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Comparing health benefit calculations for alternative energy futures

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Abstract

Emissions from energy production, conversion, and use are associated with adverse effects on human health and climate. We use the Community Multiscale Air Quality (CMAQ) model and the Benefits Mapping and Analysis Program (BenMAP) to quantify effects of three potential emission abatement policies in the USA. The policies impose emission fees designed to internalize externalities associated with ozone and particulate matter (PM) pollution and greenhouse gas emissions. A business as usual case is compared to policies in which fees are applied to energy sector emissions of health impacting pollutants: NO_x, SO_2, PM_{10}, $PM_{2.5}$, and volatile organic compounds (VOCs), and/or greenhouse gases: CO_2 and CH_4. Net policy benefits are calculated by summing the health and climate benefits and subtracting the increased energy system cost. For comparison with the detailed model results, benefits are also estimated by the simplified approach of multiplying emission changes by fixed estimates of health damages per ton of emissions. Annual net benefits in 2045 are $173 billion with health-related fees and $116 billion with climate-based fees. A combined policy, with fees on emissions of both greenhouse gases (GHG) and health impacting pollutants, has annual net benefits of $189 billion in 2045. Co-benefits are unevenly distributed. Health benefits of GHG fees are only 40% as large as health benefits from air quality fees. Climate benefits of health fees are 87% as large as those from climate-based fees. Thus, each policy has comparable climate benefits, but air quality and corresponding health improvements are smaller when not specifically targeted.

Keywords Health benefits · Air quality · Energy · Damages

Introduction

Energy production, conversion, and use produce emissions that have harmful effects on human health through exposure to NO_2, SO_2, PM, ozone, and other pollutants and also have negative consequences for the Earth's climate, ecological diversity, and manmade materials. In the following analysis, we focus on human health effects associated with increased concentrations of ozone (O_3) and $PM_{2.5}$ (particulate matter less than 2.5 μm in diameter) due to emissions of NO_x, SO_2, PM_{10}, $PM_{2.5}$, and volatile organic compounds (VOCs), and climate impacts from CH_4 and CO_2 emissions. Ozone is a secondary pollutant formed in the atmosphere from NO_x and VOCs, while PM results from both direct emissions and secondary production involving NO_x, SO_2, and VOCs. O_3 and $PM_{2.5}$ have many effects on human health, particularly on cardiovascular and respiratory systems, which can lead to societal and medical costs. There is extensive literature on health impacts of air pollution, including the Global Burden of Disease (GBD 2017 Risk Factor Collaborators, 2018), which found that 6% of deaths in 2017 were attributable to ambient ozone and PM pollution. These negative effects are externalities because they are not included in the price of energy. Marginal damages refer to the external cost associated with an additional unit of emissions, such as the value of mortality and other health effects associated with an additional ton of emissions. Marginal damages for health-impacting pollutants are calculated in several papers for emissions from different sources including electricity generation; residential and commercial energy use (National Research Council Committee on Health, Environmental, and Other External Costs and Benefits of Energy Production and Consumption, 2010); several energy and industrial sources (Fann et al., 2012), based on season and region (Heo et al. 2016); and even in non-monetary terms (Penn et al. 2017). The largest

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component of the damage values is $PM_{2.5}$-related mortality. Those damage values are estimated using concentration–response functions (e.g., Krewski et al. 2009, Laden et al. 2006, and Woodruff et al. 1997) that describe the relationship between atmospheric concentrations and a health endpoint, in this case mortality. Other health impacts are also important to quality of life, but for purposes of valuation, mortality is the key driver.

Air quality modeling and health assessment tools are frequently employed to evaluate the monetized benefits of air pollution regulations. Fann and Risley (2011) used observed concentrations, and the BenMAP (Benefit Mapping and Analysis Program) to determine the overall reduction in mortality from O_3 and $PM_{2.5}$ under the influence of the National Ambient Air Quality Standards (NAAQS). Fann et al. (2012b) estimated that in the USA, over 100,000 premature mortalities were associated with modeled 2005 levels of air pollution. The Regulatory Impact Analysis (RIA) (US EPA, 2012) performed by the EPA when the NAAQS for $PM_{2.5}$ was strengthened from 15 to 12 $\mu g/m^3$ used the Community Multiscale Air Quality (CMAQ) model, a continental-scale atmospheric chemistry and transport model, and BenMAP to estimate the expected effects of the regulation. EPA estimated net benefits in 2020 from \$4.7 billion to \$11 billion. A similar analysis (US EPA, 2015) was performed when the O_3 standard was strengthened from 75 to 70 ppb using the Comprehensive Air Quality Model with Extensions (CAMx).

Previous research has coupled energy systems modeling with air quality modeling. Saari et al. (2015) used a coupled economic and air quality modeling system comprised of the US Regional Energy Policy (USREP) model and CAMx to explore the air quality co-benefits from two climate policies. They found that with a cap and trade climate program, the air quality co-benefits completely offset the cost of the emission reductions, although these co-benefits are not distributed uniformly across the USA. In much of the western USA costs are larger than benefits, and benefits are particularly concentrated in the East. Thompson et al. (2014) used USREP to determine the costs and approximate emission changes associated with three different climate policies. They then used CMAQ with scaled emissions to determine ambient concentrations of O_3 and $PM_{2.5}$ and calculated monetized health co-benefits with BenMAP. They found that policies, such as fees or emission trading programs, that are flexible in how emission reductions are achieved are less costly than policies that predetermine the source of emission reductions and that the air quality co-benefits can offset the cost of some but not all climate policies. Rudokas et al. (2015) analyzed several climate policies using MARKAL (the MARKet ALlocation energy economic model) and found that SO_2 and NO_x emissions are lower with many, but not all, climate policies.

Trail et al. (2015) continued this work, coupling the MARKAL results with CMAQ. They found that O_3 and $PM_{2.5}$ decrease with most CO_2 policies considered, but increased NO_x emissions in some cases lead to increased O_3. In some urban areas there is an increase in $PM_{2.5}$ associated with fuel switching. Lee et al. (2016) used emissions predicted in MARKAL with multiple aerosol models to calculate health and radiative forcing effects of the altered particulate concentrations. Abel et al. (2018) scaled emissions from electricity generation scenarios with CMAQ and BenMAP to evaluate atmospheric aerosol concentrations and health effects from increased solar energy. A series of papers (Loughlin et al. 2011, Ran et al. 2015) describe an Emission Scenario Projection methodology to link MARKAL with CMAQ, but it requires significant additional computational effort from other models to generate air quality results. We use a similar methodology but add a comparative element. We compare the assumption that marginal health impacts can be used to calculate the health benefits of emission reductions against the modeled benefits. We also compare the health benefit values used in the policy against two calculations of the realized benefits.

