The Social Cost of Atmospheric Release

Electronic Supplementary Material

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1. Methods: Additional Description

1.1 SCAR methodology for basic climate damages and context with the SCC

Social costs are typically assessed in integrated assessment models (IAMs) using global mean surface temperature changes, with those in turn being driven by radiative forcing (RF). In my calculations, RF due to the short-lived species CO, NO_x and NH_3 is based on the AR5 (Myhre et al., 2013). As noted in the main text, RF attributable to individual aerosol precursors including indirect cloud effects was not provided in AR5, and hence to incorporate this component for SO_2, BC and OC I use a combination of modeling and literature analysis (Shindell et al., 2012a; Shindell et al., 2009; United Nations Environment Programme and World Meteorological Organization, 2011). Indirect aerosol-cloud effects may also be important for NH_3, and weakly so for NO_x, but results for those were not available. The forcing per unit emission (W m^{-2} per Tg) of aerosol and aerosol precursors based on these studies is -6.63×10^{-9} for SO_2, 9.63×10^{-8} for BC, and -1.33×10^{-8} for OC. For context, these yield total industrial-era forcings (assuming ¼ of current biomass burning is due to industrial-era increases) attributed to aerosols of -0.73 W m^{-2} for sulfate, -0.34 W m^{-2} for OC, and +0.60 W m^{-2} for BC (including indirect effects). The net forcing for these three is thus -0.47 W m^{-2}, a value comparable to the net RF in AR5 for these three plus all aerosol-cloud forcing and rapid adjustments to aerosols (-0.61 W m^{-2}). RF per unit emission (W m^{-2} per Tg) of other short-lived species is -9.36 x 10^{-10} for NO_x, -1.78 x 10^{-9} for NH_3, and 1.43 x 10^{-8} for CO, yielding industrial-era forcings of –0.15, -0.06 and 0.23 W m^{-2}, respectively (as in AR5).

All responses are calculated for emissions changes during a single year (pulse emissions, rather than sustained changes). RF for short-lived species takes place during the first year following their emission only, except for CO and NO_x that cause chemical responses in methane (both) and CO_2 (CO) (not including the carbon-cycle feedback by which all species cause changes in CO_2). The evolution of CO_2 is based on the four exponential decay timescales given in the IPCC AR4 (Forster et al., 2007). Methane's evolution is calculated using the observationally-constrained perturbation timescale of 12.4 yr (Prather et al., 2012) and the equilibrium response per unit methane emissions change calculated with the GISS-PUCCINI model (Shindell et al., 2009) (equivalent to a 100 year global warming potential of ~32, very similar to that quoted in AR5). RF due to CO_2 and methane is computed using the standard IPCC formulation (Ramaswamy et al., 2001). Forcing by N_2O and HFC-134a is calculated based on the lifetimes and integrated forcing reported in (Hodnebrog et al., 2013) and the IPCC AR5 (Myhre et al., 2013) (121 and 13.4 year lifetimes and 100-yr global warming potential of 265 and 1300, respectively). As noted in the main text, uncertainties in RF presented in the AR5 (Myhre et al., 2013) are used for all emissions, and the relative uncertainties are applied to both the direct and indirect RF due to SO_2, BC and OC.

The resulting global mean surface temperature changes serve as a proxy for damages to agriculture, human health, coastal areas (due to sea-level rise), outdoor recreation, forestry, water, energy, human settlements, and ecosystems in a warming climate, though some costs such as agriculture and forestry can also depend upon CO_2 concentrations and damages associated with sea-level rise are sometimes calculated separately (e.g. (Hope, 2013; Narita et al., 2010; Nordhaus, 2010; Nordhaus and Boyer, 2000)). The IAMs contain relatively simple equations relating impacts to temperature changes, typically separated into several major economic sectors and world regions, but these are based on a large volume of primary studies that the IAMs attempt to aggregate into the best available representation of climate damages. The available data on climate impacts is quite limited for many sectors and/or regions, however.

Climate damages in the IAMs generally scale with roughly the square of the global mean temperature change (typical powers range from 1 to 3) or depend upon both the magnitude and rate of temperature change. Some IAMs also include estimates for the occurrence of 'catastrophic' changes. Impacts such as biodiversity loss and ocean acidification are typically not accounted for in these models (and hence they are also not accounted for in the SCAR). Human health impacts may include changes in vector-borne diseases such as malaria and dengue, as well as responses to changes in air quality due to climate change, the sum of which is referred to here as climate-health impacts (as distinct from composition-health impacts).

The DICE damage function is based on regionally aggregated damages across major economic sectors, especially human health and amenities, agriculture, and forestry, and uses a willingness-to-pay approach to estimate what societies might spend as 'insurance' to avoid the climate-related damages. Damages are calculated as a function of temperature change, regional output per capita at present and at the time of the future temperature change, and the authors' assessment of available data on the monetized impact of a particular amount of warming (and associated climate changes). The latter includes an enormous analysis of the literature, which cannot easily be summarized here for even a single IAM, but an example for the case of climate-health impacts is discussed further below. As described in the main text, the DICE damage function has damages proportional to the square of the temperature change and equal to 1.8% of world output at 2.5°C. For comparison, the PAGE IAM finds fairly similar results, with damages of just under 2% of world GDP at 3°C (Hope, 2013) and the DICE result lies well within the range of ~0.5-2.5% of world GDP for 2.5°C warming given in the IPCC AR4 (Yohe et al., 2007) (or a similar range in *Stern* (2006)).

The maximum tolerated warming is relatively unconstrained, so I selected a value that leads to mean basic climate damages that roughly match the average USG2013 estimates for CO_2. This choice effectively calibrates the single SCAR model and scenario used here to the mean obtained across the sampling of model and scenario uncertainties in the USG study. IAM studies often include an arbitrarily limited time horizon rather than a maximum tolerated warming to keep their valuation bounded at low discount rates (NRC2010).

Note that additional substances could be examined using the SCAR framework. Many ozone-depleting substances affect both climate and health (nitrous oxide (N_2O) is evaluated, and affects stratospheric ozone and hence skin cancer rates, but valuation of that chain of effects has not been performed and so is excluded here). Most ozone-depleting substances are now controlled and decreasing (Myhre et al., 2013), however. They are being replaced by ozone-friendly hydrofluorocarbons (HFCs). These influence climate, and in come cases their emissions are rapidly increasing and hence even if they cause small damages now preventing continued increases may lead to great benefits, and so I include the most important to date, the compound HFC-134a as an example. Volatile organic compounds also affect both air quality and climate, but as these are a family of many compounds a single emission metric is of limited use. Note also that both ozone chemistry and aerosol-climate interactions can be highly non-linear, and as such values for emission metrics will vary as background conditions change.

