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SUPPLEMENTARY INFORMATION

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A systems approach to evaluating the air quality co-benefits of US carbon policies

Methods

USREP Model. USREP combines the behavioral assumption of rational economic agents with the analysis of equilibrium conditions, and represents price-dependent market interactions as well as the origination and spending of income based on microeconomic theory. Profit-maximizing firms produce goods and services using intermediate inputs from other sectors and primary factors of production from households. Utility-maximizing households receive income from government transfers and from their supply to firms of factors of production (labor, capital, land, and resources). Income thus earned is spent on goods and services or is saved. The government collects tax revenue which is spent on consumption and household transfers.

The USREP model is built on state-level economic data from the Impact analysis for PLANning (IMPLAN) dataset covering all transactions among businesses, households, and government agents for the base year 2006 (ref. 1). Energy data from the Energy Information Administration's State Energy Data System (SEDS) are merged with the economic data to provide physical flows of energy for greenhouse gas accounting. Economic and greenhouse gas datasets in USREP are aggregated to 12 US regions and 17 commodity groups (see below for a description of regions and sectors). This structure separately identifies larger states, allows representation of separate electricity interconnects, and captures some of the diversity among states in use and production of energy. Our commodity aggregation identifies five energy sectors (including coal, natural gas, crude oil, refined oil, and electricity) and five non-energy composites (including energy-intensive products, other manufacturing, agriculture, transportation, and services). Rausch et al.[2] provides a detailed description of the nesting structure for each production sector and household consumption.

Energy supply is regionalized for USREP by incorporating regional fossil fuel reserves data from the U.S. Geological Service and the Department of Energy. Several advanced energy supply options are specified as "backstop" technologies that enter endogenously if and when they become economically competitive with existing technologies. Competitiveness of different technologies depends on the endogenously determined prices for all inputs, as those prices depend on climate policy, depletion of resources, and other economic growth drivers.

Figure S1 presents eleven regions of the US that are modeled independently in USREP. Alaska and Hawaii are combined to form the twelfth region but are not included in regional air quality modeling. States modeled independently in the model include California, Texas, Florida, and New York. The remaining US States are grouped into regions by combining states with similar energy use and production characteristics.

Seventeen economic sectors are modeled independently in USREP. Energy commodities identified and modeled in our study include coal, natural gas, crude oil, refined oil, and electricity. These sectors allow us to distinguish energy goods and specify substitutability between fuels in energy demand. Additionally we distinguish energy intensive industry, other industry, private transportation, commercial transportation, agriculture, and service sectors. The following three sectors are each further split by three energy source types (to make nine independently modeled sectors): electric, energy intensive industry, and other industry are each split into oil, gas and coal energy sources.

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Figure S1. Twelve (including Alaska and Hawaii – not shown) regions of the continental US are modeled individually in USREP.

These sectors are matched to individual emissions inventory data points using Standard Classification Codes that describe the activity in detail. For example, Standard Classification Codes 101001xx, 101002xx, and 101003xx (where x represents any number) represents all external combustion boilers fueled by coal for the purpose of electricity generation (coal-fired power plant). Individual emissions reported from a process at any facility that is assigned one of these codes will be scaled using the ratio from USREP electricity generation by coal: 2030 output versus 2006 output. All Standard Classification Codes were matched in detail to USREP sectors in the same manner.

Policy Scenarios. We consider three policy instruments to achieve identical year-on-year carbon emissions reductions that differ with respect to their sectoral scope: (i) a clean energy standard (CES) instrument that is focused on the electricity sector; (ii) an economy-wide cap-and-trade (CAT) regulation implying that each sector in the economy has to pay an equal price on carbon inputs and (iii) a sectoral carbon cap imposed on private and commercial transportation (TRN).

To construct the CES scenario, we constrain USREP to achieve a certain clean electricity fraction target in each modeled year, defined as the ratio of total clean energy electricity generation to total electricity sales. The amount of generation from each technology that is considered clean depends on the technology. Specifically, all renewable technologies (wind, solar, hydropower, biopower, and geothermal) and nuclear are considered 100% clean, natural gas with carbon capture and storage (CCS) is considered 95% clean, coal with CCS is considered 90% clean, and gas combined cycle is considered 50% clean. Both existing installations and new investments in these technology types earn a credit. The CES targets are assumed to increase linearly from 42% in 2012 to 80% by 2035. Then targets increase linearly from 2035 to 2050, achieving a final value of 95% in 2050. These targets are similar, but slightly less stringent, than what was proposed under the Clean Energy Standard Act of 2012.