This paper describes an integrated assessment of the air quality and health benefits of applying damage-based fees to emissions from energy production, conversion, and use. We combine energy system, air quality, and health effect modeling to determine whether internalizing externalities through fees provide a net benefit. We calculate health benefits using a reduced-form approach and a more time- and resource-intensive benefit calculation, which allows us to compare the two. We also calculate both health and climate benefits for three fee cases considered, which allows us to compare the co-benefits of health-targeted policy on climate and the co-benefits of climate-targeted policy on health. Brown et al. (2017) used the MARKAL model to project how future fuels, energy technologies, and emission controls might change in response to application of emission fees that are designed to internalize externalities by incorporating damage costs into the cost of energy. Of the cases, one set of fees targeted only health impacting pollutants (HIP), specifically $PM_{2.5}$ emissions and precursors and O_3 precursor emissions. A second set of fees targeted only greenhouse gas (GHG) emissions, and a third set of fees targeted both. We detail how the emissions for each case are calculated in "Emissions from energy cases" and "Emission cases." The CMAQ model, described in "CMAQ simulations," is used to evaluate the air quality in 2045 for a No Fee case as well as three fee cases. BenMAP-CE, described in "BenMAP-CE," is used to estimate the human health effects that would occur in response to these fees, and the corresponding economic benefit. We present the air quality results in "Air quality" and health effects in "Health effects." "Net benefit" compares the costs and benefits. We discuss the differences and other conclusions in "Discussion."

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Methods

Emissions from energy cases

In this study, four emission cases for the year 2045 are considered. These cases were developed by modeled application of fees assessed on emissions produced in the US energy system using MARKAL. MARKAL is an energy system model that can be used to determine the lowest cost system of fuels and processing, conversion, and end-use technologies that will satisfy a specified level of demand for energy services. MARKAL produces energy results, such as electricity output by primary energy source and industrial energy use by fuel type, as well as the associated emissions. MARKAL covers the energy extraction, conversion, distribution, and end-use stages of the energy system, with end-use sectors including transportation in on-road as well as non-road vehicles, shipping, rail, and air travel; energy used in residential and commercial buildings; and industrial energy use. It does not include non-energy-related emissions from the agricultural sector such as enteric fermentation. Emissions from different energy extraction, conversion, and use processes are defined based on quantity and type of fuel as well as age, efficiency, and use of emission control devices for each technology. The total system cost each year includes the annualized investment in new technologies, the operation and maintenance costs, the cost of importing and producing fuels, revenue from energy resource exports, and costs to transport the fuel. The difference in total system cost in a year with a fee enforced compared to cost in the *No Fee* simulation without fees is interpreted as the cost of the policy. Unless otherwise stated, all currency values in this paper are presented in year 2018 USD. The MARKAL modeling is more fully described in Brown et al. (2017), in which the energy and emission implications of the cases are introduced.

The first case we consider represents a business as usual scenario, which includes existing policies such as state renewable portfolio standards that were enacted by 2011, the Corporate Average Fuel Economy standards (requiring 54.5 mpg fleet average by 2025), and the Clean Air Interstate Rule, which has since been replaced by the Cross-State Air Pollution Rule. This is referred to as the *No Fee case*.

The other cases include emission fees in addition to the existing policies. National emissions from each case are presented in Fig. 1. The fees are based on literature estimates of marginal damages associated with the emissions. In the *HIP case*, fees are levied on some common health impacting pollutants (NO_x, SO_2, PM_{10}, $PM_{2.5}$, and VOCs) from energy-related emission sources. The fees vary by energy sector to capture some of the location dependence of the damages. For instance, industrial emissions tend to be located near population centers and will lead to more exposure and health effects than electric sector emissions that are often located further from dense populations. The fees used here are equivalent to damage estimates from Fann et al. (2012) with the following exceptions: VOC fees are based on Fann et al. (2009), and the

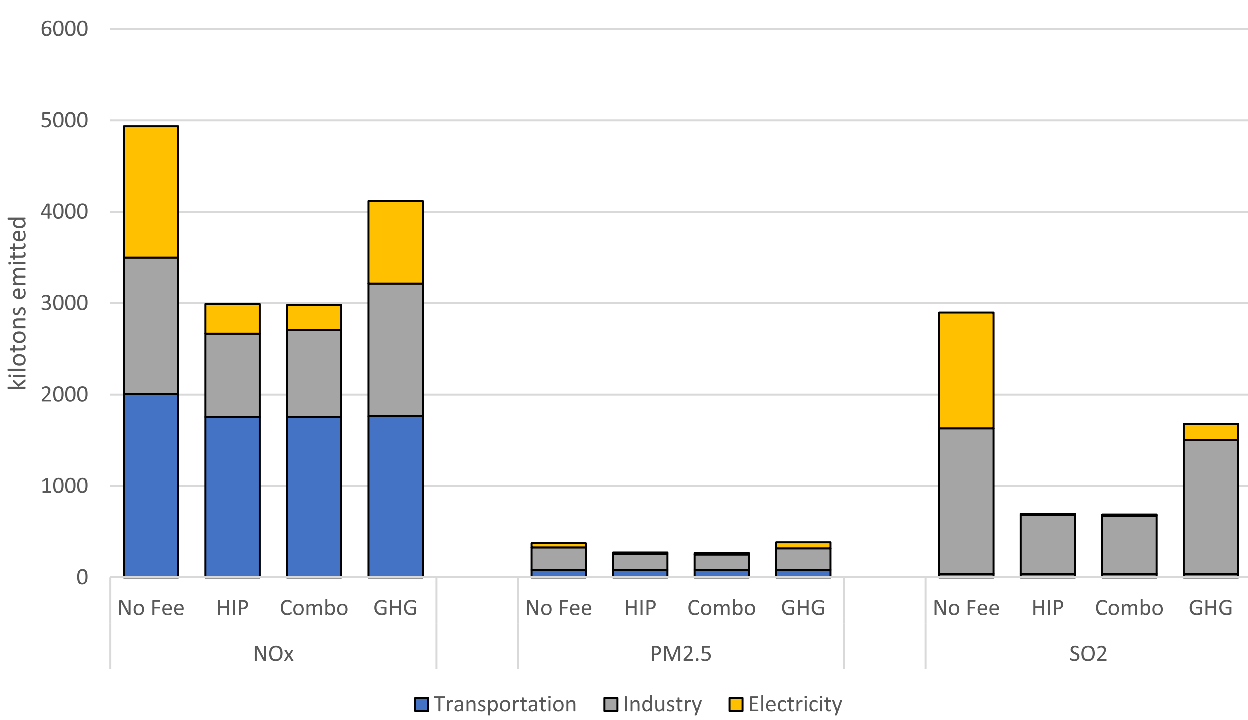

Fig. 1 Emissions in 2045 in each case

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PM_{10} and commercial sector values are based on National Research Council (2010) estimates, scaled to match the generally higher estimates in Fann et al. (2012). Fees for the commercial sector are applied to natural gas use (not emissions) because emission-specific damage estimates were not available for this sector; most commercial energy is from natural gas or electricity. Turner et al. (2015) and Buonocore et al. (2014) discuss the influence of emission location on the marginal damage per unit emission. Fowlie and Muller (2019) determine that emission fees have better welfare outcomes if fees are differentiated by damages. Source-sector differentiated fees are used here to address some of these issues. Regional values might provide different insights but would need to be calculated at a resolution compatible with MARKAL.

