American Economic Journal: Economic Policy 2020, 12(4): 244–274
https://doi.org/10.1257/pol.20190390

Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation†

By Stephen P. Holland, Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates*

Using integrated assessment models, we calculate the economic value of the extraordinary decline in emissions from US power plants. Annual local and global air pollution damages fell from $245 to $133 billion over 2010–2017. Decomposition shows changes in emission rates and generation shares among coal and gas plants account for more of this decline than changes in renewable generation, electricity consumption, and damage valuations. Econometrically estimated marginal damages declined in the East from 8.6 to 6 cents per kWh. Marginal damages increased slightly in the West and Texas. These estimates indicate electric vehicles are now cleaner on average than gasoline vehicles. (*JEL* H23, L94, Q53, Q58)

Despite its necessary role in the economy, electricity generation produces emissions of global and local pollution that causes hundreds of billions of dollars in damages annually.[1] However, during the past decade, these emissions 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 United States during 2010–2017. While emissions of each pollutant declined, some of the reductions are precipitous: SO_2 fell 75 percent. Further, a historical perspective suggests changes in emissions after 2009 (especially those of SO_2 and CO_2) clearly deviate from past trends.[2]

* Holland: Department of Economics, Bryan School of Business and Economics, University of North Carolina at Greensboro, P.O. Box 26170, Greensboro, NC 27402, and NBER (email: sphollan@uncg.edu); Mansur: Tuck School of Business, Dartmouth, 100 Tuck Hall, Dartmouth College, Hanover, NH 03755, and NBER (email: erin.mansur@dartmouth.edu); Muller: Department of Engineering and Public Policy, Tepper School of Business, Carnegie Mellon University, Posner 254C, 5000 Forbes Avenue Pittsburgh, PA 15213, and NBER (email: nzm@andrew.cmu.edu); Yates: Department of Economics and Environment, Ecology, and Energy Program, University of North Carolina at Chapel Hill, CB 3305 University of North Carolina Chapel Hill, NC 27599 (email: ajyates@email.unc.edu). Lucas Davis was coeditor for this article. We would like to thank Arik Levinson, Emily Blanchard, and Matthew Kotchen, and seminar participants at Energy Institute at Haas, TREE, Boston University, Harvard University, Tufts University, Carnegie Mellon University, NBER EEE, University of Illinois, University of Maryland, University of Kansas, 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.

† Go to https://doi.org/10.1257/pol.20190390 to visit the article page for additional materials and author disclosure statement(s) or to comment in the online discussion forum.

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

[2] See Figure A1 in the Appendix for data on the period 1990–2017.

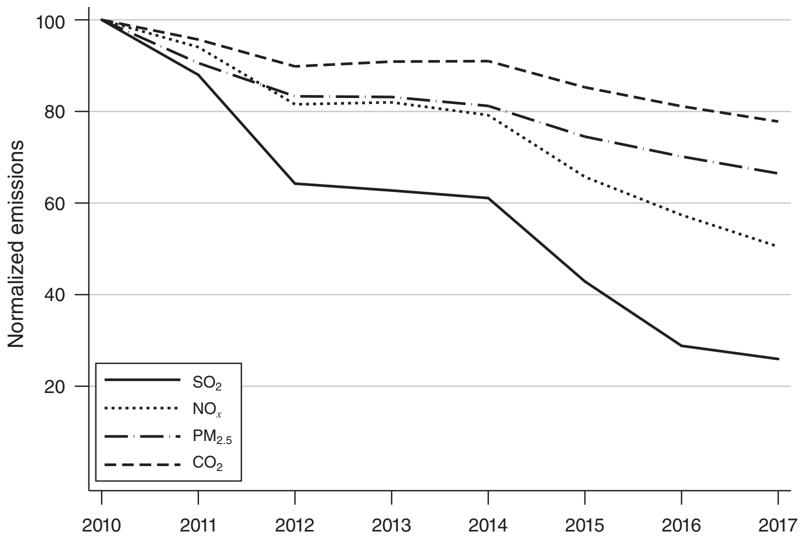

FIGURE 1. POWER PLANT EMISSIONS OF FOUR POLLUTANTS, 2010–2017

Note: This figure is normalized such that emissions in 2010 equal 100.

Source: EPA's Continuous Emissions Monitoring System (EPA 2010–2017)

Several studies have analyzed the causes and consequences of this decline by focusing on pollutants in isolation.[3] In contrast, we calculate the economic value of these reductions. The distinguishing characteristic of our analysis is matching time- and location-specific damage valuations to corresponding emissions, which enables three unique contributions. First, we calculate the magnitude of the decline in total damages and how this decline is distributed across location. Second, we use a decomposition to quantify the relative importance of various factors such as fuel switching and pollution control equipment to the decline in damages. Third, we econometrically estimate whether the changes in the electricity sector that led to the decline in total damages also led to a decline in the marginal damage of electricity consumption.

Our first contribution calculates the decline in damages. We use the social cost of carbon and the AP3 integrated assessment model (Clay et al. 2019) to assess pollution exposure, physical impacts, and, ultimately, monetized damage. Three factors complicate the translation of emission changes into damages. First, the importance of a given pollutant depends not only on the level of emissions but also on

[3] Feng et al. (2015), Kotchen and Mansur (2016), Cullen and Mansur (2017), Holladay and LaRiviere (2017), and Fell and Kaffine (2018) analyze factors that contribute to the decline in CO_2. Linn and McCormack (2019) examine the effect of markets and regulation on the decline in NO_x and SO_2 emissions. Krumholz (2018) analyzes factors that contribute to the decline in SO_2. Knittel et al. (2015) and Coglianese et al. (2017) analyze the reduction in coal production rather than emissions directly. Henneman, Choriat, and Zigler (2019) focus on health outcomes due to the decline in emissions from coal plants. Contemporaneous work by Andaloussi (2018) is perhaps closest to our analysis because it considers all pollutants, does a decomposition, and does a back-of-the-envelope damage calculation. Our work differs from Andaloussi (2018) in that we decompose damages rather than emissions, determine marginal damages from electricity consumption, and, most importantly, link emissions to time- and location-specific damage valuations.

damages per unit of emissions. Second, damages per unit of 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 local population, the atmospheric conditions affecting secondary $PM_{2.5}$ formation, and the global stock of CO_2 in the atmosphere. Accounting for all three factors, we find that total damages from power plants fell from $245 billion in 2010 to $133 billion in 2017, which is a decline of $112 billion or about $350 per capita. The largest reductions in damages per capita accrue to residents of West Virginia, Pennsylvania, and Ohio.