To construct the CAT and TRN scenarios, we take the year-to-year and total base CO_2 reductions as calculated with the CES scenario and apply them to the entire economy and the transportation sector, respectively. Previous studies evaluated the change in consumer welfare, i.e. the amount needed to compensate consumers for losses under these policies[3].

CAMx. We use a well-documented year-long air quality episode developed and fully evaluated by the US EPA to evaluate the potential impact of the recently upheld (by the US Supreme Court) federal air quality policy[4]. Emissions inventories include a 2005 base case and a 2012 future case and were speciated and spatially and temporally processed using the SMOKE preprocessing system[5]. The 2005 base case inventory represents calculated year 2005 emissions, while the 2012 emissions inventories were forecast from 2005 to 2012 by incorporating population and economic growth, technological advancements and all air quality regulations in place by 2010.

Meteorological inputs representing year 2005 were developed by the US EPA fusing the Pennsylvania State University/ National Center for Atmospheric Research Mesoscale Model (MM5; ref. 6). A performance evaluation was conducted also by the US EPA on the meteorological inputs in order to make sure they met current performance standards[7]. O_3 and $PM_{2.5}$ outputs for 2005 were previously evaluated as part of recent federal air quality regulatory analysis, and detailed evaluation is provided by the U.S. EPA[4]. The GEOS-Chem global chemical transport model was used for boundary and initial conditions[8].

Economic Sensitivity Scenarios. For our economic sensitivity analysis, we rerun each of the three USREP scenarios (CES, TRN and CAT) with varying baseline economic growth and CO_2 emissions, cost of renewables, and fuel efficiency improvements. The first sensitivity scenario (High-Base) applies a high economic and CO_2 growth by 2030 (7,100 mmt, a 14.5% increase). The second scenario (Low-Cost) is economically optimistic, including low cost renewables and optimistic assumptions on fuel efficiency improvement in private transportation. Renewable cost is adjusted by reducing the cost of wind technologies by 15% compared to the base case, and fuel efficiency improvement is represented by increasing the flexibility in the model to substitute fuel inputs with (powertrain) capital in private vehicles. A third, economically pessimistic scenario (High-Cost) has higher renewable costs (applied by increasing wind technology cost by 15% compared to the base case) and a more pessimistic view of fuel efficiency improvement in private transportation (decreasing the flexibility in the model to substitute fuel inputs with powertrain capital in private vehicles).

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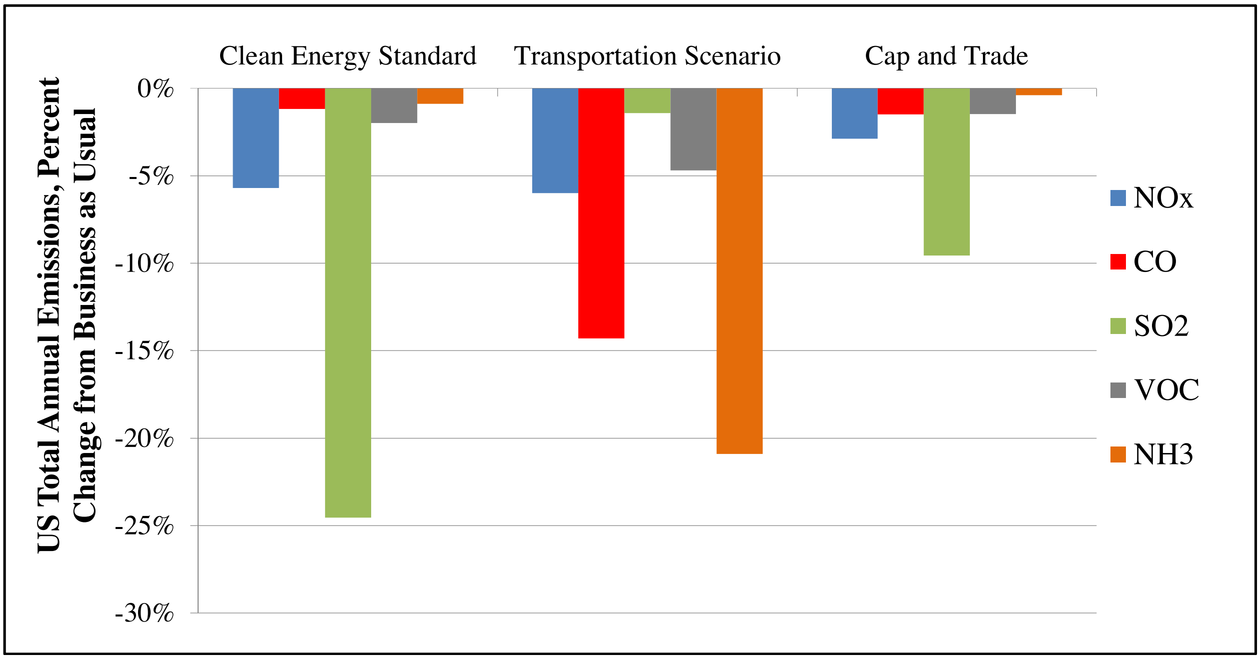