Another fee case (*GHG Fee*) is designed to address climate externalities, by imposing fees on GHG emissions (methane and CO_2) from energy. The fees in this case vary across years because the effect increases as total carbon load increases with time. The GHG fees are based on the Social Cost of Carbon (Interagency Working Group on Social Cost of Carbon, 2013) for the 2.5% discount rate, a value of \$110/ton CO_2 for 2045. Methane fees are determined from the Social Cost of Carbon using a 100-year global warming potential (GWP) of 28 (Myhre et al., 2013). Emission results for fees based on the social costs with 3% and 2.5% discount rates are presented in Brown et al. (2017) and are quite similar. Due to the more computationally intensive nature of CMAQ, only one set of emission changes is modeled here. Lastly, we also consider a *Combined (Combo) Fee case* in which both the HIP and GHG fees are applied simultaneously.

Emission cases

In order to estimate the air quality effects of the policies modeled in Brown et al. (2017), we need to map the change in emissions modeled with MARKAL to the emission inventory used by the air quality model. This is done using scaling factors that represent the change in emissions between 2010 and 2045 as estimated using MARKAL for nine regions of the country, mapped in Fig. 2. This methodology applies a simplified assumption that the spatial distribution of emissions at scales finer than these regions remains the same as for the 2011 inventory. Although this assumption is unlikely to be precisely true as older facilities are retired and newer ones built, many emissions will be in similar locations as demands will still be near the same cities, resources, or industries. Scaling at a regional level provides some ability to evaluate differences across the country, although changes in specific urban areas are not accounted for. Scaling factors are applied only to emissions within the USA, not to the boundary conditions or the emissions in the parts of Canada and Mexico included in the CMAQ modeling domain.

To calculate the pollutant and sector emissions $\varepsilon_{R,S,C,2045}$ the 2045 MARKAL emissions are compared to the 2010 No Fee emissions from MARKAL. The scaling factor values for each case are presented in the Online Resource 2 and calculated within the parenthesis of Eq. 1.

$$\varepsilon_{R,S,inv,2010}\left(1+\frac{\varepsilon_{R,S,C,2045}-\varepsilon_{R,S,C,2010}}{\varepsilon_{R,S,C,2010}}\right)=\varepsilon_{R,S,C,2045} \qquad (1)$$

where ε refers to the emissions of NO_x, CO, SO_2, VOC, or $PM_{2.5}$; inv refers to the emission inventory; *R* denotes the regions 1–9; and *C* indicates the case (HIP, GHG, Combined, No Fee). *S* indicates the sector: electricity from coal, electricity from natural gas, other electricity generation, on-road transportation, off-road transportation, air travel, shipping and rail, or industrial. Year 2010 is chosen as a base year because it is the closest model year in MARKAL to the 2011 emission inventory used in CMAQ.

In most cases, the scaling factor represents a decrease in emissions from the historical level, even for the No Fee case. The major exceptions are that industrial sector emissions increase over time due to economic growth and natural gas–fired electric sector emissions sometimes increase although overall electric sector emissions decrease. The electric sector changes are due to an increase in total demand for electricity combined with a decrease in coal-fired generation. This leads to an increase in natural gas generation and renewable electricity. While consideration of full life-cycle emissions is important, upstream emissions from fuel production were not changed in CMAQ because of a lack of location information. Previous analysis (Brown, 2016) attempted to model the upstream emission effect considering upstream emission changes as a uniform change, but benefits were overstated because further analysis noted that upstream sources were not uniform.

CMAQ simulations

The CMAQ model is a three-dimensional Eulerian air quality model (Byun and Schere, 2006). CMAQ includes treatment of gaseous, aqueous, and solid phase chemistry and aerosol dynamics to simulate the interaction of pollutants with each other and the environment. The formation of secondary aerosols such as sulfate and nitrate are also modeled.

The entire year of 2011 was modeled with the CMAQ model version 5.2 (Appel et al., 2017). CMAQ was applied with carbon bond-based gas phase chemistry (Hildebrandt Ruiz and Yarwood, 2013), ISORROPIA II inorganic partitioning (Fountoukis and Nenes, 2007), aqueous phase chemistry (Fahey et al., 2017), and secondary organic aerosol production from anthropogenic and biogenic VOC precursors (Pye et al., 2015). Biogenic VOC and NO_x emissions were estimated using the Biogenic Emissions Inventory System (BEIS) version 3.6.1 (Bash et al., 2016), which has been