1.2 Climate-Health Valuation

The DICE model damage function used here includes climate-health impacts based on the 1996 Global Burden of Disease assessment of tropical disease burdens and some simple assumptions: (1) climate change affects health via tropical diseases only, and (2) climate change decreases projected reductions in tropical diseases by half, or the response can be estimated using the regression between current tropical disease burdens and mean regional temperatures (Nordhaus and Boyer, 2000) (the DICE2007 version description does not describe any changes to the 2000 climate-health modeling). These assumptions are clearly quite crude (e.g. impacts via malnutrition or heatwaves are ignored), and serve as a reminder of how the data that the IAM creators rely on to define regional and sectoral damage functions is often quite limited or unavailable.

The analysis presented here uses a distribution from prior modeling of the effects of carbonaceous aerosols and associated emissions on human health to derive the global mean value of a statistical life for climate-health calculations. This means that the global mean VSL is based on climate-health impacts being more prevalent in developing nations with high current carbonaceous aerosols, consistent with the general pattern of baseline mortality and vulnerability to climate-health impacts (such as malnutrition and tropical disease spread) being larger there (Campbell-Lendrum and Woodruff, 2007). The prior work used an elasticity of 0.40 between the per capita income in each country and the willingness-to-pay and examined the effects of emissions changes on 210 countries using country specific incomes and pollutant levels (Shindell et al., 2012a). Whereas health literature often uses disability adjusted life years, which are arguably more informative since they incorporate the age of the affected individuals, I use VSL as this is a better established metric in the economics literature (e.g (Viscusi and Aldy, 2003)). Note that although I assume VSL is proportional to the per capita GDP, I do not assume that baseline mortality is tied to GDP since the link between medical spending and reduced mortality is unclear (Cutler et al., 2006; Rothberg et al., 2010). I also point out that since population growth increases the number of people exposed to health impacts while reducing per capita GDP by the same amount the valuation is not sensitive to the precise value of the growth rate (though the population growth drives part of the GDP increase, which does affect valuation).

Although the valuation for climate-health impacts is directly tied to temperature change, this is used as a proxy for all climate impacts. In the case of cooling agents (SO_2, OC, NO_x and NH_3), the global mean temperature change is negative, and hence the basic climate damages are also negative. The net climate-related damages are positive, however, once the regional disruption of the hydrologic cycle is accounted for, and hence in this study the climate-health damages are also taken to have positive values. I find that simply assuming damages are proportional to the temperature squared for cooling agents, as for warming agents, produces climate-health values that have a similar, though slightly lower, ratio to the net climate-related damages to that found for BC or CO (simpler cases as all damages have positive values; except in the case of NO_x for which net climate impacts are very small compared with composition-health impacts). Hence I use the positive climate-health damages for cooling aerosols that stem from the temperature squared calculation, although clearly further work is needed to better understand the net impact of cooler temperatures along with disruptions to precipitation patterns on human health.

1.3 Valuation of Regional Precipitation Changes due to Aerosols

IPCC AR4 WGII (Yohe et al., 2007) indicates the impact affecting the largest number of people by far is exposure to increases in water resources stress, followed by increased risk of hunger (especially when CO_2 fertilization is not included, as would be the case for warming induced by non-CO_2 forcing). This provides motivation to evaluate differences in the influence of inhomogeneous forcers on precipitation relative to that of CO_2.

Several prior studies have examined this issue, as noted in the main text. In particular, the response to scenarios reducing emissions of BC and co-emitted pollutants shows that the spatial pattern of July-September precipitation changes is in general similar to that seen in response to well-mixed greenhouse gas (WMGHG) forcing, but with a substantially stronger magnitude (Shindell et al., 2012a). The mean response for those reductions compared with equivalent forcing reductions in WMGHGs (and hence equal global mean temperature changes in this methodology) is 4.2 times greater (median 6.2), and 2/3 of locations show a response more than double that for WMGHGs (Figure S1). There is a substantial area of negative response ratios, nearly all of which are located in the Amazon, where BC causes increased precipitation while WMGHGs cause drying. In contrast, in most parts of the globe the responses are similar in sign, with both WMGHGs and BC leading to increased precipitation over India and decreases in the Sahel, in Southern Africa, and around the Mediterranean. Excluding the Amazon locations brings the mean response ratio up to 6.6 (median 7.8), and then ~80% of locations experience more than twice the WMGHG response, which corresponds to the relative impact that would be felt in most of the world, offset by the opposing response in the Amazon. While this analysis includes only points with precipitation changes that are significant at the 1.6-sigma level (95% confidence), using all land points give the same mean while using all land and ocean points the mean is only slightly different at 4.0. In addition, analysis of multiple experiments with an earlier version of the same climate model showed that both scattering and absorbing aerosols typically induce a substantially greater precipitation response per unit RF than WMGHGs (Shindell et al., 2012b). I do not include an enhanced regional precipitation response to ozone as the prior modeling did not clearly indicate a distinctly different response relative to CO_2 (Shindell et al., 2012b). Hence the regional enhancement for NO_x applies only to the portion of the climate impacts that take place via changes in nitrate. Though not dependent on the sampling used in this analysis, the results may be model dependent.

The assumption that regional aerosol impacts can be represented by assigning precipitation impacts to be ~4× greater and assuming precipitation changes account for half of climate damages are clearly first order assumptions meriting further refinement. A recent review paper on agriculture and climate, for example, highlighted both the importance of changes in temperature and precipitation means and extremes and the many uncertainties that prevent determination of the relative impact of each factor (Gornall et al., 2010). Hence it is difficult to determine the portion of damages attributable to precipitation changes, though I find that this factor contributes only a small amount to the overall uncertainty in valuation for all species (see ESM section 6). Aerosols, being primarily in the Northern Hemisphere extratropics, would also have a greater impact on Arctic/Greenland melting, for example, than WMGHGs, and on snowpack accumulation and melting in much of the Northern extratropics, topics that could be examined in future studies.

While this valuation of the hydrologic cycle response to aerosols represents only an initial attempt to include climate responses that are not simply proportional to the global mean temperature change, it leads to two key conclusions. First, although uncertainties are large for both the fraction of damages due to precipitation changes and for the precipitation response to aerosols, including disruption to the hydrologic cycle can lead to net climate benefit for cooling aerosol or NO_x reductions. Second, for scattering aerosols and NO_x, climate impacts either based on global mean temperature change alone or including precipitation changes are small compared with health impacts (Table 2). Hence even if reductions in these emissions were to have a net beneficial impact via climate, the health benefits are dominant based on economic valuation.