Figure S2. Percent Change (from Business as Usual) of total US emissions in the year 2030, of five air pollutants for three climate policies in our base case.

Emissions Inventories. The emission inventory used includes all relevant criteria pollutants and major precursors and was previously developed and applied by the U.S. EPA using a combination of measured and modeled data[9]. Most large point sources (including electricity generating units) in the US are required to measure and report hourly emissions, providing modelers with detailed emissions data from each source including hourly, daily, and monthly changes. By also including detailed location and stack height data, the model is able to incorporate the different atmospheric processes that can occur when emissions are released into layers above the lowest mixed layer of the troposphere. In contrast, most ground level "area" sources (vehicle and home emissions for example) are developed using models designed to estimate and spatially and temporally distribute those inventories and they are assumed to be homogeneous dispersed in the lowest mixed layer. Total emissions are projected to 2030 for each Business As Usual (no policy) economic sensitivity scenario with a 2005 emissions inventory starting point, plus an additional BAU base run, also projected to 2030, but with a 2012 emissions starting point.

Figure S2 shows projected emissions changes for five air pollutants (O_3 and $PM_{2.5}$ precursors) in 2030 due to the three climate policy base case scenarios. Table S1 presents the annually averaged emissions values in thousand short tons per year for the same species for the two EPA estimating base year emissions (2005 and 2012), plus BAU case as well as the change from BAU for each of the corresponding policy scenarios in the same unit (for example: CAT '05 High Growth is compared to BAU '05 High Growth). In all cases, the high growth sensitivity run leads to much higher total emissions with much higher emissions reductions and therefore larger human health benefits.

The BAU 2030 emissions are estimated to increase by approximately 30% over the corresponding base year emissions for all pollutants (SO_2 which increases by only 2% is the exception). While this might not be a best estimate of air quality in 2030, as it is impossible to forecast all technological advancements and air quality regulation, it is strictly intended to serve as an economic baseline from which we can evaluate the impacts of co-benefits sensitivity tests. The 2012 emissions inventory starts with annual emissions totals that are on average 20% lower (across species) than the 2005 inventory and leads to emissions reductions that are also 20% lower on average[9].

Table S1. Absolute values in Thousand Tons/Year of emissions for 2005 and 2012 inventories without any scaling applied, each Business as Usual case projected to 2030, plus the difference between each policy scenario and the corresponding BAU case projected to 2030.