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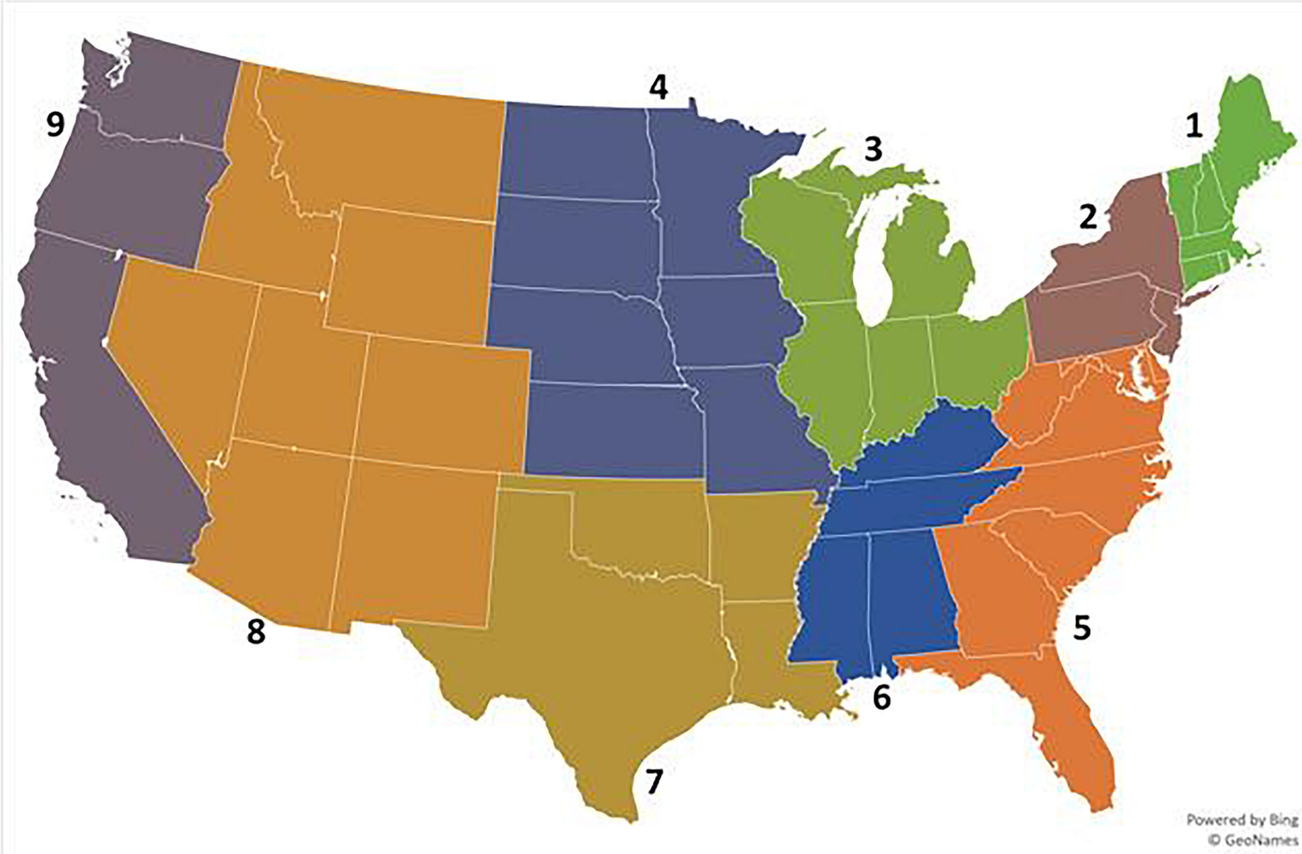

Fig. 2 The nine MARKAL regions, for which emission changes are calculated for CMAQ inputs

shown to compare well with ambient biogenic VOC in both the southeast USA (Carlton and Baker, 2011) and California (Bash et al., 2016). Wild and prescribed fire emissions are based on timing and location information from satellites and incident reports (Baker et al., 2016). Cropland burning emissions are also based on satellite information about timing and location (Pouliot et al., 2016; Zhou et al., 2018). Anthropogenic emissions were based on the 2011 National Emission Inventory (NEI) version 2 (US Environmental Protection Agency, 2016).

Meteorological inputs to CMAQ were generated using the Weather Research and Forecasting (WRF) model (Skamarock et al., 2005). The model domain covered the contiguous USA with 12-km-sized grid cells and 35 vertical layers resolving the surface to model top at 50 mb. Thinner layers are used closer to the surface to best resolve diurnal fluctuation in the planetary boundary layer, which has been shown to be well predicted by the modeling system in urban (Baker et al., 2013) and rural (Zhou et al., 2018) areas. Initial conditions and lateral boundary inflow of chemical species was based on a global GEOS-Chem simulation of 2011 (Baker et al., 2015). Aggregated maximum daily 8-h average (MDA8) O_3 mean bias (1.6 ppb) and normalized bias (3.7%) were within the range reported by other regional modeling studies (Simon et al., 2012), while mean error (6.8 ppb) and normalized mean error (15.5%) were below the median value of these metrics reported by other studies (Simon et al., 2012). Aggregated annual $PM_{2.5}$ mean bias (− 0.2 μg/m^3), normalized mean bias (− 4.3%), mean error (2.4 μg/m^3), and normalized mean error (50.8%) were all within the range of reported metrics for other regional modeling studies (Simon et al., 2012). Additional evaluation of the model performance can be found in Online Resource 1.

Meteorology is held constant at 2011 conditions to allow comparisons of emission projections only. Any choice of meteorology for the future will introduce uncertainty due to the variability surrounding climate change, and the cases themselves would imply different GHG trajectories for the USA. However, including the effects of climate change is likely to lead to higher concentrations of O_3 (Trail et al., 2014; Garcia-Menendez et al., 2015; Fiore et al., 2012). The effects of climate change on $PM_{2.5}$ are more uncertain (USGCRP, 2018). The benefits are calculated based on the difference between air quality in two future cases, so the effect of neglecting climate change on benefits estimates may be smaller than the effect on air quality.

BenMAP-CE

The Environmental Benefits Mapping and Analysis Program-Community Edition, BenMAP-CE version 1.1, was created

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by the US EPA to estimate health effects and economic benefits related to changes in air quality (US EPA, 2018). BenMAP-CE includes a variety of health impact functions, population data, and baseline health data. These functions relate changes in air pollutant concentrations with changes in health. This calculation considers the exposed population, baseline incidence rate of the effect, concentration of the pollutants considered, and concentration–response function chosen to relate the pollutants to the health effects. BenMAP-CE considers health effects associated with ozone and $PM_{2.5}$.

The pollutant concentrations from CMAQ are used as an input to the BenMAP-CE model, as has been done previously (Hubbell et al., 2009; Fann et al., 2011; Nowak et al., 2013). BenMAP-CE is used to calculate benefits for each of the three fee cases compared to the No Fee case in 2045. The health impact functions and valuation functions are from the set of EPA standard functions (US EPA, 2018), and we have used studies specific to the USA wherever possible to better represent the area of the study. Mortality estimates used in this article, which dominate the valuation, are calculated based on Krewski et al. (2009) for $PM_{2.5}$ in adults, Woodruff et al. (1997) for $PM_{2.5}$ in children, and Levy et al. (2005) for short-term O_3 exposure. Alternative mortality estimations are provided in Online Resource 2 based on other concentration–response functions (Bell et al. 2005, Huang et al. 2005, Bell et al. 2004, Ito et al. 2005, Jerrett et al. 2009, Lepeule et al. 2012, Schwartz 2005, Smith et al. 2009, Zanobetti and Schwartz, 2008). Other $PM_{2.5}$ health impacts considered include asthma (Babin et al. 2007, Sheppard et al. 1999, Glad et al. 2012, Mar et al. 2004, Mar et al. 2010, Slaughter et al. 2005, Ostro et al. 2001), chronic lung disease (Moolgavkar 2000), cardiovascular hospitalization (Bell et al. 2008, Zanobetti et al. 2009, Peng et al. 2009, Moolgavkar 2000), other respiratory issues (Kloog et al. 2012, Zanobetti et al. 2009, Schwartz and Neas, 2000, Pope and Dockery 1991, Dockery et al. 1996), heart attacks (Peters et al. 2001), and activity or work restriction (Ostro 1987, Ostro and Rothschild 1989). Some O_3 health impacts considered are asthma related (Schildcrout et al. 2006, Mortimer et al. 2002, Glad et al. 2012, Peel et al. 2005, Sarnat et al. 2013, Wilson et al. 2005, Ito et al. 2007, Mar and Koenig 2009), but other respiratory impacts (Katsouyanni et al. 2009) and reduction in school attendance or activity are also included (Chen et al. 2000, Gilliland et al. 2001, Ostro and Rothschild 1989). We apply a value of statistical life (VSL), based on 26 value-of-life studies, which has a value of \$8.3 million and has been used frequently in regulatory applications (US EPA, 2018). Alternative valuations of premature mortality also exist (OECD, 2012). The 2040 population data at 12-km resolution (the latest available in BenMAP-CE) are used to evaluate the impacts. This difference in year may lead to a slight underestimate of health impacts, but projecting this information further into the future is outside the scope of this work. The total population is projected to increase only 2% from 2040 to 2045 (Colby and Ortman, 2014). Baseline mortality incidence is based on the 2020 projections, which is the latest available in BenMAP-CE. Baseline incidence data for other health impacts is from 2007, except school loss days and acute bronchitis, which are from 2000, and the asthma prevalence dataset from 2008 is used. EPA standard income growth was projected to 2017. Health effects are calculated at the CMAQ 12-km grid level, then aggregated to the national level.