1.4 Composition-Health Valuation

Damages attributable to atmospheric composition changes are based upon prior modeling of the response of surface pollutants to emissions. Adverse health impacts of chronic $PM_{2.5}$ exposure are calculated as described in the main text. Epidemiological data to separate the effects of individual $PM_{2.5}$ components is minimal, and so impacts are typically calculated for aggregate $PM_{2.5}$. For the aerosol and aerosol precursor emissions included here, the relative contributions to annual average population weighted $PM_{2.5}$ are: BC 5.5%, OC 32%, SO_2 37%, NO_x 8% and NH_3 11% (Shindell et al., 2012a). Composition-health impacts for secondary organics were not included as they are not a result of a single precursor emission (mineral dust was also excluded). Composition-health impacts of CO and NO_x via ozone are based on the same methodology used for methane health effects via ozone in which global gridded composition-climate model output is used to calculate damages due to local premature mortalities attributable to ozone accounting for exposure, population and income (Shindell et al., 2012a), although using results from only one global composition-climate model as results from the second (used for methane) were not available for these cases. Total present-day premature mortalities attributable to ozone are roughly 500,000 via NO_x, 50,000 via CO and 60,000 via methane. Assuming VOCs contribute an amount similar to CO, the total is quite consistent with the 0.7 million reported in Anenberg et al. (2010) (though substantially higher than the value reported in Lim et al. (2013)). The underlying concentration-response functions are based on epidemiological data for long-term exposure to ozone (Jerrett et al., 2009) and $PM_{2.5}$ (Pope et al., 2002) as described in *Shindell et al.* (2012a) and *Anenberg et al.* (2012).

Composition-health impacts are based on population aged 25 and older for most effects, as in the epidemiological literature (e.g. (Cohen et al., 2004)), which is a potential source of low bias. Values might, however, be biased high for marginal changes as the concentration-response function (CRF) may saturate at very high exposure levels (which was not assumed to happen in the prior work underlying these results). Hence there are potential biases in either direction. Similarly for ozone, only premature death associated with respiratory disease related to long-term exposure is included (Smith et al., 2009). The assumed uncertainty in the CRF is very large, however, and the overall uncertainty (~80%; including differences in the modeled concentration response to emissions changes (United Nations Environment Programme and World Meteorological Organization, 2011)) is dominated by the CRF and likely encompasses most of the potential biases discussed here. Note that impacts on indoor health have not been included here, as these depend strongly on the exposure pattern and are thus not well-suited to generalized emission metrics, but these may be quite large (Lim et al., 2013) and have consequently large valuation (e.g. (Mehta and Shahpar, 2004)).

This analysis includes only valuation of premature deaths from outdoor $PM_{2.5}$ and ozone exposure. Both chronic physical health problems (e.g. (West and Fiore, 2005)) and mental health problems can also be caused by air pollution. For example, studies have demonstrated that exposure to $PM_{2.5}$ contributes to cognitive decline in older people (Weuve et al., 2012) and to decreases in memory and IQ in children (Calderon-Garciduenas et al., 2011; Suglia et al., 2008). Exposure to air pollution has also been shown to contribute to anxiety and depression (Marques and Lima, 2011), with attendant economic impacts. Hence the composition-health valuation is biased low by excluding these effects.

2. Valuation of Future Emissions

In the main text, values are presented for 2010 emissions in 2007 $US (as in USG2013). Numerical values for the results shown in Figure 1 are given here (Table S1). SCAR values in future years are substantially larger, though the increase is uneven across pollutants (Table S2). Values increase substantially over time for most pollutants due to the dependence of the climate impacts on the square of the temperature change and on GDP (as both temperature and GDP are increasing) and the increase in VSL following per caption GDP growth (though these are partially offset by projected decreases in baseline mortality rates). Values increase more slowly with time for those pollutants for which damages are dominated by composition-health impacts (SO_2, OC, NO_x and NH_3).

3. Comparison of CH_4 and N_2O valuation with prior calculations

The ratios of the SCAR values for CH_4 and N_2O to CO_2 using 5% discounting are 49 and 282, respectively, with only the traditional IAM-based climate-health impact and no additional composition-health impact for methane (or 42 and 247 without the carbon-cycle response to non-CO_2 emissions). These are fairly similar to the values of 39 and 372 for the social costs calculated by *Marten and Newbold* (2012) using comparable assumptions (earlier work, summarized in *Marten and Newbold* (2012), used older, incompatible assumptions). Differences may arise from the use of different carbon-cycle models, atmospheric lifetimes and radiative efficiencies. Inclusion of the additional effects considered here, however, brings the ratio to 98 for methane and to 440 for N_2O The ratios increase primarily due to the inclusion of the higher estimated climate-health impacts via malnutrition owing to the lack of offsetting CO_2 fertilization (a qualitatively similar increase in non-CO_2 costs relative to CO_2 due to the lack of fertilization has been noted previously, e.g. (Waldhoff et al., 2011)). The ratio increases more strongly for methane due to the slow decrease in baseline health vulnerability, as that effect is weighted towards the near-term for methane relative to N_2O or CO_2 due to the shorter methane lifetime.

The ratio of the SCAR for a non-CO_2 compound relative to that for CO_2 can also be compared with other emission metrics normalized to CO_2, such as the Global Warming Potential (GWP) or the Global Temperature change Potential (GTP). The SCAR evaluates damages associated with temperature change over all times, whereas the GTP evaluates the temperature change at a single time horizon *H* and the GWP integrates RF, a driver of temperature change, out to a time horizon *H*. The SCAR damages are proportional to the temperature change squared, which tends to make them increase with time, but also include a discounted value of money with time. In contrast, the GWP has equal weighting for all times 0 to *H* and zero weighting thereafter, and for the GTP there is again zero weighting after time *H* and strictly speaking zero weighting before time *H* in terms of temperature change although the climate system does integrate the prior RF to produce the temperature change at time *H*. Hence both the quantity being assessed (discounted dT^2, RF or dT) and the temporal weighting are quite different across these metrics, and hence we would not expect much relationship between them. Interestingly, the SCAR ratio decreases from 98 to 40 for methane going from 5% to 1.4% discounting, somewhat similar to the relative change in the GWP for methane going from a time horizon of 20 to 100 years (consistent with similarities between methane's GWP and global damages noted previously (Boucher, 2012)). SCAR values are indeed not closely related to GWPs or GTPs for other species, however.