Our second contribution decomposes the decline in damages. Decomposition analysis is widely used to quantify the relative importance of various factors and can provide a road map or testable hypotheses for subsequent analysis.[4] Our preferred approach decomposes the decline in damages from fossil-fired electricity generation into four effects: technique (capturing changes in emissions rates), composition (capturing fuel switching among fossil-fired power plants), scale (capturing changes in total fossil generation), and valuation (capturing changes in the spatially and temporally heterogeneous damage valuations). The first three effects decrease damages, the largest being technique ($63 billion primarily at coal plants with new SO_2 control technology) and composition ($60 billion primarily from coal plants that reduced generation or exited), but the scale effect ($25 billion primarily from renewables) is also substantial. The valuation effect increases damages by $35 billion. Ignoring the spatial and temporal heterogeneity in the damage valuations would overstate the decline in damages but not change the rank ordering of the technique, composition, and scale effects.

Although damages from electricity generation have greatly decreased, this fact does not in and of itself have implications for policies such as support for transportation electrification or distributed renewable energy. To evaluate these policies, one must determine the change in damages from a change in consumption of electricity (i.e., the marginal damages). Our third contribution econometrically estimates whether marginal damages declined concurrently with total damages. To estimate marginal damages in the three electricity interconnections, we simplify and extend the econometric methods pioneered in Graff Zivin, Kotchen, and Mansur (2014) and Holland et al. (2016).[5] Marginal damages decline in the East from 8.6 cents per kilowatt-hour

[4] Our decomposition technique is most closely related to Levinson (2009, 2015), although his application is trade and the environment. Sun (1998) and Melitz and Polanec (2015) provide overviews of decomposition techniques. Other prominent environmental decompositions include Antweiler, Copeland, and Taylor (2001); Metcalf (2008); and Shapiro and Walker (2018). See Fortin, Lemieux, and Firpo (2011) for a survey of decompositions in labor economics and Ang and Zhang (2000) for a survey in environmental economics.

[5] Our analysis is distinguished by the more recent time frame, our multipollutant approach, and estimation of standard errors. Siler-Evans et al. (2013) and Callaway, Fowlie, and McCormick (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, Kuss, and Margolis (2013) and McLaren et al. (2016); or simply analyze the average emissions factor within a state, for example: Samaras and Meisterling (2008); Michalek et al. (2011); and Nealer, Reichmuth, and Anair (2015).

(kWh) in 2010 to 6 cents per kWh in 2017. In the West and Texas, marginal damages in 2010 are lower than in the East but increase slightly over time. In contrast, average damages decline in all three regions, illustrating that average damages are not a good proxy for marginal damages in policy analysis.

We use our estimates of marginal damages to evaluate one policy that increases grid electricity consumption (subsidies for electric vehicles) and another policy that decreases it (subsidies for solar panels). From 2010 to 2017, electric vehicles switch from being dirtier on average than their gasoline-powered counterparts to being cleaner, though considerable heterogeneity across locations remains. The environmental benefit of solar panels decreases over time in the East but increases in the West and Texas.

Myriad public policies and market forces influenced electricity consumption, generation, and pollution control during this period. On the consumption side, market forces include the electrification of transportation, the rise of data centers, and improvements in heating and cooling technologies, while public policies encourage energy efficiency and technology adoption.[6] 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.[7] 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 were tightened for both $PM_{2.5}$ and tropospheric ozone. States with counties that violate these standards 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.[8] An important caveat to our work is that we do not attempt to assign causal implications to any of the these market forces or policies, but rather we calculate their combined effect on damages, decompose the effect into broad categories, and estimate marginal damages.

I. Calculating Damages

A. *Data and Methods*

Calculating the decline in damages requires data on emissions over time and a method for valuing the emissions of different pollutants at different times and locations. EPA's Continuous Emissions Monitoring System (CEMS) reports hourly electricity generation and hourly emissions of SO_2, NO_x, and CO_2 at approximately 1,500 regulated fossil-fuel fired power plants (generally above 25-megawatt capacity) (EPA 2010–2017). Emission rates from the National Emissions Inventory

[6] Examples include weatherization programs, Energy Star appliance rebates, and electric vehicle subsidies.
[7] Examples include renewable production tax credits and state-level renewable portfolio standards.
[8] These include the Acid Rain Program, the Clean Air Interstate Rule, the Cross-State Air Pollution Rule, the Clean Power Plan, and the Mercury and Air Toxics Standards. Note that these regulations may also affect generation.

(NEI) and hourly generation are used to impute hourly $PM_{2.5}$ emissions (NEI 2008, 2011, 2012).[9] Plant characteristics and locations come from the EPA's Emissions and Generation Resource Integrated Database (EPA 2009–2016).

To value these emissions, define *damage valuations* v_{pit} as the damage per unit of pollutant p emitted by source i at time t. 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), which is \$35.36 per metric ton of CO_2 in 2010 and grows at 3 percent annually.[10]

For local pollutants, the AP3 integrated assessment model determines damage valuations for each individual plant. For primary $PM_{2.5}$ emissions, AP3 models physical dispersion. For SO_2 and NO_x, AP3 accounts for chemical and physical processes in the atmosphere to map emissions of these pollutants from a source location (i.e., an electric power plant) into ambient concentrations of secondary $PM_{2.5}$ at various receptor locations (i.e., counties in the contiguous United States). AP3 then maps ambient concentrations of $PM_{2.5}$ into premature mortality risk using peer-reviewed concentration-response functions.[11] Finally, it monetizes mortality risk using the value of statistical life (EPA 2010). 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 NEI.[12] 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.[13] Table A2 in the Appendix shows that average damage valuations increase over time.