Damage-scaled emissions

In addition to calculating health benefits using BenMAP, we also estimate benefits of the alternative fee policies using damage-scaled emissions (DSEs), which is a common approach in energy policy studies (e.g., Brown and O'Sullivan, 2020, Millstein et al., 2017, Tschofen et al., 2019). In this work, damage-scaled emissions are the monetary value obtained by multiplying emission reductions calculated with the MARKAL energy system model by the HIP damage values (in units of \$ per ton) from Fann et al. (2012). Fann et al.'s (2012) damage estimates account for the health benefits associated with a reduction in $PM_{2.5}$ and $PM_{2.5}$ precursor emissions. That paper did not provide marginal damage values for commercial emissions, so we use the residential values for commercial emissions, treating these as a single buildings sector. The DSEs are most directly comparable to the total $PM_{2.5}$-related benefits, because the Fann et al. (2012) values did not consider O_3. Avoided GHG damages are calculated using the same method but multiplying GHG emission reductions by 2.5% average social cost of carbon (\$110/ton CO_2 in 2045). These values are useful for evaluating total benefits and net benefits. Calculating the health benefits using both the computationally expensive CMAQ-BenMAP method and the DSE approach allows for an evaluation of the value of the increased complexity.

Results

Air quality

Pollutant concentrations are generally higher in the eastern half of the USA, but some hotspots exist in the western USA near urban areas and in the central valley in California. $PM_{2.5}$ concentrations are lower across all regions with fees compared to the No Fee case, see Fig. 3. The reductions in $PM_{2.5}$ concentrations are smallest with GHG fees compared to the other fee cases. The geographical distribution of concentration reductions is similar across cases. Although the magnitude of the changes differs, the areas with reduced $PM_{2.5}$ concentrations are largely similar, such as near the Ohio River

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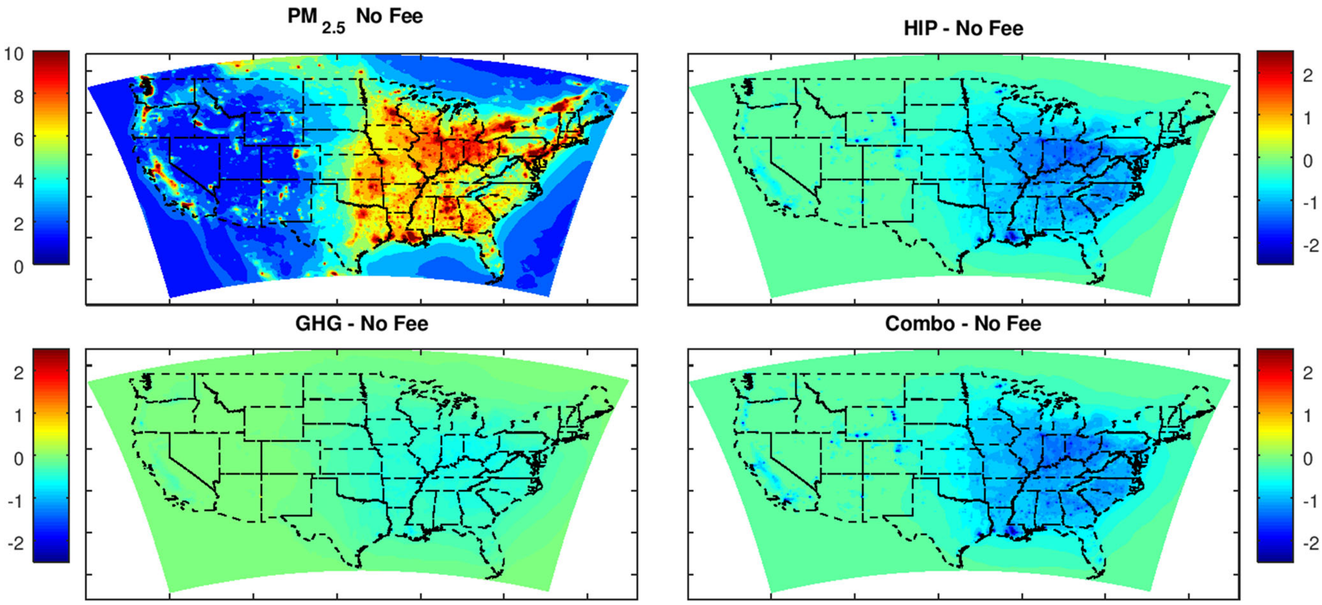

Fig. 3 Annual average modeled surface-level $PM_{2.5}$ concentrations in μg/m^3. The No Fee case is a future without emission fees in 2045, HIP is the case where fees were modeled on health impacting pollutants, GHG is the case in which fees were modeled applied to GHG emissions, and Combo is the case in which both fees were added in combination. The differences in concentration are plotted for the fee cases to show the effect of the fees

and the Central Valley of California. This is likely because the emission reduction options available were the same in each case. Particular opportunities to shift away from combustion or improve efficiency are available to respond to each set of fees. The largest absolute reductions in concentration occur with combined fees, but the Combined Fee case is very similar to the HIP Fee case. The largest air quality improvements occur in the Midwest because without fees this region has many highly polluting energy sources, including coal-fired power plants. In the fee cases these technologies are used much less.

