NBER WORKING PAPER SERIES

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Working Paper 25339
http://www.nber.org/papers/w25339

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2018

We would like to thank Emily Blanchard and Matthew Kotchen and seminar participants at Energy Institute at Haas, TREE, and the EPRI electrification conference for helpful comments, as well as Samuel Krumholz for providing data on New Source Review start dates and litigation. Kenneth Walsh provided research assistance. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

At least one co-author has disclosed a financial relationship of potential relevance for this research. Further information is available online at http://www.nber.org/papers/w25339.ack

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NBER Working Paper No. 25339
December 2018
JEL No. D62,H23,Q53,Q54

ABSTRACT

We determine the change in air pollution damages from U.S. power plant emissions over 2010 to 2017. Annual damages fell from $245 billion to $133 billion over this period, with most of the decline occurring in the East. Decomposition shows that changes in emissions rates reduced damages by $63 billion, changes in generation shares reduced damages by $60 billion, and a reduction in fossil generation reduced damages by $25 billion. However, changes in damage valuations per ton of emissions increased damages by $35 billion. We estimate that marginal damages declined in the East from about 9¢ per kWh in 2010 to 6¢ in 2017. This decrease is slower than the decrease in total damages. Despite little or no change in total damages in the West and Texas, marginal damages increased. The environmental benefit of electric vehicles increased so that they are now cleaner than gasoline vehicles on average, though substantial heterogeneity remains. The environmental benefit of solar panels decreased in the East but increased elsewhere.

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A data appendix is available at http://www.nber.org/data-appendix/w25339

1 Introduction

Electricity is a critical input to firms and households alike. Despite its necessary role in the economy, electricity generation produces emissions of global and local pollution that cause hundreds of billions of dollars in damages annually.[1] However, during the past decade, emissions from electricity generation have fallen. Figure 1 shows the emissions of four major pollutants (sulfur dioxide SO_2, nitrogen oxides NO_X, fine particulate matter $PM_{2.5}$, and carbon dioxide CO_2) from electric power plants in the contiguous U.S. during 2010-2017.[2] While emissions of each pollutant declined, some of the reductions are precipitous: SO_2 fell 75%. Further, an historical perspective suggests changes in emissions after 2009 (especially those of SO_2 and CO_2) clearly deviate from past trends.[3]

The extraordinary decline in emissions from 2010 to 2017 raises three questions. First, how big was the corresponding decline in damages? Second, how did changes in electricity generation and pollution valuation interact to bring about this decline? Third, what are the implications for environmental policy?

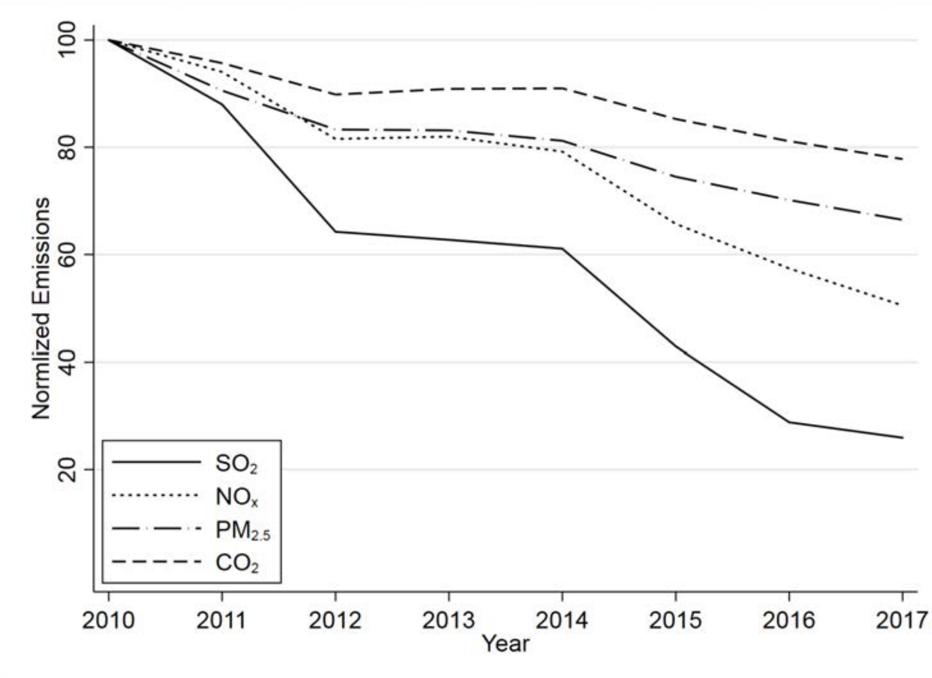
Although the changes in emissions shown in Figure 1 are suggestive, how these aggregate patterns affect welfare depends on an assessment of exposure, physical impacts, and, ultimately, monetized damage. Three factors complicate the translation of emission changes into damages. First, the importance to total damages of a given pollutant depends not only on emissions but on damages per unit of emissions as well. Second, damages per unit emission from local pollutants depend on where they are emitted and their dispersion through the atmosphere. A large decline in emissions need not imply a large decline in damages if emissions shift from low damage locations to high damage locations. Third, emissions produced by a particular facility may be more or less harmful over time because of changes in the levels and demographic composition of local population, atmospheric conditions that drive the formation of secondary $PM_{2.5}$, and the accumulation of CO_2 in the atmosphere.

[1] See National Research Council (2010), Muller, Mendelsohn, and Nordhaus (2011), and Muller (2014).

[2] These data are from the EPA's Continuous Emissions Monitoring System (see Section 2 for details). Numerical values are given in Table i in the Appendix.

[3] See Figure i in the Appendix. The evidence is less compelling for NO_X and $PM_{2.5}$. As we shall see, however, SO_2 and CO_2 lead to the vast majority of the damages.

Figure 1: Power Plant Emissions of Four Pollutants, 2010-2017



Notes: Normalized such that emissions in 2010 equal 100.

We use the AP3 integrated assessment model (Clay et al 2018) and a time-variant social cost of carbon to account for these complexities in translating emissions into monetary damages.

We calculate that total annual damages from power plants fell from \$245 billion in 2010 to \$133 billion in 2017 (damages are reported in real 2014 dollars).[4] Most of the decline in damages is due to SO_2 emissions, coal-fired power plants, and the East. The air quality model in AP3 identifies the locations of the individuals harmed by emissions of local pollutants. We calculate large reductions in damages (\$1232 to \$784 per capita) to residents of West Virginia, Pennsylvania, and Ohio. Furthermore, damages from power plants are regressive (i.e., higher damages occur to individuals with lower incomes) and the reduction in damages is progressive.[5]

[4]This result contributes to the growing literature that studies changes in the electricity industry over the last two decades. Some papers analyze changes in how power markets operate (Knittel et al 2015, Holladay and LaRiviere 2017, Cullen and Mansur 2017, and Fell and Kaffine 2018) and others attribute changes in emissions to various factors (Feng et al 2015, Kotchen and Mansur 2016, and Krumholz 2018).

[5]These results contribute to the literature on distributional effects and environmental justice (see for example Gray et al 2012, Fowlie et al 2012, Muller et al 2018, and Holland et al 2019).

We decompose the decline in total annual damages of $112 billion into four effects and a small error.[6] Three of these effects decrease damages. The technique effect, which captures changes in emission rates at a given plant, accounts for $63 billion in decreased damages. The composition effect, which captures shifts in generation from dirty to cleaner power plants, accounts for $60 billion. The scale effect, which captures decreasing aggregate fossil fuel generation, accounts for $25 billion. The fourth effect, valuation, captures changes in damages from a unit of pollution over time. This effect increased damages by $35 billion. Dividing these four main effects into component parts provides additional insight. For example, the most important contributor to the scale effect is renewable generation and half of the composition effect is due to exit of coal plants.

What are the ramifications of these considerable changes in damages for environmental policy? To answer this question we estimate the marginal damages from electricity consumption.[7] Marginal damages declined in the East from 8.6¢ per kWh in 2010 to 6.0¢ per kWh in 2017. In the West and Texas, the marginal damages in 2010 are much lower (2.0¢ in the West and 2.8¢ in Texas) but have a small but statistically significant increase over this time period. These patterns suggest convergence across regions. We then analyze what these changes in marginal damages imply for one policy that encourages grid electricity consumption (subsidies for electric vehicles) and another policy that discourages it (subsidies for solar panels). We calculate that, from 2010 to 2017, electric vehicles switch from being dirtier on average than their gasoline-powered counterparts to being cleaner, though con-

[6] Oaxaca (1973) and Blinder (1973) pioneered the use of econometric decomposition to analyze wage discrimination by decomposing wage differentials into components from different observables (e.g., education) and from different estimated coefficients (indicating unexplained differences or discrimination). See Fortin et al (2011) for a summary of decompositions in labor economics. Other papers use decompositions to study changes in pollution, trade, energy use, and combinations thereof. See Sun (1998), Ang and Zhang (2000), Antweiler et al (2001), Metcalf (2008), Levinson (2009), Fortin et al (2011), Levinson (2015), Shapiro and Walker (2018).

[7] We extend the earlier analyses of Graff Zivin et al (2014) and Holland et al (2016). Our analysis is distinguished by the more recent time frame, our multi-pollutant approach, and estimation of standard errors. Siler-Evans et al (2013) and Callaway et al (2017) use an alternative approach to estimate damages as a function of fossil electricity generation within an electricity grid region. In sensitivity analyses, we offer comparable estimates and extend this work by instrumenting for endogenous generation. Other alternatives use generation cost modeling to simulate grid dispatch and calculate marginal emissions factors: Denhom et al (2013) and McLaren et al (2016); or simply analyze the average emissions factor e.g., within a state: Samaras & Meisterling (2008), Michalek et al (2011), and Nealer et al (2015).

siderable cross-sectional heterogeneity remains. The environmental benefit of solar panels decreases in the East but increases in the West and Texas.

An important caveat is that we do not attempt to assign causal implications to any one of the myriad public policies and market forces that influence electricity consumption, generation, and pollution control. On the consumption side, market forces include the rise in data centers, electrification of transportation, and improvements in heating and cooling technologies, while public policies encourage energy efficiency and technology adoption.[8] On the generation side, technological improvements in natural gas development and renewable generation combined with public policies led to a substantial reduction in the relative price of generating electricity from gas and renewable power plants.[9] This in turn decreased wholesale electricity prices, reduced generation from baseload coal-fired and nuclear generation, led to plant closings, and increased the need for generation that can quickly respond to intermittent renewable generation. As for pollution control, between 2010 and 2017, the National Ambient Air Quality Standards (NAAQS) were tightened for both $PM_{2.5}$ and tropospheric ozone O_3. States with counties that violate the NAAQS often focus emission reductions on large point sources such as power plants. There were also a number of active and proposed regulations during this time that may have influenced adoption of pollution control technology.[10] Against this backdrop of changing market forces and policies we next examine the change in total damage, before exploring the decomposition, and the implications for environmental policies.