With these damage valuations in hand, total damages D_t are given by

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

where e_{pit} are emissions of pollutant p from power plant i at time t. Equation (1) assumes that local damage valuations are independent of the emissions from power plants. If this does not hold, equation (1) understates the decline in damages.[14]

The US electricity grid is divided into the East, West, 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

[9] Power plants not in the NEI are assigned an average $PM_{2.5}$ emissions rate by fuel type. See the Appendix. Summary statistics for the emission data are given in Table A1 in the Appendix and are illustrated in Figure 1.

[10] See https://19january2017snapshot.epa.gov/climatechange/social-cost-carbon_.html. All values in the paper are reported in 2014 dollars.

[11] 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 because of 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.

[12] NEI are published with a three-year lag.

[13] Alternatively, we could use linear extrapolation to extend the trend from 2011 to 2014 forward to 2017. As shown in Table B-11 and Figure B-1 of online Appendix B, our results are robust to this alternative.

[14] An alternative procedure that holds damage valuations fixed at their final 2017 values overstates the decline in damages. This procedure is analyzed in the online Appendices.

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								
East	213.7	196.5	163.8	166.9	173.6	139.2	113.5	103.5
West	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

Note: Damages in billions of 2014 dollars aggregated across all CEMS power plants using AP3 damage estimates.

we refer to the quantity demanded of electricity as "load," and the quantity supplied as "generation."[15]

B. *Total Damages and Their Distribution*

Evaluating equation (1) for each year gives the total damages from emissions of local and global pollutants by CEMS power plants. Table 1 shows that total damages in 2010 were $245 billion, or about $800 per capita. By 2017, damages had fallen 46 percent to $133 billion. This is a decline of $112 billion, or about $350 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 equation (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 ($138 billion) followed by CO_2 emissions ($79 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 percent of the decline in damages is due to reduction in damages from SO_2 emissions, and this large decline caused SO_2 to become a less important source of harm. Panel B shows the damages by fuel type. Damages from coal-fired power plants are the main source of

[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.

damages, and their damages decline dramatically over time. They account for more than 100 percent of the decline from 2010 to 2017 because damages from gas-fired power plants actually increased. Panel C shows the damages by 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 determine which locations benefited from the decline in damages, we calculate damages received. Because CO_2 is a global pollutant, we do not include it in these calculations.[16] Due to the dispersal of pollutants in the atmosphere, a given location may receive damages from many power plants. Let δ_{pijt} be the damages in county j due to emissions of a unit of local pollutant p from plant i as determined by AP3. The damages received by county j are determined by adding across all local pollutants and all power plants:

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

The damage received by each county in 2010 are shown in Figure 2, panel A. Counties in Pennsylvania, New York, and Ohio, including rural counties, account for a large share of the damages in 2010. In addition, we see significant damages in other large metropolitan areas. Holding the scale constant, Figure 2, panel B shows the damages received in 2017. There are large reductions in damages relative to 2010, particularly in the Northeast.

Because damages depend on the number of people harmed, we also examine this change in damages received on a per capita basis in Figure 3. This figure reflects improvements in air quality as experienced by the average person in the county. The declines are greatest in the Mid-Atlantic region, but are also substantial throughout the Northeast and parts of the Midwest and South. Aggregation of these results to the state level reveals that the average individual in West Virginia received damages of $1,746 in 2010 and $492 in 2017, for a decline of $1,253.[17] Pennsylvania and Ohio also received large per capita reductions in damages ($988 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. It is important to stress that damages received by a state may be influenced by emissions in other states. For example, much of the decline in damages in West Virginia is due to emissions reductions from power plants throughout the Ohio River Valley.

We next explore the factors that contributed to the significant decline in damages.

[16] The SCC measures global damages from carbon over hundreds of years. It is difficult to attribute this damages to specific places in the United States.

[17] Online Appendix A contains additional information about the distribution of damages received, including damages received by county for each year in 2010–2017 (see Figure A-2), the decline in damages over 2010–2017 by county (see Figure A-3), and the aggregation to the state level (see Table A-1).

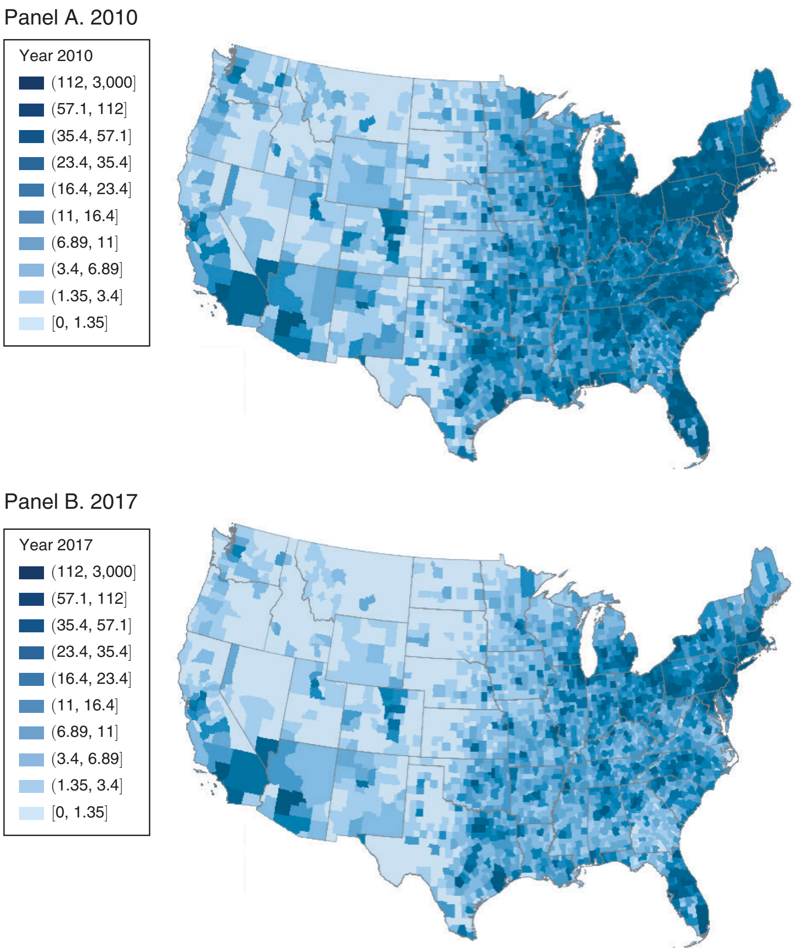

Figure 2. Local Damages Received by County and Year (millions of 2014 dollars)

