that there are significant differences in costs and expenditures among regions within these countries. For example, radically different energy sectors characterized East and West Germany following reunification of the country in 1990, with East Germany mainly dependent upon relatively “dirty” lignite (brown coal) as its primary fuel, and West Germany committed to environmental protection. However, in the past few years, and in step with legislation in the European Union, the German power market has become one of the most competitive in Europe (U.S. Department of Energy 2001). The continuing trade in power supply is likely to erode any large regional differences. Large regional differences also characterize India; for example, 75% of wind power is located in one state, and two other states have most of the remainder.

We also omit imports of electricity; for example, although Germany produced more power than it consumed in 1999, it is a small net electricity importer because of transmission losses and proximity to foreign sources of generation (U.S. Department of Energy 2001).

Our data are collected from international energy statistics, energy experts, and other sources. Data on costs and expenditures often inconsistently incorporate the variety of taxes, subsidies, and other policies that complicate comparisons among countries. In Germany, these include subsidies to the hard coal industry; “eco-taxes” that are to increase energy taxes 10% during 2001–2004 (although, in late 2001, the chancellor’s chief economic adviser indicated that these taxes may be suspended for a year or two to stimulate the economy); the 2000 Renewable Energy Law, which extends provisions of the 1991 Electricity Feed Law requiring electric utilities to purchase renewable energy at guaranteed prices and seeks to double the share of renewable energy in the electricity market from 5% to 10% by 2010; (and subsidized interest rates on loans for investment in wind capacity (U.S. Department of Energy 2001; Climate Net News, undated). In India, public policies provide for guaranteed prices for wind energy purchases by several state electric boards, exemptions from excise duties and sales taxes for wind, accelerated depreciation for capital investment in power generation, and five-year tax holidays on income from sales of electricity (U.S. Department of Energy, undated). We have attempted to obtain comparable data, but in some cases, as we note below, our efforts were limited.

A few words are in order about some of the technologies.

Nuclear Power

We assume future availability of nuclear power in India and Germany. In the case of India, international data sources predict some growth in the capacity of nuclear power as well as increases in its share of total generation. At present, most of the nuclear plants in India operate at less than 50% capacity (Gosh et al. 2001). As we noted above, the future of nuclear power is less certain in Germany. Some representatives of the commercial power sector have claimed that the 2001 government agreement with utility companies to phase out nuclear power is reversible, and that an electricity shortage or a change in political parties could lead to a renewal of nuclear energy (U.S. Department of Energy 2001). In the United States, nuclear plant retirement decisions and opposition to new plant licensing are expected to reduce nuclear power capacity and the share of nuclear power in total generation.

Hydroelectric Power

Hydropower is expected to increase in developing countries, including India, although interstate disputes about power- and water-sharing as well as environmental opposition may hinder hydro development. Much of the hydro potential has already been exploited, and environmental considerations prevent the development of large-scale hydro plants in Germany and the United States.

Our data include the following: [12]

Generation costs, Germany

We base year 2000 generation costs of most renewable technologies, CCGT generation, and nuclear power in Germany on excise tax and subsidy inclusive generation costs at a plant utilization of 7000 hours (Commission of the European Communities 2001). Generation costs for hydro and geothermal power for Germany are from International Energy Agency 1997; these hydro and geothermal generation costs are based on a range given by the IEA for small (less than 0.5 MW) hydro generation.

[12] Where necessary, 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.

Generation costs, India

Generation costs used for India from 1999 are the upper bounds of a range of generation costs reported in Bakthavatsalam, 2001. Nuclear generation costs are from Nuclear Energy Agency et al. 1998. It was unclear from our sources whether or not the generation costs data for India contain taxes and subsidies.

Future generation costs to 2020

The International Energy Agency (2001b) gives a range of worldwide reductions expected between 2000 and 2020 by type of renewable power generation technology. We linearly interpolated costs for interim years. We assume the generation costs follow triangular distributions with upper and lower bounds equal to plus or minus 10% of the predicted generation costs. We also add an error bound due to increasing uncertainty that might be associated with year 2020 predictions made in 2000; the mean step size is 1% per year (for example, after five years, up to 5% perturbations are added or subtracted from the cost prediction). Future CCGT cost reductions are based on previous analysis from Macauley et al. (2002) under an assumption that the turbine technology is internationally mobile capital.

Fuel costs—natural gas prices

Many analysts expect potentially large fluctuations in natural gas prices during coming decades. We do not explicitly model fuel costs, but rather we assume that the uncertainty with which we characterize generation costs for CCGT reflect fuel price fluctuations. As noted above, CCGT generation costs are characterized as triangular distributions with lower and upper bounds of plus or minus 10%, and the uncertainty bounds increase with time from 2000 to 2020 in mean step sizes of 1% per year.

Generation quantities, Germany

Our data on generation quantities for Germany from the years 2000, 2005, and 2010 are from International Energy Agency 2001a. Total generation quantities are net of pumped storage generation. Renewable generation includes combustible renewables and waste as well as geothermal, solar, tide, wind, and hydropower generation. Geothermal and tide generation are negligible. The CCGT generation quantities are based on the assumption that all gas generation is from CCGT plants. Incremental CCGT generation quantities are calculated as the increase in CCGT generation between 2000 and 2005, and 2005 and 2010. For quantities from 2010 to 2020, we note that the data show a large increase due to the expectation that Germany will phase out its nuclear power. From 2000 to 2005, nuclear generation drops by only 0.14 billion kWh and, from 2005 to 2010, it drops by about 20 billion kWh. We assume that replacement power is CCGT. To estimate CCGT generation in 2015 and 2020, we deduct these replacements from the CCGT base in 2005 and 2010 to estimate net CCGT. We calculate that net CCGT growth between 2000 and 2015 is about 2.8% annually. We then use this percentage to extrapolate net CCGT for 2015 and 2020; add retired nuclear generation to the net CCGT base; and use this as the forecast for 2015 and 2020.

Generation quantities, India

Generation quantity data for India were gathered from International Energy Agency 2002c. Data were available for the years 2000, 2010, and 2020. Renewable generation quantities include generation from large hydropower as well as biomass, wind, solar, geothermal, and tidal/wave. Geothermal and tidal/wave generation are negligible. The CCGT generation quantities are based on the assumption that all gas generation is from CCGT plants. Incremental CCGT generation quantities are calculated assuming that half of the CCGT generation from 2000 to 2010 occurs by 2005, and that half of the CCGT generation from 2010 to 2020 occurs by 2015.

Personal consumption expenditure, Germany and India

Using historical data sets (1995 to 2001 for Germany and 1989 to 1999 for India) we regress annual PCE against time. We then forecast PCE to 2020 using the regression results. The Germany historical PCE data are from personal communication with Zoran Tomic of the German Federal Statistics Office (http://www.destatis.de). The India historical PCE data are from the Reserve Bank of India (www.rbi.org.in). The appendix contains the calculations and regression results.

Expected market price of electricity, Germany and India

The data for the average electricity price to households (using exchange rates) in both Germany and India are from International Energy Agency 2002b. The most recent price data available are for the years 2000 and 1997 for Germany and India, respectively. We extrapolated price trends from historical data to forecast future price trends based on the ratio of German and U.S. prices and Indian and U.S. prices in 2000 (and assuming the ratios remain the same during the next 20 years).