2 What Happened to Damages

2.1 Methods and Data

To determine damages from air pollution, we define the *damage valuations* v_{pit} as the damage per unit of pollutant p emitted by source i at time t and e_{pit} as the quantity of emissions.

[8]Example policies include weatherization programs, Energy Star rebates for efficient appliances, and electric vehicle subsidies.

[9]Example policies include renewable production tax credits and state level renewable portfolio standards.

[10]These include Acid Rain Program (ARP), the Clean Air Interstate Rule (CAIR), and the Cross-State Air Pollution Rule (CSAPR), the Clean Power Plan (CPP), and Mercury and Air Toxics Standards (MATS). Note these regulations may also effect generation.

Total damages D_t are given by

$$D_t = \sum_p \sum_i v_{pit} e_{pit}. \tag{1}$$

For the global pollutant (CO_2), the damage valuations are the same across all plants and are based on EPA's social cost of carbon (SCC). The SCC is \$35.36 in 2010 and grows at 3% annually.[11]

For local pollutants (SO_2, NO_X, and $PM_{2.5}$), we use the AP3 integrated assessment model to determine damage valuations. AP3 accounts for chemical and physical processes in the atmosphere to map emissions of pollutants from a source location (i.e., an electric power plant) into ambient concentrations of $PM_{2.5}$ at various receptor locations (i.e., counties in the contiguous United States). It then maps these ambient concentrations into premature mortality risk using peer-reviewed concentration-response functions.[12] Finally, it monetizes mortality risk using the value of statistical life (Viscusi and Aldy 2003). Let δ_{pijt} be the damages in county j due to emissions of a unit of pollutant p from plant i as determined by AP3. The damage valuations for local pollutants given by

$$v_{pit} = \sum_j \delta_{pijt}.$$

Because atmospheric chemistry, background (non-power plant) pollution, and population change over time, the damage valuations change over time as well. AP3 produces damage estimates for the years 2008, 2011, and 2014, which are the data years for the National Emissions Inventory (NEI), a nationally comprehensive inventory of emissions in the U.S.[13] For 2010, 2012, and 2013, we use linear interpolation to infer valuations from the NEI years and, for 2015 on, we hold valuations at 2014 levels.[14] Table ii in the Appendix shows a summary of damage valuations over time.

[11] See `https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html`.

[12] The prior version of AP3, known as AP2, tracked other consequences of exposure such as morbidity and visibility. AP3 does not include these endpoints because they contribute a small share of total damage (<5 percent), and due to concerns about double-counting illness valuations that ultimately culminate in a premature death. Other differences between AP3 and AP2 are discussed in Online Appendix A.

[13] NEI are published with a three year lag (USEPA, 2011; 2014; 2017).

[14] Alternatively, we could use linear extrapolation to extend the trend from 2011 to 2014 forward to 2017. As shown Table B-16 and Figure B-1 in Online Appendix B, our results are robust to this alternative.

By calculating total damage as damage valuation times emissions, Eq. (1) assumes that local damage valuations are independent of the aggregate level of emissions from power plants. We discuss the validity of this assumption in the Appendix and analyze the implications for our results if it does not hold in Online Appendix A. Briefly, if local damage valuations are not independent of aggregate emissions, Eq. (1) understates the decline in damages. Furthermore, an alternative procedure that holds damage valuations (the $/ton damages) fixed at their final 2017 values overstates the decline in damages. Either way, the choice of procedure does not significantly affect our results for the decomposition and marginal damage ($/kwh) estimates.

The U.S. electricity grid is divided into the Eastern, Western, and Texas Interconnections, and only trivial amounts of electricity flow across their boundaries. For this reason, we calculate many of our results at the interconnection level. Throughout the paper we refer to the quantity demanded of electricity as load, and the quantity supplied as generation.[15]

Our primary data source is EPA's Continuous Emissions Monitoring System (CEMS), which reports hourly electricity generation and emissions of SO_2, NO_X, and CO_2 at approximately 1500 regulated fossil-fuel fired power plants (generally above 25 MW capacity). Data from the NEI is used to impute $PM_{2.5}$ emissions.[16] Additional sources, including Federal Energy Regulatory Commission (FERC), EPA's Emissions & Generation Resource Integrated Database (eGRID), and Energy Information Administration (EIA), provide data on load, retail sales, regulations, and plant characteristics and locations. The Appendix gives more details on our data and the AP3 model.

2.2 Total Damages

Evaluating Eq. (1) for each year gives the damages shown in the rows labelled "Total" in Table 1. Total damages from emissions of pollutants by CEMS power plants in 2010 were $245 billion, or about $800 per capita. By 2017, damages had fallen 46% to $133 billion.

[15]In theory these should be equal, but in practice they may differ due to reporting practices, line losses, and net imports from Mexico and Canada.

[16]For power plants not identified in the NEI, we assign an average $PM_{2.5}$ emissions rate.

This is a decline of \$112 billion or about \$369 per capita, which is a substantial benefit to human health and the environment.

To analyze the sources of the decline in damages, we break up the sums in Eq.(1) in several ways. Panel A in Table 1 shows the damages by pollutant. In 2010, SO_2 emissions account for the majority of damages (\$137 billion) followed by CO_2 emissions (\$87 billion) and NO_X and $PM_{2.5}$ emissions (\$18 and \$10 billion). By 2017, this order had changed with CO_2 emissions accounting for the majority of the damages followed by SO_2, NO_X, and $PM_{2.5}$. About 88% of the decline in damages is due to reduction in damages from SO_2 emissions. The large decline in SO_2 caused it to become a less important source of harm. Panel B shows the damages by fuel type. Damages from coal-fired power plants decline dramatically over time. They account for more than 100% of the decline from 2010 to 2017 because damages from gas-fired power plants actually increased. Panel C shows the damages by electricity grid interconnection. The vast majority of damages come from power plants in the East and almost all of the decline in damages from 2010 to 2017 can be attributed to the East. In fact, damages from power plants in Texas increased slightly. Taken together, the results in Table 1 show that the dominant sources of the decline in damages are from SO_2 emissions, from coal plants, and from plants in the East.

To analyze who benefited from the decline in damages, we shift our focus to damages received by a location. When calculating damages received, we include only local pollution.[17] Due to the dispersal of pollutants in the atmosphere, a given location may receive damages from many power plants. Using the δ_{pijt} from AP3, we can write the damages received by county j as

$$\sum_p \sum_i \delta_{pijt} e_{pit}.$$

Aggregating these damages and accounting for population gives damages received per capita by state. Figure 2 shows the decline in damages received over the period 2010-2017. The declines are substantial throughout the Northeast and Mid-Atlantic states. The average individual in West Virginia received damages of \$1746 in 2010 and \$492 in 2017, for a decline of \$1253. Pennsylvania and Ohio also received large per capita reductions in damages (\$988

[17]The social cost of carbon measures global damages from carbon over hundreds of years. It is difficult to attribute this damages to specific places in the US.

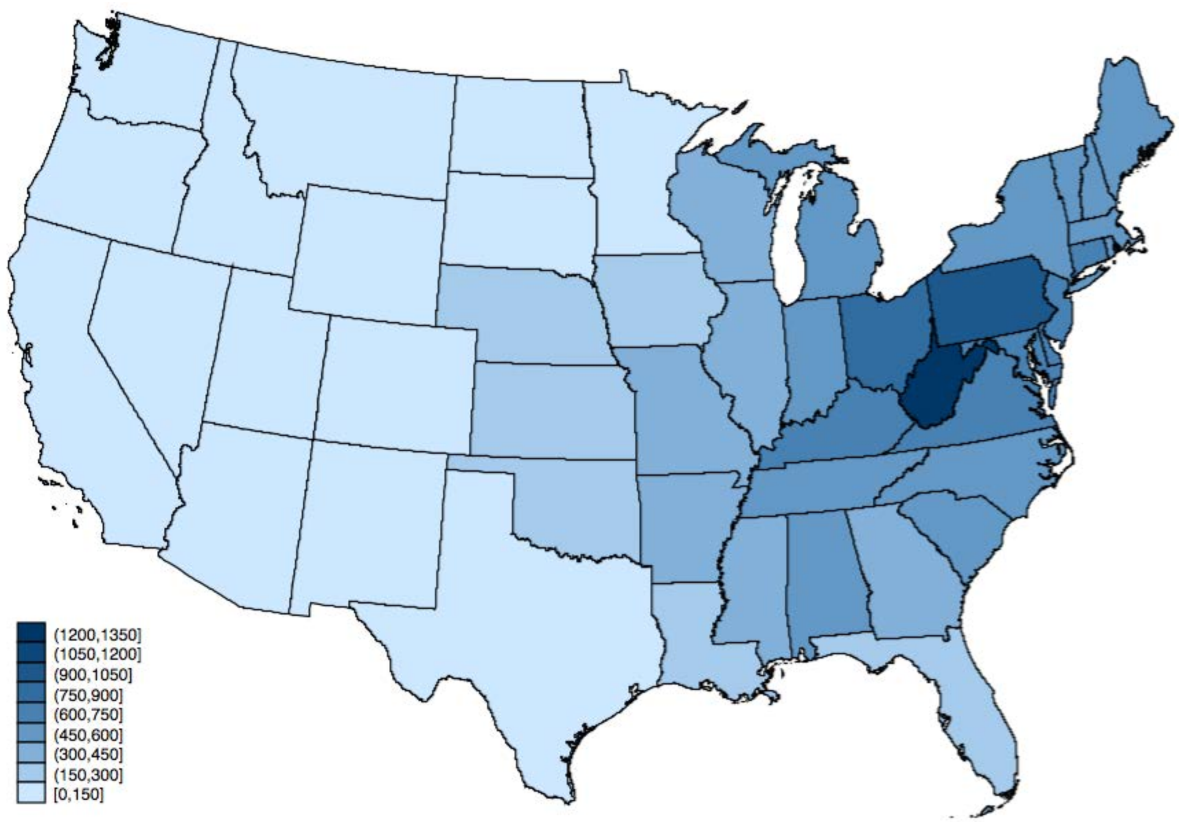
Table 1: Damages by Pollutant, Fuel, and Interconnection