4. Comparison of US sectoral and global valuation with prior estimates

Unsurprisingly, the SCAR-based values by US sector (Table S3) are larger than most prior estimates of environmental damages by sector. I also calculate two "limited-SCAR" US sectoral values including only those impacts included in previous studies: composition-health impacts of all pollutants, but climate impacts for CO_2 only and based on IAM climate-health effects (i.e. without the additional climate-health impacts incorporated in the SCAR). In the limited-SCAR 'modern' I use my calculated basic climate damages (that are similar to the USG2013 values) and composition-health based on the latest estimates of the health effects of ambient air pollution (3.2 million premature deaths annually due to outdoor $PM_{2.5}$ in the 2010 Burden (Lim et al., 2013)). In the limited-SCAR 'heritage' version I use the USG2010 SCC for CO_2, and the previous Global Burden of Disease values for the health effects of ambient $PM_{2.5}$ pollution (800,000 in the 2000 version that included urban $PM_{2.5}$ only (Cohen et al., 2004)), as these assumptions correspond to what was used in prior US sectoral analyses.

The limited-SCAR 'heritage' values are typically comparable to prior estimates when using a similar discount rate (3%). For example, previous estimates of environmental damages due to emissions from US coal-burning power plants with a limited-SCAR heritage-like method reported values of $95 billion ((International Monetary Fund, 2013); using composition-health valuation from *National Research Council* (2010)) and $53 billion (Muller et al., 2011). These are comparable to the limited-SCAR heritage valuation of $110±60 billion (Table S3). In the case of the US transportation sector, valuation for composition-health only of ~$23 billion has been reported (International Monetary Fund, 2013; Muller et al., 2011), whereas the limited-SCAR heritage composition-health component is much larger at ~$580±460 billion. The majority (92%) of this valuation comes from the effects of NO_x on ozone, and the discrepancy suggests there may be a substantial uncertainty in this particular effect (as in the aforementioned differences between the studies of Anenberg et al. (2010) and Lim et al. (2013)). Note that simply updating the components included in the older analyses (i.e. moving from the heritage to the modern limited-SCAR) in general increases the value substantially, but is clearly not sufficient to capture the full SCAR valuation.

The values found here for environmental damages by US emission sector are typically larger than those of *Muller et al.* (2011) and similar to those of *International Monetary Fund* (2013) using the same subset of impacts. The full SCAR-based valuations are substantially larger, as a result of including the additional climate-health impacts and including the climate impacts of non-CO_2 emissions. The latter can be quite important, with methane's effect on climate contributing 34% of the SCAR valuation of gas-related electricity generation damages (using 3% discount rate), for example. The shares of damages from CO_2 are 32%, 18% and 31%, for the electricity, transportation and industrial combustion sectors, respectively, for the SCAR-based analysis of current US emissions with 3% discounting.

The sectoral damages, by virtue of their not being internalized within the economic system (i.e. they are negative externalities), have sometimes been characterized as being effectively subsidies (International Monetary Fund, 2013). Regardless of the discount rate, the damages found here for US electricity generation (Table 3) dwarf the direct US government subsidies (primarily via tax expenditures and research and development credits) which were $1.4 billion for coal and $2.8 billion for natural gas in 2010 (Energy Information Administration, 2011). Similarly, the effective subsidy of environmental damages attributable to total global anthropogenic (including open biomass burning) emissions ($21 trillion using 3% discounting) is more than an order of magnitude larger than the worldwide pre-tax subsidy of $480 billion for electricity and fossil fuels (International Monetary Fund, 2013).

At the global scale, valuation of the total anthropogenic emissions of the compounds examined here is $21 trillion using 3% discounting (again, caution must be used in applying a marginal metric to total emissions). Damages attributable to SO_2 and CO_2 total $7.9 trillion, only modestly larger than values calculated by the *International Monetary Fund* (2013) based largely on the impact of these two pollutants ($1.9 trillion) accounting for the higher SCC for CO_2 and the newer health impacts used here. The increase when other components are included is dominated by the impact of PIC ($7.2 trillion), methane ($1.4 trillion) and NO_x ($2.6 trillion).

5. Valuation of Mercury Emissions

The multiple human health effects of mercury emissions to the atmosphere that bioaccumulate in fish and are eventually consumed by people have been assessed for the US (Rice and Hammitt, 2005; Swain et al., 2007). Based on the valuation per ton attributable to all health impacts (IQ reduction, cardiovascular effects and premature mortality) (Rice and Hammitt, 2005), adjusted to account for the later and hence larger VSL used here, and the 2008 US emissions of 29.5 tons from coal-fired power and 9.2 tons from industry (US EPA, 2013a), mercury emissions lead to human health damages of $5.4 and $1.7 billion for coal-fired power and industry, respectively, as noted in the main text. Comprehensive valuation of the multiple health impacts of mercury has not been performed at the global level.

6. Additional Discussion of Valuation Uncertainties

The average values for the SCC of CO_2 found by the USG2013, in 2007 $US per metric ton of CO_2 emission, are $11 for a 5% discount rate, $33 for a 3% discount rate, and $52 for a 2.5% discount rate. These values are quite consistent with those shown in the analogous basic climate valuation in Table 2 (my value with a 2.5% discount rate is $48), in accord with the aforementioned selection of maximum temperature change to roughly reproduce the USG2013 mean values. Other research (Johnson and Hope, 2012) suggests that the discount rate range should encompass substantially smaller values than in the US government analysis, with correspondingly greater SCC (which is further increased accounting for equity weighting in that study). Another study (Ackerman and Stanton, 2012) also argues for a higher SCC based on the possibility of higher climate sensitivity and high-damage impacts. The review of *Tol* (2008) found $265 per ton over a range of studies with near zero discount rate while the analysis in *Ackerman and Stanton* (2012) found values up to an order of magnitude greater than the USG. Hence substantial uncertainties remain in the choice of discount rate and in the SCC.

The 95th percentile value for the mid-range 3% discount rate in the USG2013 study is $90, a factor of 2.7x the mean value. In my results, the 95th percentile value is 3.1x the median value for basic climate damages due to CO_2 using 3% discounting. Incorporating the additional climate-health impact included in the SCAR for CO_2, this ratio becomes

2.6 (Table S4). Thus inclusion of the additional effect does not appear to greatly change the overall relative uncertainty, consistent with both climate sensitivity and the additional climate-health impact having comparably large uncertainties, and the relative width of the probability distribution obtained via my Monte Carlo calculations appears comparable to that obtained via the USG2013 methodology.