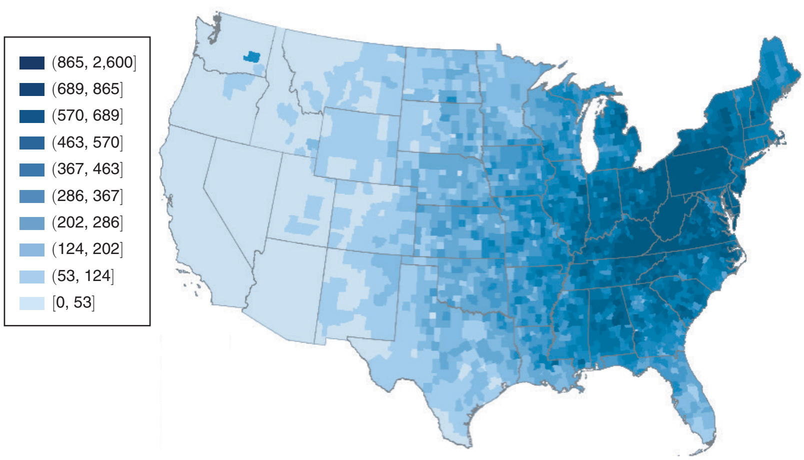

Figure 3. Reduction in Local Damages Received per Capita by County 2010–2017

II. Decomposing the Decline in Damages

Decompositions can analyze which factors are quantitatively important in the decline in damages. We could decompose equation (1) directly into a valuation effect and an emissions effect.[18] But to examine how changes in electricity generation contribute to the changes in emissions, we further decompose the emission effect into the scale, composition, and technique effects, which capture total fossil generation, generation shares, and emissions rates. This is similar to Levinson's (2009) analysis of manufacturing, except that in the electricity sector not all plants emit pollution.

To derive our decomposition equation, let q_{it} be electricity generation at fossil plant i at time t and $Q_t = \sum_i q_{it}$ be total fossil generation.[19] We can write equation (1) as

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

where $r_{ipt} = e_{ipt}/q_{it}$ is the emissions rate for pollutant p at plant i and $\theta_{it} = q_{it}/Q_t$ is the share of fossil electricity generated by plant i.[20] Next, 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 equation (2) gives our decomposition equation:

$$\begin{aligned} \Delta D = {} & \underbrace{\sum_i \sum_p \bar{v}_{ip} \bar{r}_{ip} \bar{\theta}_i \Delta Q}_{\text{Scale}} + \underbrace{\sum_i \sum_p \bar{v}_{ip} \bar{r}_{ip} \Delta \theta_i \bar{Q}}_{\text{Composition}} + \underbrace{\sum_i \sum_p \bar{v}_{ip} \Delta r_{ip} \bar{\theta}_i \bar{Q}}_{\text{Technique}} \\ & + \underbrace{\sum_i \sum_p \Delta v_{ip} \bar{r}_{ip} \bar{\theta}_i \bar{Q}}_{\text{Valuation}} + error, \end{aligned} \tag{3}$$

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, $\bar{Q} = (1/2)(Q_t + Q_0)$).

Several things are worth noting about our decomposition equation. First, it decomposes the product of four variables, which rules out some approaches used in the literature.[21] Second, the structure of equation (3) resembles the derivative of equation (1) with respect to time using the product rule. Intuitively, the product rule isolates the change in one variable while holding the other variables constant at the base value. In equation (3), the technique effect, for example, shows how much the change in emissions rates contributes to the change in damages, keeping valuation, generation shares, and fossil generation constant. Our base, which is analogous to a Marshall-Edgeworth price index, is the average of the initial and final values and is

[18] See Table B-23 in online Appendix B.

[19] Below we discuss using total generation rather than total fossil generation.

[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). See Melitz and Polanec (2015) for a similar analysis of entry and exit.

[21] Melitz and Polanec (2015) discuss several two-variable decompositions.

clear and easy to interpret.[22] Third, the product rule analogy is not perfect, however, because the change in time in equation (3) is discrete, not continuous. As a result, equation (3) includes nonzero interaction terms such as $\bar{v}_{ip} \Delta r_{ip} \Delta \theta_i \Delta Q$, which we aggregate and call "error" (the complete expression for error is given in the Appendix). Some decompositions include the interaction terms explicitly or implicitly in one of the main effects, which makes the base values difficult to interpret.[23] Our decomposition has a clear base at the cost of a small error.[24] Finally, as we shall see, our decomposition equation allows us to break up the main effects into component parts, which elucidate the underlying mechanisms.

Table 2 shows the decomposition over 2010 to 2017. The main column accounts for both spatial and temporal heterogeneity in the damage valuations and thus captures our best estimate of the decline in damages. The scale effect (totaling −\$25 billion) 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 SCC.[25] Because of the offsetting valuation effect, the scale, composition, and technique effect account for more than 100 percent of the total decline in damages.

A unique feature of our paper is the spatial and temporal heterogeneity in the damage valuations v_{ipt}. To understand the importance of this heterogeneity, we modify the decomposition by limiting the heterogeneity in three ways. First, ignore the spatial heterogeneity by holding all damage valuations fixed at the average value over all power plants for a given year. If emissions reductions occur primarily at low-damage plants then this will overstate the decline in damages. The column labeled v_{pt} in Table 2 shows that the decline in damages would be \$120 billion, which overstates the decline by about \$8 billion. Figure B-5 in online Appendix B shows that emissions reductions do occur primarily at low-damage plants for all three local pollutants. Second, ignore the temporal heterogeneity (but allow spatial heterogeneity) by holding all damage valuations fixed at the average over all years for a given plant. Because damage valuations are actually increasing over time (see Table A2 in the Appendix), this leads to an overstatement of the decline in damages. The column labeled v_{ip} in Table 2 shows the decline in damages would be \$154 billion, which overstates the decline by about \$42 billion.[26] Third, ignore both temporal and spatial heterogeneity by using a single value for each pollutant equal

[22] 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.

[23] The two variable decomposition $\Delta(xy) = x_t \Delta y + y_0 \Delta x$ is exact but has an unclear base. See Sun (1998).