	2010	2011	2012	2013	2014	2015	2016	2017
Panel A: Pollutant								
Local Pollution								
SO_2	137.6	122.0	92.5	94.8	98.7	68.5	44.1	38.6
NO_x	18.2	17.4	15.9	16.9	17.1	14.1	12.3	10.7
$PM_{2.5}$	10.4	9.6	9.3	9.5	9.5	8.9	8.6	8.0
Total Local	166.1	149.0	117.7	121.1	125.4	91.6	65.1	57.3
Global Pollution								
CO_2	78.8	77.6	75.1	78.2	80.7	77.9	76.3	75.4
Total	244.9	226.7	192.8	199.3	206.0	169.4	141.4	132.7
Panel B: Fuel								
Coal	224.6	202.8	167.1	175.1	181.8	141.3	111.2	105.0
Gas	19.3	22.5	24.8	22.1	21.9	25.9	28.1	25.9
Oil	0.7	1.0	0.5	1.2	1.3	1.2	0.7	0.5
Other	0.2	0.4	0.4	1.0	1.1	1.1	1.3	1.4
Total	244.9	226.7	192.8	199.3	206.0	169.4	141.4	132.7
Panel C: Interconnection								
Eastern	213.7	196.5	163.8	166.9	173.6	139.2	113.5	103.5
Western	17.0	15.7	16.1	17.7	17.2	16.7	14.9	14.7
Texas	14.2	14.5	12.9	14.7	15.3	13.5	13.1	14.5
Total	244.9	226.7	192.8	199.3	206.0	169.4	141.4	132.7

Notes: Damages created in billions of 2014$ aggregated across all CEMS power plants using AP3 damage estimates.

and \$775). Damages and declines are both much smaller in the West. The average individual in California received damages of \$33 in 2010 and \$22 in 2017.[18]

Figure 2: Reduction in Local Damages Received Per Capita (2014\$)



Using data on census block groups' median income and demographics, we can calculate the local pollution received by income and demographic groups within each county.[19] Damages received from power plant emissions are regressive in 2010 and in 2017 both overall and within racial groups. For example, in 2010 an individual in the lowest income decile received damages of \$610 while an individual in the highest income decile received damages of \$462. By 2017 these damages had fallen to \$212 and \$152 respectively. Because the decline is larger for lower income deciles, the decline is progressive.

[18]Online Appendix A contains maps of damages received by county for each year in 2010-2017 (see Figures A-3 to A-10), the decline in damages over 2010-2017 by county (see Figure A-11) and the data used to generate Figure 2 (see Table A-1).

[19]For details see Online Appendix A and supporting Tables A-2 to A-4.

3 How Damages Declined

We use a decomposition technique to analyze the ways in which total damages declined. As a preliminary step, we modify Eq. (1) to account for fossil electricity generation. Letting q_{it} be electricity generation at fossil plant i at time t and $Q_t = \sum_i q_{it}$ be total fossil generation, Eq. (1) becomes

$$D_t = \sum_i \sum_p v_{ipt} e_{ipt} = \sum_i \sum_p v_{ipt} \frac{e_{ipt}}{q_{it}} \frac{q_{it}}{Q_t} Q_t = \sum_i \sum_p v_{ipt} r_{ipt} \theta_{it} Q_t, \tag{2}$$

where $r_{ipt} = \frac{e_{ipt}}{q_{it}}$ is the emissions rate for pollutant p and $\theta_{it} = \frac{q_{it}}{Q_t}$ is the share of fossil electricity generated.[20]

Next we define the Δ operator as the difference across year t and year 0 (for example $\Delta Q = Q_t - Q_0$). Differencing both sides of Eq. 2 gives our decomposition:

$$\Delta D = \underbrace{\sum_i \sum_p \overline{v}_{ip} \overline{r}_{ip} \overline{\theta}_i \Delta Q}_{\text{Scale}} + \underbrace{\sum_i \sum_p \overline{v}_{ip} \overline{r}_{ip} \Delta\theta_i \overline{Q}}_{\text{Composition}} + \underbrace{\sum_i \sum_p \overline{v}_{ip} \Delta r_{ip} \overline{\theta}_i \overline{Q}}_{\text{Technique}} + \underbrace{\sum_i \sum_p \Delta v_{ip} \overline{r}_{ip} \overline{\theta}_i \overline{Q}}_{\text{Valuation}} + Error, \tag{3}$$

where the bar operator indicates our choice of base, which we define to be the average of values in the initial and final years (for example $\overline{Q} = \frac{1}{2}(Q_t + Q_0)$). This is analogous to a Marshall-Edgeworth price index.[21] The structure of Eq. (3) resembles the product rule from differential calculus: we isolate the change in one variable while holding the other variables constant at the base value. However, it has a non-zero error due to the discrete change in time. We give a formula for the error in the Appendix. Our decomposition breaks up the decline in damages into four effects: scale, composition, technique, and valuation.

Table 2 shows these effects over 2010 to 2017. First consider the U.S. total column, which aggregates damages over all three interconnections. The scale effect (totaling -\$25 billion)

[20] For plants that enter or exit, we construct a panel across the two years by setting $e_{ipt} = 0$ and $q_{it} = 0$ for years in which the plant is not generating. When r_{ip0} or r_{ipt} is undefined, we set it equal to its value when it is observed. For example, with a plant that enters we set r_{ip0} equal to r_{ipt}, which is well-defined. We follow a similar procedure for v_{ipt}. This ensures that entry and exit do not contribute to the technique effect (since emissions rates are constant) or the valuation effect (since valuations are constant).

[21] If the base corresponds to values in the initial time period, then the decomposition is analogous to a Laspeyres price index, and if the base corresponds to values in the final time period, then the decomposition is analogous to a Paasche price index.

is the decrease in damages that can be attributed to changes in overall fossil generation, holding valuations, emissions rates, and generation shares constant at their average levels. Similarly, holding the other variables constant, the composition effect (totaling -$60 billion) is the decrease in damages from changes in fossil generation shares across power plants. The technique effect (totaling -$63 billion) is the decrease in damages from changes in power plant emissions rates. The valuation effect (totaling $35 billion) is the *increase* in damages from changes in AP3 valuations and the social cost of carbon. The error is trivial.[22] The table also shows the results for the Eastern Interconnection, which accounts for the bulk of the decline in damages.[23]

To better understand each of the effects, we further divide them into component parts and provide additional context. We begin with the scale effect. Here we consider changes in load and generation from wind, solar, nuclear, and hydropower.[24] To do this, we note that the change in fossil generation, ΔQ, in Eq. (3) can be written:

$$\Delta Q = \Delta L - \Delta R - \Delta N - \Delta H - \Delta Other,$$

where ΔL is the difference in load, ΔR is the difference in renewable generation, ΔN is the difference in nuclear generation, ΔH is the difference in hydroelectric generation, and $\Delta Other$ is the residual. We use data on load from FERC form 714 and data on renewable, nuclear, and hydroelectric generation from EIA form 923 (see Table iii in the Appendix). Substituting for ΔQ in Eq. (3) gives the results under the Scale heading in Table 2. The increase in renewable generation is by far the biggest contributor to the scale effect as it reduced damages by $16 billion.

Anything that changes the generation shares (e.g., market forces or regulations that shift generation from a coal-fired to a gas-fired plant or cause entry/exit) contributes to the composition effect. The results under the Composition heading in Table 2 show the effect for

[22]Tables B-8 to B-10 present results using the Laspeyres base, the Paasche base and an yet another base we call the average base. These bases yield much larger errors.

[23]See Tables B-4 to B-7 in Online Appendix B for decompositions for each interconnection.

[24]There could also be a contribution from efficiency policy, but we cannot observe counterfactual electricity consumption. Efficiency policy may have offset increases in damages that would have occurred due to population growth and economic growth induced increases in electricity consumption.

Table 2: Decomposition of Change in Damages from 2010-2017 (billions of 2014$)

	U.S. Total	Eastern Interconnection	Fixed Valuations
Scale (Total Fossil Generation)			
Load	−3.6	−10.0	−3.9
Renewables	−15.9	−9.1	−17.6
Nuclear	0.2	−1.2	0.2
Hydroelectric	−3.0	−0.5	−3.3
Other	−2.9	−3.3	−3.2
Total Scale	−25.2	−24.1	−27.9
Composition (Generation Shares)			
Coal	−32.0	−28.8	−35.2
Switch from Coal	−5.3	−5.0	−5.8
Gas	4.5	4.3	4.9
Entry of Coal	2.4	1.9	2.4
Entry of Gas	2.7	2.1	2.7
Exit of Coal	−31.1	−30.5	−37.8
Exit of Gas	−0.4	−0.2	−0.5
Other	−0.7	−0.7	−0.8
Total Composition	−60.0	−56.9	−70.1
Technique (Emissions Rate)			
Coal - New SO_2 Control Tech.	−35.7	−33.8	−39.3
Coal - No New Tech.	−8.9	−6.9	−9.9
Switch from Coal	−15.9	−16.0	−17.6
Gas	−2.5	−2.3	−2.7
Other	0.4	0.4	0.5
Total Technique	−62.6	−58.6	−69.0
Valuation			
SO_2	15.7	13.8	0.0
NO_X	2.4	1.8	0.0
$PM_{2.5}$	1.2	1.0	0.0
CO_2	16.0	12.4	0.0
Total Valuation	35.3	28.9	0.0
Error	0.3	0.4	0.5
Total	−112.1	−110.2	−166.6

Notes: Total changes do not exactly match the aggregate decline in damages in Table 1 because the decomposition requires that we drop plants reporting zero generation. Fuel types are from eGRID. "Coal" and "Gas" denote plants whose primary fuel type did not change. "Switch from Coal" denotes plants whose primary fuel type is coal in 2010 but switches to gas or other fuels in 2017. "Entry" denotes plants that were not in the 2010 sample and "Exit" denotes plants that were not in the 2017 sample. "Other" denotes the residual category. "New SO_2 Control Tech" denotes plants that installed SO_2 emissions control technology between 2010 and 2017.

subsets of the power plants. The decline in generation share from coal plants that operated throughout the time period reduced damages by $32 billion. This is consistent with Table iii, which shows that coal's share of fossil generation fell from 64% to 38%. The exit of coal plants reduced damages by an additional $31 billion.[25] The increase in generation share from existing gas plants and the entry of new coal and gas plants only increased damages modestly.

The technique effect captures anything that changes a plants emissions rate including: installing emissions control equipment, such as scrubbers or low-NO_X burners; switching to low-sulfur coal; replacing a coal-fired boiler with a new gas-fired boiler; or switching generation at the plant from existing coal generating unit to an existing gas unit. The results under the Technique heading in Table 2 show the effect for different subsets of the power plants. The bulk of the technique effect ($36 billion) comes from coal plants that installed new emissions control technologies. Figure 3 shows a histogram of installation year for technologies to control SO_2 emissions and the price of SO_2 allowances in EPA's ARP auction. There were a substantial number of installations since 2010.[26] Figure 3 also shows the regulations that are binding on the plants.[27] Before 2010, most pollution control equipment was installed at plants under the ARP or New Source Performance Standard (NSPS). In 2010 the ARP SO_2 price fell to $40 per ton from over $1000 per ton in 2006 but emissions control continued to be installed to comply with other regulations. Additional installations in 2015-17 were installed at plants under MATS, which was announced in 2011.