I point out that the Monte Carlo calculations consist of many individual cases with specified values used for all parameters in each case. Thus although the Monte Carlo calculation yields a probability distribution encompassing uncertainty in various parameters, uncertainties in one parameter do not influence other parameters directly. In particular, neither the GDP growth rate nor the uncertainty in that rate alter the discount rate, although both future prosperity and uncertainty in future wealth affect the selection of a discount rate (e.g. (Gollier, 2008)). Ignoring the role of uncertainty can provide risk neutral estimates, but these are biased low relative to risk averse estimates (i.e. the discount rate is higher than a risk averse choice). The independent variation of GDP and discount rates in my uncertainty analysis likely accounts in part for the greater sensitivity to GDP in these results for CO_2 and N_2O than that seen in some other studies (e.g. (Anthoff and Tol, 2013; Hope, 2013); the bulk of the difference stems from the inclusion of the large additional climate-health impacts, as their valuation depends on GDP but not on the damage function). Aside from the use of a lower GDP growth rate in the case of 1.4% discounting as described in the main text, my calculations do not directly link GDP and the discount rate since the choice of discount rate is influenced by additional factors besides growth in future wealth and perceptions of risk in evaluating future wealth (e.g. future utility and the marginal utility of consumption). In the Monte Carlo analysis, cases with, for example, relatively high GDP growth rate are consistent with median results using the same discount rates assuming other parameters change, either (or both) lesser discounting of utility or greater risk aversion, although in practice GDP and the discount rate are not fully independent. Hence, as in USG2013, I present a range of discount rates with the selection left to the user based on their preference for these subjective factors. Note, however, that the assumed preferences in the median cases are therefore different for the various constant discount rates examined here (e.g. since the median GDP growth rate is 2% for both the 3% and 5% discounting cases). This discussion highlights how the separation of uncertainty attributable to individual components is imperfect in a complex non-linear system, as noted in the main text.

The range from the 5th to 95th percentile for the SCAR valuation for each pollutant is shown in Figure S2. Clearly the uncertainties are asymmetric, with a wider distribution on the positive side of the median than the negative. This stems in large part from the skewed distribution of climate sensitivity, but the symmetric uncertainty in the GDP growth rate (in percent) also leads to asymmetric uncertainty in valuation due to non-linear increase in total GDP versus the percentage growth rate. The uncertainty range also tends to follow the residence time of the pollutant, with the largest uncertainties for long-lived N_2O and CO_2, and the smallest for short-lived SO_2, OC, NO_x, and NH_3, with species with mid-range lifetimes in the middle (CH_4, HFC-134a, and CO, which influences CH_4 and CO_2). BC has a larger range on the positive side than other short-lived species due to its greater RF uncertainty (especially on the maximum value). Note that uncertainties presented for specific emissions (e.g. 1% of current, US sectoral) come solely from the SCAR as uncertainty in emissions is assumed to be much smaller.

I analyzed the uncertainty in the SCAR valuation attributable to each of the factors that went into the Monte Carlo probability calculation for each pollutant (Figure S3). The largest source of uncertainty for the long-lived gases N_2O and CO_2 is the projected GDP growth rate. As noted in the main text, changes in GDP influence how much marginal decreases in output cost society and more importantly, how much society is willing to pay to avoid health impacts (wealthier societies are willing to pay more) rather than representing uncertainties in the impacts themselves, making this particular source of uncertainty quite different from most of the other factors. The dominant source of uncertainty for SO_2, OC, NO_x, and NH_3 is the valuation of composition-health impacts. For these pollutants, uncertainties in projections of baseline mortality and GDP have only weak impacts as their composition-health impacts are almost all very near-term. For BC, CH_4, CO and HFC-134a, multiple sources of uncertainty have comparable magnitudes. In particular, climate-health, GDP, and fertilization are important for all three, with RF also a large contributor for BC. These four pollutants have their largest impact over timescales that are substantially shorter than those for N_2O or CO_2, but unlike SO_2, OC, NO_x, and NH_3 their effects via climate are greater than their effects via composition. Several of the other sources of uncertainty examined made only small contributions to the total for all pollutants, such as the non-CO_2 carbon-cycle feedback and the strength of the enhanced regional climate damages attributed to aerosols. Hence while these factors clearly merit future study, as the magnitude of their uncertainty is comparable in size to their estimated mean impact, better characterization is unlikely to greatly affect the overall valuations reported here. In contrast, better characterization of the concentration-response functions for $PM_{2.5}$ or ozone exposure could greatly improve estimates of damages attributable to emissions of SO_2, OC, NO_x, and NH_3. Damage estimates for long-lived CO_2 or N_2O could be narrowed with better knowledge of climate-health impacts, and as noted, more reliable projections of GDP. Finally, note that for emissions of SO_2, OC, NO_x, and NH_3 the choice of discount rate has a much smaller effect on the total valuation than does the uncertainty in composition-health impacts, whereas other emissions are more sensitive to the discount rate choice, and the societal preferences embodied within it, than to any of the uncertainty factors examined here. The differences in uncertainty across pollutant types is a feature that allows multi-pollutant multi-impact approaches to provide reduced overall risk relative to narrower analyses (Graham and Wiener, 1995).

The SCAR, like the SCC, values benefits that take place anywhere in the world. For CO_2, N_2O or methane, emissions from any location have the same effect, so one could argue that although damages occur globally from local emissions, there is a need to account for the global damages since local damages also result from the emissions of others. Adopting a purely local perspective in which only local damages from local emissions are accounted for would greatly increase the relative valuation of short-lived versus long-lived compounds, but seems unlikely to lead to appropriate valuation for the globally influential long-lived pollutants.

Finally, it is interesting to examine the interplay between the damage function and the discounting rate as this depends on the timescale over which impacts take place. This timescale varies greatly across the pollutants examined here according to their atmospheric residence time (Figure S4). For CO_2, if damages have a weaker dependence on temperature change than assumed here (e.g. linear instead of the square of the temperature change; maintaining the same valuation at 2.5°C), valuation would be greater for high discounting rates and less for low rates and overall less sensitive to the discounting rate. Conversely, if damages accelerate more rapidly as temperature changes increase, perhaps as catastrophic shifts take place at high temperature changes, valuations would be even more sensitive to the choice of discount rate. For a short-lived forcing agent such as methane or aerosols, a weaker damage function (e.g. linear in temperature change; maintaining the same valuation at 2.5°C) again would lead to a reduced sensitivity to changes in the discount rate, but with most of the impacts felt at short timescales the weaker damage function with the same 2.5°C damages would increase the valuation at all discount rates examined here (by a factor of 50-500%). A substantial part of the methane and BC valuation is from climate-health effects with short timescales, which is part of the reason that their valuation is more sensitive to this hypothetical change in assumptions, and grows more slowly with decreasing discount rate than CO_2. This example is illustrative of the sensitivity of the long- versus short-lived comparison to the shape of the damage function, but it may be that no IAM would produce damages of 1.8% of GDP at 2.5°C using a damage function linear in temperature.