Externality costs

We use a value for the externality associated with carbon dioxide emissions from CCGT as reported in Krupnik and Burtraw (1996, Table 6), who offer the most recent survey and critique of monetized estimates from other authors' large-scale models of the health and environmental damages from electricity in the United States and Europe. Krupnik and Burtraw report a value of about 2.9 mills/kWh (about 0.3 cents/kWh). Our value for the externality associated with nuclear power generation is also from Krupnik and Burtraw; the damages they report are based on engineering estimates of accident probabilities and consequences. They report a value of 0.3 mills/kWh. We estimate the value for thermal effluent discharged into streams and other water bodies during power generation from solar thermal, biomass, and CCGT following Macauley et al. (2002).[13] They determine how much it would cost a power plant to avoid thermal effluent entirely and allocate this additional cost as their measure of the externality. They find that the annualized capital costs of a CCGT plant would increase by about 1.5% to 3% (about 0.05 to 0.14 cents/kWh). Biomass and solar thermal are less efficient than CCGT and thus require more cooling per kWh produced. Engineering data indicate that generation costs for these technologies would increase by about 2% to 4% (about 0.15 to 0.49 cents/kWh) to avoid thermal effluent.

2.5. Uncertainty

The time horizon of our study is 20 years, consistent with the time horizon in many of the data sources (for instance, the U.S. Department of Energy, the International

[13] Small amounts of thermoelectric water also come from groundwater aquifers, whose degradation can therefore create an external costs. However, engineering data indicate that such groundwater is a negligible fraction of total thermoelectric water use.

Energy Agency). These sources also predict the future of generation costs; for all of the technologies we consider, the projections show declining costs reflecting assumptions with respect to learning by doing, returns to scale, and technological innovation.[14]

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. [15] 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 increasing marginal costs could also arise from R&D activities that 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 we explicitly incorporate and adoption effects that are implicit in but nonetheless affect the estimates in the data sourcesis 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; we believe these 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 uncertainty increases over time. We assume this follows a standard normal distribution with mean zero and standard deviation 0.01 (1%). Uncertainty grows at a step size of about 1% each year. While the use of some arbitrary assumptions is

[14] Learning by doing represents learning effects of workers and 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.

[15] 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.

unavoidable given the data and their limitations, the resulting model is very transparent and alternative assumptions can easily be explored.

3. Results

We next report results for baseline scenarios under which we vary adoption rates and whether adjustments are made for external costs, carbon taxes, and renewable portfolio standards. In the discussion of results, we also include previously estimated results for the United States for baseline scenarios (Macauley et al. 2002) and new results under carbon taxes and renewable portfolio standards.

3.1 Baseline Scenarios

Tables 1 through 4 illustrate our baseline results under four sets of assumptions. The assumptions vary the rate of adoption and whether external cost adjustments are made. In A1, we assume that the innovating technologies are adopted rapidly and that adjustments are made for external costs. In A2, we assume fast adoption but make no adjustment for external costs. In B1, we assume slow adoption and make adjustments for external costs, and, in B2, we assume slow adoption without external costs. Each row in the tables gives the estimated values for a comparison of the listed "innovating technology" compared with the "defending technology," CCGT. The results are given for estimates at the 5%, median, and 95% confidence intervals. All estimates are in discounted present value, in year 2000 dollars.

Baseline Scenario A1:

In this scenario, we parameterize the Weibull distribution to describe a fast adoption rate. We also include carbon, thermal, and nuclear external costs.

For Germany, none of the estimates in this scenario represent positive consumer surplus at the median. The smallest losses in surplus occur with wind and biomass. At the 95% interval, these technologies generate discounted surpluses of about \$360 million (wind) and \$20 million (biomass).

For India, the estimates for hydro/geothermal give positive surplus throughout the range of intervals; the median value is about $400 million. Biomass also results in a positive surplus at the median—about $310 million.

For the United States, wind gives the largest positive surplus, at all confidence intervals, for both the West Coast and the Midwest—the median value is about $4.6 billion for the West Coast and $1.75 billion for the Midwest. Geothermal gives a smaller although positive surplus of about $3.5 billion for the West Coast (as noted above, this renewable resource is not available at appreciable amounts in the Midwest).

Baseline Scenario A2:

We parameterize the Weibull distribution as in Scenario A1, but we omit adjustments for external costs.

The estimates for Germany in this case are negative at all confidence levels. Wind and biomass generate the smallest surplus losses. For India, only hydro/geothermal and biomass at the 95% confidence interval yield positive surplus. In the United States, geothermal and wind on the West Coast and wind in the Midwest have positive surplus, but these are smaller than in scenario A1 when external costs are added to the model.

Baseline Scenario B1:

Here, we parameterize the Weibull distribution to simulate a much slower adoption rate and we include external costs.

Positive surplus values result for all three countries as in Scenario A1 (which posited fast adoption with external costs), but the values are much smaller with slower adoption. For India, median values are about one-quarter as large, and for Germany, values at the 95% interval are about one-sixth to one-half as large as under fast adoption (the value for biomass is significant only at the third decimal position). For the United States, median values are about one-third as large as under fast adoption.

Baseline Scenario B2:

We specify the Weibull parameters as in scenario B1 (slow adoption) and omit external costs.

As in Scenario A2, all values for Germany are negative. Positive values for India and the United States result with the same technologies that yield positive surplus for these countries in Scenario A2. The sizes of all surplus values—which are negative for Germany, but positive for India and the United States—are smaller.

3.2 Comparing the Baseline Scenarios

The baseline results illustrate wide differences among regions, technologies, and assumptions about adoption rates and adjustments for external costs. The results show the sensitivity of surplus to changes in the relative costs of CCGT and other technologies over time and with external cost considerations. For all regions except Germany, the largest of the median discounted present values of surplus occur under fast adoption and with external costs added. This is not necessarily an argument for policy to encourage adoption of renewable technology, however. Among other reasons, recall that our estimates do not include the cost of investment that may be required to realize the cost reductions predicted by our data sources. Finally, while it is important to note that we measure gross surplus rather than overall public net benefit, our estimates do shed some light on this topic. We do not subtract the cost of public R&D energy expenditures to date, nor do we include future public expenditures that could be necessary to bring about the adoption rates we posit.

In the case of Germany, the median values are negative in all cases, as CCGT "holds its own" even as the forecast costs of renewable technologies decline over the next couple of decades. Because renewables are at a relative cost disadvantage according to the Germany data, the smallest losses in surplus (negative values in the results) occur under slow adoption of renewables and with external costs added.

The relative differences between the generation costs of CCGT and the other technologies are smaller in the cases of Germany and India than for the United States, and larger in Germany than in India. In Germany, the reported cost of CCGT generation is about $.06/kWh; renewables (other than photovoltaics) and nuclear range from about $.07/kWh to $.15/kWh; and photovoltaics is about $.80/kWh. In India, the reported cost of CCGT generation is about $.05/kWh; renewables (other than photovoltaics) and nuclear range from about $.05/kWh to $.07/kWh; and photovotaics is about $.30/kWh. In the United States, the corresponding reported costs are CCGT, about $.04–$.05/kWh;

renewables (other than photovoltaics) and nuclear, about \$.035–\$.08/kWh; and photovoltaics, about \$.30–\$.50/kWh.