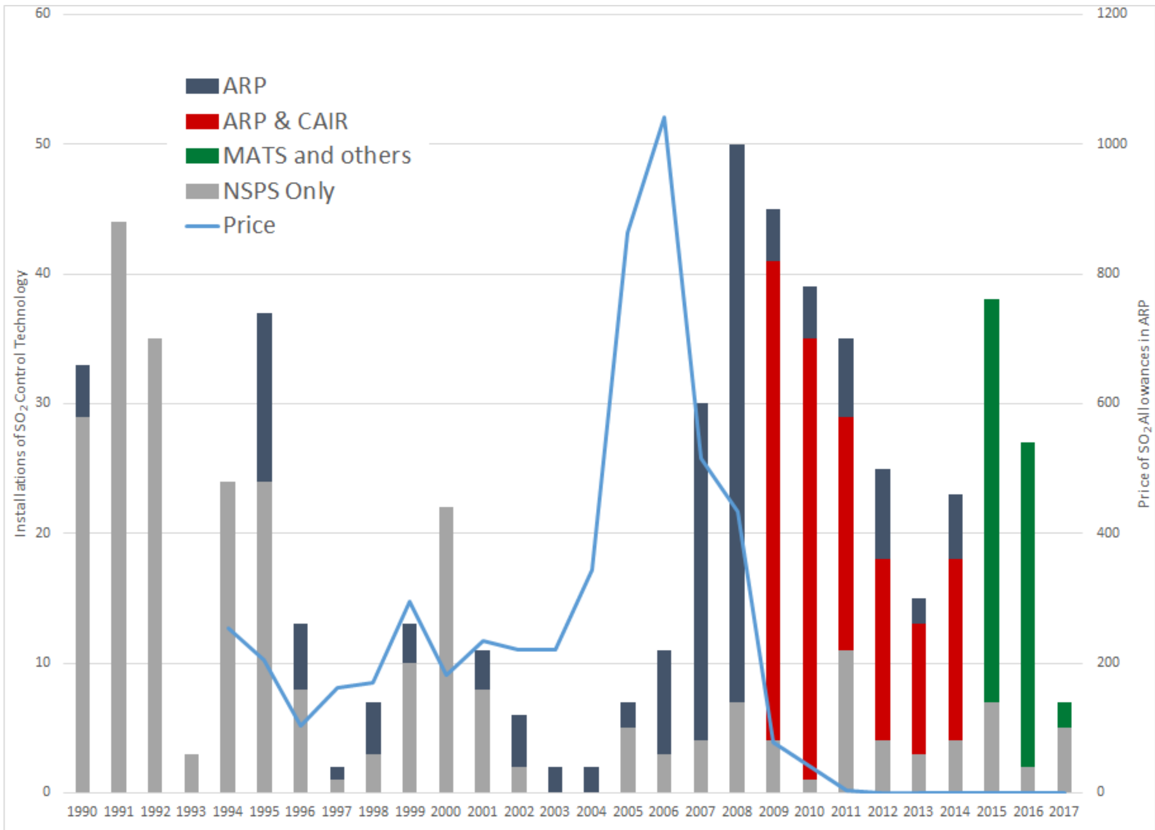
Because our emissions rates are measured at the plant level, switching to cleaner fuels within a power plant also contributes to the technique effect. About $16 billion of the technique effect is from plants that have coal as their primary fuel source in 2010 but not in 2017. These plants could have replaced coal-fired boilers with gas-fired boilers or switched generation from existing coal-fired to gas-fired unit. Table B-27 in Online Appendix B shows

[25] See Tables B-21 to B-26 in Online Appendix B for additional information on plant entry and exit.

[26] Flue gas desulfurization, or scrubbers, are one type of post-combustion pollution control equipment that primarily removes particulates such as SO_2. Scrubbers are also one compliance strategy for plants governed by MATS. Once a scrubber is installed it likely remains active through the life of the plant. Dry sorbent injection is another type of pollution control technology for SO_2. Figure B-7 in Online Appendix B shows similar data for NO_X pollution control equipment (selective catalytic reduction).

[27] The EPA Air Markets Program reports which regulations apply to each plant in CEMS.

Figure 3: Power Plant SO_2 Emissions Control Installations



Notes: The year is the first year a pollution control technology is active as indicated by EIA 860. "ARP" means Acid Rain Program; "CAIR" is the Clean Air Interstate Rule; "MATS" is the Mercury and Air Toxic Standard; and "NSPS" is the New Source Performance Standard.

that the within-plant share of generation by coal decreased while the gas share increased from 2010 to 2017.

Finally, the valuation effect shows that changes in valuations *increased* damages by \$35 billion. The valuation of damages from a unit of local pollution emitted at a power plant may change over time due to changes in factors such as population, atmospheric chemistry and ambient pollution concentrations. The SCC also increases over this time period. The results under the Valuation heading in Table 2 show the effect by pollutant. The bulk of the valuation effect comes from SO_2 and CO_2.

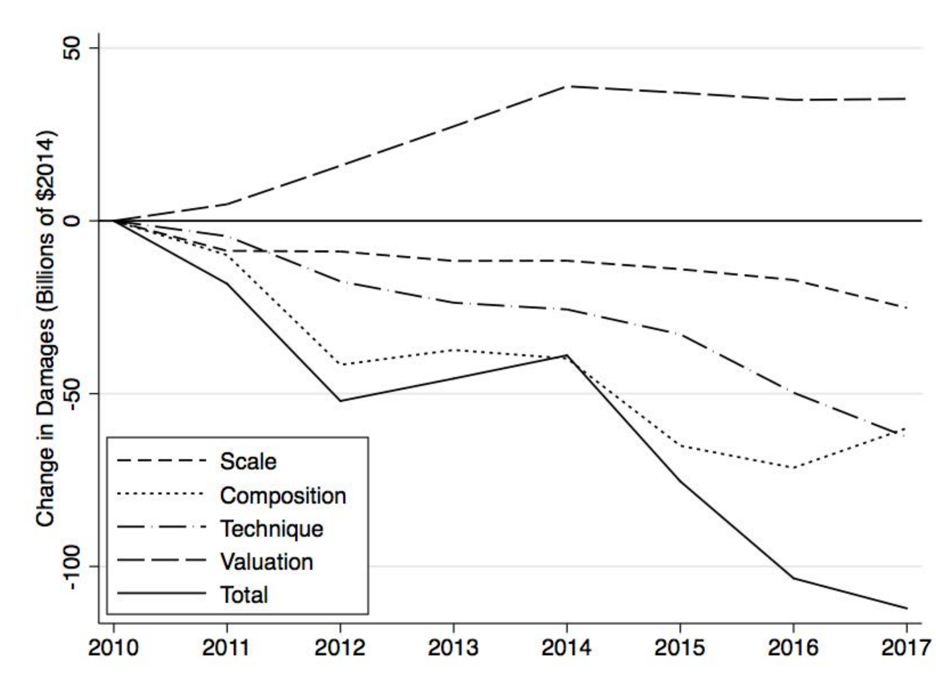
The final column of Table 2 exhibits the decomposition holding all damage valuations fixed at their values in the final year. As discussed in Online Appendix A, this procedure overstates the reduction in damages even if our assumption that emissions are independent of damage valuations does not hold. So we expect that the actual reduction in damages is no greater than \$167 billion. By definition, the valuation effect is equal to zero in this column. But the relative importance of the other effects do not change significantly: the scale effect is 17%; the composition effect is 42%; and the technique effect is 41%.[28]

Although Table 2 has the decomposition of the overall change in damages from 2010 to 2017, we can also do the decomposition by year (e.g., decompose the change in damages from 2010 to each year). The results are shown in Figure 4.[29] Damages generally decline throughout the sample, and the relative importance of the different effects is consistent in most years. However early in the sample the composition effect dominates. This effect, which is sensitive to natural gas prices, is relatively large in 2012 and 2016 when gas prices were low. The technique effect is particularly strong toward the end of the sample. The valuation effect, which increases until 2014 and then is roughly constant, illuminates our assumptions about damage valuations.

[28] In Table iv in the Appendix, we decompose emissions rather than damages. The technique effect is more prominent for SO_2.

[29] The data for this figure are given in Table B-2 in Online Appendix B. Table B-3 reports small standard errors for these effects. Standard errors are unnecessary since we have a census of CEMS power plants. However they inform whether the reductions are similar across plants or are driven primarily by outliers.

Figure 4: Decomposition of Change in Damages by Year



Notes: All changes relative to 2010.

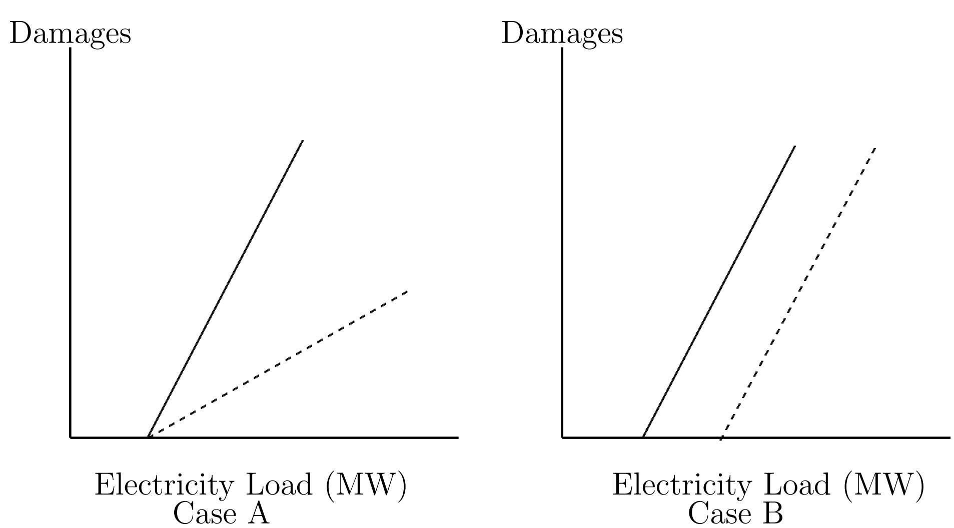
4 Marginal Damages and Policy Analysis

Optimal environmental policies for electricity use depend on marginal damages. Although electricity generation has become considerably cleaner from 2010 to 2017, this does not necessarily imply that marginal damages have decreased as well. In this section, we estimate damage functions and marginal damages and then use the latter to analyze policies for electric vehicle and solar panel adoption.

4.1 Damage Functions

Consider a damage function that relates air pollution damages to electricity use. Figure 5 illustrates two possible ways in which a damage function may change. In case A on the left, the damage function rotates down, so that marginal damages do indeed decrease as electricity generation becomes cleaner. For example, if dirty coal plants retire and are replaced by cleaner natural gas plants, this leads to lower total damages and lower marginal damages. In case B on the right, however, the damage function shifts to the right but the slope does not change. For example, if renewable generation increases, this leads to lower total damages, but no change in marginal damages.

