"The Ancillary Benefits from Climate Policy in the United States"
by

Britt Groosman, Nicholas Z. Muller, and Erin O'Neill

November 2009

MIDDLEBURY COLLEGE ECONOMICS DISCUSSION PAPER NO. 0920

DEPARTMENT OF ECONOMICS
MIDDLEBURY COLLEGE
MIDDLEBURY, VERMONT 05753

http://www.middlebury.edu/~econ

The Ancillary Benefits from Climate Policy in the United States.

Britt Groosman, Nicholas Z. Muller, and Erin O'Neill

November, 2009

Abstract

This study investigates the benefits to human health that would occur in the United States (U.S.) due to reductions in local air pollutant emissions stemming from a federal policy to reduce greenhouse gas emissions (GHG). In order to measure the impacts of reduced emissions of local pollutants, this study considers a representative U.S. climate policy. Specifically, the climate policy modeled in this analysis is the Warner-Lieberman bill (S.2191) of 2008 and the paper considers the impacts of reduced emissions in the transport and electric power sectors. This analysis provides strong evidence that climate change policy in the U.S. will generate significant returns to society in excess of the benefits due to climate stabilization. The total health-related co-benefits associated with a representative climate policy over the years 2006 to 2030 range between \$90 and \$725 billion in present value terms depending on modeling assumptions. The majority of avoided damages are due to reduced emissions of SO_2 from coal-fired power plants. Among the most important assumptions is whether remaining coal-fired generation capacity is permitted to "backslide" up to the Clean Air Interstate Rule (CAIR) cap on emissions. This analysis models two scenarios specifically related to this issue. Co-benefits increase from \$90 billion, when the CAIR cap is met, to \$256 billion if SO_2 emissions are not permitted to exceed current emission rates. On a per ton basis, the co-benefit per ton of GHG emissions is projected to average between \$2 and \$14 (\$2006). The per ton marginal abatement cost for the representative climate policy is estimated at \$9 (\$2006).

1 Introduction

This study investigates the benefits to human health that would occur in the United States (U.S.) due to reductions in local air pollutant emissions stemming from a federal policy to reduce greenhouse gas emissions (GHGs). The principal GHGs enter the atmosphere through the burning of fossil fuels; hence, achieving emission reductions depends on burning less fossil fuels or using less carbon-intensive fossil fuels. Such policies, in turn, may lead to significant reductions in local air pollutants such as particulate matter (PM), sulfur dioxide (SO_2), and nitrogen oxides (NO_x) since these pollutants are also produced when fossil fuels are burned.

In order to measure the impacts of reduced emissions of local pollutants, this study considers a representative U.S. climate policy. Specifically, the climate policy modeled in this analysis is the Warner-Lieberman bill (S.2191). This bill is broadly similar in terms of its stringency and the timing of emission reductions to many of the proposed climate bills that have been considered by the U.S. Congress. This paper estimates the effect such a policy would have on the emissions of six major pollutants (coarse particulate matter (PM_{10}), fine particulate matter ($PM_{2.5}$), volatile organic compounds (VOC), NO_x, ammonia (NH_3), and SO_2) in the transport and electric power sectors. This is accomplished through the use of a production-cost model for the electric power generation sector, and by employing fuel price demand elasticities for the transportation sector.

The paper focuses on emissions from electric power generation and transportation because together these sources account for nearly two-thirds of GHG emissions in the U.S. The remaining GHG emissions in the U.S. are produced by the following sources; industry contributes 19%, and agricultural, residential and commercial sources together account for another 18%[1].

In order to estimate the benefits of reduced emissions of these local pollutants, this analysis employs an integrated assessment model. Specifically, emissions are connected to changes in concentrations, human exposures, physical effects and monetary damages by the Air Pollution Emission Experiments and Policy model (APEEP, see Muller, Mendelsohn 2007). The co-benefits associated with reduced emissions of local air pollutants reflect the difference in damages corresponding to a baseline, or business as usual (BAU) scenario between 2006 and 2030 and the emissions of these pollutants over the same time period under the representative U.S. climate policy. These reduced human health damages are considered the *ancillary benefits* of the climate policy aimed at the reduction of GHGs.

Whilst damages from air pollution emissions are diverse, ranging from adverse effects on human health, reduced yields of agricultural crops and timber, reductions in visibility, enhanced depreciation of man-made materials, to damages due to lost recreation services, this paper focuses solely on the benefits to human health resulting from such reductions. This focus recognizes that research in this area has repeatedly shown that the vast majority of damages from such air pollutants occur to human health (Burtraw et al., 1998; USEPA, 1999; Muller and Mendelsohn, 2007).

An important question regarding climate policy is the treatment of aggregate levels of local air pollutants that are currently managed under incentive-based policies[2]. Since such policies lack

[1] Shares calculated on 2007 GHG emissions as found in table ES-7, p.ES-14 of 2009 U.S. Greenhouse Gas Inventory Report.

direct controls on individual unit-level emissions, the behavior of regulated sources under both climate and local pollutant programs is uncertain. As a result of this, we explore alternative scenarios regarding the emission levels of such sources. By capping GHG emissions, and therefore pricing carbon, climate policy is likely to generate structural changes to both the transportation and electric power generation sectors[3]. Specifically, the incentives created by policies that increase the cost of burning carbon-rich fuels will push firms to employ less carbon intensive fuels. For electric power generation, climate policy is anticipated to induce a shift away from coal-fired power towards natural gas, nuclear, and renewables. As these structural changes take root, some coal plants will likely shut down in response to the costs of compliance with climate policy. As coal-fired capacity atrophies, SO_2 emissions in particular will decline. As a result, the aggregate cap on SO_2 emissions, associated with the Clean Air Interstate Rule (CAIR), is quite likely to become non-binding for remaining coal-fired capacity. And given the inherent flexibility in cap-and-trade programs that govern SO_2 emissions, remaining facilities, in hopes of reducing their compliance costs, will have the ability to increase SO_2 emissions per kilowatt-hour. Examples of this cost-minimizing behavior may include disengaging scrubbers or returning to high-sulfur coal inputs.

The central point is that absent some additional constraint on SO_2 emissions, the remaining coal-fired capacity is likely to relax their controls on SO_2 emissions in an effort to reduce costs. In order to emulate this outcome, we model a policy scenario in which SO_2 emissions are permitted to remain at the aggregate cap in place under CAIR. Although coal-fired power plants may face constraints on how much they can lower costs (and how much they can increase their SO_2

---

[2] These include SO_2 and NO_x.
[3] The composition and input choices in the manufacturing sector will also likely change due to federal climate policy. However, the focus of this study is on the electric power and transportation sectors.

emissions), this modeling approach provides a lower bound on ancillary benefits by pursuing a maximum SO_2 emission level from the electric power generation sector.

This analysis provides strong evidence that climate change policy in the U.S. will generate significant returns to society in addition to the benefits due to climate stabilization. The total health-related co-benefits associated with a representative climate policy over the years 2006 to 2030 range between $90 and $725 billion in present value terms depending on modeling assumptions. These co-benefits are due to improvements in health status associated with projected emissions reductions of SO_2, $PM_{2.5}$, PM_{10}, NO_x, NH_3, and VOC. Although reduced emissions of each of these local pollutants yield benefits, the majority of avoided damages are due to reduced emissions of SO_2 from coal-fired power plants. This is due to the projected replacement of coal-fired generation capacity with natural gas and, to a lesser extent, renewables. The importance of benefits due to SO_2 abatement from coal-fired power plants is evidenced in the scenario that permits SO_2 emissions from such facilities to increase back to the CAIR cap. Relative to the policy scenario with default assumptions, when SO_2 emissions form the electric power generators regulated under CAIR are permitted to backslide up to the extant CAIR cap, co-benefits decrease by $167 billion in present value terms to approximately $90 billion. This result suggests that a climate policy that does not address the issue of SO_2 emissions management under CAIR is likely to forego substantial health-related co-benefits. On a per ton basis, we find that these co-benefits are 20 to 150 percent of the expected per ton abatement cost associated with the representative climate policy. Specifically, the estimated marginal co-benefits are between $2 and $14 per ton of CO_2e. The marginal abatement cost for CO_2 has been estimated to be $9 per ton (USEPA, 2008).

2 Policy Background

The U.S.' federal GHG policy approach of the past 10 years has relied primarily on voluntary programs for energy conservation (e.g. the 'Energy Star'[4] Program), research and development promotion via expenditure and tax incentives, and standards (e.g. the Energy Independence and Security Act of 2007). In addition, there have been many State and regional policy responses to global warming. These include the Assembly Bill 32 (AB 32), California's Global Warming Solutions Act of 2006, which set a binding goal for GHG reductions by 2020. On the regional scale, the Regional Greenhouse Gas Initiative (RGGI) governs CO_2 emissions for the electric power generation sector in ten Northeastern and Mid-Atlantic States using a cap-and-trade instrument. RGGI is the first mandatory, market-based CO_2 emissions reduction program in the U.S. In total, over 30 states have approved a variety of laws dealing with global warming.

In the federal policy arena, cap-and-trade is the policy mechanism that has gained the most momentum with a large number of legislative proposals calling for a federal cap-and-trade system since 2003. Specifically, there were seven federal cap-and-trade proposals introduced in 2007. These included: Bingaman-Specter's Low Carbon Economy Act (S. 1766), the Lieberman-McCain Climate Stewardship and Innovation Act (S. 280), the Kerry-Snow Global Warming Reduction Act (S. 485) , the Waxman Safe Climate Act (HR 1590), the Sanders-Boxer Global Warming Pollution Reduction Act (S. 309) , the Feinstein-Carper Electric Utility Cap and Trade Act (S. 317), the Alexander-Lieberman Clean Air/Climate Change Act (S. 1168), and the Lieberman –Warner America's Climate Security Act (S.2191).

[4] ENERGY STAR is a joint program of the U.S. Environmental Protection Agency and the U.S. Department of Energy for the promotion of energy efficient products and practices (see http://www.energystar.gov/).

Although there are important differences among these federal cap-and-trade proposals, there are strong similarities in the emission reduction targets and the timing of the emission reductions among these bills (see figures D1 and D2 in Appendix D). The scenario analyzed in this paper is that projected to occur given the enactment of S.2191. Although the analysis is specific to S.2191, this scenario is a representative U.S. climate policy in terms of both emission reduction targets and the timing of such reductions (see Appendix D). An additional advantage of using S.2191 as the representative policy is that the U.S. Environmental Protection Agency (USEPA) provides corresponding carbon allowance prices, sectoral abatement and other projections which are useful in carrying out the empirical analysis in the current paper. Specifically, in March 2008, the USEPA released its macroeconomic analysis of the Lieberman-Warner bill from 2012 to 2050 (USEPA, 2008). The modeling apparatus in the USEPA's study draws on the results from two economic models: the ADAGE model and the IGEM model[5] . The USEPA study is an analysis of the costs of reducing carbon emissions over the entire duration of the program, from 2012 through 2050[6].