Scenario	NOx	CO	SO2	VOC	NH3
2005 EPA Base Emissions Inventory	20,461	80,331	14,131	18,725	3,714
2012 EPA Base Emissions Inventory	14,288	63,627	10,839	12,630	3,819
Business As Usual 2005EI	27,309	113,138	14,442	21,783	4,646
BAU '05 High Base	32,597	133,515	17,481	26,339	5,113
BAU '05 Low-Cost	27,330	113,140	14,464	21,753	4,645
BAU '05 High Cost	27,262	112,886	14,427	21,767	4,647
Business As Usual 2012EI	19,253	89,028	10,964	15,242	4,762
Cap And Trade 2005EI	(787)	(1,684)	(1,381)	(317)	(18)
CAT '05 High Base	(2,435)	(3,951)	(4,380)	(746)	(98)
CAT '05 Low-Cost	(696)	(1,023)	(1,243)	(175)	(25)
CAT '05 High-Cost	(751)	(1,357)	(1,397)	(274)	(19)
Cap And Trade 2012EI	(600)	(1,427)	(1,145)	(266)	(18)
Clean Energy Standard 2005EI	(1,537)	(1,333)	(3,522)	(283)	(41)
CES '05 High Base	(2,399)	(1,684)	(5,134)	(415)	(140)
CES '05 Low-Cost	(1,188)	(907)	(2,240)	(152)	0
CES '05 High-Cost	(1,716)	(1,548)	(3,927)	(356)	(85)
Clean Energy Standard 2012EI	(980)	(1,021)	(2,821)	(239)	(46)
Transportation Cap 2005EI	(3,009)	(16,758)	(248)	(2,098)	(974)
TRN '05 High Base	(3,239)	(18,528)	(193)	(2,467)	(1,140)
TRN '05 Low-Cost	(2,607)	(14,416)	(215)	(1,650)	(735)
TRN '05 High-Cost	(3,397)	(18,650)	(384)	(2,452)	(1,215)
Transportation Cap 2012EI	(1,937)	(12,965)	(154)	(988)	(1,000)
Cap And Trade High Stringency	(2,492)	(4,678)	(3,904)	(853)	(171)

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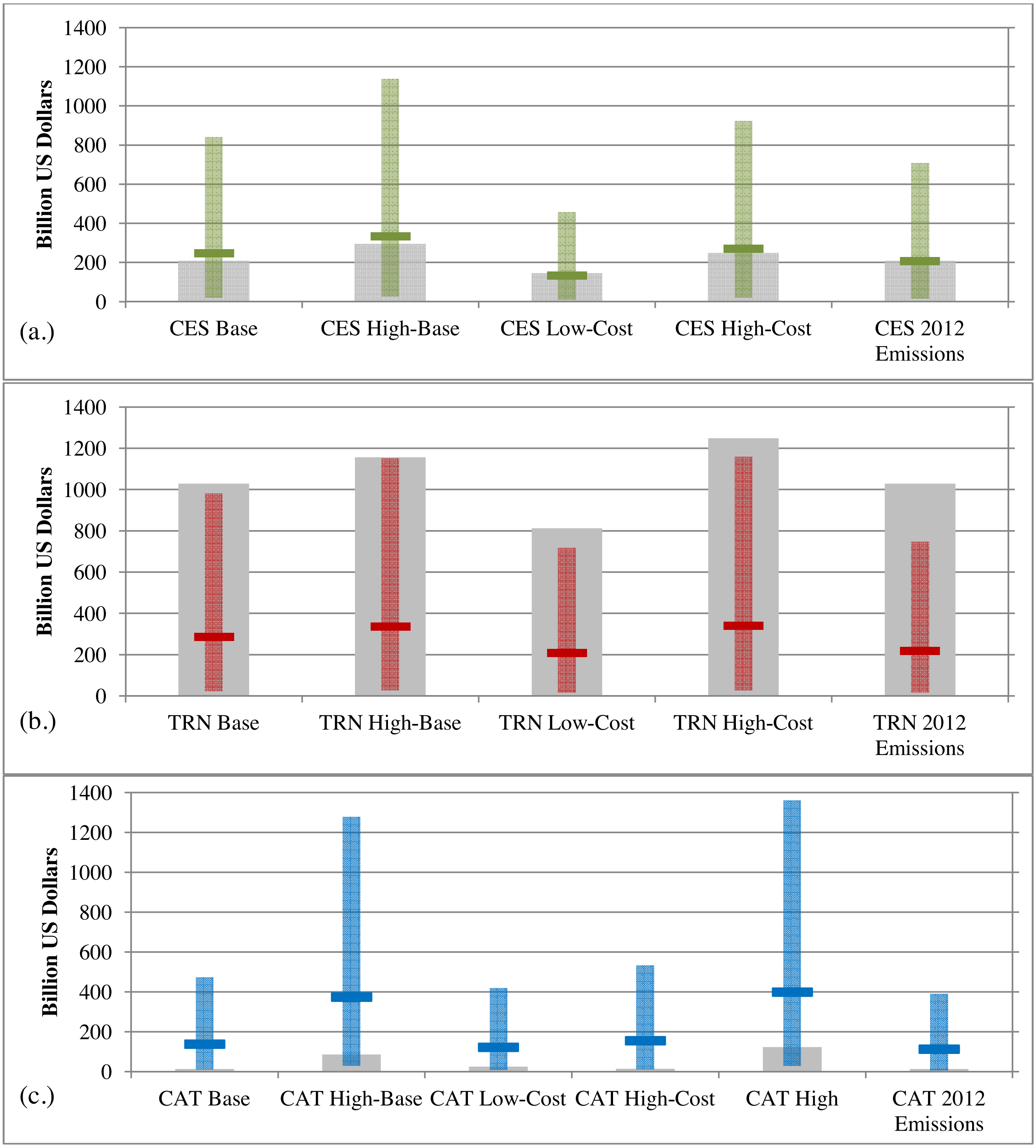