Figure 4 shows that ozone concentrations are reduced with all fees and reduced further with HIP or Combined fees. While O_3 concentrations decrease over most of the USA, there are some areas with a slight disbenefit. Due to non-linearities in O_3 chemistry, decreases in emissions can sometimes lead to increases in concentrations. Therefore, while the non-linearity of O_3formation is an issue in some areas, O_3concentrations in the majority of the country still fall by reducing emissions through damage-based fees. Several densely populated areas are projected to experience reductions in O_3, which would be highly beneficial from a human health perspective.

Health effects

To analyze the health benefit of the improved air quality under each fee case, we evaluate the avoided incidence of adverse health effects compared to the No Fee future. Incidence values and a 95% confidence interval are reported for each health endpoint in Online Resource 2. This represents the uncertainty in health impacts as estimated for the concentration–response functions used in BenMAP, not the additional uncertainty associated with emission projections and air quality modeling. Monetized values are presented in Table 1. From these values we can compare the case's benefits among each other and against the costs of the policies. The benefit results for each case indicate health benefits compared to the 2045 No Fee case.

The avoided mortalities are calculated based on Krewski et al. (2009) and Woodruff et al. (1997) for $PM_{2.5}$ and Levy et al. (2005) for O_3. Although the benefit valuation is dominated by reduced premature mortality, there are other avoided health effects. The non-mortality health effects are much smaller in monetary terms than the mortality effects, but they occur more often. Benefit valuation is driven by mortality, but the experience of the public may be more strongly tied to other health effects that they have experienced.

We can compare our BenMAP results to what we would expect based on the original damage estimates from Fann et al. (2012), which were the basis of the fees. In BenMAP, we calculate $PM_{2.5}$ benefits using the same mortality health impact functions used by Fann et al. (2012) and most of the same health impact functions for the non-mortality health impacts. We do not expect variations in health impact functions used to contribute significantly to the differences in valuation because premature mortality is so dominant for this metric. The Fann et al. (2012) study on which the fees are largely based only calculated damages for $PM_{2.5}$, so all O_3 benefits are expected to be in addition to the damage-scaled emissions.

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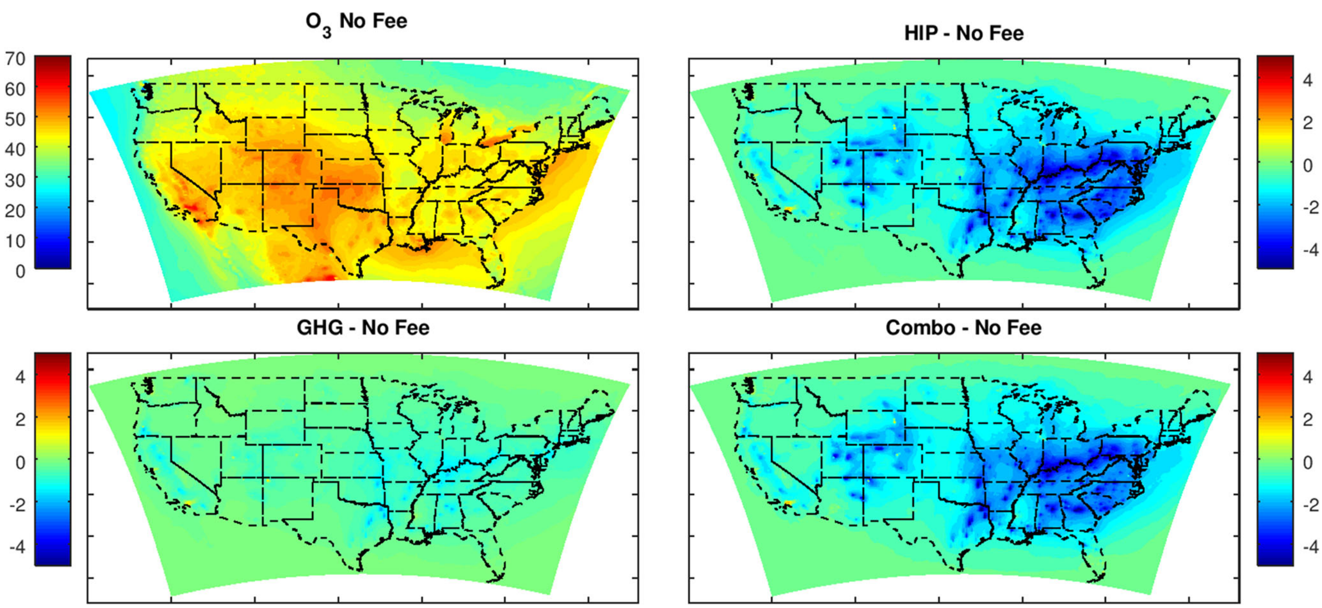

Fig. 4 Ozone model results. The ozone season average MDA8 is plotted for the No Fee case, and the difference between the No Fee MDA8 and the MDA8 for the fee cases is plotted in the other three maps. The units are in ppb

By comparing the damage-scaled emissions to the benefits we can evaluate how well the less computationally intensive scaling calculation performs in terms of estimation of nationwide benefits. For each of the three fee cases the DSE values in Table 1 are similar to, but slightly lower than, the total $PM_{2.5}$ benefits determined using CMAQ-BenMAP. However, the similarity is due to offsetting errors. The Fann et al. (2012) values are based on population in 2016, whereas the CMAQ-BenMAP values adjust for population growth through 2040. If we use BenMAP to calculate benefits for a 2016 population for the HIP Fee case keeping all else equal, we find adult mortality values based on Krewski et al. (2009) of \$86 billion, infant mortality based on Woodruff et al. (1997) of \$180 million, and total $PM_{2.5}$ benefits of \$89 billion. The DSE estimate is thus 50% higher than the CMAQ-BenMAP value estimated using 2016 population data. The discrepancies between the DSE and CMAQ-BenMAP estimates are not unexpected. While DSEs use national average values, the modeled benefits account for regional differences. Using spatially variable damage estimates, such as those developed using adjoint modeling (Dedoussi and Barrett 2014; Lee et al. 2015; Pappin et al. 2015) or other models that capture spatial variation (Goodkind et al. 2019; Wolfe et al. 2019), it might be possible to calculate DSEs that more closely match fully modeled benefits. Chemistry and transport of pollutants in the atmosphere are modeled for the specific situation here, which does not match that used by Fann et al. (2012) to calculate the marginal damage values. Lastly, the marginal damage values reflect benefit valuations for marginal changes, but for the larger air quality shifts considered here, the more computationally intensive calculation provides additional insight.