In this analysis we use the results from the ADAGE Core Scenario 2 which models the bill as written. The reason for using the results from ADAGE is that the allowance prices estimated by this model are towards the center of the range of allowance prices reported by IGEM and a recent USEPA analysis of the bill currently under discussion in Congress (ACES HR2454). The range of permit prices is shown in table C1 (Appendix C).

---

5 Both are dynamic computable general equilibrium (CGE) models The ADAGE model was developed at Research Triangle Institute (RTI) in North Carolina (see www.rti.org/adage). IGEM was developed at Harvard University (http://www.economics.harvard.edu/faculty/jorgenson/files/IGEM%20Documentation.pdf).

6 The EPA analysis is available online at http://www.epa.gov/climatechange/downloads/s2191_EPA_Analysis.pdf; the complete results are available at http://www.epa.gov/climate change/downloads/DataAnnex-S.2191.zip.

3 Emission Modeling

The analysis of ancillary benefits due to climate policy effectively compares emissions of SO_2, $PM_{2.5}$, PM_{10}, NO_x, NH_3, and VOC under two different scenarios. The first scenario projects local pollutant emissions that reflect BAU assumptions regarding demand growth between 2006 and 2030 given current environmental policies, transportation fuel prices, and electricity prices. The second scenario reflects emissions of local pollutants given the enactment of a federal climate policy over the same time period as the BAU scenario. The analysis models changes in emissions in both the electric power generation sector and the transportation sector. Emissions from other sectors are held fixed. The APEEP model accepts emission inputs associated with each of these two scenarios, and it estimates exposures, premature mortalities, increased rates of illness, and monetary damage associated with both scenarios. The ancillary benefits reported in section 4 reflect the difference in damages due to emissions of SO_2, $PM_{2.5}$, PM_{10}, NO_x, NH_3, and VOC between the BAU and the policy scenarios.

3.1 Modeling emissions from electricity production.

In order to model changes in emissions from the electric power sector, we employ the EDF Regional Electricity Model (EDF REM), a production cost model. The EDF REM is designed to mimic the results of the USEPA Integrated Planning Model (IPM) while providing the detailed results for individual plants needed as inputs to the APEEP model. IPM "is a multi-regional, dynamic, deterministic, linear programming model of the electric power sector".[7] The EDF REM is used to account for economical energy production and to evaluate production savings

---

[7] EPA's Updates to EPA Base Case v3.01from EPA Base Case 2006 (v3.0); Using the Integrated Planning Model (IPM)
http://www.epa.gov/airmarkets/progsregs/epa-ipm/docs/Documentation%20for%20EPA's%20Base%20Case%20v3.01%20Using%20IPM.pdf

from investment in generating technologies. While these modeling techniques are different, they are both standard and compatible methods commonly used in the utility industry for forecasting and planning. In this instance, the EDF REM production cost model takes the CO_2 price forecast from IPM as an input and determines the most economical way to meet electric demand given those CO_2 prices.

For consistency, the EDF REM also uses the same inputs as the USEPA IPM where practicable. For instance, fuel price forecasts for both the BAU and policy case are the same in both models, as are build limits for new technologies such as nuclear and renewable plants. Similar to IPM, the EDF REM uses the USEPA's National Electric Energy Data System (NEEDS database) for information on power plant locations and operational characteristics such as capacity, fuel type and heat rate. To ensure further consistency, the EDF REM is benchmarked to the IPM's CO_2 emissions forecast under both the BAU and policy scenarios.

This application of the EDF REM consists of two model runs; a BAU case and a policy case representing the S.2191. Emission reductions are calculated by comparing projected emissions given the two model runs. The BAU case is benchmarked to USEPA's reference case[8] and the policy case is benchmarked to the ADAGE Core Scenario 2 results for electric generation, CO_2 emissions, fuel prices, allowance prices, and new capacity additions. (Both the reference case and ADAGE Core Scenario 2 employ IPM.) It is important to note that the BAU case includes

[8] This scenario served as the benchmark case to which the various ADAGE model runs were compared.

emissions reductions associated with CAIR[9]. Further, the policy case assumes that the CAIR emission caps remain in effect.

As mentioned above, the REM provides spatially-detailed modeling results for all electricity generating sources in the contiguous U.S. greater than 25 MW in size. These generating units comprise over 9,500 point sources. Annual emission data for these 9,500 point sources are matched to APEEP according to source location and source specifications.

3.2 Modeling emissions from transportation.

The transportation BAU emission projections are based on USEPA's emission inventory for the period 2002 - 2030 (Air Quality & Modeling Center Assessment & Standards Division - U.S. EPA Office of Transportation & Air Quality)[10]. The on-road emissions are based on the National Mobile Inventory Model (NMIM) using MOBILE6[11] emission factors. The USEPA emissions projections account for all finalized USEPA regulations and include the Renewable Fuel Standard (RFS1). Some emission source projections (such as aircraft) are based on the U.S. Department of Energy, Energy Information Agency's emission forecast (USDOE, 2007[12]) and thus do not take into account any changes which may have occurred due to regulations

[9] The Clean Air Interstate Rule proposes a reduction in SO_2 and NO_x emissions in 28 Eastern states and the district of Columbia. Under CAIR, SO2 emissions would be reduced by 70 percent and NOx emissions reduced by 60 percent in the CAIR region. The CAIR is currently under litigation. See http://www.epa.gov/cair/ for more information.

[10] These data are derived from the public version of USEPA's emission inventory for 2002 -2030 as provided by the USEPA, Office of Transportation and Air Quality.

[11] The National Mobile Inventory Model (NMIM) is a computer application developed by EPA to help develop estimates of current and future emission inventories for on-road motor vehicles and non-road equipment. NMIM uses current versions of MOBILE6 and NONROAD to calculate emission inventories, based on multiple input scenarios that are entered into the system. NMIM can be used to calculate national, individual state or county inventories. Vehicle Emission Modeling Software and related presentations and training resources. MOBILE6 is an emission factor model for predicting gram per mile emissions of Hydrocarbons (HC), Carbon Monoxide (CO), Nitrogen Oxides (NOx), Carbon Dioxide (CO2), Particulate Matter (PM), and toxics from cars, trucks, and motorcycles under various conditions. NONROAD is used for estimation of air pollution emission inventories.

[12] More specifically EIA's AEO2007.

which came into force after 2007 (for example, the Energy Independence and Security Act of 2007).

The policy scenario for transport emissions of GHGs is dictated by the aggregate GHG emission cap. In this study, the effect of the GHG cap on transportation emissions is modeled through the price effects on fuels, the resulting change in consumption of transportation fuels, and corresponding change to emissions. We rely on USEPA's estimates of fuel price increases from 2012 through 2050[13] . The expected price increases of fuels from the climate policy are shown in Table C2 (Appendix C). Peer-reviewed demand elasticities are used to estimate the reduced use of fuels that would result given the price increases projected to occur as a result of climate policy. Table C3 shows estimates of the long-run gasoline price elasticity. Other transportation modes employ different fuels. For diesel, compressed natural gas (CNG) and other transport fuels we rely on the price elasticities shown in Table C4.

It is important to note that this approach produces projections which model the influence of the climate policy on demand for existing fuels based on past evidence of price impacts. However, it does not include a potential shift to fuels with much lower carbon content.

4 Modeling Air Pollution Damages

[13] The EPA analysis is available online at http://www.epa.gov/climatechange/downloads/s2191_EPA_Analysis.pdf; the complete results are available at http://www.epa.gov/climate change/downloads/DataAnnex-S.2191.zip.

This study uses the APEEP model (Muller, Mendelsohn, 2007), which is calibrated to simulate the consequences of both the BAU and policy scenarios. In terms of its structure, APEEP is a traditional integrated assessment model in that it resembles integrated assessment models used by USEPA and other researchers to measure the impacts of air pollution (Mendelsohn, 1980; Nordhaus, 1992; USEPA, 1999). Specifically, the model begins with emissions and then it uses an air quality model to determine where emissions travel to and the degree to which they react with other pollutants in the atmosphere. Next APEEP computes exposures of people to ambient air pollution. Finally, APEEP determines the resulting human health impacts and the monetary value of such impacts. The following sections describe the key components of the APEEP model in more detail.

The emission sources modeled in APEEP are grouped into four broad categories. First are the ground-level emissions which include mobile sources and stationary sources without a tall smokestack. These are further subdivided according to vehicle type, fuel type, and for stationary sources, the different categories that the USEPA identifies in its national emission inventory: agriculture, forestry, and mining, for example. APEEP also models point sources with three distinct effective heights[14]; low stack sources (effective height less than 250 meters): including most manufacturing facilities; medium stack sources (effective height between 250 and 500 meters); and tall stack sources (with an effective height of greater than 500 meters). The four source categories listed above encompass all of the emissions of the six pollutants modeled by APEEP in the contiguous U.S. as reported by the USEPA (USEPA, 2006). Emissions from each of the first three categories are aggregated, by pollutant, to the county level. Emissions from the tall stack sources are modeled at the facility level.

[14] Effective height is defined as stack height plus eventual plume rise.

The spatial detail in APEEP's documentation of sources is important because, unlike the effects of greenhouse gas emissions which are independent of source location, the health effects of the air pollutants modeled in APEEP are relatively localized. Following the documentation of emissions, APEEP uses an air quality model to predict seasonal and annual average county concentrations for $PM_{2.5}$, PM_{10}, VOC, NO_x, SO_2, NH_3 and tropospheric ozone (O_3). The air quality model simulates transport, chemical transformation into other pollutants, and deposition of each emitted species. This model is discussed in Muller, Mendelsohn (2007). Note that APEEP takes atmospheric chemistry into account. This is important because, following emission, some of the pollutants tracked by the model transform in the atmosphere into more harmful pollutants; for example, SO_2 emissions become particulate sulfate and NO_x emissions contribute to concentrations of both particulate nitrate and O_3. The damages from these secondary pollutants are attributed to the sources that produced the emission.