7. Sensitivity of Valuation to Geographic Location

While valuation allows the various impacts of long-lived and short-lived species to be placed on a common scale, and the choice of discount rate allows one to weight the relative importance of the very different timescales on which these pollutant classes operate, the SCAR does not fully account for the different geographical distribution of impacts caused by long- versus short-lived pollutants. In particular, the impacts of short-lived pollutants will be localized more closely to the region where emissions changes take place, especially for composition-health. Not only would this lead to differences between valuations across nations, but even within small areas (e.g. urban versus rural) or by source location (e.g. ground versus smokestack) based on population density, country-specific income and local physical conditions affecting the lifetime of compounds in the atmosphere. In addition, even the global mean climate impact for short-lived species depends somewhat on the location of emissions, with, for example, greater impact from BC emitted near snow and ice covered regions.

Prior analyses using global climate metrics suggest that impacts typically vary by a factor of up to 3 for emissions from different regions (e.g. (Fuglestvedt et al., 2010)), less than the effect of the choice of discount rate on valuation of climate damages but as large or larger than many other sources of uncertainty. Composition-health impacts would depend even more strongly on emission location, but are less sensitive to the choice of discount rate. Hence the values given here, being averages from worldwide changes in emissions, provide only a broad overview of the impacts due to emissions changes for any particular location.

Since composition-health valuation could vary greatly with location, I test the effect of using global mean valuation versus US-specific valuation for this impact as the latter were available from complementary simulations performed with the same model as used in the derivation of the global values. Those simulations modeled the response of surface pollutants to changes in US emissions only, and the associated valuation uses the US VSL. Valuation of composition-health damages due to US emissions by sector increase by 24-29% using US-specific composition-health valuation. Total environmental impacts rise to $990B for transportation, $640B for electricity generation, and $230B for industrial combustion with 3% discounting. These values are 13-21% greater than the total valuation using global mean composition-health impacts (a smaller increase as climate-related valuations are unchanged). Similarly, the damages per kWh at 3% discounting increase from 24¢ to 28¢ for coal and from 8.4¢ to 8.7¢ for natural gas (Figure S5). Finally, the damages associated with vehicles increase to $2100 per year for gasoline, $960 for an EV powered by electricity from coal, and $300 for an EV powered by electricity from natural gas. The relative increases in this latter case are greater for the higher costs, as those contain a larger fraction of damages due to degraded air quality, which exacerbates the difference across fuel sources.

Hence the use of global mean values slightly underestimates the environmental damages for the US, but the difference is much smaller than the uncertainty range associated with the global mean valuations. In comparison with the exposure-weighted global mean (which is weighted toward developing countries), the US average population density is less but the VSL is more than double, so that the net valuation per unit emission is not vastly different. That does not mean that the global mean values would be a good approximation in all areas, however, as in areas that are both relatively poor and sparsely populated (e.g, parts of Africa) these effects might lead to lower valuation whereas in areas that are both relatively wealthy and densely populated (e.g. Japan, Korea, parts of Europe) the valuation might be larger.

In addition, valuation could depend on variations within nations. For example, damages associated with electricity generation will depend upon the location of emissions relative to downwind population. Similarly, the damages associated with gasoline vehicles might be higher taking into account that most are operated in areas with high population density. Hence accounting for emission location could increase the ratio of gasoline to EV damages further. Thus further analysis could explore the effect of including regional variation in the SCAR based on the emission location, perhaps using the global mean SCAR valuation to guide the choice of which local/regional emissions changes might be most valuable to study with greater detail specific to a particular locality. Accounting for such spatial variations is also clearly important for informing local policy decisions. It must also be recognized, however, that there is a tradeoff in the design of any metric between comprehensiveness versus simplicity and transparency, making it questionable whether it is better to maintain a single globally representative value or develop many local values. The fairly close agreement between the valuation based on global mean impacts and that based on US specific impacts suggests that the global mean SCAR may in fact provide a useful value in many cases.

8. Methane Emissions in the Illustrative Applications

Emissions of methane from the US EPA inventory (US EPA, 2013b) are assigned to sectors differently here than in that inventory’s aggregate results. Emissions from petroleum systems are assumed to have gasoline as their primary end-use, and hence are assigned to transportation. Emissions from coal mining and natural gas systems are assigned to electricity generation (rather than to industry, as in the EPA aggregation), with the former included in the coal-fired and the latter in the gas-fired power generation analyses. Emissions from iron, coke and steel production are assigned to the industry sector.

Fugitive methane emissions associated with natural gas extraction, transport and storage have substantial uncertainties, with some estimates yielding lower methane emissions than the 1.4% used in current EPA inventories (e.g. (Cathles et al., 2012)), and seeming to be supported by measurements at many surface locations ((Allen et al., 2013); though note that these measurements were only taken where industry permitted access), while other estimates are much larger (e.g. (Howarth et al., 2011)) and seem to be supported by at least some atmospheric measurements (Karion et al., 2013; Miller et al., 2013).

Table S1. Valuation of 1% of 2010 anthropogenic emissions (billions \$2007 US)

	CO_2	CH_4	N_2O	HFC-134a	BC	SO_2	CO	OC	NO_x	NH_3
5% discounting	10	8.4	1.5	0.12	19	45	4.6	38	26	10
3% discounting	31	14	4.6	0.22	24	47	7.1	41	26	10
1.4% discounting	53	19	7.6	0.30	28	49	9.2	42	26	11
Declining discounting	40	15	5.8	0.23	25	48	8.2	41	26	10

Table S2. Valuation of emissions in different years (damages per ton in \$2007 US)

Year/ discount rate	CO_2	CH_4	N_2O	HFC-134a	BC	SO_2	CO	OC	NO_x	NH_3
2010 / 5%	28	2700	12000	86000	210000	39000	410	63000	66000	24000
2030 / 5%	48	4500	21000	150000	360000	56000	680	92000	90000	34000
2050 / 5%	80	7400	35000	260000	580000	81000	1100	130000	120000	47000
2010 / 1.4%	150	6000	62000	210000	310000	43000	820	70000	66000	25000
2030 / 1.4%	200	8100	81000	290000	440000	53000	1100	88000	78000	30000
2050 / 1.4%	250	11000	100000	390000	600000	67000	1500	110000	92000	37000

Values are medians from 1000 sample Monte Carlo calculations, so the 2010 values may differ slightly from those shown elsewhere.