Net benefit

The changes in costs from the MARKAL results (Brown et al. 2017) are presented in Fig. 5. Cost Increase represents the increase in cost of the energy system in 2045 when fees are applied compared to the No Fee case. The energy system cost includes extraction and conversion of energy carriers, as well

Table 1 Benefits in year 2045 (Billions of 2018 USD)

Fee case	Mortality benefit			Non-mortality benefit		Total benefit			Simplified benefits	
	$PM_{2.5}$		O_3			Total	$PM_{2.5}$	O_3	Damage-scaled emissions	Avoided GHG damages
	Adult	Infant		$PM_{2.5}$	O_3					
HIP	147	0.20	26	4	0.49	178	151	26	134	92
Combined	148	0.20	24	4	0.45	177	152	24	138	128
GHG	61	0.09	8	2	0.15	70	62	8	56	106
HIP (2016 population)	86	0.18	15	3	0.40	105	89	16	–	–

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as energy use in the residential and commercial building sectors, the industrial sector, and the transportation sector. The costs in Table 2 are calculated with investment costs annualized over the lifetime of the technology, so prior year investments affecting 2045 are accounted for in 2045 costs. Revenues collected in the form of fees are not included in this cost increase, because this expense could be used in many ways, including offsetting the cost of emission reductions in the energy system or using them to defray costs for addressing the remaining externalities. Therefore, we present this value separately in the Fees Collected column. The cost increases represent only 1–2% of the total system cost, and the fees collected increase the total energy system cost by 6–15%.

Fees can be considered to be neutral within the energy–environment–health system in which we are internalizing externalities. Total benefits include the avoided GHG damages and all avoided mortality and non-mortality health benefits. The net benefits are the sum of the health and climate benefits less the cost increase from MARKAL. To get the health benefits we use the total benefits from BenMAP in Table 1. For climate benefits, we use the Avoided GHG Damage value in Table 1, and the costs can be read from the Cost Increase in Fig. 5. For 2045, the net benefits from the HIP Fee case are \$173 billion. The net benefits from the GHG Fee case are \$116 billion, and the net benefits of the Combined case are \$189 billion. The co-benefits are an important part of this net benefit value. The co-benefit of avoided GHG reductions in the HIP case is 87% of the climate benefit in the GHG case. This means that the majority of the climate benefits are achieved with HIP fees. In contrast, the health co-benefit of the GHG fees is only 40% as large as the health benefit of the HIP Fee case. This means that either policy will have large climate benefits, but the health benefits are less likely to occur when not specifically targeted.

Discussion

We analyzed application of damage-based fees in the US energy system to internalize externalities such that health and climate costs are considered when choosing how to produce and use energy. Economic theory suggests that internalizing externalities should lead to a more socially efficient outcome as long as the externalities are large enough to affect the outcome. Our calculations found that not only did the expected benefits outweigh the costs, significant co-benefits exist. Based on the existence of co-benefits and economic theory, we expect that the result that benefits outweigh costs to be robust despite inherent uncertainties in modeling. When emission reductions associated with fees were modeled in CMAQ, air quality improved in almost all areas of the country. Air quality improved even for GHG focused fees, because the efficiency improvements and fuel switching used to achieve the GHG emission reductions also reduced all co-emitted pollutants. Additional details on fuel switching can be found in Brown et al. (2017). However, the air quality co-benefits of GHG fees are not as large as the climate benefits of air quality fees. As we would expect, the air quality improved more with HIP fees than GHG fees. The distinction between the HIP and Combined Fee cases was small. The $PM_{2.5}$ benefits are highest for the Combined case, but the O_3 benefits are higher for the HIP case. This is due to localized differences in air quality between the cases. The health-related benefits are very close in both cases, but the net benefits are highest for the Combined case because it has larger climate benefits.

The GHG damage-scaled emissions provide the climate benefit or co-benefit of the policies. Some studies (Moore and Diaz, 2015; Dietz and Stern, 2015; Lontzek et al., 2015) suggest that climate damages may be an underestimate as there are still many uncertainties surrounding climate change

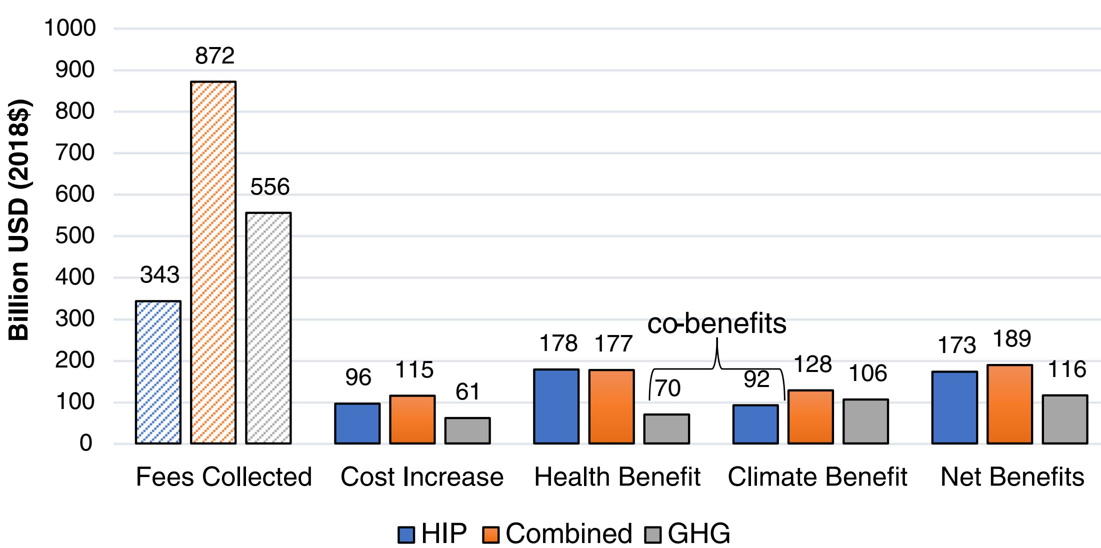

Fig. 5 Energy system costs associated with fees from MARKAL in billion 2018 USD

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predictions. Even in the HIP Fee case, where there was no incentive to reduce GHGs, the climate co-benefits are only 13% less than the climate benefits of the GHG Fee case. Therefore, co-benefits are an important part of the benefit calculation. However, the air quality co-benefit of GHG fees is much smaller.

Benefits are larger than the costs of each policy. Although the fees paid increase the energy price, emissions affect the well-being of the population. If the fees collected are put toward reducing the cost of externalities by those affected, it could reduce the cost of the larger energy-environment-health system. Otherwise, the fees paid will be government revenue and could be used to reduce other taxes, offset higher energy costs, or otherwise improve social welfare. Due to the large quantity of fees collected, it is worth careful consideration of how that revenue is used.