APEEP then calculates human exposures to the predicted concentrations by multiplying county-level pollution concentrations by the county-level population data. Current population levels are provided by the U.S. Department of the Census while future population projections are provided by the Center for Disease Control. In the APEEP model, populations are differentiated by age because the health impacts of local air pollution are proportional to baseline incidence rates which are age-dependent.

APEEP translates exposures into physical effects using concentration-response functions published in peer-reviewed studies in the epidemiological literature. The full list of concentration-response functions used in APEEP is found in Muller and Mendelsohn (2007). Because premature mortalities account for the majority of damages due to exposures to the local air pollution, we focus here on the concentration-response functions that govern the relationship between the annual mean level of $PM_{2.5}$ and adult mortality rates, infant mortality rates, as well as the relationship between exposures to O_3 and all age mortality rates. To model the relationship between $PM_{2.5}$ exposures and adult mortality rates APEEP employs the results from Pope et al., (2002). The relationship between infant mortality rates and exposure to $PM_{2.5}$ is captured using the findings in Woodruff et al., (2006). Finally, the results from Bell et al. (2004) govern the impact of O_3 exposure on mortality rates of all ages. APEEP also measures the damages due to chronic illnesses such as chronic bronchitis and asthma in addition to mortality (Abbey et al. 1999; McDonnell, 1999).

APEEP expresses the value of the physical effects resulting from exposures to air pollution in dollar terms[15]. Applying monetary values to effects on human health, especially premature mortalities is methodologically difficult and politically controversial. The published literature relies upon two approaches to value premature mortality risks: revealed preference and stated preference methods (Cropper, Oates, 1992; Viscusi, Aldy, 2003). For mortality valuation, APEEP uses the results from a meta-analysis that encompasses both the revealed preference literature that uses hedonic wage models to estimate the relationship between wages and occupation-specific mortality rates and the stated preference literature which asks people what they would be willing to pay to avoid mortality risks on surveys (USEPA, 1999). The literature notes that dividing the risk premium (R), which reflects how much workers require in extra pay

[15] Note that all values are expressed in constant year 2006 U.S. dollars.

in order to assume an additional, incremental risk of death, by the change in the probability of death ($\Delta\gamma$) yields the value of a statistical life (VSL) , (Viscusi, Aldy, 2003).

$$VSL=(R/\Delta\gamma) \tag{1}$$

One complication in the application of VSLs is whether this parameter should be applied uniformly to people of all ages or whether the VSL should be differentiated by age. This is important because the estimates of VSL are derived from studies that focus on working age people but most of the mortalities from air pollution affect the elderly and the very young. This study adopts the approach employed by the USEPA and other federal agencies which apply the VSL uniformly to populations of all ages (USEPA, 1999).

In addition to the baseline scenario, scenario 1, which employs the modeling assumptions for human health impact described above, we conduct a sensitivity analysis in order to test the importance of specific assumptions in the model to the benefit estimates for emission reductions. In the first alternative scenario, scenario 2, we employ an alternative concentration-response function relating long-term $PM_{2.5}$ exposures to adult mortality rates using the results from Laden et al., (2006). In scenario 3, we employ the modeling assumptions of scenario 1, however, SO_2 emissions from coal-fired power plants are permitted to reach the CAIR cap. Since the CAIR cap is the emission limit in our BAU scenario, scenario 3 sets SO_2 emissions to their levels in the BAU. There are no co-benefits from SO_2 in the electric power generation sector under scenario 3.

Because the study extends far into the future we must project how personal income will change over the life of the policy (until 2030). We employ the rate of income growth used in the ADAGE model (3.0% annual growth). Further, we use the USEPA's reported value for the elasticity between income and willingness to pay to avoid mortality risk: 0.5. This is employed to adjust the VSL in future years. Finally, APEEP discounts all future benefits to their present value at a 5% discount rate. We employ discount rates of 3% and 2% in order to test the impact of the discount rate on the co-benefit estimates.

The health damages reported in this analysis are described in equations (2) through (4). The damages (premature mortality plus morbidity) in time period (t) under the policy scenario is denoted (D_{pol}) and under the BAU scenario is denoted (D_{BAU}) as shown in equations (2) and (3).

$$D_{BAU(t)} = (\textstyle\sum_{r,k,s,i}((Pop_{i,t,r})(\gamma_{i,t,r,k})(\beta_{s,k}C^{BAU}{}_{s,t,r})(\alpha_{t,k})))(1+\delta)^{-t} \qquad (2)$$

where : $Pop_{i,t,r}$ = population of age group (i), at time (t), in county (r).
$\gamma_{i,t,r,k}$ = incidence rate of health state (k), at time (t), for age group (i), in county (r).
$\beta_{s,k}$ = dose-response parameter for health state (k), for pollutant (s).
$C^{BAU}{}_{s,t,r}$ = BAU ambient concentration of pollutant species (s), at time (t), in county (r).
$\alpha_{t,k}$ = valuation parameter at time (t) for health state (k) = VSL.
δ = discount rate (5%).

$$D_{pol(t)} = (\textstyle\sum_{r,k,s,i}((Pop_{i,t,r})(\gamma_{i,t,r,k})(\beta_{s,k}C^{pol}{}_{s,t,r})(\alpha_{t,k}))\ )(1+\delta)^{-t} \qquad (3)$$

where: $C^{pol}{}_{s,t,r}$ = with policy ambient concentration of pollutant species (s), at time (t), in county (r).

The co-benefits of climate policy in any one time period (t) is the difference in damages between the policy (D_{pol}) and the BAU (D_{BAU}) scenarios. The total benefits are the discounted sum of the difference between BAU and policy damages over (t) as shown in (4).

$$D = \sum t(D_{BAU(t)} - D_{pol(t)}) \quad (4)$$

As this study has focused solely on the health benefits it is a de facto underestimate of the actual total ancillary benefits. Some examples of the benefits this study does not capture include: reduced yields of agricultural crops and timber due to tropospheric ozone (O_3), reductions in visibility from reduced emission of fine particles (PM_{10}, PM_2 and SO_2), enhanced depreciation of man-made materials (buildings and historical monuments) from acid rain contributed to by emission of NO_x and SO_2; and damages due to lost recreation services (deterioration of water quality in recreational fishing areas). Muller and Mendelsohn (2007) found that human health impacts accounted for over 90% of the total damages from the local air pollutants modeled in APEEP.

5 Results

Table 1 displays both the estimated premature mortalities using the default assumptions in the APEEP model as well as the annual co-benefits of climate policy from 2006 until 2030 for each of the three modeling scenarios. Since climate policy begins with modest reductions in GHGs, the emission reductions of local pollutants are also relatively small in the early years of this analysis. As a result, both the co-benefits and the projected avoided mortalities begin low and increase as the climate policy becomes more stringent. The right-hand column in Table 1 indicates the premature mortalities avoided begin at 1 case in 2006 and then increase to greater than 200 in 2011. The number of avoided deaths continues to grow to just less than 5,000 in 2020 and finally rises to over 7,000 avoided deaths in 2030.

Table 1 also reports the aggregate ancillary benefits of the GHG abatement policy in present value terms (discounted at 5%). The results are broken down by year in order to show the relative magnitudes of the benefits generated over the 25 year time period covered in this paper. The first column (second from the left) corresponds to modeling scenario 1, which uses the dose-response function relating adult mortality rates to exposures to $PM_{2.5}$ derived from Pope et al., (2002), personal income growth of 3%, and the elasticity between willingness-to-pay to avoid mortality risks and income of 0.5.

The first pattern of note is that the estimated co-benefits generally increase from the first year of the policy through 2026. This occurs for three reasons. First, greater amounts of GHGs are abated (as the aggregate cap on emissions becomes tighter). This implies that increasing amounts of local pollutants are abated as well. Second, populations are projected to grow between 2006 and 2030; as a result the population potentially exposed to local air pollutants increases as well. Hence, for a given reduction in emissions, the health-related benefits of such reductions will increase with greater populations. These first two factors are reflected in the increasing number of avoided mortalities reported in Table 1. That is, greater reductions in harmful emissions and larger exposed populations translates into more avoided deaths. The final factor that has an influence on the increasing co-benefits through time is the following; as income grows, the value attributed to avoided mortality risk becomes larger, too. Therefore, each avoided mortality is attributed a larger value because the willingness-to-pay to avoid mortality risks is an increasing function of personal income.

With the scenario 1, benefits begin at $4 million in 2006, and increase to $16.2 billion in 2026. Thereafter, benefits decline to $16.1 billion in 2030. Benefits decline in the distant future because of discounting. Hence, although the projected number of avoided mortalities grows steadily from 2006 through 2030, the co-benefits begin to decline in 2027 due to discounting.

The total benefit of climate change policy in the default case is $256 billion, in present value terms. For modeling scenarios 2 and 3 the pattern in benefits accrued through 2030 is quite similar to the default case; benefits begin at modest levels and then they increase through 2026 and then begin to decline in 2027 through 2030. However, the magnitude of the co-benefits are considerably larger in the second scenario. Recall that scenario 2 employs an alternative dose-response function corresponding to the adult mortality-$PM_{2.5}$ relationship (Laden, et al., 2006). In particular, the dose-response parameter reported in the Laden et al. (2006) study is nearly three times larger than the parameter reported in the Pope et al. (2002) study. Total co-benefits in scenario 2 are $725 billion. Scenario 3 reflects the SO_2 emissions from coal-fired power generators increasing up to the CAIR cap. Since the CAIR cap is met in the BAU scenario, effectively SO_2 benefits from power production are equal to zero in this case. As a result, total co-benefits are considerably smaller than in scenarios 1 and 2. Total co-benefits for scenario 3 are equal to $90 billion in present value terms.

Table 2 tests the impact of the discount rate on the magnitude of the co-benefits. In addition to the default discount rate of 5%, table 2 reports co-benefits using 3% and 2%. With the discount rate set to 3%, total co-benefits increase to $364 billion; recall that co-benefits total $256 billion with a discount rate of 5%. With the discount rate set to 2%, co-benefits increase to $437 billion.

Note that the only parameter that has changed (with respect to modeling scenario 1) is the discount rate. Hence, table 2 indicates that the magnitude of the co-benefits is sensitive to the choice of the discount rate.

Table 3 provides an alternative perspective on the co-benefits of climate change policy. This table expresses the co-benefits per ton of GHG (CO_2e) abated for each year in the analysis. In scenario 1, benefits per ton of GHG begin at $0.60 in 2006, and then increase to around $6 between 2014 and 2019. Thereafter, per ton benefits decline to $3.30 in 2030. The inter-temporal average co-benefit/ton CO_2e for scenario 1 is $4.2. The results shown in this table are especially powerful when viewed in conjunction with recent estimates of the marginal abatement costs for GHGs. Specifically, USEPA finds that the inter-temporal average present value marginal abatement costs are projected to be $9/ton CO_2e (USEPA, 2008).