Table S3. Valuation of environmental damages (billions \$2007 US) by sector, 2011 US emissions

Discount rate / Sector	Full SCAR			Limited SCAR heritage	Limited SCAR modern	Composition -health only
	5%	3%	1.4%	3%	3%	3%
Electricity	410	570 (+400/-240)	720	120±70	360±240	300±240
coal-fired	370	480 (+310/-210)	600	110±60	340±230	290±230
gas-fired	36	74 (+88/-39)	110	16±6	20±11	7±6
Transportation	690	820 (+490/-390)	950	180±120	630±460	580±460
Industrial combustion	150	200 (+130/-90)	240	47±27	150±100	130±100

SCAR calculations using emissions data from (US EPA, 2012, 2013a, b). Coal- and gas-fired are subsets of the electricity generation sector. Transportation emissions include those associated with petroleum extraction and refining as well as direct vehicle emissions. Health damages from mercury emissions contribute an additional ~\$5 billion to damages due to coal-fired power plants and \$2 billion to industrial combustion (see ESM section 5).

Table S4. Range in total valuation of 2010 emissions (damages per ton in $2007 US)

Valuation; discount rate	CO_2	CH_4	N_2O	HFC-134a	BC	SO_2	CO	OC	NO_x	NH_3
5th percentile; 5%	12	1400	4100	36000	120000	19000	230	32000	27000	11000
5th percentile; 3%	28	2000	9100	57000	140000	21000	330	35000	27000	11000
5th percentile; 1.4%	57	2500	21000	73000	150000	22000	420	36000	27000	12000
5th percentile; declining rate	29	1900	9000	54000	140000	21000	360	35000	27000	11000
95th percentile; 5%	58	5200	29000	180000	380000	60000	650	97000	110000	38000
95th percentile; 3%	220	9800	110000	360000	530000	64000	1200	100000	110000	39000
95th percentile; 1.4%	340	14000	160000	520000	680000	67000	1700	110000	110000	39000
95th percentile; declining rate	330	11000	150000	410000	570000	65000	1500	110000	110000	39000

See Table 2 in the main text for notes.

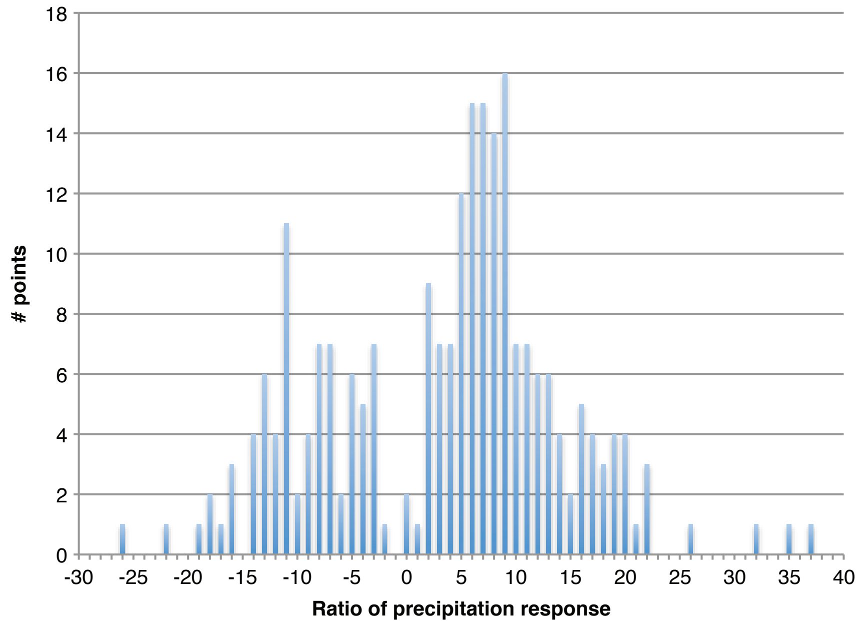

Figure S1. The ratio of precipitation changes in response to forcing by BC and co-emitted species relative to equal global mean WMGHG forcing. Values are from analysis of ~250 land locations from 60°S–60°N where responses were statistically significant in both sets of simulations (Shindell et al., 2012a).

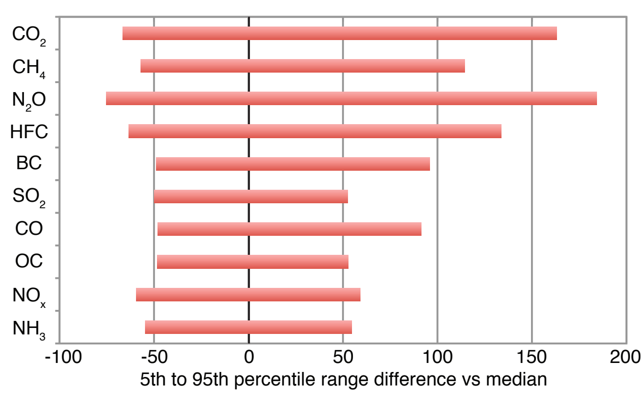

Figure S2. Probability distribution of the SCAR valuation for each pollutant. Total uncertainty due to all examined factors is given as the 5th to 95th percentile range of the Monte Carlo calculations in units of percent difference relative to the median SCAR value using a 3% discount rate.