Figure S3. Total economic welfare costs for each scenario are shown in grey. The total calculated dollar amount of the human health benefits point estimate is shown by the horizontal line with the 95% confidence interval, associated with both human health response and valuation, shown using the vertical line. Values are in billions of year 2006 US dollars. a.) Clean Energy Standard Results. b.) Transportation Scenario Results. c.) Cap and Trade Results.

BenMAP. We use the US EPA's Benefits Mapping (BenMAP) program to calculate the economic benefits of the human health response to co-benefits of carbon policy. Our benefits values represent total values for health benefits realized during the year 2030. BenMAP has built in population projections out to 2040 that incorporate economic predictions of changing population spatial distributions, which could be important given that pollution is often not spatially homogeneous[10]. Population-weighted concentration reductions for CES, TRN, and CAT respectively are 0.58, 0.99 and 0.21 ppb for O_3, and 0.97, 1.16 and 0.56 μg m^{-3} for $PM_{2.5}$.

We compare the values of these predicted health benefits in 2030 to welfare costs estimated by USREP also in 2030. Results presented in this paper represent pooled mortality concentration response functions plus morbidity estimates for both ozone and $PM_{2.5}$. We use fixed effects pooling, a method that weights the impact estimated by each study by the inverse of the variance of that study, in order to capture the uncertainty associated with all available crfs for both ozone and $PM_{2.5}$. Results from individual mortality functions are discussed below. We follow the procedures of the latest US EPA Regulatory Impact Analysis to calculate morbidity[11].

Individual Concentration Response Functions (CRFs). The concentration-response functions applied in this study are those peer-reviewed epidemiological studies in BenMAP version 4.0.67 that estimate increased mortality risk due to changes in ambient concentrations of ozone and $PM_{2.5}$. Ozone crfs include those described by Schwartz[12], Bell et al.[13,14], Huang et al[15], Ito et al.[16], Levy et al.[17]. $PM_{2.5}$ crfs include those described by Krewski et al.[18] and Lepeule et al.[19]. Figures S4 a&b show the mean change in mortality (represented by the slashes: green = CES, red = TRN, and blue = CAT) plus the 95% confidence interval estimated by each of these crfs for the three base scenarios. For each scenario, the largest mean mortality change estimated by a single ozone crf is approximately 3.5 times the smallest mean mortality change (over 300% larger). The largest mean mortality change estimated by a single $PM_{2.5}$ crf is 2.3 times larger than the smallest mean mortality change.

Co-benefit values are reported undiscounted, therefore benefits assume no lag time between exposure and health response. While the US EPA approves the use of the 20-year-lag[11], a recent study conducted for the US EPA to investigate lag time assumptions, acknowledges a lack of evidence to support any single lag structure[20]. This study also found that the difference in final calculated benefits between no lag structure and the 20-year-lag was small, 13% or less. Therefore, given the evolving evidence and the apparent minimal impact of its selection, we assumed no lag, an assumption more consistent with the findings by Schwartz et al.[21] which suggests that effects occur within two years of exposure.