[24] Online Appendix Table B-6 presents results using the Laspeyres base, the Paasche base, and yet another base we call the average base. These bases yield much larger errors.

[25] In Table A4 in the Appendix, we decompose emissions rather than damages. The technique effect is more prominent for SO_2. Online Appendix Table B-4 shows the decompositions for each interconnection.

[26] By definition, the valuation effect is zero.

Table 2—Decomposition of Change in Damages from 2010 to 2017

	Main	Limited heterogeneity		
	v_{ipt} Spatial temporal	v_{pt} No spatial temporal	v_{ip} Spatial no temporal	v_{p} No spatial no temporal
Scale	−25.19	−27.90	−25.69	−28.55
Composition	−59.98	−61.42	−63.97	−66.54
Technique	−62.58	−69.91	−64.56	−72.22
Valuation	35.28	38.14	0.00	0.00
Error	0.33	0.43	0.43	0.46
Total	−112.14	−120.65	−153.79	−166.84

Note: Effects are in billions of 2014 dollars.

to the average of all valuations for all power plants. The v_p column shows the interaction between ignoring both the spatial and temporal heterogeneity exacerbates the individual effects and leads to an \$55 billion overestimate of the decline in damages. The relative importance of the scale, technique, and composition effect does not vary much across columns. In contrast, the heterogeneity has a large effect on the estimate of total damages, primarily from the temporal heterogeneity.

To illustrate the mechanisms underlying the four effects of our decomposition, we divide the effects into component parts. For the scale effect, consider changes in load and generation from wind, solar, nuclear, and hydropower.[27] Because load must equal total generation, the change in fossil generation, ΔQ, in equation (3) can be written

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

where ΔL is the change in load, ΔR is the change in renewable generation, ΔN is the change in nuclear generation, ΔH is the change in hydroelectric generation, and ΔO is the residual.[28] Substituting for ΔQ in equation (3) gives the results in panel A in Table 3. The increase in renewable generation is by far the biggest contributor to the scale effect as it reduced damages by \$16 billion.

The composition effect captures anything that changes the generation shares: market forces or regulations that shift generation from coal-fired to gas-fired plants or cause entry/exit. To study these mechanisms, we group the power plants into eight categories and then determine the composition effect for a given category by summing the plant specific composition effect $\left(\sum_p \bar{v}_{ip} \bar{r}_{ip} \Delta\theta_i \bar{Q}\right)$ over all the power plants in that category. The "Coal" row in panel B of Table 3 shows the portion of the composition effect attributable to plants whose primary fuel type is coal throughout the time period is \$32 billion. The "Exit of coal" plants contributed an additional

[27] 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.

[28] Annual load comes from Federal Energy Regulatory Commission form 714 (FERC 2010–2017) and renewable, nuclear, and hydroelectric generation come from Energy Information Administration form 923 (EIA 2010–2017a). See Table A3 in the Appendix and Table B-15 in online Appendix B for summary statistics.

Table 3—Components of the Decomposition of Change in Damages from 2010 to 2017

	Main
Panel A. Scale (total fossil generation)	
Load ΔL	−3.56
Renewable $-\Delta R$	−15.86
Nuclear $-\Delta N$	0.15
Hydroelectric ΔH	−3.00
Other $-\Delta O$	−2.92
Total scale	−25.19
Panel B. Composition (generation shares)	
Coal	−32.03
Switch from coal	−5.31
Gas	4.48
Entry of coal	2.40
Entry of gas	2.68
Exit of coal	−31.05
Exit of gas	−0.43
Other	−0.71
Total composition	−59.98
Panel C. Technique (emissions rate)	
Coal—new SO_2 control technology	−35.71
Coal—no new technology	−8.92
Switch from coal	−15.92
Gas	−2.45
Other	0.42
Total technique	−62.58
Panel D. Valuation	
SO_2	15.69
NO_x	2.37
$PM_{2.5}$	1.22
CO_2	16.00
Total valuation	35.28
Error	0.33
Total	−112.14

Notes: Effects are in billions of 2014 dollars. Fuel types are from EPA's Emissions and Generation Resource Integrated Database (EPA 2009–2016). "Coal" and "Gas" denote plants in which the primary fuel type did not change. "Switch from coal" denotes plants in which the 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 technology" denotes plants that installed SO_2 emissions control technology between 2010 and 2017.

$31 billion and the "Switch from coal" plants reduced damages by $5 billion.[29] These results are consistent with Table A3, which shows that coal's share of fossil generation fell from 64 percent to 38 percent. The increase in generation share from existing gas plants and the entry of new coal and gas plants only contributed modestly to the composition effect.

[29] See Tables B-16 to B-21 in online Appendix B for additional information on plant entry and exit.

The technique effect captures anything that changes a plant's emissions rate including: installing emissions control technologies; 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. To study these mechanisms we group the power plants into five categories. Panel C of Table 3 shows that a \$36 billion decline in damages comes from coal plants that installed SO_2 emissions control technologies, such as flue gas desulfurization (scrubbers) or dry sorbent injection, between 2010 and 2017. These plants account for over half of the technique effect and approximately 25 percent of the overall decline in damages.

As discussed in the introduction, power plants were subject to a number of pollution regulations during this time period. Some evidence about the influence of these regulations on the decision to adopt SO_2 emission control can be gleaned from EPA's Air Market Program, which reports the regulations that apply to each plant in CEMS in each year. Figure 4 summarizes the regulations listed for a plant in the year in which the plant installed SO_2 emissions control.[30] Before our sample period begins in 2010, most pollution control equipment was installed at plants under EPA's Acid Rain Program or New Source Performance Standard. The Acid Rain Program features a cap-and-trade market for SO_2 permits, and the permit price from the annual EPA auction is also shown in Figure 4 (EPA 1994–2017). In 2010, the SO_2 permit price fell to \$40 per ton from over \$1,000 per ton in 2006, but emissions control continued to be installed to comply with other regulations. Indeed, there were a substantial number of installations since 2010, and plants that made these installations were responsible for the \$36 billion decline in damages noted above. Between 2010 and 2014, most of the installations were under the Acid Rain Program and the Clean Air Interstate Rule. After 2014, most of the installations were under the EPA's Mercury and Air Toxics Standards. As it turns out, scrubbers are one compliance strategy for these standards.