Figure 5: Shifts in the Damage Function: Two Possibilities



Empirically assessing changes in damage functions requires several choices. First, the geographic scope must be determined. Our main analysis focuses on the electricity interconnections: East, West, and Texas.[30] Second, the measure of electricity use must be determined. We use load as our primary measure of electricity use but revisit this assumption below.

We first use non-parametric regressions to estimate the damage function using flexible functional forms. Figure 6 shows local polynomial regressions for each of the three interconnections in the early (2010-12) and late (2015-17) years of our sample. For the East, the damage function shifts down between the early and late years indicating that electricity is cleaner at all load levels. The marginal damage (slope) is positive, and the function appears to be flatter for 2015-17. The West and Texas are different. There is no clear downward shift in the damage function. In fact, for these regions the more recent estimated damage function is lower for low load levels, but higher for high load levels. This suggests that marginal damages are increasing over time in these regions.[31]

The univariate non-parametric regressions do not show evidence of substantial non-linearities. To examine the effect of adding control variables, we regress damage and load on hour of day by month of sample fixed effects, and then repeat the non-parametric regressions on the residuals. The results are shown in Figure C-4 in Online Appendix C. Once again we see no substantial non-linearities, so we turn to linear regression.

4.2 Estimating Marginal Damages

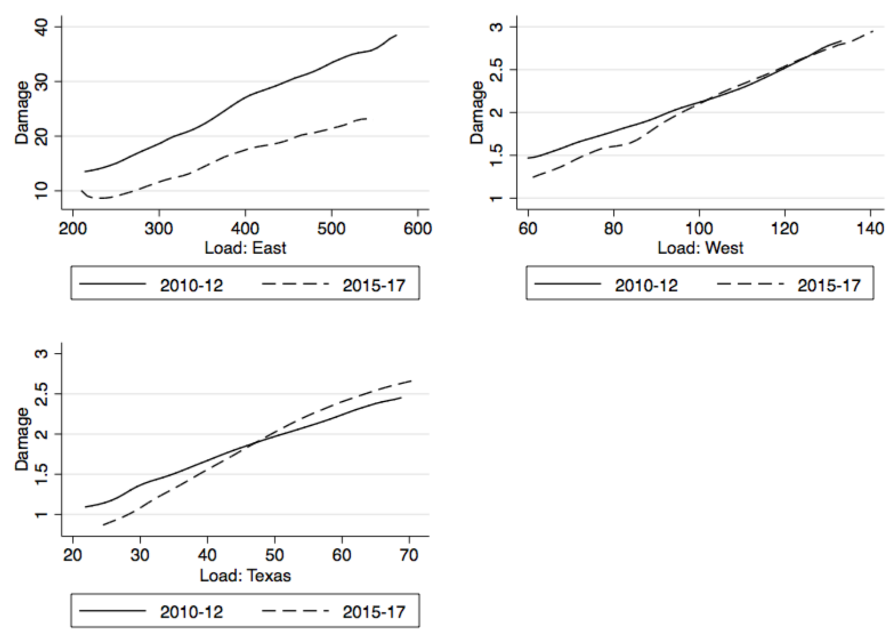
Parametric regression analysis allows us to estimate marginal damages precisely and to statistically test whether marginal damages changed. Our main estimating equation is

$$D_t = \beta Load_t + \gamma Load_t Year_t + \alpha_{mh} + \epsilon_t, \tag{4}$$

[30] We explore other definitions of geographic scope in Appendix Table C-4.

[31] Figures C-1to C-3 in Online Appendix C also present the damage functions as functions of fossil generation, which shows that the general relationship between load and damages is similar whether we measure electricity usage by load or by fossil generation.

Figure 6: Local polynomial estimates of damage functions



Notes: Graphs are local polynomial regressions of hourly damages on hourly load for the three interconnections: Eastern, Western, and Texas. Load measured in thousands of MWhs, and damages measured in millions of 2014$. In East, mean load is 339 and mean damages is 21. In Texas, mean load is 39, and mean damage is 1.8. In West, mean load is 85, and mean damage is 2.2.

where D_t is damages from emissions in hour t, $Load_t$ is load in hour t, α_{mh} are month of sample times hour fixed effects (8 years * 12 months * 24 hours fixed effects), and $Year_t$ is the annual trend since 2010. The coefficients of interest are β, which is the marginal damage, and γ, which is the annual change in the marginal damage. We specify units such that marginal damages are in $ per kWh and estimate Newey-West standard errors using 24 hour lags.

The results of estimating Eq. (4) are given in Table 3. For the East, the marginal damage estimate over the sample is $0.073 per kWh with a tight standard error. This is a substantial cost relative to the average retail price of electricity($0.13 per kWh in 2017).[32] The year trend shows a statistically significant decrease in marginal damages over this time frame starting at about $0.086 per kWh in 2010 and decreasing by about $0.0038 per kWh per year to about $0.06 per kWh in 2017. Figure 7 illustrates this trend line and shows that the annual point estimates are tightly clustered around the trend line.[33] In the West and Texas, the marginal damages estimated over the sample are much lower: $0.025 per kWh in the West and $0.032 per kWh in Texas. However, the trends show *increasing* marginal damages of $0.001 per kWh per year. This increase is small but is statistically significant. Annual estimates with confidence intervals, shown in Figure 7, are again tightly clustered around the increasing trend lines.

Marginal damages are appropriate for policy, but total damages and average damages (damages divided by load) are frequently used measures of grid cleanliness.[34] To compare these measures, we calculate compound annual growth rates. The results are shown in Table 4. The compound annual growth rates for total and average damages are similar to each other, but they substantially overstate the decline in marginal damages in all three regions. These differences suggest that focusing on total or average damages gives a misleading implication for the degree to which policies may need to be adjusted due to the cleaner electricity generation.

[32] From the EIA: https://www.eia.gov/energyexplained/index.php?page=electricity_factors_affecting_prices.

[33] The annual point estimates and standard errors are reported in Table C-1 in Online Appendix C.

[34] For example, see the electric vehicle webpage for the Union of Concerned Scientists. https://www.ucsusa.org/clean-vehicles/electric-vehicles/life-cycle-ev-emissions#.W8y2TVJRcdU. See Table C-5 in Online Appendix C for average damages.

Table 3: Marginal Damage Estimates: Main

Variables	(1)	(2)
East		
Load (β)	0.07321***	0.08644***
	(0.00056)	(0.00077)
Load Trend (γ)		−0.00377***
		(0.00019)
West		
Load (β)	0.02492***	0.02032***
	(0.00025)	(0.00039)
Load Trend (γ)		0.00122***
		(0.00010)
Texas		
Load (β)	0.03227***	0.02825***
	(0.00044)	(0.00072)
Load Trend (γ)		0.00110***
		(0.00019)
Observations	70,128	70,128

*** p<0.01, ** p<0.05, * p<0.1

Newey-West Standard errors (24 hour lag)

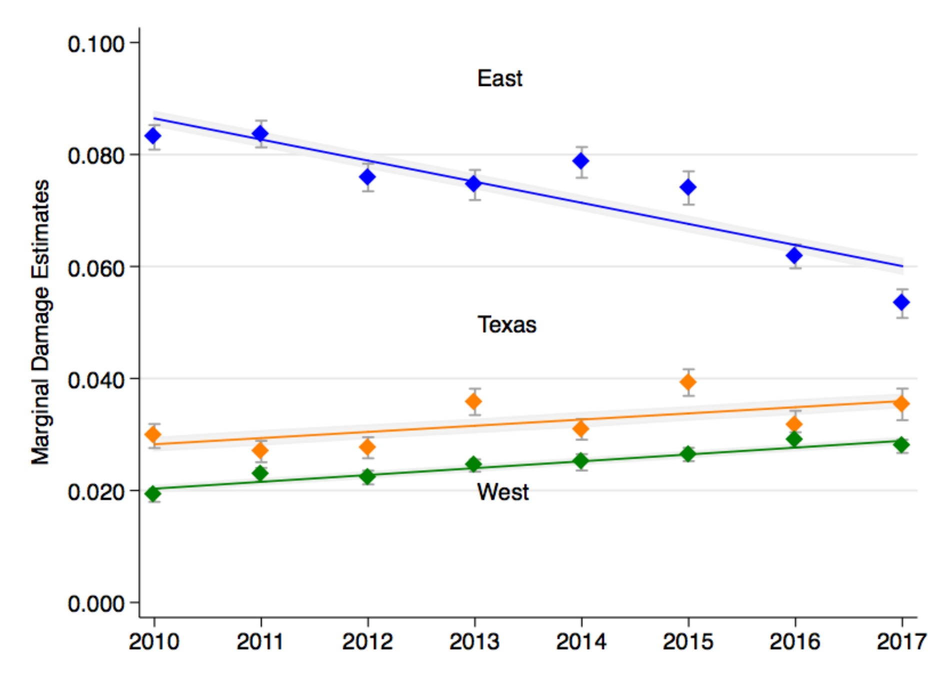
Notes: Dependent variable is hourly damages in the interconnection. Coefficient estimates in $ per kWh. Regressions are unweighted and include month of sample by hour fixed effects, i.e., 2,304 (=8*12*24) fixed effects.

Table 4: Compound Annual Growth Rates 2010-2017

Interconnection	Total Damages	Average Damages	Marginal Damages
East	-9.84%	-9.32%	-5.07%
West	-2.08%	-2.70%	5.14%
Texas	0.38%	-1.29%	3.51%

Notes: Compound annual growth rate is defined as (end value/begining value)$^{1/7} - 1$.

Figure 7: Marginal Damages by Interconnection



Notes: Estimates in $ per kWh. Predicted trends are from regressions reported in Table 3. Annual point estimates with 95% confidence intervals are from regressions reported in Table C-1.

Our main results weight all hours equally. These results can be used to evaluate a use of electricity that is distributed uniformly across hours and seasons, e.g., refrigeration. However, other electricity uses may have different profiles. For example, electric vehicle charging occurs primarily in the nighttime with some charging at midday but very little charging during peak commuting hours. Electric lighting is primarily at night, whereas industrial applications may use electricity primarily during the day. Air conditioning, one of the heaviest uses, occurs primarily during the day in the summer months. Table 5 shows results for a variety of profiles. For the East, relative to the main results, the electric vehicle charging profile shows increased marginal damages and a steeper decline. Conversely, the Day Time Hours profile shows lower marginal damages and a shallower decline. Overall, the differences are larger across regions than across profiles within a region.