Health benefits are quantitatively dominated by changes in $PM_{2.5}$, consistent with the findings of previous studies[22,23]. $PM_{2.5}$ mortality values account for 97% of total benefits value on average. This in part explains the similarities in quantified benefits due to different policies. While CES reduces SO_2 (a major precursor to $PM_{2.5}$) by approximately 25%, the decreases come from power plants, often located far from population centers, thus reducing human impact. TRN reduces NO_x and VOCs as well as primary $PM_{2.5}$ but less SO_2. However, as transportation emissions are often co-located with high population centers, the impacts to human exposure from these emissions reductions can be larger. These two influences counteract to produce approximately the same aggregate benefits.

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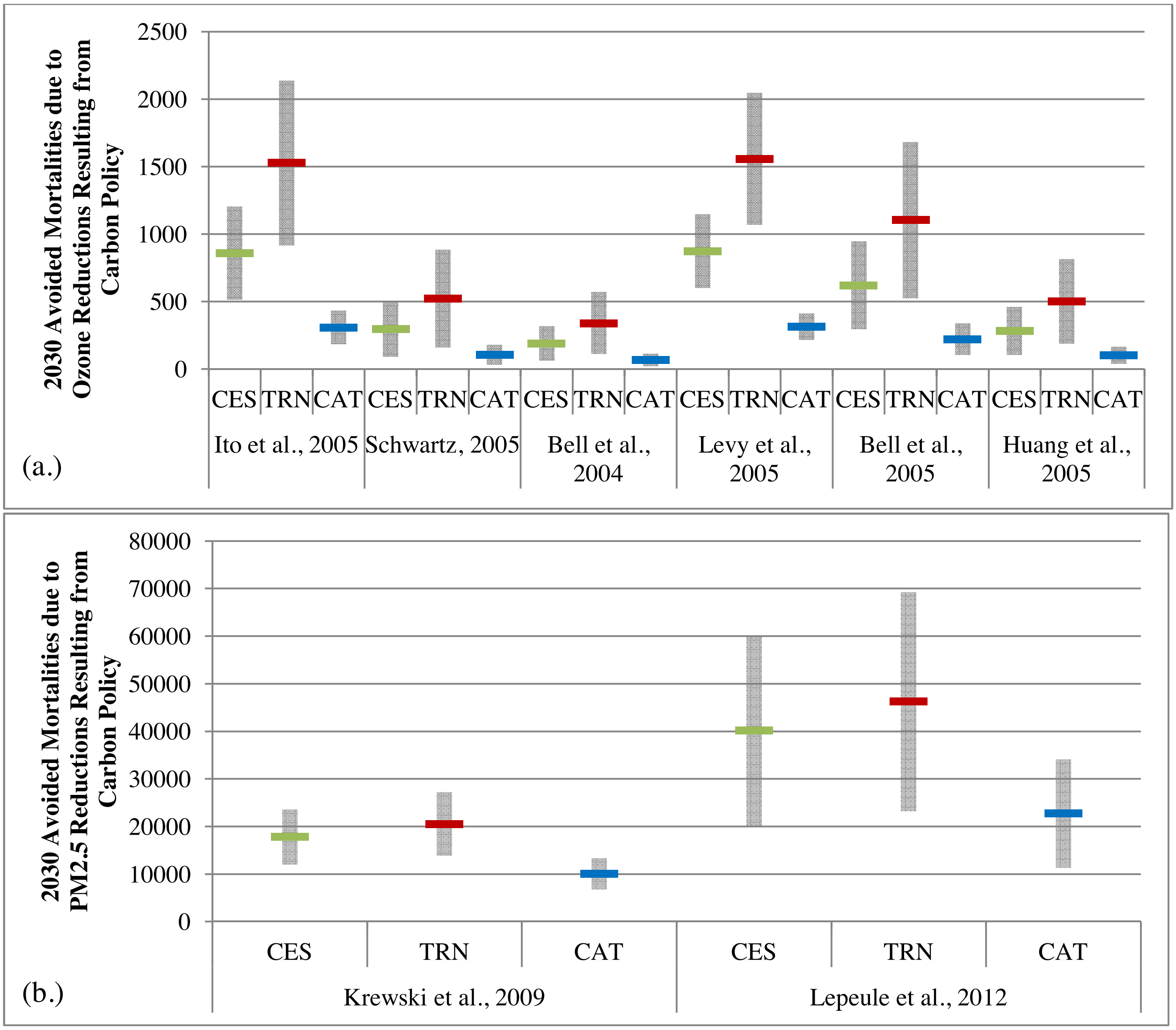