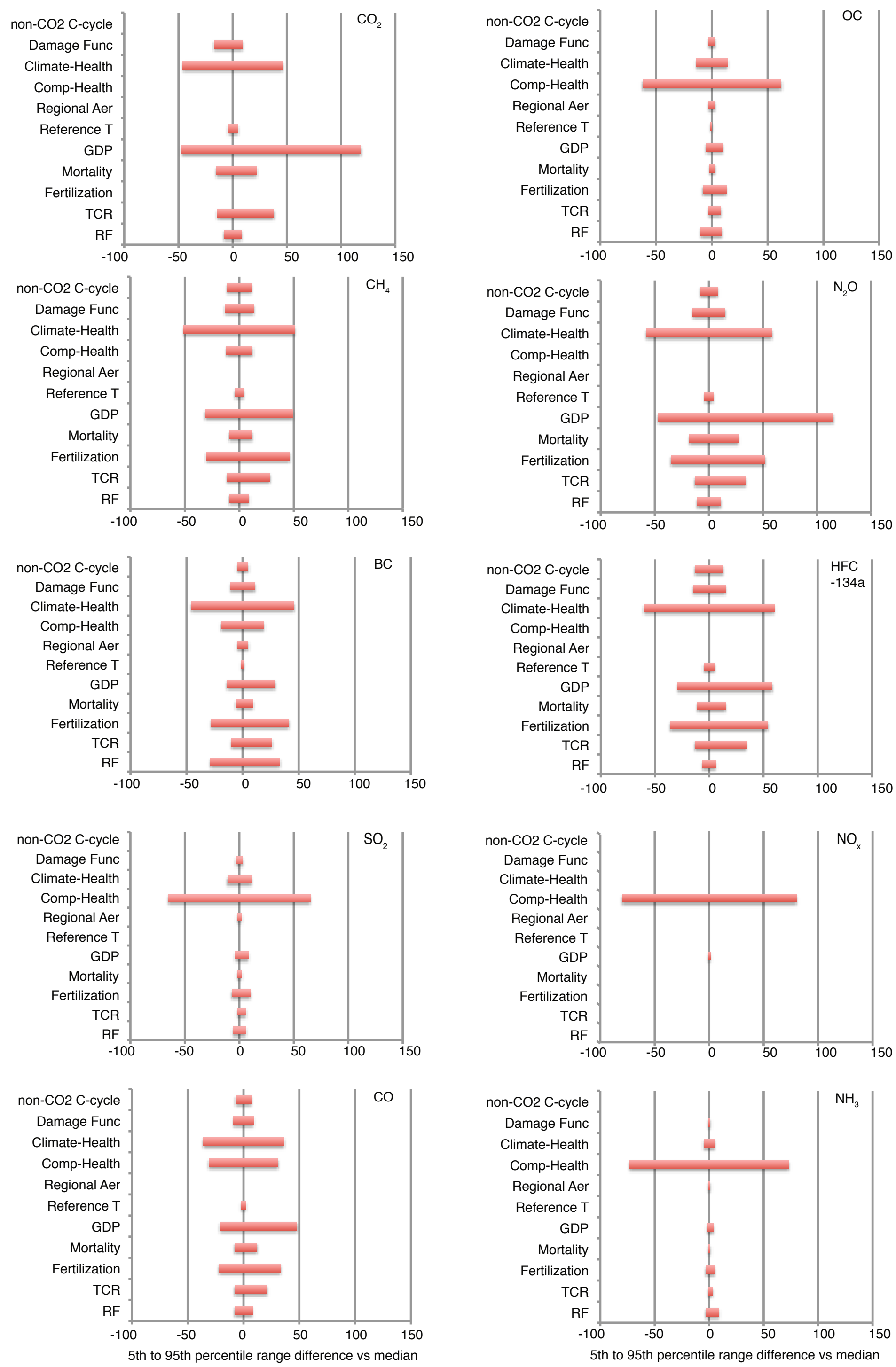

Figure S3. Uncertainty range in the SCAR valuation by pollutant attributable to each individual source of uncertainty examined, as indicated. Ranges are given in units of percent difference relative to the median SCAR value and represent the 5th to 95th percentile range for a given factor using a 3% discount rate.

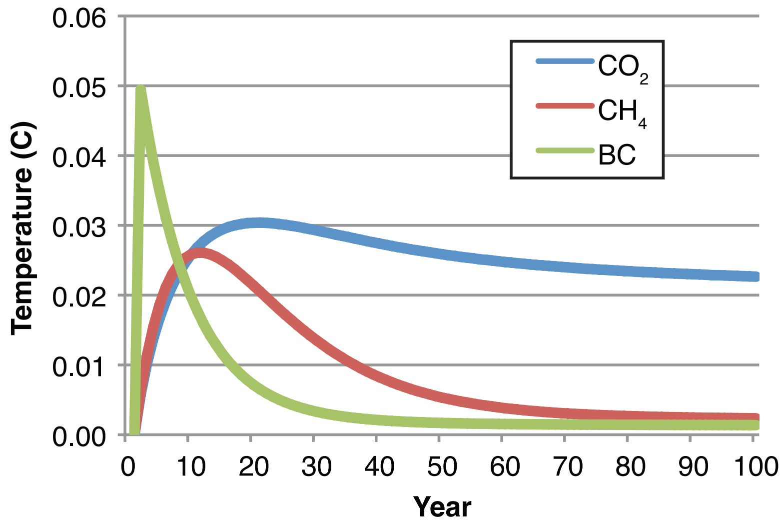

Figure S4. Timescales of temperature response to different forcers (°C per kg x 1 year's worth of current global anthropogenic emissions (excluding open biomass burning)).

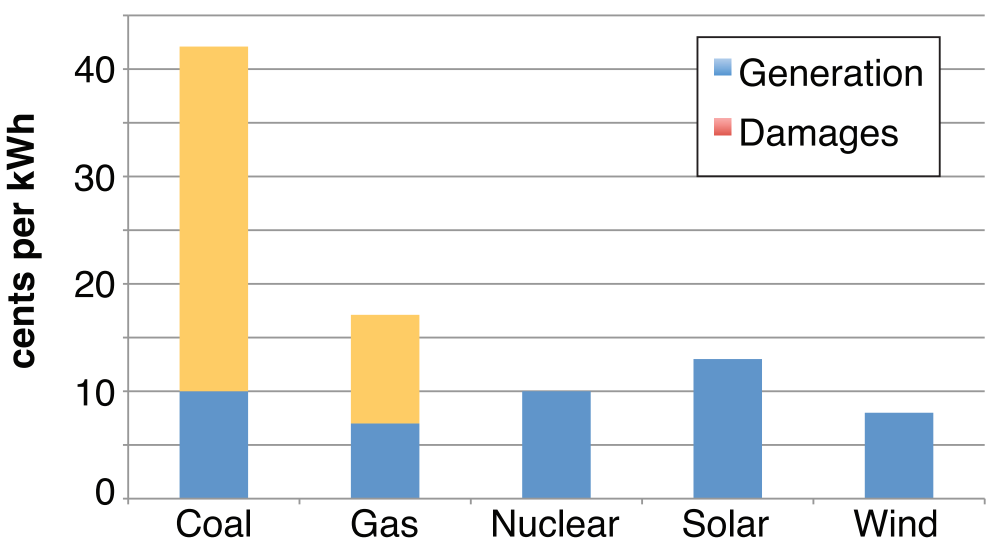

Figure S5. Levelized generation costs for new US electricity generation and SCAR-based environmental damages by fuel type as in Figure 2 except using US-specific health valuation within the SCAR (3% discounting). Damages are inflated to 2012 $US to match generation costs.

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