We apply the results in Table 5 to assess two prominent environmental policies. First is the subsidy for electric vehicle purchases. Electric vehicles cause air pollution damages due to the emissions from power plants that charge them. Gasoline vehicles cause damages due to

Table 5: Heterogeneous Marginal Damage Estimates

	East		West		Texas		
	Level	Trend	Level	Trend	Level	Trend	N
Main Results							
	0.0864***	-0.0038***	0.0203***	0.0012***	0.0283***	0.0011***	70,128
	(0.0008)	(0.0002)	(0.0004)	(0.0001)	(0.0007)	(0.0002)	
Electric Vehicle Charging							
	0.0918***	-0.0042***	0.0213***	0.0013***	0.0309***	0.0006***	70,128
	(0.0009)	(0.0002)	(0.0005)	(0.0001)	(0.0009)	(0.0002)	
Day Time Hours (8:01am to 6:00pm)							
	0.0827***	-0.0034***	0.0196***	0.0012***	0.0245***	0.0017***	29,220
	(0.0005)	(0.0001)	(0.0002)	(0.0001)	(0.0005)	(0.0001)	
Night Time Hours (6:01pm to 8:00am)							
	0.0903***	-0.0042***	0.0213***	0.0012***	0.0317***	0.0006***	40,908
	(0.0005)	(0.0001)	(0.0003)	(0.0001)	(0.0005)	(0.0001)	
Summer (May-October)							
	0.0868***	-0.0046***	0.0206***	0.0012***	0.0267***	0.0009***	35,328
	(0.0009)	(0.0002)	(0.0005)	(0.0001)	(0.0010)	(0.0003)	
Winter (November-April)							
	0.0863***	-0.0028***	0.0198***	0.0012***	0.0293***	0.0015***	34,800
	(0.0013)	(0.0003)	(0.0007)	(0.0002)	(0.0011)	(0.0003)	
Summer Day Time							
	0.0812***	-0.0039***	0.0199***	0.0012***	0.0241***	0.0015***	14,720
	(0.0006)	(0.0001)	(0.0003)	(0.0001)	(0.0006)	(0.0002)	

Notes: *** p<0.01, ** p<0.05, * p<0.1, Newey-West Standard errors (24 hour lag). "Electric Vehicle Charging Profile" weights all hours according to a charging profile from EPRI. Other profiles restrict the sample to the indicated hours. "Level" refers to β and "Trend" refers to γ in Eq.(4).

emissions from their tailpipes. Holland et al (2016) show that the environmental benefit of an electric vehicle is equal to the damages from the forgone gasoline vehicle minus damages from the electric vehicle. We use estimates of marginal damages in the electric vehicle charging profile row in Table 5 to determine the damages from the electric vehicle. For the gasoline vehicle, we use emissions from Holland et al (2016) and damage valuations from AP3 to determine damages. Table 6 shows the summary statistics for the distribution of the annual environmental benefit across all counties in the contiguous U.S. For 2010, the average value of the environmental benefit (assuming 15,000 miles per year) is slightly negative (-\$81 per year) with a substantial range across counties from -\$390 to \$781. In 2017, the environmental benefit increases by about \$150 so the average is now positive. The increase is largest in the East: about \$200 across the distribution. Even though marginal damages from electricity use increased in both the West and Texas, the environmental benefit of electric vehicles has increased in these regions because damages from gasoline vehicles grew faster. Overall, the environmental benefit increases over time, but considerable heterogeneity across counties remains. Holland et at (2016) show that the optimal purchase subsidy for an electric vehicle is equal to the lifetime environmental benefit. For comparison, all electric vehicles in the U.S. are eligible for a federal tax credit of \$7,500 and many states offer additional incentives. Using the 2017 environmental benefits and assuming a 10 year lifetime and a 3% discount rate, the federal subsidy is much greater than the NPV of the average lifetime environmental benefit (\$630), but smaller than the NPV of the maximum lifetime environmental benefit (\$8250).

The second policy is the subsidy for household solar adoption. The electricity from solar panels reduces the demand for grid electricity and thus reduces air pollution damages. In this case the environmental benefit is simply the product of the electricity created by the panel and the marginal damages from electricity generation in the interconnection in which the panel is located. Following the methodology in Siler-Evans et al (2013), Vaishnav et al (2017), and Sexton et al (2018), we combine information on solar insolation with marginal damage estimates from the Day Time Hours row in Table 5.[35] Table 7 shows the summary statistics for the distribution of environmental benefit per year for a 6 kW system across

[35]See details on solar insolation in Online Appendix C.

approximately 83,000 unit areas in the contiguous U.S. Overall the mean benefit is $418 in 2010 with a range across locations from $94 to $830. In 2017, the mean benefit fell to $356 and the range narrowed. Across regions, the environmental benefit is largest in the East because the grid is dirtiest. The environmental benefit decreased in the East (because marginal damages fell) but increased in the West and Texas (because marginal damages increased). Overall, these changes caused the range of the environmental benefit to become smaller in 2017. Solar panels are eligible for a tax credit of 30%, which implies a subsidy $5652 for the average system.[36] Using the 2017 environmental benefits and assuming a 20 year lifetime and a 3% discount rate, the average environmental benefit ($5455) is approximately equal to the subsidy.

4.3 Robustness

The regression in Eq. (4) estimates the damage function as the relationship between electricity load and damages. This may underestimate marginal damages if load is correlated with omitted non-fossil generation. An alternative specification that estimates damages as a function of fossil generation may have endogeneity bias. This bias can be large if interregional trading is not modeled.[37] Table C-3 in Online Appendix C explores potential endogeneity bias in our estimates. In particular, we use two alternative specifications: one with fossil generation as the independent variable and another that instruments for fossil generation with electricity load. Table C-3, which shows the three specifications for levels and annual trend models, finds that the bias is not extreme, likely due to our aggregation to the interconnection level.

Our modeling requires assumptions about key parameters. Table 8 explores the robustness of our marginal damage estimates to other reasonable assumptions about these parameters. Our main results use AP3 damage valuations for NEI years (2008, 2011 and 2014) and interpolate valuations for non-NEI years. Column (2) presents estimates in which all damage valuations are held fixed at the final year values.[38] Under the fixed valuations,

[36] `https://www.energystar.gov/about/federal_tax_credits/2017_renewable_energy_tax_credits`. The average cost of a 6 kW system is $18840.

[37] Marginal distributional losses are another possible source of bias (Borenstein and Bushnell 2018).

[38] Table C-2 in Online Appendix C shows the results for both levels and trends.

Table 6: Environmental Benefit of an Electric Vehicle ($ per year)

Interconnection	Year	Min	Mean	Max
East	2010	-390	-192	657
	2017	-186	13	939
West	2010	20	233	781
	2017	0	258	910
Texas	2010	-24	75	183
	2017	-14	107	246
National	2010	-390	-81	781
	2017	-186	72	939

Notes: VMT weighted average across all counties in contiguous US. Comparison of 2014 gasoline and electric powered Ford Focus.

Table 7: Environmental Benefit of an Solar Panel System ($ per year)

Interconnection	Year	Min	Mean	Max
East	2010	488	622	830
	2017	348	443	591
West	2010	94	170	213
	2017	134	242	305
Texas	2010	184	213	252
	2017	274	316	375
National	2010	94	418	830
	2017	134	356	591

Notes: We assume a 32 square meter system (approximately 6 kW) with 13% efficiency. Each observation is the environmental benefit in a 0.1 degree by 0.1 degree unit area in the contiguous US.

the 2010 point estimates are higher and marginal damages fall more or increase less. In particular, the Texas trend is statistically insignificant instead of positive. Another important assumption is the social cost of carbon. Columns (3) & (4) use high and low values for the SCC. The high SCC values increase the marginal damages (and low values decrease the marginal damages). The trends are more positive for the higher SCC values reflecting the higher growth of the SCC. Column (5) uses a smaller VSL than our baseline calculation.[39] This change has the greatest effects on the results, particularly in the East where damages are higher. Overall, the results are largely robust to these different modeling assumptions.

[39]Baseline VSL is $8.8 million and the smaller value is $3.3 million.

Table 8: Marginal Damage Estimates: Sensitivity

Variables	(1) Base	(2) Fixed Value	(3) SCC=51	(4) SCC=31	(5) Low VSL
East					
Load (β)	0.0864***	0.1029***	0.0917***	0.0812***	0.0459***
	(0.0008)	(0.0009)	(0.0008)	(0.0008)	(0.0004)
Load Trend (γ)	−0.0038***	−0.0065***	−0.0036***	−0.0040***	−0.0010***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
West					
Load (β)	0.0203***	0.0248***	0.0236***	0.0170***	0.0161***
	(0.0004)	(0.0005)	(0.0005)	(0.0003)	(0.0003)
Load Trend (γ)	0.0012***	0.0006***	0.0015***	0.0010***	0.0011***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Texas					
Load (β)	0.0283***	0.0349***	0.0323***	0.0242***	0.0210***
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0004)
Load Trend (γ)	0.0011***	0.0001	0.0013***	0.0009***	0.0008***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Observations	70,128	70,128	70,128	70,128	70,128

*** p<0.01, ** p<0.05, * p<0.1

Newey-West Standard errors (24 hour lag)

Notes: Dependent variable is hourly damages in the interconnection. Coefficient estimates in $ per kWh. Regressions are unweighted and include month of sample by hour fixed effects, i.e., 2,304 (=8*12*24) fixed effects. The alternative SCC of $31 and $51 (relative to the main model of $41) are for year 2015 and grow at 3% annually.

5 Conclusion

Since 2010, the U.S. population grew by over five percent and real gross domestic product expanded by more than 15 percent. Despite these trends, electric power consumption remains effectively unchanged. Concurrently, emissions of several important pollutants have fallen. This paper translates emissions into monetary damage, finding that the total annual damages from emissions fell by $112 billion, or 46 percent, over eight years. The benefits of these reduced emissions were particularly concentrated among low-income households and households in the Mid-Atlantic and Northeastern states.

This paper decomposes the change in damages into four effects. The technique effect measures within plant changes in emission rates. This contributed $62 billion in decreased damages. The composition effect, which captures changes in generation shares across plants, contributed a similar amount ($60 billion). By comparison, the entry of renewables and reduction in load produced a fall in damages that was considerably smaller (the scale effect is about $25 billion). Running counter to these three effects, the valuation of damage per unit of emissions increased damages by $35 billion. This phenomenon was driven by changes in the composition of the atmosphere, population growth and demographic change, and increases in the social cost of carbon.

The paper also examines the ramifications of changes to the electricity sector for environmental policy. Our econometric analysis of the relationship between load and damages reveals that marginal damages did fall in the Eastern Interconnection but at a much slower rate than total damages or average damages. Despite lower overall emissions in the Western and Texas Interconnections, marginal damages have increased in these markets. We find that grid-powered electric vehicles are now cleaner than gasoline vehicles, on average, though substantial heterogeneity remains.

Although the paper demonstrates an extraordinary reduction in both damages and emissions from the U.S. power generation sector, we offer the following caveats. First, this is not a causal analysis of which policies and market forces drove these changes. We explore plausible explanations, but do not disentangle them completely. The installation of scrubbers was the result of several state and federal policies including the Mercury and Air Toxics Standards.