As with Table 1, the inter-temporal pattern in benefits per ton of abatement are similar across the three scenarios while the magnitudes are quite different for scenarios 2 and 3. That is, the benefits per ton of GHG are nearly three-times larger when using scenario 2. Notably, benefits per ton increase to $17/ton CO_2e between 2014 and 2019. For scenario 3, the per ton co-benefits follow a similar pattern through 2030, and the average is $1.5.

Another interesting pattern is evident in Table 3. Benefits per ton of GHG increase from 2006 until 2010, then per ton benefits decline in 2011 and 2012 and begin to increase again in 2013. This occurs because the emission reductions in the transportation sector begin in 2011, since the quantity of GHGs abated increases significantly the benefit per ton of CO_2e decreases.

Figure 1 provides a comparison of the present value of marginal co-benefits per ton CO_2e with the marginal abatement costs. The figure includes the marginal co-benefits estimated with APEEP modeling scenario 1, 2, and 3. With scenario 1, marginal co-benefits average \$4.8 per ton CO_2e over the period from 2012 – 2030. Under modeling scenario 2, the average co-benefit is nearly \$14 per ton CO_2e. Finally, for scenario 3, the average co-benefit per ton CO_2e is \$1.7. Over the same time period, marginal abatement costs average \$9. This implies that the estimated marginal co-benefit for abatement of GHG is comparable to the marginal abatement cost without including direct benefits of climate stabilization. Because the co-benefits reported in this paper nearly balance the costs of abatement at the margin, the argument for aggressive abatement of GHGs is significantly strengthened.

Table 4 displays the co-benefits per ton CO_2e abated for the three discount rates. Like table 2, this table employs 2%, 3%, and 5%. With the discount rate set to 3%, the average co-benefit per ton CO_2e is \$5.6 over the entire 25-year period. Employing a discount rate of 2% increases the co-benefit per ton CO_2e to \$6.5. The trajectory of the co-benefits per ton CO_2e through 2030 is not sensitive to the discount rate. Figure 2 displays the co-benefits per ton CO_2e as a function of the discount rate between 2012 and 2030.

Figure 3 displays the spatial distribution of benefits from climate change policy in the year 2020. In general, the aggregate benefits occur in states with large populations. New York, Pennsylvania, Ohio, Illinois, and Texas all are projected to incur co-benefits of greater than \$750 million in the year 2020. It is interesting to note that California, which has the largest state population, is not in the highest benefit category. This is the case for two reasons. First, with prevailing winds from the west, California does not have any emission sources of local pollutants directly upwind. Second, much of California's energy is produced with natural gas and much of the aggregate co-benefits in other states are due to the reduced use of coal in energy production.

Figure 4 displays the per capita co-benefits by state. The spatial pattern in Figure 2 is striking; all of the states that are projected to experience the largest per capita co-benefits of climate change policy are located east of the Mississippi River. These include: Indiana, Ohio, Kentucky, Maryland, Delaware, New Jersey, Georgia, and North Carolina. This figure emphasizes the importance of coal to the overall co-benefits analysis. That is, much of the total co-benefits estimated to occur as a result of this climate change policy stem from a reduction in the amount of coal burned to produce electricity. Since, most of the coal-fired electric power generation capacity is located in the Southeast and the Midwest, the benefits due to burning less coal will accrue in areas proximal to these generators and areas downwind (to the east).

Table 5 provides a detailed decomposition of the total co-benefits by pollutant and by sector. First, Table 5 indicates that of the $256 billion total co-benefits that are projected to occur (under the default modeling scenario) $207 billion are a result of emission reductions in the electric power generation sector. This implies that $50 billion worth of the co-benefits stem from abatement in the transportation sector. With the electric power generation sector, SO_2 reductions account for the largest share of benefits: $167 billion of the $207 total. This is due to burning less coal in order to generate electricity. This result reinforces the pattern evident in figure 3; most of the co-benefits occur in the eastern U.S. where coal is the predominant fuel used to generate power. The next largest share of benefits within the power generation sector is due to abatement of NO_x; benefits attributable to NO_x abatement are worth $21.2 billion. Finally, abatement of fine particulate matter ($PM_{2.5}$) generates benefits of $18 billion. Within the transportation sector, reduced emissions of NO_x yield benefits of nearly $14 billion. Abatement of VOC and NH_3 produce benefits of $15 billion and $8.5 billion, respectively. Reduced emissions of $PM_{2.5}$ correspond to benefits of nearly $8 billion.

6 Conclusions

This analysis provides strong evidence that climate change policy in the U.S. will generate significant returns to society in addition to the returns due to climate stabilization. Aside from the benefits stemming directly from reduced GHG emissions, the health-related co-benefits associated with a representative climate policy range between $90 and $725 billion, in present value terms, depending on modeling assumptions. These co-benefits are due to improvements in health status associated with projected emissions reductions of SO_2, $PM_{2.5}$, PM_{10}, NO_x, NH_3, and VOC. Since the co-benefits estimated in this paper do not account for the manufacturing sector, the co-benefits stemming from federal climate policy in the U.S. are likely to be larger than what is reported herein.

The analysis finds that the co-benefits of climate change policy are not uniformly distributed across the U.S. Total co-benefits are clustered in the states with the largest populations. This is intuitive given that the benefits modeled in this study concentrate on human health impacts. However, in per capita terms the co-benefits display a far more interesting pattern. Specifically, the states that are projected to enjoy the greatest per capita co-benefits are all east of the

Mississippi River. The reason for this striking spatial pattern is that the majority of the co-benefits are projected to be due to reduced reliance on coal in electric power generation. Much of the existing generation capacity located in the Midwestern and eastern U.S. uses coal. As climate change policy creates incentives to move away from coal towards natural gas and renewables, the health-related benefits of this shift are likely to occur in states nearby and downwind of the large existing coal-fired power plants. In fact, nearly two-thirds of the total projected co-benefits stem from reduced SO_2 emissions from electric power generators. Much of this SO_2 abatement is a result of moving away from the use of coal to generate electric power.

On a per ton GHG basis, these co-benefits over the time period 2012 - 2030 are estimated to average between $1.7 and $14. USEPA estimates for total abatement costs permit an estimation of[16] the marginal abatement cost for a ton of CO_2e. Over the period 2012 to 2030, the marginal abatement costs are predicted to average $9. This implies that the estimated marginal co-benefit for abatement of GHG is worth between 20 and 150 percent of the marginal abatement cost *without* including direct benefits of climate stabilization. Because the co-benefits reported in this paper nearly balance the costs of abatement at the margin, this analysis strengthens the argument for aggressive abatement of GHGs in the U.S.

[16]See slide 74 of the, *EPA Analysis of the Lieberman-Warner Climate Security Act of 2008, S. 2191 in 110th Congress,* March 14, 2008. The abatement from the electricity sector for the Adage scenario 2 model run was provided to us by the RTI modeling group. The abatement from the transport sector was estimated to be proportional to the forecast reductions in petroleum use for this same model run

Table 1 : Avoided Mortalities and Total Co-Benefits of Climate Policy ($2006, million)

Year	Total co-benefits, PV under three scenarios			Avoided Mortalities Scenario 1.
	Scenario 1	Scenario 2	Scenario 3	
2006	4	12	3	1
2007	63	179	9	10
2008	117	334	15	20
2009	172	541	14	40
2010	262	743	49	50
2011	1,141	3,225	197	230
2012	1,951	5,522	332	420
2013	5,895	16,576	2,561	1350
2014	8,988	24,043	4,038	2020
2015	10,252	28,586	4,268	2530
2016	11,465	32,568	4,532	2950
2017	12,979	36,488	4,889	3470
2018	14,209	39,993	5,059	3970
2019	14,955	41,562	5,377	4280
2020	15,428	43,755	5,466	4580
2021	15,465	43,819	5,457	4770
2022	15,319	43,686	5,283	5000
2023	15,546	44,231	5,274	5270
2024	15,692	44,631	5,214	5540
2025	15,890	45,187	5,178	5830
2026	16,205	46,331	5,291	6160
2027	16,161	46,178	5,326	6370
2028	16,011	45,623	5,263	6580
2029	16,172	45,870	5,430	6792
2030	16,088	45,431	5,365	7050
Totals	256,000	725,000	89,900	85,300

Scenario 1: Pope et al., 2002, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%.
Scenario 2: Laden et al., 2006, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%.
Scenario 3: Pope et al., 2002, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%, SO_2 Emissions from Power Plants at CAIR cap.

Table 2 : Discounting and Total Co-Benefits of Climate Policy ($2006, million)

Year	Total co-benefits, PV. Modeling Scenario 1.		
	2%	3%	5%
2006	4	4	4
2007	67	65	63
2008	127	124	117
2009	193	186	172
2010	303	288	262
2011	1,358	1,280	1,141
2012	2,390	2,232	1,951
2013	7,708	7,040	5,895
2014	12,100	10,944	8,988
2015	14,152	12,693	10,252
2016	16,251	14,447	11,465
2017	18,883	16,640	12,979
2018	21,217	18,534	14,209
2019	23,004	19,895	14,955
2020	24,408	20,911	15,428
2021	25,184	21,367	15,465
2022	25,656	21,563	15,319
2023	26,778	22,294	15,546
2024	27,797	22,926	15,692
2025	28,947	23,650	15,890
2026	30,385	24,585	16,205
2027	31,206	25,002	16,161
2028	31,819	25,247	16,011
2029	33,119	26,014	16,172
2030	33,902	26,374	16,088
Totals	437,000	364,000	256,000

Table 3: Co-Benefits per ton of GHG Abated ($ 2006), PV

Year	Scenario 1	Scenario 2	Scenario 3
2006	0.6	1.6	0.4
2007	2.2	6.3	0.3
2008	2.7	7.8	0.3
2009	2.8	8.9	0.2
2010	3.2	9.2	0.6
2011	2.6	7.4	0.5
2012	2.5	7.1	0.4
2013	5.3	14.9	2.3
2014	6.2	16.7	2.8
2015	5.8	16.2	2.4
2016	5.8	16.5	2.3
2017	6.0	16.9	2.3
2018	6.0	17.0	2.2
2019	5.9	16.5	2.1
2020	5.7	16.2	2.0
2021	5.3	15.1	1.9
2022	4.9	14.1	1.7
2023	4.7	13.4	1.6
2024	4.5	12.8	1.5
2025	4.3	12.3	1.4
2026	4.1	11.8	1.3
2027	3.9	11.1	1.3
2028	3.7	10.4	1.2
2029	3.5	10.0	1.2
2030	3.3	9.4	1.1
Average	4.2	12.0	1.4

Scenario 1: Pope et al., 2002, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%.
Scenario 2: Laden et al., 2006, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%.
Scenario 3: Pope et al., 2002, E_d = 0.5, Personal Income Growth = 3%, Discount Rate = 5%, SO_2 Emissions from Power Plants at CAIR cap.