We find that different technologies produce the largest surplus values for each country—hydro and biomass in India, wind and biomass in Germany (that is, investment in these generation technologies minimizes the loss in surplus), and geothermal and wind in the United States. These differences in part reflect geographic differences in resource endowments and, in turn, differences in generation costs as noted above. However, we find it interesting to note that even though wind capacity in India has grown to 1 GW (about 1% of capacity) and plans are to continue to increase wind capacity, wind gives negative surpluses for India over the next decades (to be sure, wind is still expected to account for a very small percent of future capacity in India). Part of the explanation may be the imprecision in generation costs, as it is difficult to identify the effects of the favorable tax treatment and other support for wind in all three of the countries.

Not surprisingly, photovoltaics generate the largest losses in surplus across all of the countries—the data on generation costs for photovoltaics indicate costs per kilowatt hour in 2000 of about 80 cents in Germany, 30 cents in India, and 30 to 40 cents in the United States—some 5 to 10 times the corresponding costs reported for CCGT. Even with external costs or a carbon tax, photovoltaics generate negative surpluses.

These differences alone do not explain the sizeable differences in estimated surplus among countries. The smaller surpluses estimated for Germany and India, and for India in particular, are driven by the much smaller size of personal consumption expenditure (our data-variable PCE) in these countries than in the United States (to see this effect, recall equation (2)).

The results shed some light on the effects on surplus of policies to promote renewable technologies as these countries add new capacity during the coming years. For example, in the case of Germany, the results suggest that fast adoption of photovoltaics would result in lost discounted consumer surplus of about \$500 per household (dividing the median surplus in A1 or A2 by the number of households). In India, the lost surplus would be about \$60 per household. The largest positive surplus for India is suggested under fast adoption of hydro or biomass—these generate surpluses of about 15 cents to 20 cents per household (for the poorest households in India, these are not inconsequential amounts).

3.3 A Carbon Tax

We impose carbon taxes to span the range in size of taxes most frequently discussed in much of the literature about economic approaches to greenhouse gas mitigation. We select carbon taxes of $15, $35, and $50 per ton of carbon emissions under our assumptions of fast adoption and no external cost adjustments.[16] We select these baseline assumptions for two reasons: fast adoption in our baseline scenarios leads to the largest consumer surplus, and consideration of a carbon tax without additional external cost adjustments at this time most closely represents current policy discussion. An important additional assumption, based on results in Burtraw et al. 2001, is that taxes at this level cause negligible switches of coal-fired baseload capacity to renewable power.

Table 5 shows results for a $15 carbon tax. The tax increases surplus achievable from renewables compared with the case represented by fast adoption and no external cost adjustments (scenario A2). A small positive median surplus now results in India for wind and biomass. However, the tax reduces surplus compared with fast adoption and the external cost adjustments we make (scenario A1), because the adjustment to carbon is slightly less and others of the technologies are more costly after adding external costs. Under this tax, the negative surplus in Germany declines to about -$460 million (wind) and the surplus in India is about $170 million (biomass). In the United States, the largest surpluses are $4.1 billion on the West Coast (for wind) and $1.6 billion in the Midwest (for wind).

Results for a $35 carbon tax, in Table 6, further increase the size of surpluses if no external cost adjustments are made and assuming fast adoption (comparing Table 6 and scenario A2 in Table 2). At this level of the tax, the surplus values are quite close—within a few percent—of the surplus values under our assumptions of fast adoption and external cost adjustments.

[16] The carbon content of natural gas is the lowest of the fossil fuels and, coupled with the high conversion efficiency of CCGT technology, these releases are relatively modest. To apply the carbon tax to our CCGT generation data, we follow this procedure: We make the standard assumption that CCGT units have a conversion efficiency of 55%, which gives a heat rate of 6.2 MMBtu/mWh. (The IEA reports that new Indian CCGT plants have a conversion efficiency of about 52%.) We multiply the conversion efficiency by the emission factor for natural gas, 0.01447 MT/MMBtu (U.S. Department of Energy 1995). This gives 0.1 MT per thousand kwh. Burtraw et al. 2002 2001 in references find that at roughly $25, a carbon tax or permit fee negligibly affects renewable power generation—wind is the only renewable that is affected—and the effects are minimal.

At a $50 carbon tax, in Table 7, the trends from lower carbon tax credits continue. We note that median surplus values for Germany remain negative (although they are smaller). Surpluses are now larger than in the case of adjustments for external costs.

These tax simulations illustrate the sensitivity of surplus to tax levels and permit comparison to other approaches to managing external effects, as in our external cost adjustments. We show a crossover tax rate—at roughly $35—at which consumer surplus becomes larger than under a more complex alternative of a combined set of external cost adjustments for carbon, thermal effluent, and nuclear safety.

3.4 Renewable Energy Portfolios

In another exercise of the model, we construct hypothetical renewable "portfolios." We ask, "What surplus values are predicted by [combing] combining? renewable technologies?" We first assume that an equal fraction of expected new generation will be supplied by each of the renewables. We then 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 0.2 for both Germany and India. In the variable weight case (VARWTRP), the fractions for Germany and India are:

	Photovoltaic	*Hydro/Geothermal*	*Wind*	*Biomass*	*Nuclear*
Germany	0.025	0.055	0.46	0.46	0
India	0.01	0.48 .	0.02	0.48	0.01

We applied these weights under all of the baseline sets of assumptions regarding adoption and treatment of external costs. Table 8 shows a subset of results—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 for Germany and India when adoption rates are slow and external costs are included. For Germany, the median value is about -$2.1 billion; for India, it is about -$1.1 billion. It might be expected that the more expensive renewables in the portfolio offset the cost advantages of less expensive renewables to generate the negative values. It is less easy to predict, however, the effect of the offset when all externalities are included as some of the externalities increase the costs of some of the renewables relative to other renewables and relative to CCGT.

Under the variable weights that favor some renewables, the best performing portfolio in the case of Germany still generates negative values. The assumptions that underlie the smallest negative result are as in the equal weight scenario—a slow adoption rate and adjustments for external costs. It is possible to find weights to give a positive median value for India, however, and the table illustrates a result of $80 million under A1 ($30 million under B1—not shown in the table) and, in both cases, adjusting for external costs but positing different adoption rates.

In our U.S. results, we also found that equal-weighted portfolios result in negative surplus values. Under the variable weights that favor some renewables, a portfolio can generate positive surplus values. The assumptions that led to these results required weighting wind heavily, fast adoption, and inclusion of external costs. The largest values were never as large as values obtained in some of the pairwise comparisons between CCGT and a renewable technology.

These results suggest the difficulty policymakers encounter in specifying quantities in designing RPS programs. Their effects will depend on a variety of exogenous influences and other policies, including the expected time path of generation costs for competing technologies, whether accounting for external costs is considered, rates of adoption, and regional differences in geographic endowments.