The fuel switching and coal plant retirements were likely affected by the decreased prices for natural gas due to hydraulic fracturing. Renewable investment was likely affected by policies like the federal Production Tax Credit and Investment Tax Credit, states' Renewable Portfolio Standards, and technological improvements that have lowered costs and improved operations. Second, the application of AP3 to estimate air pollution damage imparts considerable uncertainty on our results. This arises through parameter uncertainty (especially the VSL and the functional linkage between exposure to $PM_{2.5}$ and adult mortality), and through the representation of air quality modeling in AP3. Third, we also note that the social cost of carbon is a necessarily uncertain parameter, both in its level and rates of change through time.

The results presented in this paper provide useful benchmarks for future research on the causes behind the reported changes in emissions and damages. For example, low gas prices could cause the composition effect and parts of the technique effect, but are unlikely to cause increases in renewable generation or lead to installation of pollution control equipment on coal plants. The paper also effectively demonstrates the importance of tracking emissions through to their final monetary damage. Simply reporting emission reductions, while an important step, masks crucial heterogeneity in the toxicity of different pollutants, changes in the exposed populations, and trends in valuation due to changes in environmental conditions.

Appendix

Details on Emissions Data

The CEMS (Continuous Emissions Monitoring System) database is part of EPA's Air Markets Program.[40] CEMS power plants do not include non-fossil power plants, small fossil plants (capacity < 25 MW), and plants in Hawaii or Alaska. The CEMS database provides hourly emissions of SO_2, NO_X, CO_2, and gross generation, which includes electricity use within the plant. We measure a plant's annual $PM_{2.5}$ emissions through the following steps. First, we calculate its emissions rate as the ratio of $PM_{2.5}$ emissions from the National Emissions Inventory over the annual gross generation from CEMS. The NEI is only available every third year (2008, 2011, and 2014) and only for some plants. For years not in the NEI, we use linear interpolation. Average emissions rates are assigned to plants not in the NEI. Second, we calculate $PM_{2.5}$ emissions at a plant as the product of these rates and the plant's gross generation from CEMS. Table i shows annual emissions of the pollutants from the CEMS data. Figure 1 illustrates this same data normalized to 2010 emissions.

Table i: Aggregate Emissions of Four Pollutants

Pollutant	2010	2011	2012	2013	2014	2015	2016	2017
SO_2	10.33	9.09	6.64	6.48	6.31	4.43	2.98	2.68
NO_x	4.28	4.02	3.49	3.51	3.39	2.81	2.46	2.16
$PM_{2.5}$	0.45	0.41	0.38	0.37	0.37	0.34	0.32	0.30
CO_2	2.46	2.35	2.21	2.23	2.23	2.09	1.99	1.91

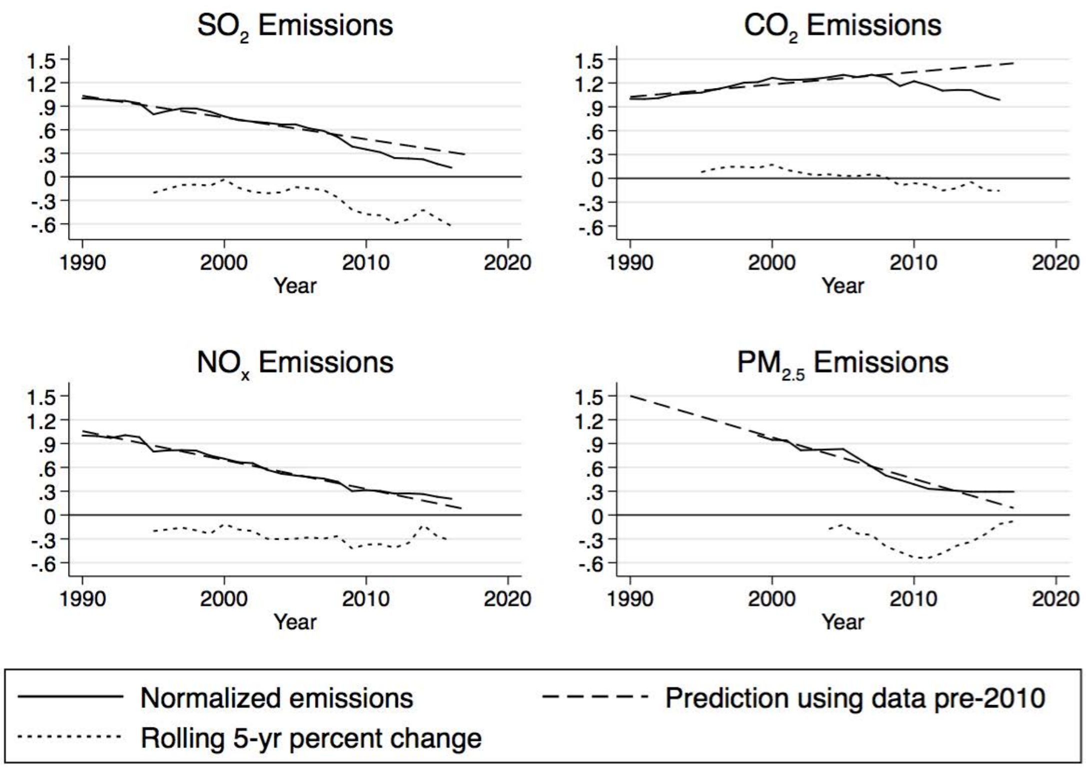
Notes: Total emissions from all CEMS power plants. SO_2, NO_X, and $PM_{2.5}$ emissions in billion pounds. CO2 emissions in billion tons.

For a historical perspective, we illustrate emissions from 1990-2016 in Figure i.[41] For each pollutant, the solid line shows power plant emissions normalized to 1 in 1990. The dashed line shows the trend line from a regression based on data from 1990 to 2009, and the dotted line shows the rolling five-year percentage change in emissions. For SO_2 and CO_2, emissions from 2010 to 2017 clearly deviate below trend.

[40] The database is accessed through the public ftp site ftp://newftp.epa.gov/DMDnLoad/.

[41] The data source for this figure is the Energy Information Administration (see EIA-767, EIA-906, EIA-920, and EIA-923). The data are posted at `https://www.eia.gov/electricity/data/state/emission_annual.xls`.

Figure i: Power Plant Emissions from 1990 to 2016



Notes: Data are from EIA's US Electric Power Industry Estimated Emissions by State.

Table ii: Damage Valuations

Year	SO_2	NO_x	$PM_{2.5}$	CO_2
2010	14.8	5.3	34.8	35.4
2011	15.1	5.3	35.6	36.4
2012	16.1	5.6	36.8	37.5
2013	17.1	6.0	37.9	38.6
2014	18.1	6.3	39.0	39.8
2015	18.0	6.3	38.9	41.0
2016	18.0	6.3	39.0	42.2
2017	18.0	6.3	38.9	43.5

Notes: SO_2, NO_X, and $PM_{2.5}$ damages in 2014$ per pound are the unweighted average of the damage per pound from the AP3 model across the unbalanced panel of all power plants reporting CEMS emissions in that year. CO_2 damages in 2014$ per metric ton.

Details on AP3

Table ii summarizes the AP3 damage valuations across the pollutants. Although AP3 reports damage valuations for all counties and for different stack heights, we focus on damage valuations at reporting CEMS power plants. The table shows the mean damage valuations across the unbalanced panel of power plants. Reflecting our interpolation assumptions, local pollutant damages are flat after 2014. Also included in Table ii are CO_2 damage valuations, which increase throughout the sample period.

As discussed in the main text, we assume that damage valuations are independent of aggregate power plant emissions. This assumption may not hold because atmospheric conditions affect the efficiency with which emissions of NO_X and SO_2 form secondary $PM_{2.5}$. In particular, damage valuations in AP3 are generally increasing over time from 2008-2014. This is due, at least in part, to lower total emission levels of NO_X and SO_2 over time, which leaves considerably more free ammonia (NH_3) in the atmosphere. This implies that marginal emissions of NO_X and SO_2 are more likely to interact with the free ammonia to form ammonium sulfate and ammonium nitrate, both of which are important constituents of ambient $PM_{2.5}$. And at least part of the decreased total NO_X and SO_2 emissions may be due to reduction in power plant emissions. In Online Appendix A, we discuss an alternative procedure to determining the decline in damages and show how our main procedure and the alternative procedure can be used to put bounds on the decline in damages when damage valuations and power plant emissions are not independent.

Details on Electricity Generation

Table iii shows electricity generation by fuel type over time from EIA Form 923. Gas, solar, and wind generation are increasing over time, coal is decreasing over time, and nuclear and hydro vary but show no dominant pattern.

Table iii: Total Electricity Generation by Fuel Type

Fuel	2010	2011	2012	2013	2014	2015	2016	2017
Fossil								
Coal	1,845.1	1,730.6	1,511.1	1,579.1	1,578.9	1,344.8	1,237.1	1,202.4
Gas	994.5	1,020.1	1,233.8	1,132.4	1,131.8	1,329.7	1,387.2	1,304.5
Oil	28.0	20.7	14.6	19.1	22.7	20.3	16.7	13.8
Total Fossil	2,867.7	2,771.4	2,759.6	2,730.6	2,733.4	2,694.9	2,641.0	2,520.8
Renewable								
Wind	94.1	119.1	139.1	167.0	180.5	189.9	226.1	253.5
Solar	1.2	1.8	4.2	8.9	17.5	24.7	35.9	53.0
Total Renew	95.3	120.9	143.3	176.0	198.0	214.6	262.0	306.5
Other								
Nuclear	807.0	790.2	769.3	789.0	797.2	797.2	805.7	804.9
Hydro	258.7	317.7	274.4	267.0	257.7	247.3	266.1	298.6
OtherGen	77.7	78.5	81.0	84.4	85.9	86.8	84.6	84.1
Total Other	1,143.4	1,186.3	1,124.8	1,140.5	1,140.8	1,131.3	1,156.3	1,187.7
Grand Total	4,106.3	4,078.6	4,027.6	4,047.0	4,072.2	4,040.7	4,059.2	4,015.0

Notes: Annual net generation from all power plants in EIA 923 in millions of MWh's. Fuel type as reported in EIA 923.