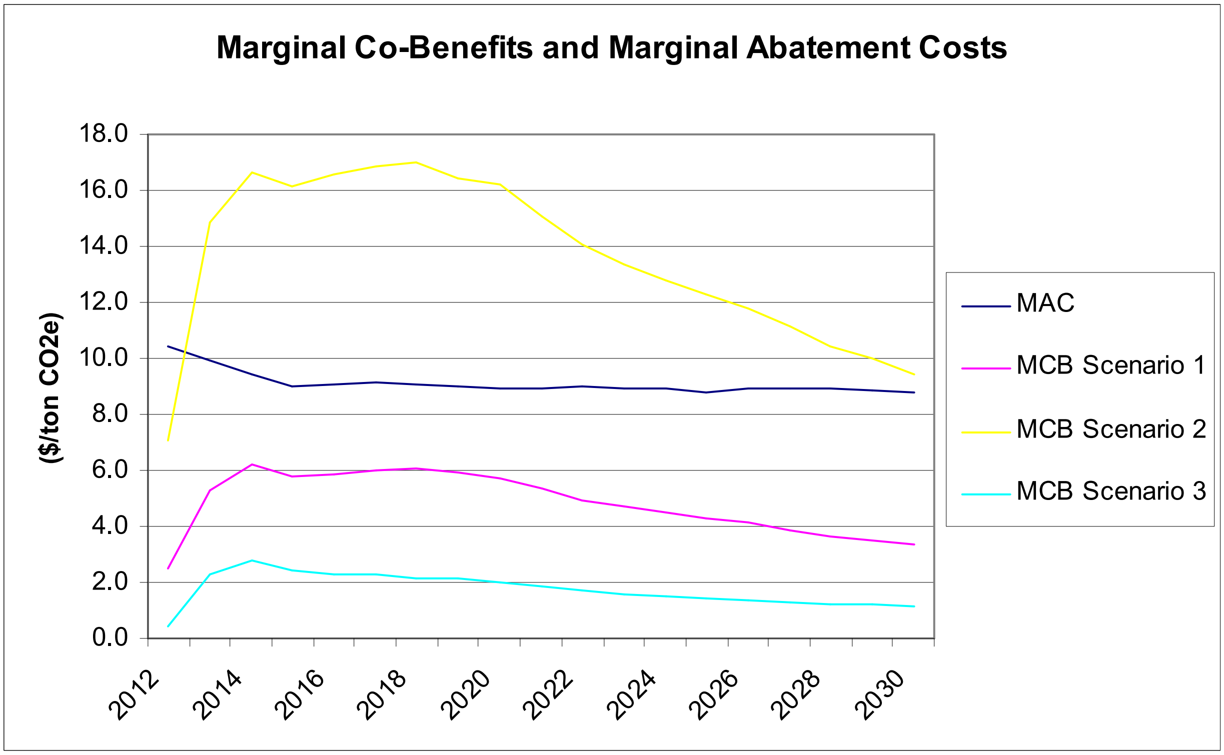
Table 4: Discounting and Co-Benefits per ton of GHG Abated ($ 2006), PV

Year	Co-Benefits/ton GHG, PV Modeling Scenario 1.		
	2%	3%	5%
2006	0.6	0.6	0.6
2007	2.3	2.3	2.2
2008	3.0	2.9	2.7
2009	3.2	3.1	2.8
2010	3.7	3.6	3.2
2011	3.1	2.9	2.6
2012	3.1	2.9	2.5
2013	6.9	6.3	5.3
2014	8.4	7.6	6.2
2015	8.0	7.2	5.8
2016	8.3	7.3	5.8
2017	8.7	7.7	6.0
2018	9.0	7.9	6.0
2019	9.1	7.9	5.9
2020	9.1	7.8	5.7
2021	8.7	7.4	5.3
2022	8.3	6.9	4.9
2023	8.1	6.7	4.7
2024	8.0	6.6	4.5
2025	7.9	6.4	4.3
2026	7.7	6.3	4.1
2027	7.5	6.0	3.9
2028	7.3	5.8	3.7
2029	7.2	5.7	3.5
2030	7.0	5.5	3.3
Average	6.6	5.6	4.2

Table 5: Co-Benefits by Sector and by Pollutant ($ 2006) million, PV
Modeling Scenario 1.

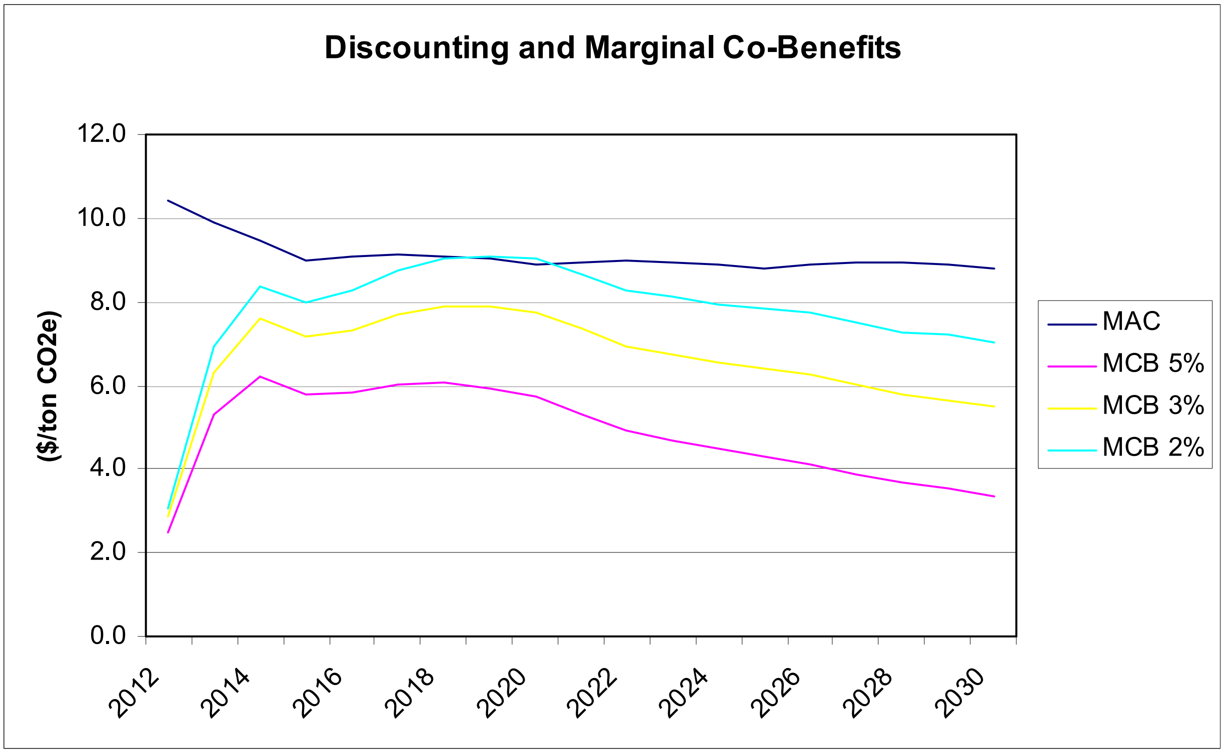
Pollutant	Transportation	Power Generation
SO_2	4,010	167,000
$PM_{2.5}$	7,780	18,000
PM_{10}	170	1,420
VOC	15,230	53
NO_x	13,800	21,220
NH_3	8,490	-270

Figure 1: Marginal Abatement Costs and Marginal Co-Benefit: Three Modeling Scenarios.



Scenario 1: Marginal Co-Benefit corresponding to default modeling scenario (Pope et al., 2002, Ed = 0.5, Personal Income Growth = 3%, Discount Rate = 5%).
Scenario 2: Marginal Co-Benefit corresponding to scenario 2 (Laden et al., 2006, Ed = 0.5, Personal Income Growth = 3%, Discount Rate = 5%).
Scenario 3: Marginal Co-Benefit corresponding to scenario 3 (Pope et al., 2002, Ed = 0.5, Personal Income Growth = 3%, Discount Rate = 5%, SO_2 Emissions from Power Plants at CAIR cap).

Figure 2: Marginal Abatement Costs and Marginal Co-Benefits: Discounting.



Scenario 1: Marginal Co-Benefit corresponding to default modeling scenario (Pope et al., 2002, Ed = 0.5, Personal Income Growth = 3%, Discount Rate = 5%).

Figure 3: Co-benefits of Climate Change Policy By State of Incidence for 2020.