4. Conclusions

We seek to offer a conceptually sound but readily implemented approach to considering changes in consumer surplus as an important dimension of public policies influencing the allocation of the electricity fuel mix among competing technologies. We extend a cost index that is well-grounded in demand theory and develop a simulation model to estimate changes in the value of consumer surplus over the period 2000–2020, for different regions of the world and under a variety of assumptions about adoption rates, external costs, and policies that include taxes on carbon and renewable portfolio standards. 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. While the usual demand elasticities are explicit in the cost index, we use hypothesized adoption rates, described by the Weibull function, to characterize how future market demand will evolve during the twenty-year time period.

We find significant differences in the effects of basic assumptions about fuel mixes in different countries, which belie international discussion and difficulty in reaching agreement over different policy approaches. We also find marked differences in the effects of alternative policies on consumer surplus across countries, although in some cases some results are common to all of the countries—for example, the relatively poor performance of photovoltaics.

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

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

With these caveats in mind, we believe that the model provides useful guidance for decisionmakers and researchers alike. Our results illustrate the usefulness of the framework to test assumptions and evaluate scenarios with respect to their implications for consumer surplus and indicate the extent to which different policies may be more or less promising in their contribution to surplus.

Appendix

Estimates of Personal Consumption Expenditures

Using a historical data set (1995 to 2001 for Germany and 1989 to 1999 for India), we regress annual personal consumption expenditure (PCE) against time. We then forecast PCE to 2020 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.

Personal Consumption Expenditure Regression Results—Germany (Billion 2000$)

To forecast PCE for each year, we use the following regression results for Germany:

$PCE_t = \alpha + \beta t$
$t = 1, 2, \ldots, 7$ (corresponding to the years 1995, 1996, …, 2001)
Dependent Variable: PCE

Analysis of Variance

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Prob > F*
Model	1	20467.5869	20467.5869	139.04	< 0.0001
Error	5	736.019463	147.203893		
Total	6	21203.6063	3533.93439		

Other Results

Root MSE	12.133
Dependent Mean	149.871
Coefficient of Variance	8.0956
R-Squared	0.9653
Adjusted R-Squared	0.9583

Parameter Estimates

Variable	*DF*	*Parameter Estimate*	*Standard Error*	*t Value*	*Prob > | t |*
Intercept	1	1381.724	10.25405	134.749	< 0.0001
Year	1	27.03674	2.292876	11.792	< 0.0001

Personal Consumption Expenditure Regression Results—India
(Billion 2000$)

To forecast PCE for each year, we use the following regression results for India[17]:

$PCE_t = \alpha + \beta t$
t = 1, 2, …, 11 (corresponding to the years 1989, 1990, 1996…,1999)
Dependent Variable: PCE

Analysis of Variance

Source	*DF*	*Sum of Squares*	*Mean Square*	*F Value*	*Prob > F*
Model	1	10441.2558	10441.2558	263.43	< 0.0001
Error	9	356.727931	39.6364368		
Total	10	10797.9837	1079.79837		

Other Results

Root MSE	6.2957
Dependent Mean	220.2807
Coefficient of Variance	2.8580
R-Squared	0.9670
Adjusted R-Squared	0.9633

[17] Some data are from Asian Demographics Ltd. Weekly Demographic Insight. 2002

Parameter Estimates

Variable	*DF*	*Parameter Estimate*	*Standard Error*	*t Value*	*Prob > | t |*
Intercept	1	161.8244	4.07127	39.748	< 0.0001
Year	1	9.742716	0.600276	16.230	< 0.0001