Details on Decompositions

Deriving a decomposition formula involves specifying the base; writing the main terms of the decomposition formula in terms of the base and changes in the variables, and then determining the error. Here we derive the error for our Marshall-Edgeworth base. First note that the LHS of Eq. 3 can be written $\Delta D = \sum_i \sum_p \Delta(v_{ip} r_{ip} \theta_i Q)$. Ignoring the summations

Table iv: Decomposition of Change in Emissions from 2010-2017 (percent of 2010 total emissions)

	SO_2	NO_X	CO_2	$PM_{2.5}$
Effect				
Scale	−7.7	−9.7	−11.5	−10.7
Composition	−24.4	−23.3	−10.1	−14.8
Technique	−41.9	−16.8	−0.7	−8.2
Error	−0.1	0.2	0.1	0.1
Total	−74.0	−49.6	−22.2	−33.5

and subscripts we can write the decomposition as[42]

$$\Delta(vr\theta Q) = \bar{v}\bar{r}\bar{\theta}\Delta Q + \bar{v}\bar{r}\bar{\Delta}\theta Q + \bar{v}\Delta r\bar{\theta}\theta Q + \Delta v\bar{r}\bar{\theta}\theta Q + Error$$

where

$$Error = (\bar{v}\Delta r\Delta\theta\Delta Q + \Delta v\bar{r}\Delta\theta\Delta Q + \Delta v\Delta r\bar{\theta}\Delta Q + \Delta v\Delta r\Delta\theta\bar{Q})/4$$

The *Error* for Eq. 3 simply sums this equation over all i and p.

In the main paper, we present decompositions of damages. We can also decompose emissions. We set $v_{ipt} = 1$ for every i, p, and t in Eq. (3) and calculate the decomposition for each pollutant separately (rather than summing over p). The results are given in Table iv (expressed in percentage of total emissions in 2010).

[42] To derive the decomposition, note that the difference of a product can be written $\Delta(xy) = \Delta x\bar{y} + \bar{x}\Delta y$ and the mean of a product can be written $\overline{xy} = \overline{x} \cdot \overline{y} + \Delta x\Delta y/4$. Repeatedly applying these formulas to the product $vr\theta Q$ yields the decomposition and error.

References

[1] Ang, B.W., and S.Y. Lee. 1994. "Decomposition of industrial energy consumption: Some methodological and application issues." *Energy Economics*, 16, 83-92.

[2] Ang, B.W., and F.Q. Zhang. 2000. "A survey of index decomposition analysis in energy and environmental studies." *Energy*, 25, 1149-1176.

[3] Antweiler, W., B. Copeland, and M. Scott Taylor. 2001. "Is free trade good for the environment?" *American Economic Review*, 91, 877-908.

[4] Blinder, A. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources* 8 (4), 436-455.

[5] Borenstein, S., and J. Bushnell. 2018. "Do Two Electricity Pricing Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency", NBER working paper number 24756.

[6] Callaway, Duncan, Meredith Fowlie, and Gavin McCormick. 2017. "Location, Location, Location: The Variable Value of Renewable Energy and Demand-side Efficiency Resources." *Journal of the Association of Environmental and Resource Economists*, 5(1), 39-75.

[7] Clay, Karen, Akshaya Jha, Nicholas Z Muller, and Randy Walsh. 2018. "The External Costs of Shipping Petroleum Products by Pipeline and Rail: Evidence of Shipments of Crude Oil from North Dakota." *Energy Journal*, forthcoming.

[8] Cullen, Joseph A., and Erin T. Mansur. 2017. "Inferring Carbon Abatement Costs in Electricity Markets: A Revealed Preference Approach Using the Shale Revolution." *American Economic Journal: Economic Policy* 9 (3): 106-33.

[9] Denhom, Paul, Michael Kuss, and Robert Margolis. 2013. "Co-benefits of large scale plug-in hybrid electric vehicle and solar PV deployment." *Journal of Power Sources* 236:350 356. http://dx.doi.org/10.1016/j.jpowsour.2012.10.007.

[10] Fell, Harrison and Daniel T. Kaffine. 2018. "The Fall of Coal: Joint Impacts of Fuel Prices and Renewables on Generation and Emissions." *American Economic Journal: Economic Policy*. Vol. 10, No. 2. May. Pp. 90-116.

[11] Feng, Kuishuang, Stephen Davis, Laixiang Sun, and Klaus Hubacek. 2015. "Drivers of the US CO_2 emissions 1997-2013." *Nature Communications*, Volume 6, Article number: 7714.

[12] Fortin, N., T. Lemieux, and S. Firpo. 2011. "Decomposition Methods in Economics." Chapter 1 in *Handbook of Labor Economics*, Elsevier.

[13] Fowlie, M., S. Holland, and E. Mansur. 2012. "What Do Emissions Markets Deliver and to Whom? Evidence from Southern California's NO_X Trading Program." *American Economic Review* 102(2): 965-93.

[14] Graff Zivin, J.,M. Kotchen, and E. Mansur. 2014. "Spatial and temporal heterogeneity of marginal emissions: Implications for electric cars and other electricity-shifting policies." *Journal of Economic Behavior and Organization*, 107 (A), 248-268.

[15] Gray, W., R. Shadbegian , and A. Wolverton. 2012. "Environmental Justice: Do Poor and Minority Populations Face More Hazards?" in *Oxford Handbook of the Economics of Poverty*, Jefferson Philip N., ed., Oxford University Press.

[16] Holladay, J. Scott, and Jacob LaRiviere. 2017. "The impact of cheap natural gas on marginal emissions from electricity generation and implications for energy policy." *Journal of Environmental Economics and Management* 85: 205-27.

[17] Holland, S., E. Mansur, N. Muller, and A. Yates. 2016. "Are there environmental benefits from electric vehicles? The importance of local factors." *American Economic Review*, 106, 3700-3729.

[18] Holland, S., E. Mansur, N. Muller, and A. Yates. 2019. "Distributional effects of air pollution from electric vehicle production." To appear *Journal of the Association of Environmental and Resource Economists.*

[19] Knittel, Christopher R., Konstantinos Metaxoglou, and Andre Trindade. 2015. "Natural Gas Prices and Coal Displacement: Evidence from Electricity Markets." National Bureau of Economic Research (NBER) Working Paper 21627.

[20] Kotchen, Matthew J. and Erin T. Mansur. 2016. "Correspondence: Reassessing the contribution of natural gas to US CO_2 emission reductions since 2007," *Nature Communications*, Volume 7, Article number: 10648.

[21] Krumholz, S. 2018. "What caused the US coal-fired sulphur dioxide decline? An examination of causes, costs, and market interactions." Working Paper, University of California, San Diego.

[22] Levinson, A. 2009. "Technology, international trade, and pollution from US manufacuring." *American Economic Review*, 99, 2177-2192.

[23] Levinson, A. 2015. "A direct estimate of the technique effect: Changes in the pollution intensity of US manufacturing, 1990-2008." *Journal of the Association of Environment and Resource Economists*, 2, 43-56.

[24] McLaren, Joyce, Miller, John, OShaughnessy, Eric, Wood, Eric, and Evan Shapiro. 2016. "CO_2 emissions associated with electric vehicle charging: The impact of electricity generation mix, charging infrastructure availability and vehicle type." *The Electricity Journal*. 29. 72-88. 10.1016/j.tej.2016.06.005.

[25] Michalek, Jeremy J., Mikhail Chester, Paulina Jaramillo, Constantine Samara, Ching-Shin Norman Shiau, and Lester B. Lave. 2011. "Valuation of Plug-in Vehicle Life-Cycle Air Emissions and Oil Displacement Benefits," *Proceedings of the National Academy of Sciences of the United States of America*, 108(40): 16554-16558.

[26] Muller, N., R. Mendelsohn, and W. Nordhaus. 2011. "Environmental Accounting for Pollution in the United States Economy." *The American Economic Review*, 101(5), 1649-1675.

[27] Muller, N. 2014. "Towards the Measurement of Net Economic Welfare: Air Pollution Damage in the United States National Accounts - 2002, 2005, 2008." in *Measur-*

ing Economic Sustainability and Progress. Eds. Jorgensen, D.W., J.S. Landefeld, and P.Schreyer. NBER Book Series in Income and Wealth Vol. 72.

[28] Muller, N., P. Matthews, and V. Wiltshire-Gordon. 2018. "The distribution of income is worse than you think: Including pollution impacts into measures of income inequality." *PLoS ONE*, 13: e0192461. https://doi.org/10.1371/journal. pone.0192461.

[29] National Research Council. 2010. *Hidden Costs of Energy: Unpriced Consequences of Energy Production and Use*. Washington, DC: The National Academies Press.

[30] Nealer, Rachael, David Reichmuth, Don Anair. 2015. "Cleaner Cars from Cradle to Grave How Electric Cars Beat Gasoline Cars on Lifetime Global Warming Emissions," *Union of Concerned Scientists Report*. https://www.ucsusa.org/sites/default/files/attach/2015/11/Cleaner-Cars-from-Cradle-to-Grave-full-report.pdf

[31] Metcalf, G. 2008. "An empirical analysis of energy intensity and its determinants at the state level." *The Energy Journal*, 29, 1-26.

[32] Oaxaca, R. 1973. "Male-Female Wage Differentials in Urban Labor Markets." *International Economic Review*, 14 (3), 693-709.

[33] Samaras, Constantine and Kyle Meisterling. 2008. "Life Cycle Assessment of Greenhouse Gas Emissions from Plug-in Hybrid Vehicles: Implications for Policy," *Environmental Science and Technology*, 42: 3170-3176.

[34] Sergi, B., I. Azevdo, S. Davis, and N. Muller 2018. "Health damages from the transfer of air pollution across U.S. counties from 2008 to 2014." Working Paper.

[35] Sexton, Steve, A. Justin Kirkpatrick, Robert Harris, and Nicholas Muller. 2018. "Inefficient Siting of Rooftop Solar in the United States: Consequences for the Environment and the System Grid." Forthcoming as NBER Working Paper (October 2018)

[36] Shapiro, J., and R. Walker. 2018. "Why is pollution from U.S. manufacturing declining? The role of environmental regulation, productivity, and trade." NBER Working Paper 20879.

[37] Siler-Evans, K., I. Azevedo, M. Morgan, and J. Apt. 2013. "Regional variations in the health, environmental, and climate benefits of wind and solar generation." *PNAS*, 110(29), 11768-11773.

[38] Sun, J.W. 1998. "Changes in energy consumption and energy intensity: A complete decomposition model." *Energy Economics*, 20, 85-100.

[39] United States Environmental Protection Agency. 2011. National Emissions Inventory (NEI), 2008. Washington, DC: Office of Air Quality Planning and Standards, Emissions Inventory Group; Emissions, Monitoring, and Analysis Division.

[40] United States Environmental Protection Agency. 2014. National Emissions Inventory (NEI), 2011. Washington, DC: Office of Air Quality Planning and Standards, Emissions Inventory Group; Emissions, Monitoring, and Analysis Division.

[41] United States Environmental Protection Agency. 2017. National Emissions Inventory (NEI), 2014. Washington, DC: Office of Air Quality Planning and Standards, Emissions Inventory Group; Emissions, Monitoring, and Analysis Division.

[42] Vaishnav, P., N. Horner, and I. Azevedo. 2017. "Was it worthwhile? Where have the benefits of rooftop solar photovoltaic generation exceeded the cost?" *Environmental Research Letters*, 12, 094015.

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