The largest component of the benefit estimate is mortality associated with $PM_{2.5}$, due to the large monetary value associated with mortality as well as the large decreases in modeled $PM_{2.5}$ concentrations. The lowest measured level (LML), or lowest measured $PM_{2.5}$ concentration, for determining the health impact functions is higher than some of the concentrations modeled here, which means that there is uncertainty in the estimates for $PM_{2.5}$ benefits because the shape of the health impact functions may be different at these lower concentrations. For Krewski et al. (2009) the LML is 5.8 μg/m$_3$. It is obvious from Fig. 3 that $PM_{2.5}$ concentrations in 2045 in some regions are projected to be below this level.

The HIP and Combined Fee cases have similar benefits, given the similar air quality between cases. Although O_3 is the same or greater in the HIP case compared to the Combined case for much of the USA, the Combined case has higher O_3 in some heavily populated regions. There is higher O_3 around Los Angeles in the Combined case. This area is particularly complex for air quality considerations, but it is worth noting that industrial NO_x and natural gas–fired power plant emissions of NO_x and VOC are larger along the West Coast (Region 9) in the Combined case compared to the HIP case. Southern Florida also has higher O_3 in the Combined Fee case. The southeast (Region 5) has higher VOC emissions from natural gas power plants in the Combined case compared to the HIP case. The somewhat counterintuitive result that the Combined case has smaller O_3 benefits due to spatially different concentration reductions highlights the value of spatially differentiated damage-based fees. This would encourage emission reductions in the most beneficial locations.

Due to complex chemistry and transport of air pollutants as well as uneven population distribution, the differences between the modeled benefit calculation and the damage-scaled emissions provide interesting insights. Although the damage-scaled emission values are similar to the calculated benefits, it appears that this method is likely getting the right answer for the wrong reason. When using the same population, the two values differ by 50%. Benefits calculated using CMAQ and BenMAP should be better able to capture the differences across geographic regions. The marginal damage values vary by source category, which accounts for some difference in nearby population, mainly between urban, suburban, and rural densities. However, the nationally averaged values do not capture variations in population density between different regions of the USA. As the modeled damages are lower than the damage-scaled emissions when using the same year population, it seems that the marginal damages overestimate benefits of emission reductions in less dense states. Future work using more location-specific damage estimates, such as those developed using adjoint modeling (Dedoussi and Barrett 2014; Lee et al. 2015; Pappin et al. 2015) or reduced-form modeling (Goodkind et al. 2019), might help close this gap.

Additional costs and benefits that have not been considered in the calculations here include the value of effects beyond climate change and health impacts from $PM_{2.5}$ and O_3. Smith et al. (2015) analyzed a larger set of environmental impacts from GHG emission reductions in the UK. The emission fees analyzed here had much less effect on transportation and no change in diet compared to the policy analyzed in Smith et al., which found many benefits in those sectors. They found that industrial sector improvements similar to those seen with fees could lead to improved working conditions and productivity, which would be additional benefits not accounted for here. Smith (2013) describes additional sources of co-benefits. Another area that may have additional benefits is in the timing of the policies. We analyze the costs and benefits associated with a single future year, but there may be issues of timing associated with these policies. As GHGs are long-lived in the atmosphere, earlier emission reductions can be very impactful. Similarly, there are parts of the USA that are currently in non-attainment for ozone and $PM_{2.5}$, so reducing those pollutants earlier would improve the health of people in those counties sooner.

There are uncertainties in the results of the energy system model because the future prices of fuels and technologies are unknown. If the relative cost of a certain fuel or generation technology is much different than what we have used, then the response to fees and the cost of the response could be different. Based on recent declines in prices for renewables, we expect the conclusion to hold that health benefits will be larger than the cost of reducing emissions.

Modeling future air quality also introduces uncertainty. By calculating the difference between two modeled air quality futures, some errors associated with modeling will cancel out. Using 2011 meteorology introduces uncertainty but allows us to more clearly attribute changes in concentrations to emission changes. As the energy-system modeling was not done at the facility level, additional uncertainty remains as emissions for each source type were modified across a region, not individual sources. While this may be a useful tool for a

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first pass analysis or scenarios with smaller changes, a more complex analysis is warranted for final evaluations. Other sources of discrepancy may be related to the definition of sectors and models used. The marginal damage estimates were calculated with more discrete industrial sectors than used here, and Fann et al. (2012) used CAMx, which is similar but not identical to CMAQ. Concentrations in any particular grid cell are only rough estimates, as we have altered emissions broadly rather than targeting individual locations. We have more confidence in the national-scale cost comparison as local inaccuracies should average out.

There are also uncertainties associated with the health benefit calculations. Uncertainties in the concentration–response functions themselves are quantified in Online Resource 2, but other uncertainties remain. Baseline incidence rates for mortality and other health effects will change as healthcare evolves and socio-economic status of those affected changes. Projecting regional population level and related energy demand into the future requires many assumptions. The population growth rate for the USA has been decreasing, but changes in domestic migration and immigration, life expectancy, or birth rate projections could alter the population. This affects both our projections of future demand and the calculation of future benefits in a way that will likely compound. If the population in 2045 is larger than projected, there will be more energy demand that will likely lead to larger emissions and worse air quality. This poor air quality would affect more people and therefore compound the increase in damages.

Although there are uncertainties associated with estimating the effect of future emission reductions, it is still an important exercise to undertake when considering policies. Additional information about likely locations of concentration reductions associated with a policy leads to more informed benefit calculations. Analyzing the concentration changes associated with emission changes is also useful considering the non-linearities in air chemistry particularly for ozone benefits. We also find that the changing population with time has a large effect on the benefit of emission reductions. Improving the representation of upstream emission locations can also provide a more complete picture of the air quality effects. For example, Nsanzineza et al. (2019) modeled scenarios for both electricity generation and resource extraction for the Rocky Mountain region. They found that when considering emissions from both source categories at their known locations, the net effect of assuming greater production and use of natural gas was to increase ozone and climate damages compared to their 2030 reference case. In contrast, these damages were reduced when system-wide greenhouse gas fees were applied.

The results of this research can inform policy decisions about similar fee structures, including in other countries or states. We consider the existence of co-benefits to be a robust result despite modeling uncertainty. Emission reductions can be achieved quite effectively through efficiency improvements and shifting away from combustion-based energy sources. These measures will reduce all pollutants considered here, leading to co-benefits. One important point that future decision makers should consider in examining these results is that for this policy to be cost-neutral, the ultimate use of the fees is important. Another important point for consideration is the effect of population on the benefits. We found that the population growth and demographic shifts increased the value of damages over time, and therefore, fees should be re-evaluated accordingly with time. Also, in calculating the benefits of any emission change, the population change should be factored into the valuation of benefits. Emission fees lead to higher energy costs, which may disproportionately affect low-income households. Although there is a benefit gained through the fees, it would be prudent for decision makers to consider possible distributional aspects of the burden.

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