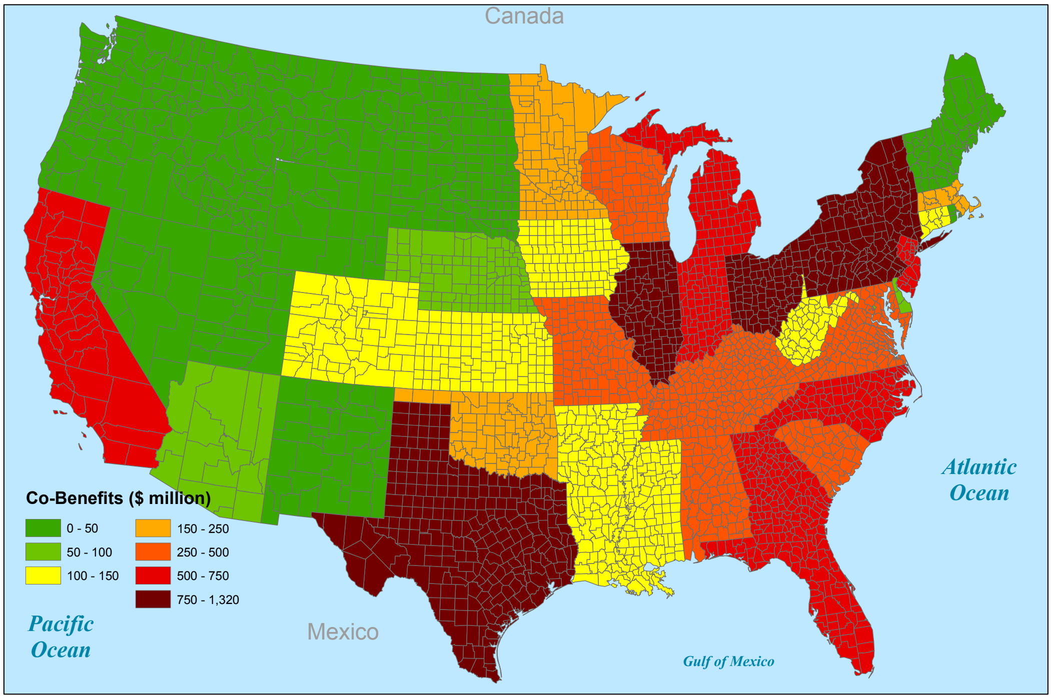
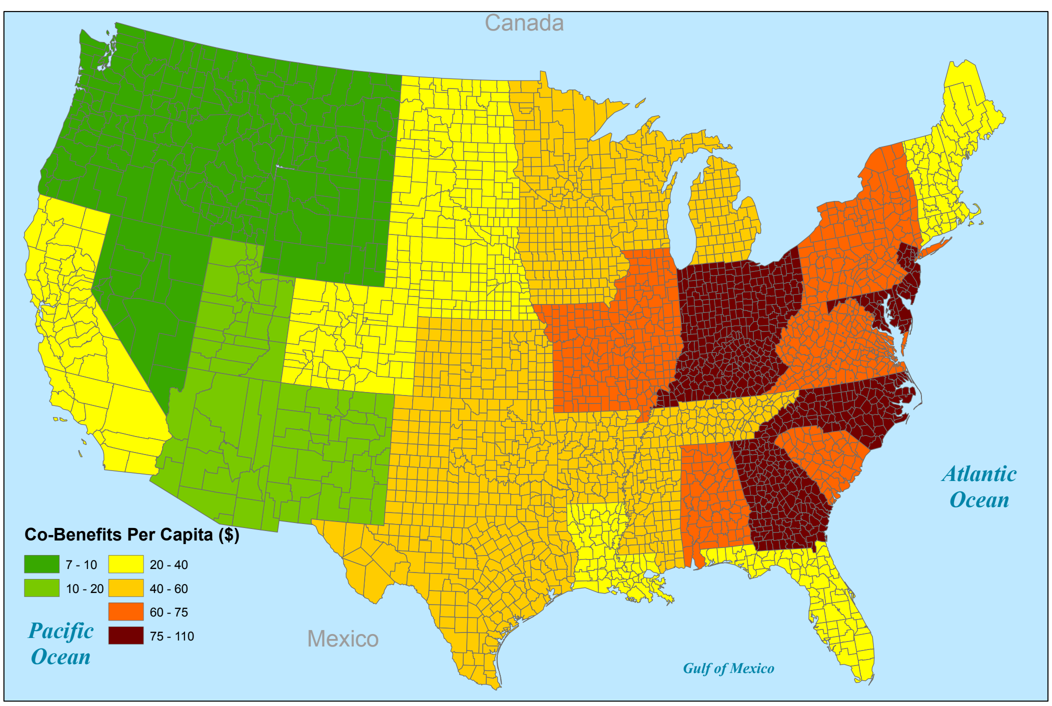


Figure 4: Per Capita Co-Benefits of Climate Change Policy By State for 2020.



References

Bell, Michelle L., Adrian McDermott, Scott L. Zeger, Jonathan M. Samet, and Francesca Domenici. "Ozone and Short-Term Mortality in 95 US Urban Communities, 1987-2000." Journal of the American Medical Association, 292(19):2372-2378. 2004.

Brons M, Nijkamp P, Pels E, and Rietveld P. A meta-analysis of the price elasticity of gasoline demand. A SUR approach. Energy economics. 2105-2122, Volume 30, Issue 5, 2008.

Cropper, M.L., W.E. Oates. Environmental Economics: A Survey. Journal of Economic Literature. 30(2): 675-740. 1992.

Espey M, Gasoline demand revisited: an international meta-analysis of elasticities. Energy Economics. 273-295, Volume 20, Issue 3, 1998.

Goodwin P, Dargay J and Hanly M. Elasticities of Road Traffic and Fuel Consumption with Respect to Price and Income: A Review. Transport Reviews. 275 – 292, Volume 24, Number 3, 2004.

Graham D and Glaister S. The demand for automobile fuel: a survey of elasticities. Journal of Transport Economics and Policy. 36(1): 1-25, 2002.

Hagler, B. *Potential for fuel taxes to reduce greenhouse gas emissions in transportation*, Fuel tax policies report, prepared for the Department of Public Works and Government Services, Science Directorate, Science, Informatics and Professional Services Sector, Canada, June 1999.

Hughes J, Knittel C, and Sperling D. Evidence of a Shift in the Short-Run Price Elasticity of Gasoline Demand. Center for the Study of Energy Markets. Paper CSEMWP-159. 2007.

F. Laden, J. Schwartz, F.E. Speizer, D.W. Dockery. Reduction in Fine Particulate Air Pollution and Mortality: Extended Follow-up of the Harvard Six Cities Study, Amer. J. of Respiratory and CriticalCare Medicine, 173: 667-672. 2006.

Muller, N.Z., R.O. Mendelsohn,. Measuring the Damages of Air Pollution in the United States. Journal of Environmental Economics and Management. 54(1):1-14. 2007

Nicol, C. Elasticity of Demand for Gasoline in Canada and the United States. Department of Economics, University of Regina. 2000.

Puller S., L. Greening. Household adjustment to gasoline price change: an analysis using 9 years of US survey data. Energy Economics. 37-52, Volume 21, Issue 1, 1999.

Romero A. Revisiting the Price Elasticity of Gasoline Demand. Department of Economics, College of William and Mary. Working paper 63. 2006.

Small, K. K. Van Dender, Fuel Efficiency and Motor Vehicle Travel: The Declining Rebound Effect. The Energy Journal. 25-51, Volume 28, Number 1, 2007.

U.S. Department of Energy, (USDOE) 2007.
http://tonto.eia.doe.gov/ftproot/forecasting/0383(2007).pdf

U.S. Environmental Protection Agency (USEPA). The Benefits and Costs of the Clean Air Act: 1990 - 2010. EPA Report to Congress. EPA 410-R-99-001, Washington, DC, Office of Air and Radiation, Office of Policy. 1999.

U.S. Environmental Protection Agency (USEPA). National Emissions Inventory (NEI): 2002. Washington, DC: Office of Air Quality Planning and Standards, Emissions Inventory Group; Emissions, Monitoring, and Analysis Division. 2006.

U.S. Environmental Protection Agency (USEPA), Office of Atmospheric Programs, *EPA Analysis of the Lieberman-Warner Climate Security Act of 2008, S. 2191 in 110th Congress,* March 14, 2008.

U.S. Environmental Protection Agency (USEPA) *Inventory of US Greenhouse Gas emissions and Sinks: 1990 – 2007,* EPA 430-R-09-004, April 15, 2009.

Victoria Transport Policy Institute (VTPI), Online TDM Encyclopedia, British Columbia, http://www.vtpi.org/tdm/, Updated May 2009.

Viscusi, W. Kip and Joseph E. Aldy. "The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World." Journal of Risk and Uncertainty, 27(1): 5-76. 2003.

Woodruff, Tracey J., Jennifer D. Parker, and Kenneth C. Schoendorf. "Fine Particulate Matter (PM2:5) Air Pollution and Selected Causes of Postneonatal Infant Mortality in California" Environmental Health Perspectives, 114(5):786-790. 2006.

Appendix A: Local Pollution Emission Reductions

Table A.1: Projected Emission Reductions

Year	**NH_3**	**NO_x**	**PM_{10}**	**$PM_{2.5}$**	**SO_2**	**VOC**
2006	**7.22E+01**	**1.53E+03**	**1.45E+02**	**5.60E+01**	**4.64E+02**	**5.30E+01**
2007	**1.24E+02**	**4.78E+03**	**6.75E+02**	**2.63E+02**	**9.91E+03**	**1.03E+02**
2008	**1.75E+02**	**8.03E+03**	**1.21E+03**	**4.69E+02**	**1.93E+04**	**1.52E+02**
2009	**4.68E+02**	**1.65E+04**	**2.78E+03**	**1.08E+03**	**3.15E+04**	**3.81E+02**
2010	**7.61E+02**	**2.50E+04**	**4.36E+03**	**1.69E+03**	**4.37E+04**	**6.09E+02**
2011	**5.22E+02**	**1.32E+05**	**2.61E+04**	**7.92E+03**	**2.17E+05**	**9.11E+02**
2012	**2.84E+02**	**2.38E+05**	**4.79E+04**	**1.41E+04**	**3.91E+05**	**1.21E+03**
2013	**9.32E+03**	**5.90E+05**	**1.43E+05**	**4.95E+04**	**8.28E+05**	**1.27E+05**
2014	**1.24E+04**	**8.41E+05**	**2.35E+05**	**7.98E+04**	**1.26E+06**	**1.70E+05**
2015	**1.59E+04**	**9.84E+05**	**2.91E+05**	**1.00E+05**	**1.55E+06**	**2.11E+05**
2016	**1.63E+04**	**1.09E+06**	**3.46E+05**	**1.19E+05**	**1.84E+06**	**2.15E+05**
2017	**1.59E+04**	**1.27E+06**	**4.41E+05**	**1.50E+05**	**2.23E+06**	**2.19E+05**
2018	**1.54E+04**	**1.44E+06**	**5.37E+05**	**1.82E+05**	**2.62E+06**	**2.22E+05**
2019	**1.67E+04**	**1.55E+06**	**5.89E+05**	**1.99E+05**	**2.85E+06**	**2.26E+05**
2020	**1.79E+04**	**1.66E+06**	**6.40E+05**	**2.16E+05**	**3.07E+06**	**2.30E+05**
2021	**1.93E+04**	**1.71E+06**	**6.65E+05**	**2.25E+05**	**3.20E+06**	**2.35E+05**
2022	**2.07E+04**	**1.77E+06**	**6.90E+05**	**2.34E+05**	**3.33E+06**	**2.39E+05**
2023	**2.17E+04**	**1.85E+06**	**7.35E+05**	**2.50E+05**	**3.52E+06**	**2.44E+05**
2024	**2.28E+04**	**1.94E+06**	**7.80E+05**	**2.66E+05**	**3.72E+06**	**2.48E+05**
2025	**2.38E+04**	**2.02E+06**	**8.33E+05**	**2.84E+05**	**3.94E+06**	**2.53E+05**
2026	**2.59E+04**	**2.10E+06**	**8.87E+05**	**3.03E+05**	**4.16E+06**	**2.65E+05**
2027	**2.87E+04**	**2.15E+06**	**9.18E+05**	**3.14E+05**	**4.29E+06**	**2.77E+05**
2028	**3.16E+04**	**2.21E+06**	**9.48E+05**	**3.25E+05**	**4.41E+06**	**2.90E+05**
2029	**3.42E+04**	**2.26E+06**	**9.90E+05**	**3.40E+05**	**4.57E+06**	**3.02E+05**
2030	**3.67E+04**	**2.32E+06**	**1.03E+06**	**3.55E+05**	**4.72E+06**	**3.14E+05**