Figure S4. a.) Mortalities avoided due to changes in ozone concentrations between the 2030 Business As Usual Scenario and each of the three policy scenarios, calculated using six different concentration response functions. b. Mortalities avoided due to changes in $PM_{2.5}$ concentrations between the 2030 Business As Usual Scenario and each of the three policy scenarios calculated using two different concentration response functions (crfs).

In some high population centers, seasonal average daily maximum 8-hr O_3 increases under TRN due to reductions in NO_x titration of O_3. NO_x titration (NO reacts with O_3 forming NO_2 and oxygen) generally occurs in areas with high emissions of NO_x, e.g. urban centers with heavy traffic. By reducing traffic related NO_x, TRN reduces NO_x titration and thus increases O_3, although this generally occurs when O_3 concentrations have been artificially reduced by NO_x titration and thus are relatively low. The NO_x titration effect is generally very localized. Peak ozone concentrations in areas downwind of heavy traffic centers generally decrease when NO_x emissions are decreased.

In order to capture the combined uncertainty associated with all crfs commonly presented in regulatory applications, we used the random/fixed effects pooling method to pool the crfs mentioned above. Crfs for O_3 and $PM_{2.5}$ mortality were pooled individually. BenMAP then included the uncertainty associated with VSL. These benefit values were then added together with morbidity estimates (morbidity also includes uncertainty associated with both response and value functions). This total benefit is presented as the main estimate in the paper.

We show in Figure S5 that the uncertainty range associated with the two pooled $PM_{2.5}$ crfs is similar to the uncertainty range associated with the VSL function. The upper end of the benefit value was larger when only crf uncertainty was considered, and the lower end of the benefit value was lower when only VSL function uncertainty was considered. Additionally, the relative importance of uncertainty associated with crfs versus uncertainty associated with value functions has been studied previously[20]. The analysis shows that the difference between individual crfs, specifically for $PM_{2.5}$, had a larger impact on the range of benefits than did changing the valuation function.

Table S4 presents benefits per short ton of reductions in the emissions of SO_2 and NO_x. Speciated $PM_{2.5}$ was run through BenMAP, using the same procedures used for total $PM_{2.5}$ benefits, to calculate benefits associated with particulate nitrate and particulate sulfate individually. Benefits per ton for NO_x were calculated by adding benefits associated with changes in particulate nitrate to benefits associated with changes in ozone, for each scenario, and divided by tons of NO_x reduced, also by scenario. For sulfate, benefits associated with changes in particulate sulfate were divided by tons of SO_2 reduced.

Table S2. Costs per Tonne of CO_2 reduction for all scenarios.

Costs (in Dollars) per Tonne CO_2 Reduction				
	Base	High-Base	Low-Cost	High-Cost
Clean Energy Standard	\$255	\$231	\$230	\$269
Transportation Cap	\$1,257	\$906	\$1,286	\$1,356
Cap and Trade	\$17	\$68	\$41	\$16
Cap and Trade High	\$78			

Table S3. Benefits (Dollars) per Tonne of CO_2 reduction for all scenarios.

Benefits (in Dollars) per Tonne CO_2 Reduction				
	Base	High-Base	Low-Cost	High-Cost
Clean Energy Standard	\$302	\$261	\$212	\$294
Transportation Cap	\$351	\$264	\$332	\$369
Cap and Trade	\$170	\$294	\$195	\$170
Cap and Trade High	\$252			