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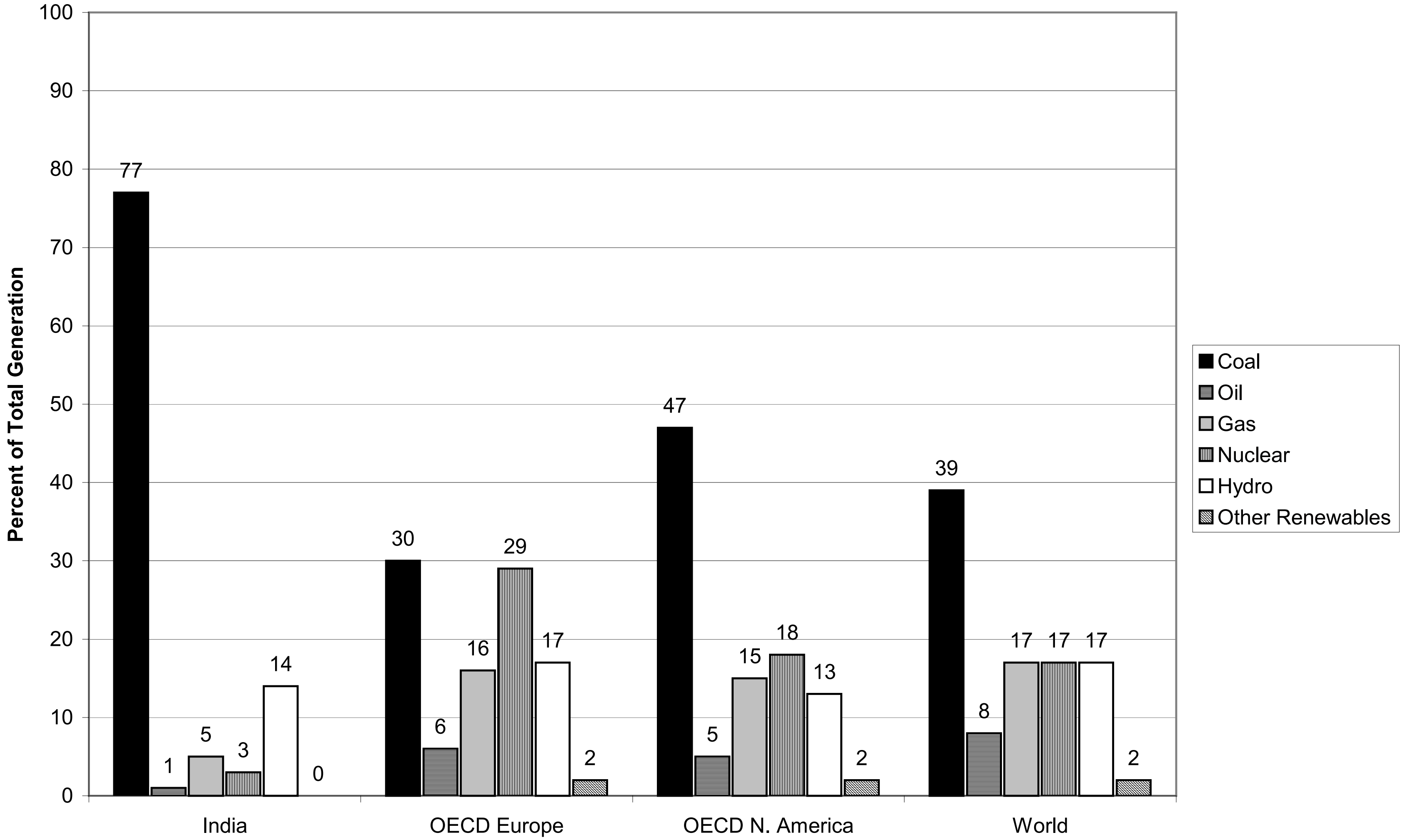
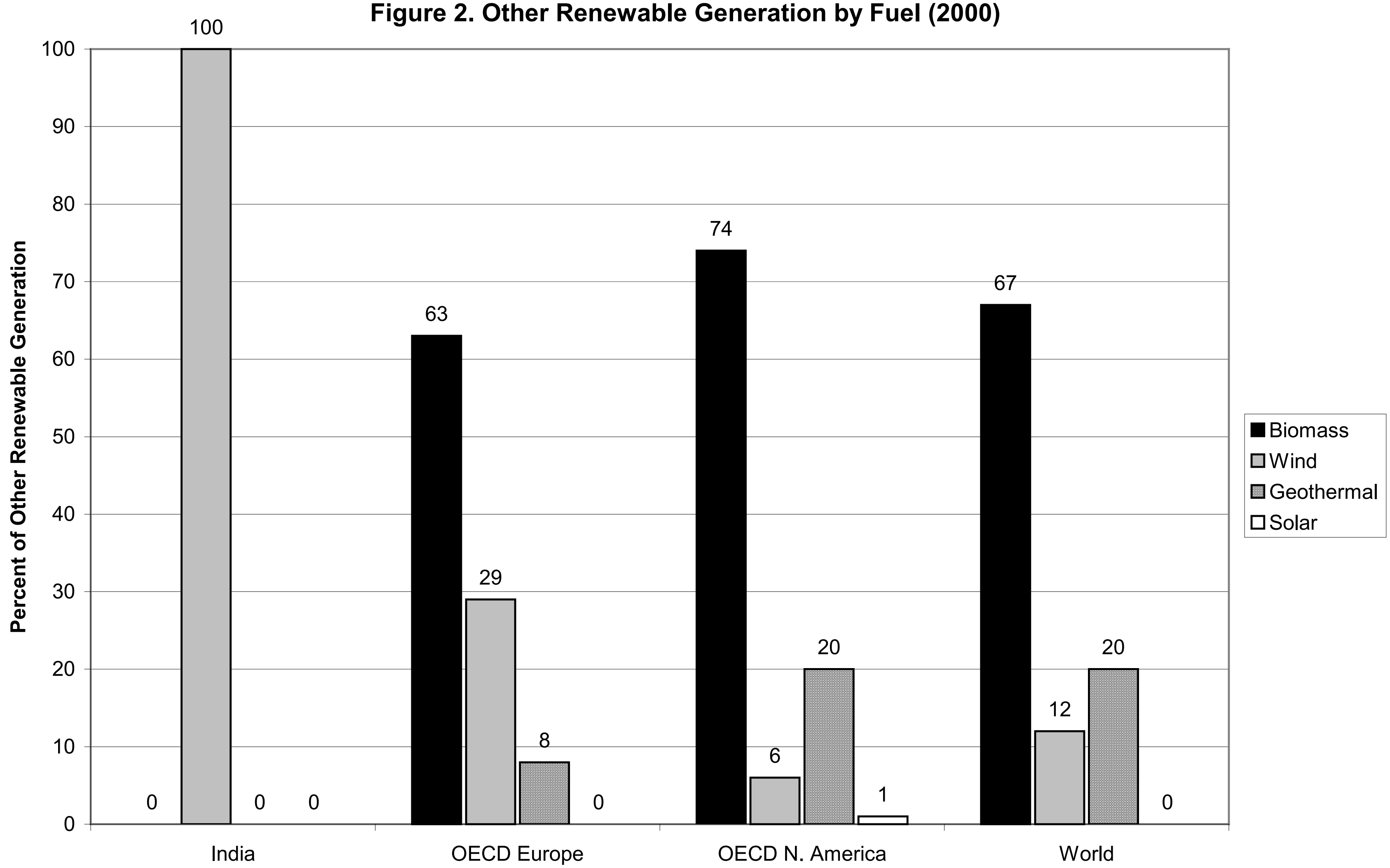
Figure 1. Total Generation by Fuel (2000)



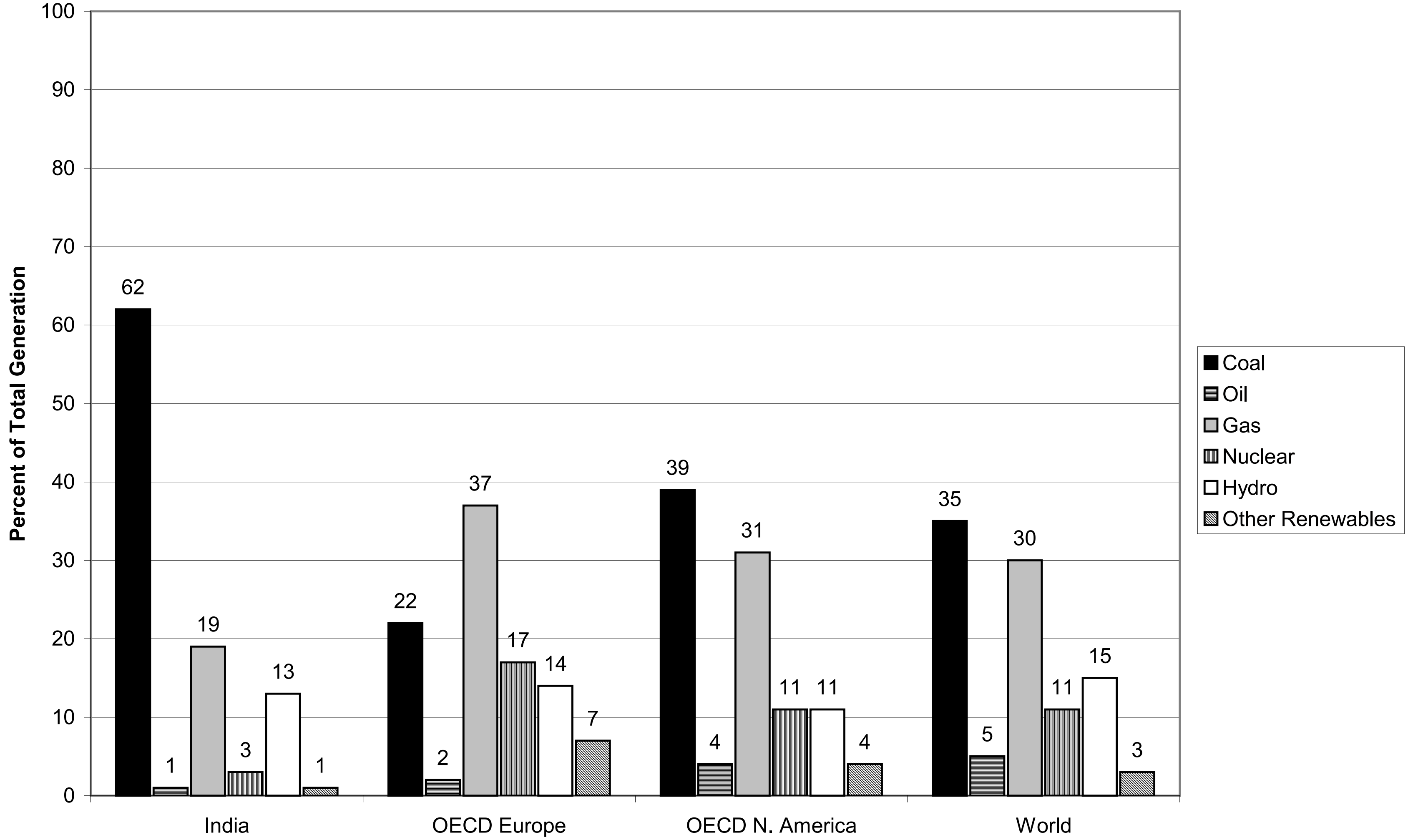
Source: International Energy Agency, 2002c.