Lastly, we consider the component parts of the valuation effect. Damage valuations 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. To study these effects, we calculate the valuation effect separately for each pollutant. Panel D of Table 3 shows the bulk of the valuation effect comes from SO_2 and CO_2.

There are two important caveats to interpreting our decompositions. First, because our emissions rates are measured at the plant level, switching to cleaner fuels within a power plant contributes to the technique effect. An alternate decomposition might label this as composition effect. About \$16 billion of our 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 units. Table B-22 in online Appendix B shows that the within-plant share of generation by coal decreased while the gas share increased from 2010 to 2017. Second, our scale effect is based on total

[30] Figure B-4 in online Appendix B shows similar data for NO_x pollution control equipment.

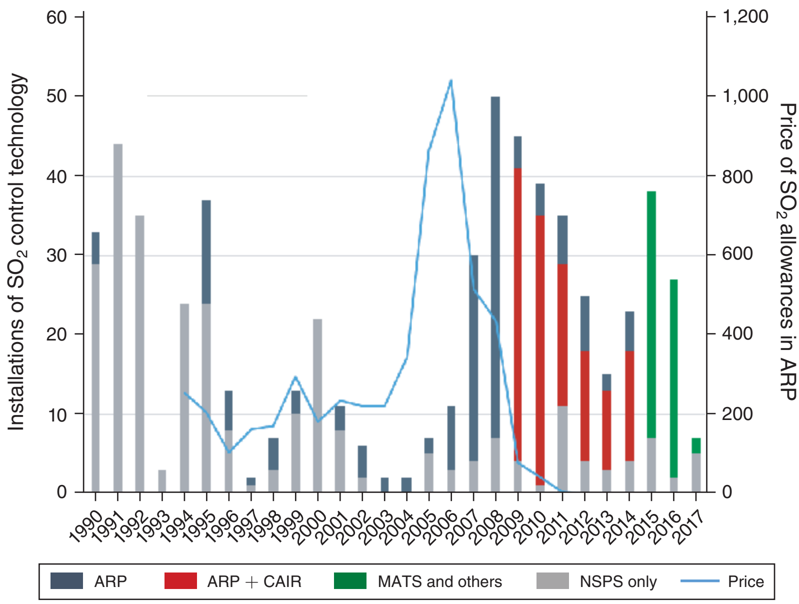

FIGURE 4. POWER PLANT SO_2 EMISSIONS CONTROL INSTALLATIONS

Notes: The year is the first year a pollution control technology is active as indicated by EIA form 860 (EIA 2010–2017b). "ARP" is Acid Rain Program; "CAIR" is Clean Air Interstate Rule; "MATS" is Mercury and Air Toxic Standard; and "NSPS" is New Source Performance Standard.

fossil generation, so changes in renewables contribute to it. An alternate decomposition might label this as composition effect. Using total electricity load L_t instead of fossil generation Q_t, the decomposition in Table B-5 in online Appendix B shows that almost all of the scale effect is shifted into the composition effect. However, this decomposition does not allow us to quantify the effects of renewables on damages.

Although Table 2 decomposes the change in damages over the entire time period, we can also decompose the change in damages for each year relative to 2010, as shown in Figure 5.[31] Damages generally decline throughout the sample so the effects are increasing over time. However, the relative importance of the different effects is consistent in most years. 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.

We conclude this section with a sensitivity analysis of two key parameters in our method for determining damages: the SCC and the value of statistical life (VSL). The baseline VSL of \$8.7 million is the EPA's recommended estimate (see EPA 2010, Appendix B, converted from year 2006 dollars). We consider a low value of

[31] Online Appendix Table B-3 reports small standard errors for these effects. Standard errors are unnecessary since we have a census of CEMS power plants. However, the standard errors inform whether the reductions are similar across plants or are driven primarily by outliers.

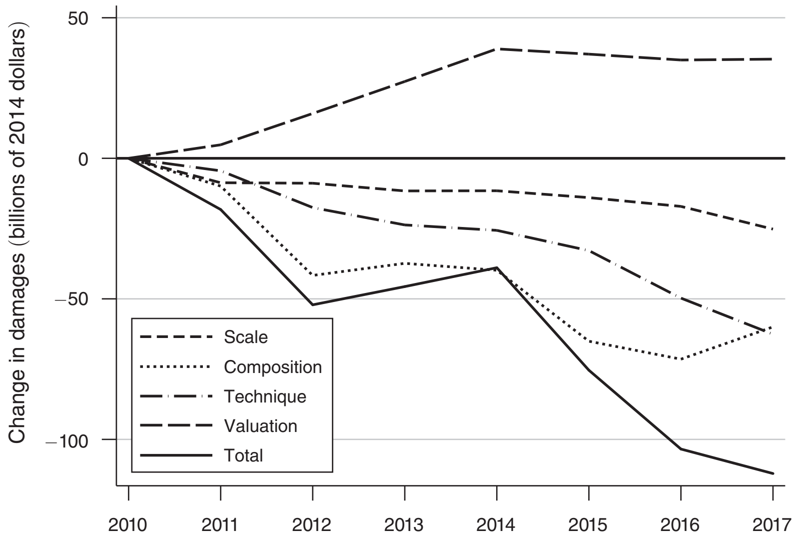

Figure 5. Decomposition of Change in Damages by Year

Notes: All changes are relative to 2010. Data are in online Appendix Table B-2.

$3.9 million based on stated preference studies and a high value of $13.3 million based on hedonic wage studies (see Kochi, Hubbell, and Kramer 2006, Table II, converted from year 2000 dollars). The baseline SCC is also the EPA's recommended estimate, which starts at $35.36 in 2010 and grows at 3 percent per year. We consider a high value that starts at $44.00 and a low value that starts at $26.74 in 2010, which are approximately 25 percent deviations.

The sensitivity of our damage calculations are given in Table 4 and the sensitivity of our decompositions are given in Table 5. Both the VSL and the SCC have a significant effect on the absolute level of damages. The VSL also has a significant effect on the change in damages over time, but the SCC does not. As for the decompositions, there is some variation in the magnitudes of the various effects, but, in general, their relative importance is similar across all values for the VSL and SCC.