Table A.2: Projected CO_2 Emission Reductions (million metric tons)

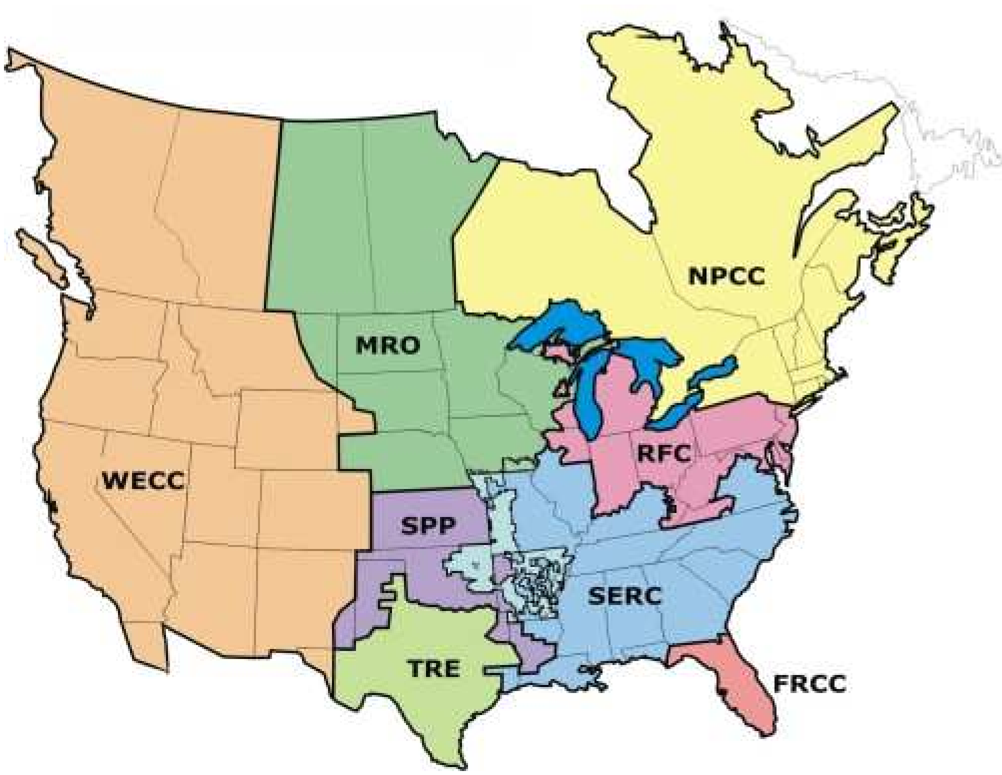
Year	CO_2
2005	**0**
2006	**7.488458**
2007	**28.45958**
2008	**42.80875**
2009	**60.64727**
2010	**80.83277**
2011	**436.894**
2012	**779.6579**
2013	**1114.222**
2014	**1443.999**
2015	**1768.925**
2016	**1969.037**
2017	**2162.47**
2018	**2348.985**
2019	**2526.462**
2020	**2695.084**
2021	**2903.342**
2022	**3105.232**
2023	**3302.92**
2024	**3496.121**
2025	**3684.403**
2026	**3920.703**
2027	**4151.93**
2028	**4376.768**
2029	**4597.892**
2030	**4814.992**

Appendix B: Overview of EDF Regional Electricity Model Inputs

1. Regional Definition

The Environmental Defense Fund Regional Electricity Model (EDF REM), provides a detailed model of the US electricity sector. The country is broken down into 8 electrical regions based roughly on the NERC regions:

Figure B.1



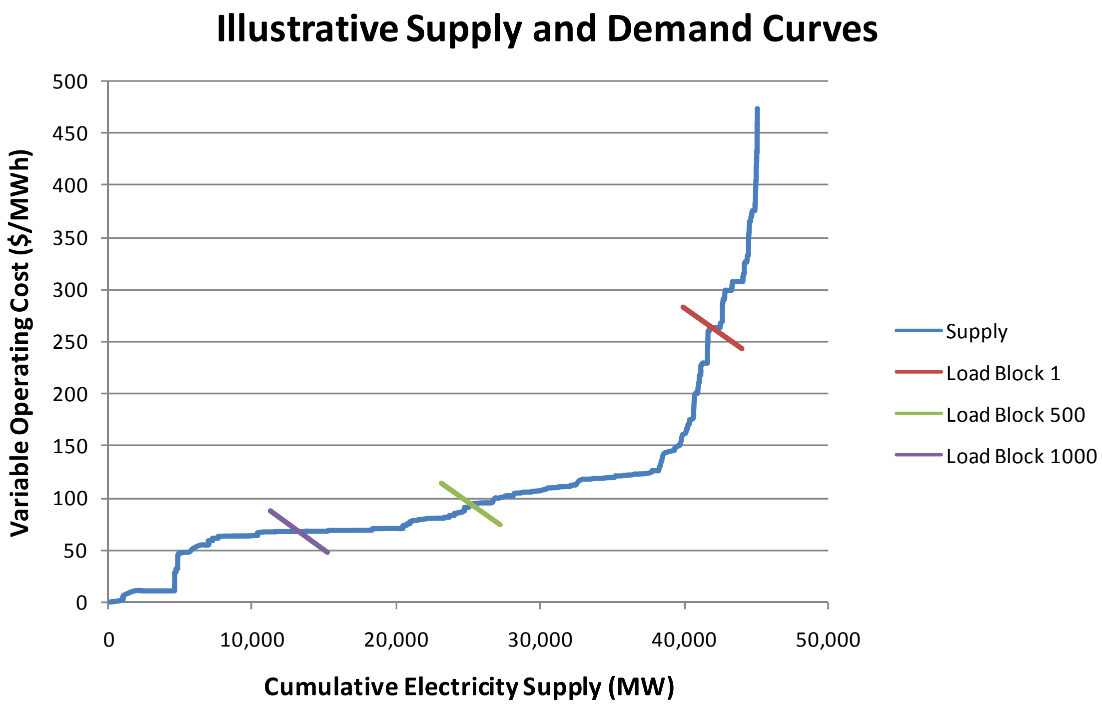
Source: Energy Information Administration
(http://www.eia.doe.gov/cneaf/electricity/chg_str_fuel/html/fig02.html)

The EDF REM does not include Canadian portions of the WECC, MRO and NPCC. In addition, the EDF REM breaks down regions along state lines. For instance, a small portion of Montana is electrically located in the MRO region but in order to bench mark to historical state reporting, the EDF REM models Montana wholly within the WECC region.

2. Supply and Demand Curve

The main engine of the EDF REM is the electrical supply and demand curves. For this study the model is run through the year 2030 and each year is broken down into 1,095 8-hour load segments. In each time period, the database of electricity supply units is sorted from least to most expensive. The model "turn on" generating units starting with the least expensive until demand is satisfied). This intersection of supply and demand determines which units operate in each 8-hour load block.

Figure B.2



2a. Supply Curve

The starting point for the regional electric supply curve is a database of existing generating units. This database was developed using Platts Energy Advantage. The Platts database supplies detailed characteristics on all existing generating units including their location, size in MW, fuel type, Heat Rate (HR) in Btu/kWh, emission rates for SO_2, NOx, and CO_2, and the variable operating and maintenance (O&M) cost in \$/MWh. This data is then used to calculate the annual operating cost for each generating unit as follows:

$$\text{Var. Cost} = \text{Fuel Price*HR} + \text{Var. O\&M} + CO_2\text{ Rate*}CO_2\text{ Price} + SO_2\text{ Rate*}SO_2\text{ Price} + \text{NOx Rate*NOx Price}$$

Along with data on existing power plants, the Platts data also provides information about announced new capacity. Each new plant is assigned a probability based on its stage of development and the plant capacity is scaled by its probability of completion. This new planned capacity is added to the model according to the projected on-line year reported in Platts.

Plant emission rates for VOCs, NH3, PM 2.5 and PM 10 are based on the EPA published emission factors by plant fuel type and firing type[17].

2b. Demand Curve

The starting point for the electricity demand curve is the total annual energy demanded in each region. The forecast for the annual energy demand is based on the NERC Report "2008-2017 Regional and National Peak Demand and Energy Forecasts Bandwidths." This report details the expected demand growth by NERC region. The total annual demand is broken down into 1,095 8-hour load blocks in order to represent the variation in demand across time within a given year. The hourly demand curve is developed from the EPA IPM regional load curves: "Appendix 2-1. Load Duration Curves used in Base Case 2006". This curve of 8,760 hours per year is aggregated into 8-hour blocks such that block 1 contains the highest 8 demand hours of the year and block 1,095 has the 9 lowest demand hours. These demand blocks are scaled each year to reflect the annual demand growth.

3. Fuel and Emissions Price Forecasts

Fuel and emission price forecast are derived from a number of differing sources.

Coal Price

Platts Energy Advantage provides plant specific coal-price forecasts. The coal price for new announced coal plants with a specific site location are tied to the price forecast for the nearest existing coal plant. A weighted average coal price is developed by region for use in new economic coal plant additions.

Natural Gas and Oil Price

The natural gas price forecast is based on the national price forecast used by EPA in their IPM modeling. This national price is broken down into a regional price forecast based on actual historical delivered natural gas prices as reported by Platts. EPA provides a natural gas price forecast for both Base Case and Policy Case model runs.

CO_2 Price

The CO_2 price forecast is an output of the EDF REM model. The model starts with an input of the desired CO_2 emissions over time based on the policy analyzed. The model runs iteratively in order to determine the CO_2 price projection consistent with the CO_2 emissions targets.

[17] See http://www.epa.gov/ttn/chief/efpac/index.html for more information on EPA's emission factors for electric generating units.