Figure 2. Other Renewable Generation by Fuel (2000)



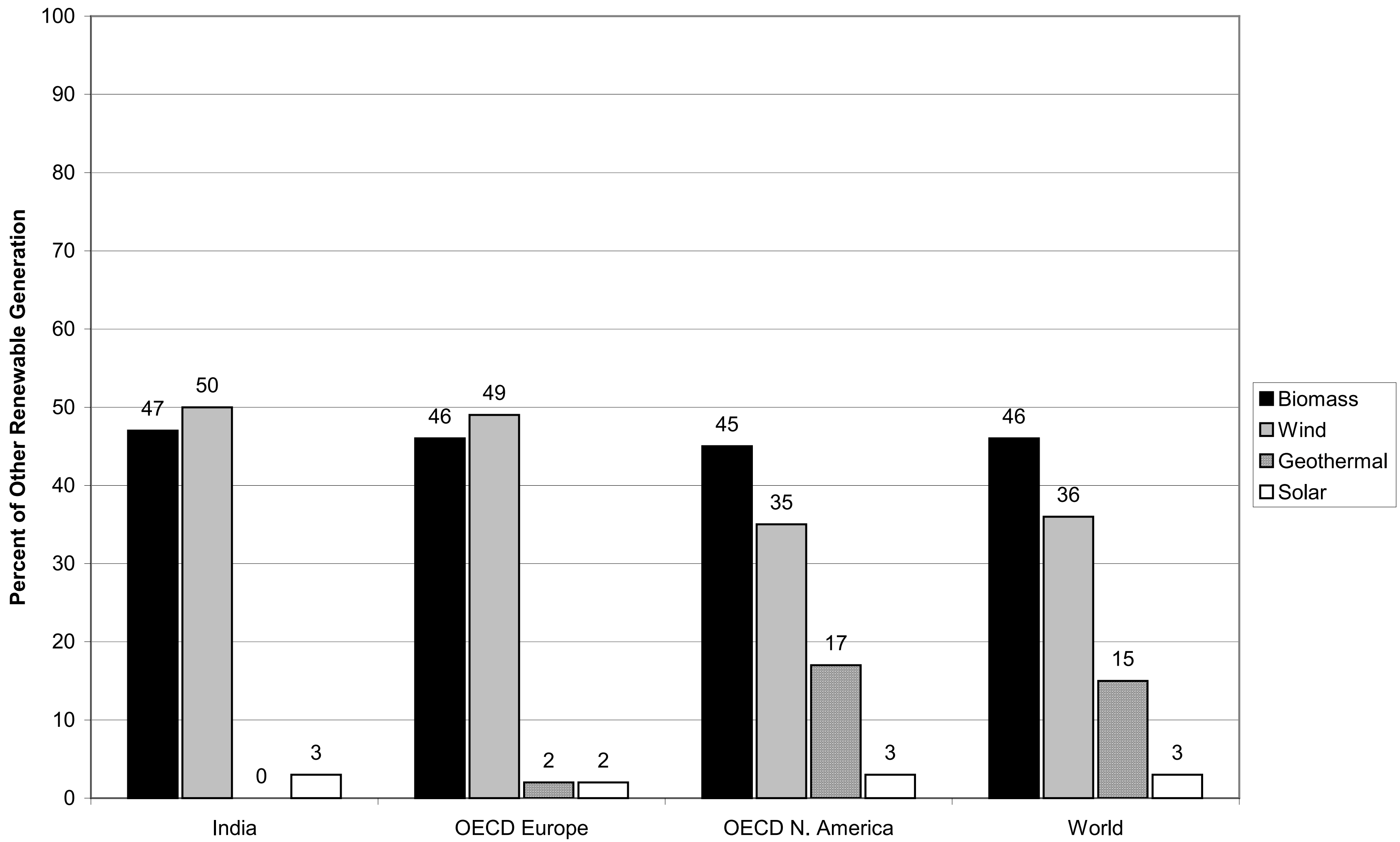
Source: International Energy Agency, 2002c.

Figure 3. Total Generation by Fuel (2020)



Source: International Energy Agency, 2002c.

Figure 4. Other Renewable Generation by Fuel (2020)



Source: International Energy Agency, 2002c.