III. Implications for Policy Analysis

Sections I and II showed that the grid has become much cleaner and explored the mechanisms of how this occurred. We now assess how these changes in the grid have implications for policies that affect electricity consumption. For this, we need to calculate a damage function that specifies how a change in consumption changes damages. One way to calculate the damage function that would follow directly from the results above is to assume a proportional relationship between damages and consumption (i.e., simply calculate average damages). We adopt a more general procedure that estimates marginal damages of consumption and use them to evaluate policies for electric vehicle and solar panel adoption.

Table 4—Damages from 2010 to 2017: Sensitivity

	2010	2011	2012	2013	2014	2015	2016	2017
Baseline	245	227	193	199	206	169	141	133
High VSL	332	305	254	263	272	217	175	163
Low VSL	142	134	119	122	126	111	100	96
High SCC	264	246	211	218	226	188	160	151
Low SCC	226	208	174	180	186	150	123	114

Notes: Effects are in billions of 2014 dollars. Baseline VSL is \$8.7 million, high VSL is \$13.3 million, and low VSL is \$3.9 million. Baseline SCC starts at \$35.36 in 2010, high SCC starts at \$44.00, and low SCC starts at \$26.74.

Table 5—Decomposition of Change in Damages from 2010 to 2017: Sensitivity

	Baseline	High VSL	Low VSL	High SCC	Low SCC
Scale	−25.19	−32.84	−15.98	−27.78	−22.61
Composition	−59.98	−84.63	−30.53	−63.13	−56.82
Technique	−62.58	−97.66	−20.13	−61.52	−63.65
Valuation	35.28	45.38	21.21	39.18	31.38
Error	0.33	0.63	−0.13	0.27	0.39
Total	−112.14	−169.12	−45.56	−112.98	−111.31

Notes: Effects are in billions of 2014 dollars. Baseline VSL is \$8.7 million, high VSL is \$13.3 million, and low VSL is \$3.9 million. Baseline SCC starts at \$35.36 in 2010, high SCC starts at \$44.00, and low SCC starts at \$26.74.

A. *Damage Functions*

Figure 6 illustrates two possible ways in which a damage function that relates air pollution damages to electricity use may change over time. In Case A, 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, 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. Notice that simply calculating average damages would not correctly capture any of these functions nor the changes illustrated.

Empirically assessing changes in damage functions requires several choices, starting with the geographic scope. Our main analysis focuses on the electricity interconnections: East, West, and Texas.[32] Second, the measure of electricity use must be determined. We use load as our primary measure of electricity use but revisit this assumption below. Third, power plants face dynamic production decisions due to ramping constraints and startup costs. These considerations may complicate the relationship between the time at which electricity is consumed and how power plants operate. Our estimates examine the average response to these dynamic processes.[33]

[32] We explore other definitions of geographic scope in Table C-4 in online Appendix C.
[33] Mansur (2008), Reguant (2014), and Cullen (2015) analyze dynamic considerations in other contexts.

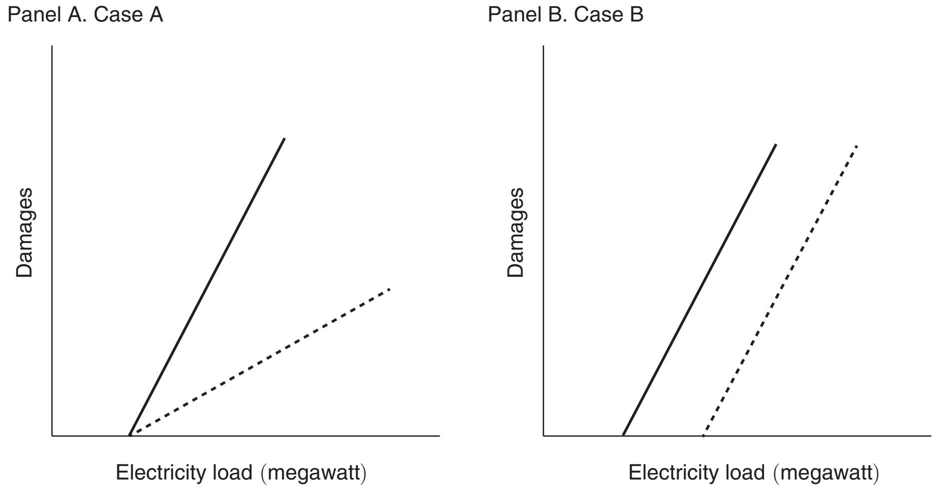

Figure 6. Shifts in the Damage Function: Two Possibilities

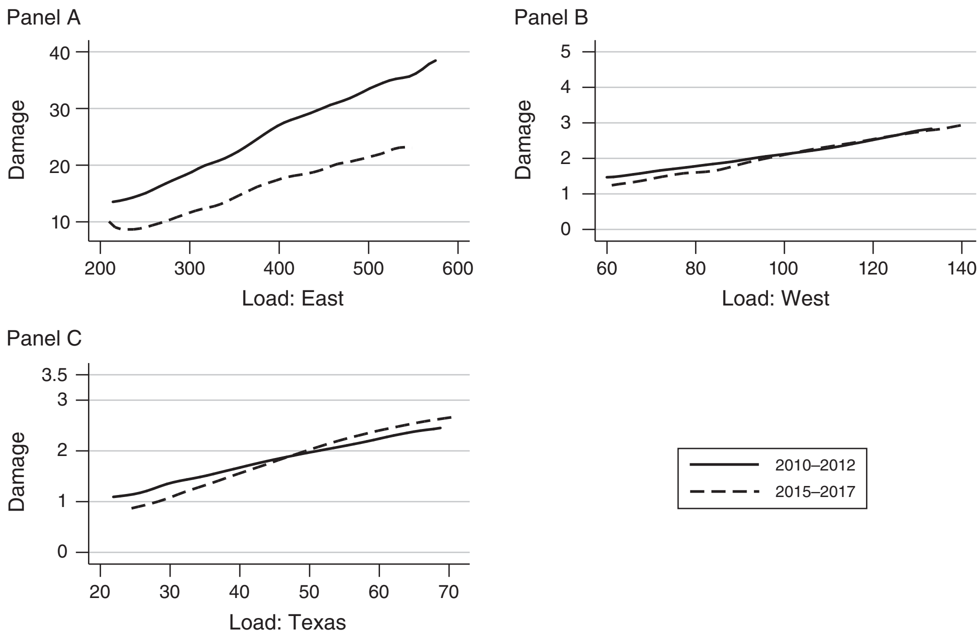

Figure 7. Local Polynomial Estimates of Damage Functions

Notes: These panels are local polynomial regressions of hourly damages on hourly load for the three interconnections: East, West, and Texas. Load is measured in thousands of megawatt-hours, and damages are measured in millions of 2014 dollars. In the East, mean load is 339 and mean damage is 21. In Texas, mean load is 39, and mean damage is 1.8. In the West, mean load is 85, and mean damage is 2.2.