4. New Capacity Additions (economics, characteristics, and types)

The model examines the economic viability of the following types on new generation: nuclear, integrated gasification/combined cycle with carbon capture and sequestration (IGCC CCS), pulverized coal, gas turbine, gas combined cycle, wind, and biomass. The cost and performance of new power plants are estimated from EPA data (see EPA *Documentation for EPA Base Case 2006 v3.0*), from EIA *Table 8.2 Cost and Performance Characteristics of New Central Station Electricity Generating Technologies*, and from market data for currently planned new generation. These data include estimates for the technological improvement in new unit heat rates as well as reductions in the costs of building and operating new power plant over time.

New capacity is added in each year based on plant economics. The model calculates the net revenues accruing to a hypothetical new plant in each year based on the following formula:

$$\sum_{t=1}^{1095} Max\left(0, P_t - MC\right)$$

where: t = time block (1,095 8-hour time blocks per year)
P_t = Electricity Market Clearing Price for time block t
MC = Marginal Cost for the hypothetical new power plant

The stream of net revenues is discounted back to the date of the capital investment and compared versus the required return on investment (ROI). The ROI varies depending on the type of generating plant based on estimates from market information (e.g., a nuclear plant demands a higher ROI than a gas combined cycle plant based on the riskiness of the investment). While this formulation simplifies the actual operation of generating plants (e.g., it ignores minimum run times), it is adequate to gain the basic understanding of the relative economics of the different generating technologies needed for the model to make investment decisions.

New build limits for new nuclear, renewables (wind and biomass combined) and CCS plants are implemented by applying the limits used by the EPA in the IPM model.   In addition, new renewable capacity is schedule to come on-line to meet the current state Renewable Portfolio Standards (RPS). This provides a minimum level of renewables to meet current statutes. Additional, economic renewables may be added up to the EPA IPM model limits.

5. Model benchmarking to Historical Reported Data

The model benchmarks results for 2005 through 2007 versus actual reported data in order to establish proper model operation. The model is benchmarked versus the following information:

- EIA *Electric Power Annual 2007 - State Data Tables* (aggregated by region):
  - Total generating capacity
  - Generating capacity by fuel type
  - Total generation
  - Generation by fuel type
  - CO_2, SO_2 and NOx emissions
- EPA eGRID 2005 plant emissions report
  - Mercury emissions

Appendix C: Allowance prices and input data for transport sector modeling

Table C1: Modeled Allowance Prices Under S.2191 ($2005 per tCO2e)

S.2191 Core Scenario 2	**2015**	**2030**	**2050**
Adage	$29	$61	$159
IGEM	$40	$83	$220
H.R.2454	*$13*	*$26*	*$69*

Table C2: Estimated price indices for petroleum and natural gas under a climate policy

Price Indices						
Petroleum ($/mmbtu)	2005	2010	2015	2020	2025	2030
BAU	1.00	1.06	1.09	1.11	1.13	1.15
S. 2191 Scenario 2	1.00	1.05	1.08	1.10	1.09	1.10
Natural Gas ($/mmbtu)						
BAU	1.00	0.74	0.68	0.71	0.77	0.83
S. 2191 Scenario 2	1.00	0.74	0.67	0.69	0.73	0.77

ADAGE Core Scenario 2 for the analysis of S. 2191.

Table C3: Gasoline price elasticity estimates

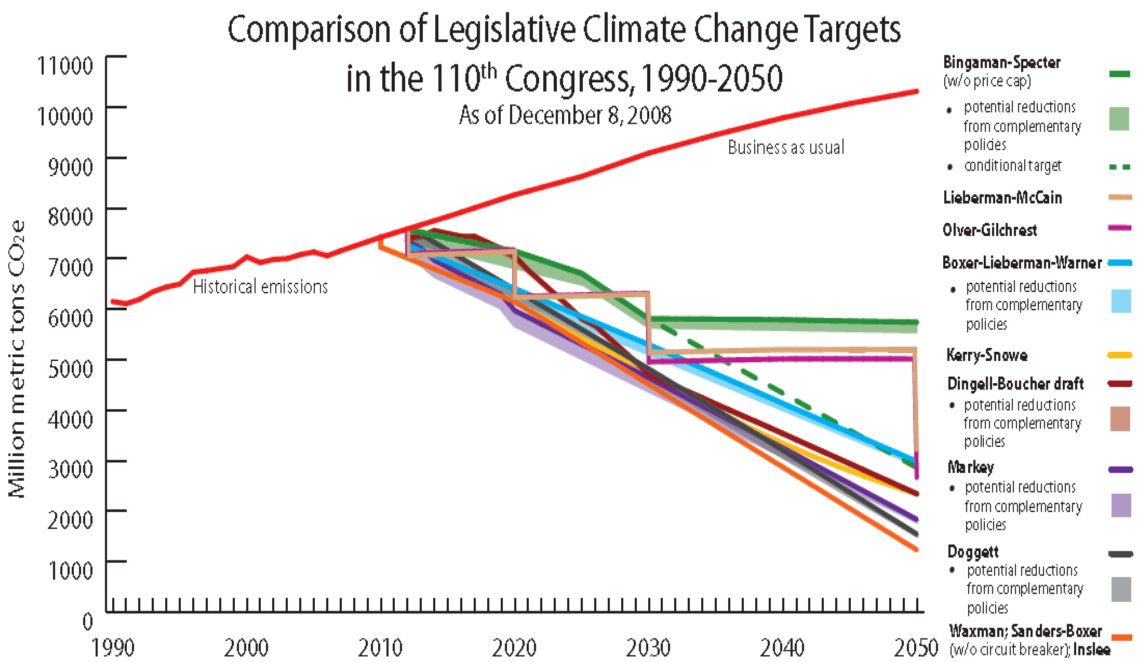
Authors	**Year of study**	**Long-run**	
		Low	**High**
Nicol	2000	-	-
Brons, Nijkmamp, etc.	2006	-.81	-.84
Goodwin Dargay & Hanly	2004	-.64	-.64
Espey	1998	-.43	-.43
VTPI	2006		
Graham & Glaister	2002	-.6	-.8
Small & Van Dender (OLS)	2007	-.5695	-.5695
Small & Van Dender (3SLS)	2007	-.3813	-.3813
Romero	2007	-	-
HKS	2006	-	-
Mean		-.571	-.610
Median		-.585	-.605

Table C4: Fuel Price Elasticities (Hagler Bailly ,1999)

	Elasticity
Road Gasoline	-0.60
Road Diesel	-0.30
Road Propane	-0.60
Road CNG	-0.60
Rail Diesel	-0.40
Aviation	-0.30
Marine Diesel	-0.30

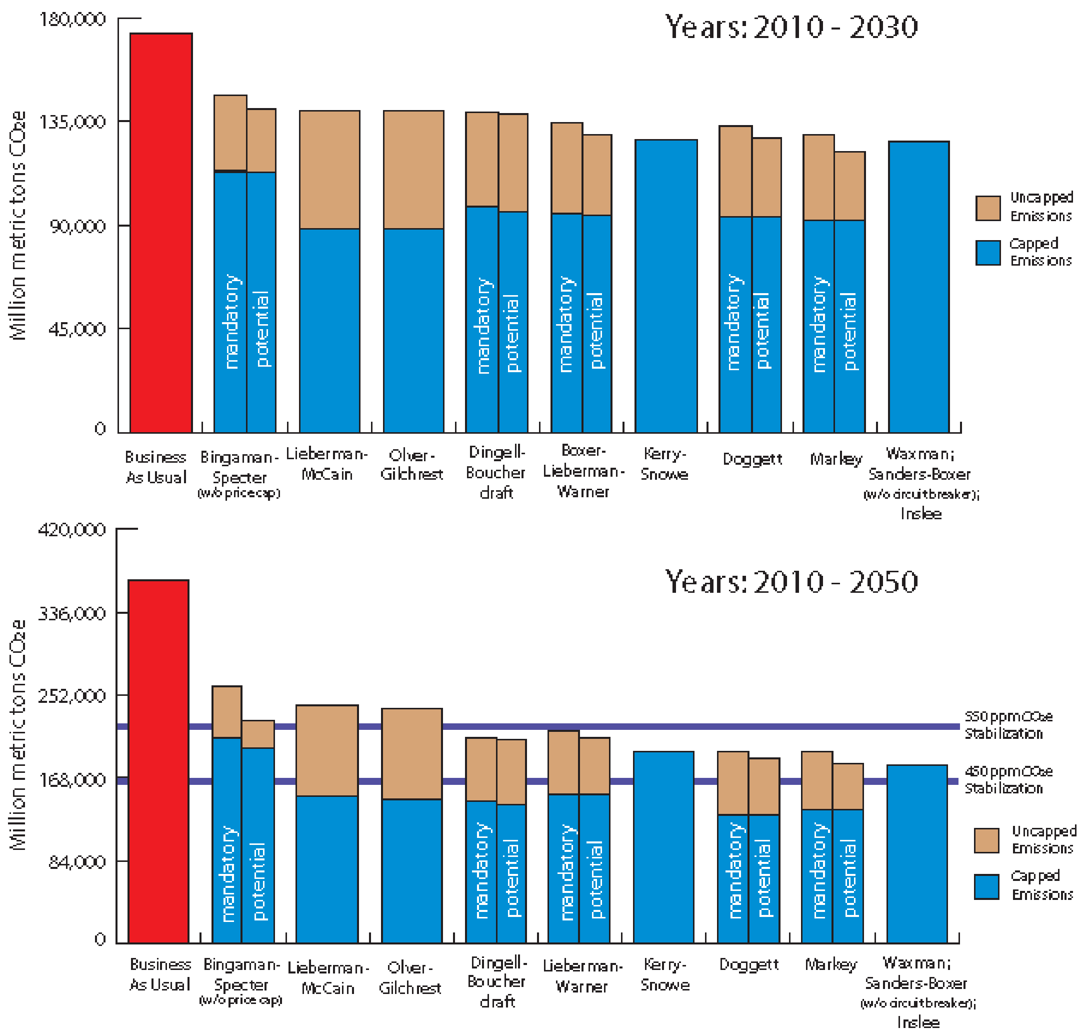
Appendix D: S.2191 as a "representative" climate policy

Figure D.1



Source: http://pdf.wri.org/usclimatetargets_2008-12-08.pdf

Figure D.2: **Comparison of Cumulative Emissions Ranges under Legislative Climate Change Targets in the 110th Congress (WRI)**



Source: http://pdf.wri.org/usclimatetargets_2008-12-08.pdf