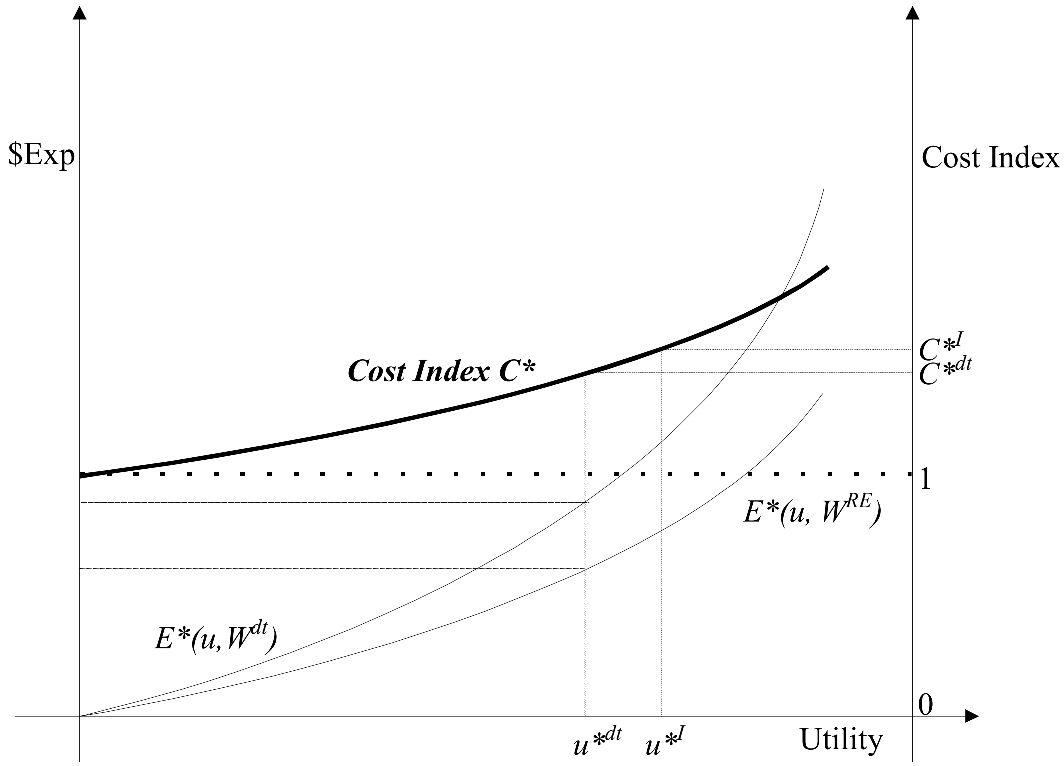
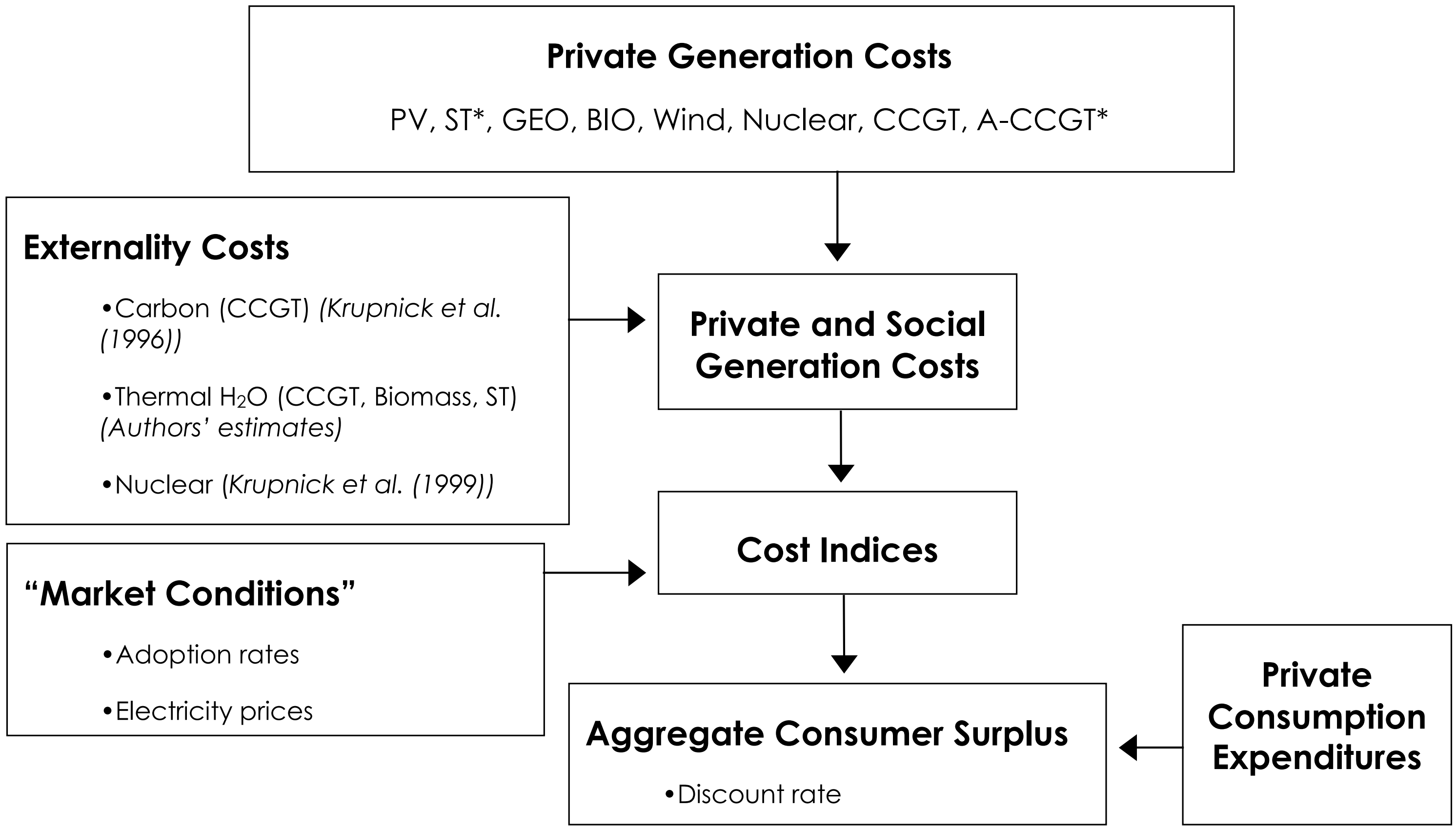


Figure 5. Expenditure and cost index relationships



- Triangular and normal distributions combined with Monte Carlo draws characterize uncertainty.
- ST and A-CCGT are used in the U.S. model; only selected results from this model are reported in this paper.

Figure 6. The Model

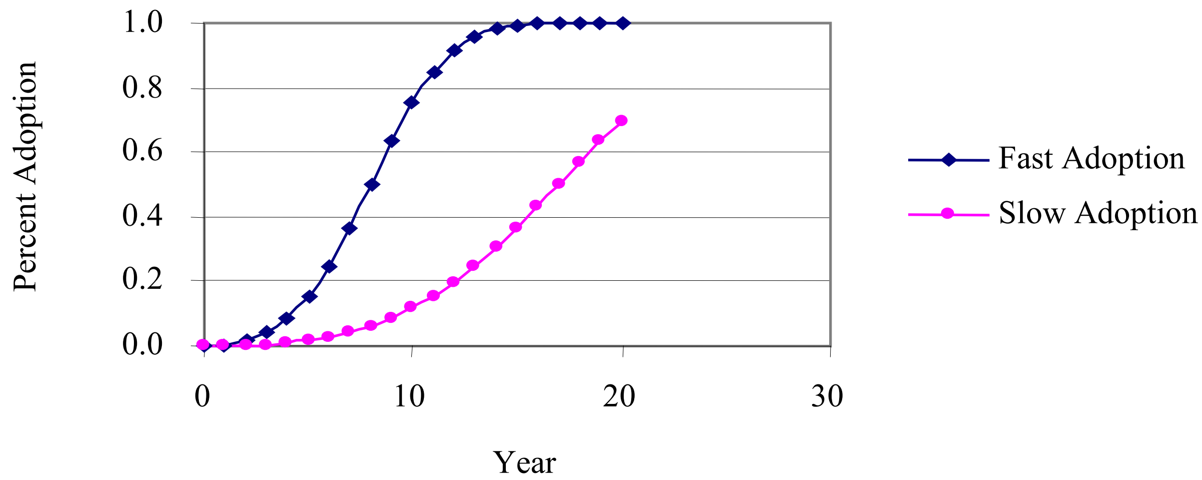


Figure 7. Weibull adoption rate curves

Results: Baseline Scenarios A1, A2, B1, and B2

Table 1 Baseline Scenario: A1	**Weibull: 0.1, 3.5** *Externalities: Carbon, Water, Nuclear* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-23.83, -20.04, -16.29)	(-14.49, -11.96, -9.52)	(-13.6, -10.8, -8.04)	(-6.40, -4.62, -2.92)
Hydro / Geothermal	(-6.14, -4.89, -3.81)	(0.07, 0.40, 0.74)	(2.62, 3.47, 4,45)	N / A
Wind	(-0.70, -0.14, 0.36)	(-1.62, -1.10, -0.68)	(3.50, 4.60, 5.80)	(1.14, 1.75, 2.41)
Biomass	(-1.00, -0.45, 0.02)	(-0.04, 0.31, 0.67)	(-5.37, -3.99, -2.74)	(-1.61, -1.10, -.0.64)
Nuclear	(-1.89, -1.25, -0.71)	(-1.65, -1.11, -0.68)	N / A	N / A