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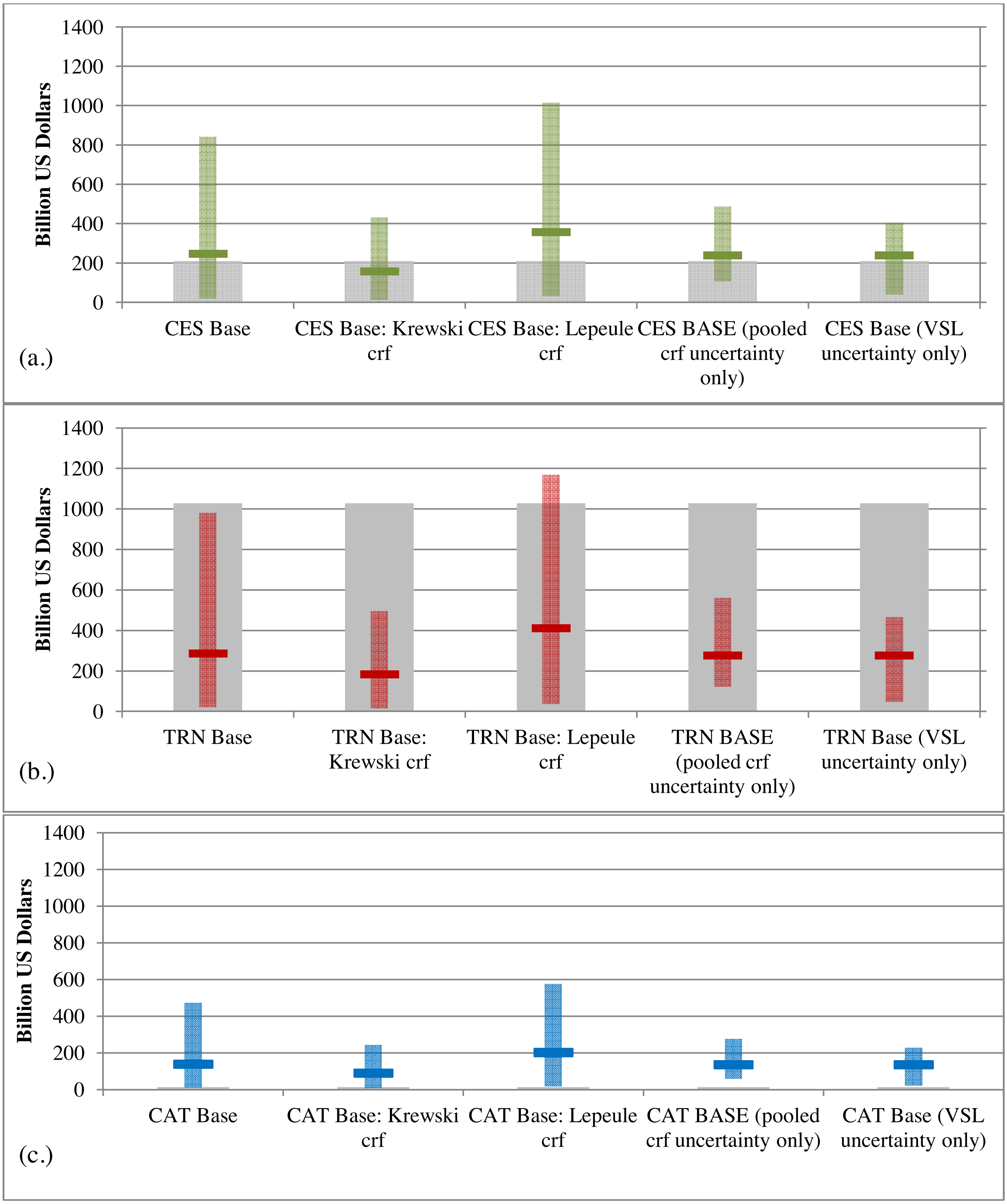

Figure S5. Total economic welfare costs for each scenario are shown in grey. The total calculated dollar amount of the human health benefits point estimate is shown by the horizontal line with the 95% confidence interval, associated with both human health response and valuation function (unless otherwise noted), shown using the vertical line. Values are in billions of year 2006 US dollars. a.) Clean Energy Standard Results. b.) Transportation Scenario Results. c.) Cap and Trade Results.

Table S4. Benefits (Dollars) per Ton of NO_x and SO_2 emissions reduction for three base scenarios.

Benefits (in Dollars) per Ton Emissions Reduction	NO_x	SO_2
Clean Energy Standard	$815	$43,201
Transportation Cap	$37,880	$84,115
Cap and Trade	$2,319	$44,070

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