Table 2 Baseline Scenario: A2	**Weibull: 0.1, 3.5** *Externalities: None* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-24.66, -20.77, -16.96)	(-15.35, -12.77, -10.27)	(-14.6, -11.7, -8.87)	(-6.70, -4.88, -3.17)
Hydro / Geothermal	(-6.77, -5.47, -4.35)	(-0.52, -0.16, 0.19)	(1.86, 2.66, 3.59)	N / A
Wind	(-1.21, -0.62, -0.14)	(-2.25, -1.70, -1.22)	(2.74, 3.79, 4.94)	(0.91, 1.50, 2.13)
Biomass	(-1.29, -0.75, -0.22)	(-0.42, -0.06, 0.31)	(-5.96, -4.58, -3.32)	(-1.80, -1.27, -0.82)
Nuclear	(-2.38, -1.72, -1.12)	(-2.24, -1.67, -1.20)	N / A	N / A

Table 3 Baseline Scenario: B1	**Weibull: 0.05, 3.5** *Externalities: Carbon, Water, Nuclear* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-8.18, -6.71, -5.34)	(-5.05, -4.00, -2.98)	(-6.07, -4.69, -3.35)	(-3.39, -2.40, -1.47)
Hydro / Geothermal	(-1.37, -1.07, -0.81)	(0.01, 0.11, .019)	(0.82, 1.10, 1.41)	N / A
Wind	(-0.09, -0.01, 0.06)	(-0.42, -0.26, -0.14)	(1.04, 1.40, 1.78)	(0.35, 0.56, 0.77)
Biomass	(-0.17, -0.09, 0.00)	(-0.01, 0.09, 0.18)	(-2.08, -1.50, -0.99)	(-0.66, -0.43, -0.23)
Nuclear	(-0.38, -0.26, -0.16)	(-0.51, -0.34, -0.19)	N / A	N / A

Table 4 Baseline Scenario: B2	**Weibull: 0.05, 3.5** *Externalities: None* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-8.50, -7.06, -5.66)	(-5.43, -4.34, -3.29)	(-6.62, -5.22, -3.82)	(-3.62, -2.59, -1.65)
Hydro / Geothermal	(-1.52, -1.22, -0.94)	(-0.15, -0.04, 0.05)	(0.60, 0.87, 1.17)	N / A
Wind	(-0.19, -0.10, -0.02)	(-0.61, -0.43, -0.30)	(0.84, 1.18, 1.55)	(0.29, 0.49, 0.70)
Biomass	(-0.24, -0.14, -0.06)	(-0.11, -0.01, 0.09)	(-2.38, -1.76, -1.24)	(-0.75, -0.51, -0.31)
Nuclear	(-0.49, -0.35, -0.25)	(-0.68, -0.49, -0.34)	N / A	N / A

Results: Policy Scenarios Carbon Tax of $15, $35, and $50

Table 5 Policy Scenario: Carbon Tax of $15 / ton	*Weibull: 0.1, 3.5* *Externalities: None* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-24.22, -20.61, -16.80)	(-14.77, -12.47, -10.00)	(-14.12, -11.31, -8.56)	(-6.54, -4.77, -3.06)
Hydro / Geothermal	(-6.50, -5.26, -4.14)	(-0.28, 0.04, 0.41)	(2.05, 3.00, 4.01)	N / A
Wind	(-0.96, -0.46, 0.05)	(-1.98, -1.46, -1.04)	(2.91, 4.14, 5.31)	(1.02, 1.59, 2.23)
Biomass	(-1.11, -0.57, -0.07)	(-0.17, 0.17, 0.51)	(-5.57, -4.24, -3.07)	(-1.68, -1.18, -0.73)
Nuclear	(-2.18, -1.54, -0.97)	(-2.01, -1.45, -0.98)	N / A	N / A

Table 6 Policy Scenario: Carbon Tax of $35 / ton	*Weibull: 0.1, 3.5* *Externalities: None* **Discounted Present Value, 2000– 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-24.02, -20.20, -16.38)	(-14.40, -12.03, -9.61)	(-13.60, -10.83, -8.12)	(-6.30, -4.63, -3.02)
Hydro / Geothermal	(-6.14, -5.04, -3.91)	(-0.03, 0.32, 0.69)	(2.44, 3.39, 4.51)	N / A
Wind	(-0.75, -0.24, 0.22)	(-1.63, -1.17, -0.77)	(3.29, 4.54, 5.87)	(1.03, 1.73, 2.42)
Biomass	(-0.87, -0.36, 0.13)	(0.09, 0.43, 0.82)	(-5.19, -3.99, -2.83)	(-1.50, -1.04, -0.65)
Nuclear	(-1.95, -1.30, -0.82)	(-1.66, -1.16, -0.75)	N / A	N / A

Table 7 Policy Scenario: Carbon Tax of $50 / ton	*Weibull: 0.1, 3.5* *Externalities: None* **Discounted Present Value, 2000 – 2020, Billion 2000$** ***Defending Technology: Combined Cycle Gas Turbine*** **(5%, Median, 95%)**			
Innovating Technology	Germany	India	US West Coast	US Midwest
Photovoltaics	(-23.66, -20.02, -16.23)	(-14.02, -11.74, -9.36)	(-13.12, -10.55, -7.97)	(-6.14, -4.56, -2.91)
Hydro / Geothermal	(-5.98, -4.87, -3.76)	(0.20, 0.52, 0.89)	(2.65, 3.68, 4.81)	N / A
Wind	(-0.58, -0.09, 0.37)	(-1.38, -0.96, -0.61)	(3.48, 4.80, 6.16)	(1.15, 1.80, 2.51)
Biomass	(-0.70, -0.19, 0.28)	(0.32, 0.63, 1.01)	(-4.54, -3.50, -2.49)	(-1.40, -0.94, -0.58)
Nuclear	(-1.77, -1.17, -0.62)	(-1.40, -0.96, -0.57)	N / A	N / A

Table 8.
Largest Median Surplus Gains Under An Exogenously Specified "Portfolio"
Discounted Present Value 2000–2020 [$2000 Billions]
Billion 2000$ used in other tables

(5%, Median, 95%)

	Germany	India	US – West Coast	US – Midwest
Equal Weight Assumptions	(-2.54, -2.07, -1.59) Weibull:0 .05, 3.5 External Effects: Carbon, Water	(-1.40, -1.10, -0.78) Weibull:0 .05, 3.5 External Effects: Carbon, Water	(-1.54, -1.11, -0.72) Weibull:0 .05, 3.5 External Effects: Carbon, Water	(-1.07, -0.72, -0.42) Weibull:0 .05, 3.5 External Effects: Carbon, Water
Variable Weight Assumptions	(-0.48, -0.36, -0.25) Weibull:0 .05, 3.5 External Effects: Carbon, Water	(-0.24, 0.08, 0.34) Weibull:0 .1, 3.5 External Effects: Carbon, Water	(0.41, 0.84, 1.28) Weibull:0 .1, 3.5 External Effects: Carbon, Water	(0.59, 0.92, 1.25) Weibull:0 .1, 3.5 External Effects: Carbon, Water