We first use nonparametric regressions to estimate the damage function using flexible functional forms. Figure 7 shows local polynomial regressions for each of the three interconnections in the early (2010–2012) and late (2015–2017) 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 2015–2017. The West and Texas are different, as 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.[34]

The univariate nonparametric regressions do not show evidence of substantial nonlinearities. 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 nonparametric regressions on the residuals. The results are shown in Figure C-4 in online Appendix C. Once again we see no substantial nonlinearities, so we turn to linear regression.

B. *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

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

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 $\times$ 12 months $\times$ 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 cents per kWh and estimate Newey-West standard errors using 48-hour lags.

The results of estimating equation (4) with and without the annual trend are given in Table 6. For the East, the marginal damage estimate over the sample is 7.3 cents per kWh with a tight standard error. This social cost is substantial relative to the average retail price of electricity (13 cents per kWh in 2017).[35] The annual trend shows a statistically significant decrease in marginal damages over this time frame starting at 8.6 cents per kWh in 2010 and decreasing by 0.38 cents per kWh per year to 6 cents per kWh in 2017. Figure 8 illustrates this trend line and shows that the annual point estimates are tightly clustered around the trend line.[36] In the West and Texas, the marginal damages estimated over the sample are much lower: 2.5 cents per kWh in the West and 3.2 cents per kWh in Texas. However, the trends show a small but statistically significant *increase* in marginal damages of 0.1 cents per kWh per year. Annual estimates with confidence intervals, shown in Figure 8, are again tightly clustered around the increasing trend lines.

[34] Figures C-1 to 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.

[35] https://www.eia.gov/energyexplained/index.php?page=electricity_factors_affecting_prices.

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

Table 6—Marginal Damage Estimates: Main

Variables	(1)	(2)
East		
Load (β)	7.321	8.644
	(0.071)	(0.096)
Load trend (γ)		−0.377
		(0.024)
West		
Load (β)	2.492	2.032
	(0.03)	(0.047)
Load trend (γ)		0.122
		(0.011)
Texas		
Load (β)	3.227	2.825
	(0.053)	(0.085)
Load trend (γ)		0.11
		(0.023)
Observations	70,128	70,128

Notes: Newey-West standard errors (48-hour lag). Dependent variable is hourly damages in the interconnection. Coefficient estimates are in cents per kWh. Regressions are unweighted and include month of sample by hour fixed effects—i.e., 2,304 (= 8 × 12 × 24) fixed effects.

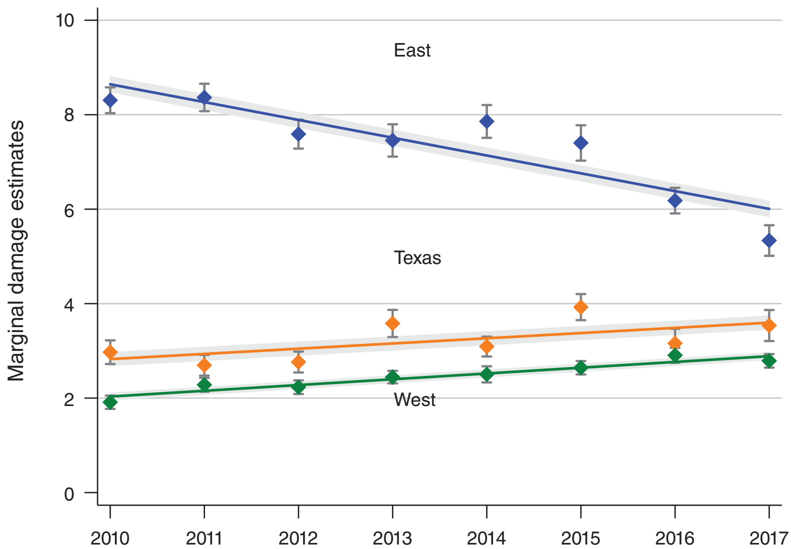

Figure 8. Marginal Damages by Interconnection

Notes: Estimates are in cents per kWh. Predicted trends are from regressions reported in Table 6. Annual point estimates with 95 percent confidence intervals are from regressions reported in online Appendix Table C-1.

Marginal damages are appropriate for policy, but total damages and average damages (damages divided by load) are frequently used measures of grid cleanliness.[37]

[37] 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.

Table 7—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%

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

In 2010, average damages were 7.0, 2.3, and 4.4 cents per kWh in the East, West, and Texas, respectively (see online Appendix Table C-5). Table 7 shows that 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.

Our main results weight all hours equally and are appropriate to evaluate a use of electricity that is distributed uniformly across hours and seasons (e.g., refrigeration). However, other electricity uses may have different time 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 8 shows marginal damage estimates from weighted regressions that account for various time profiles. For the East, relative to the main results, the electric vehicle charging profile shows higher initial marginal damages and a steeper decline. Conversely, the "Daytime hours" profile shows lower initial 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 8 to assess two prominent environmental policies: the subsidy for electric vehicle purchases and the subsidy for household solar adoption. 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. Electric vehicles cause air pollution damages due to the emissions from power plants that charge them. The marginal damages in the "Electric vehicle charging" row in Table 8 together with electricity use (kWh per mile) determine the damages per mile from an electric vehicle in each interconnection. Gasoline vehicles cause damages due to emissions from their tailpipes. Emissions per mile from Holland et al. (2016) and damage valuations from AP3 determine damages per mile for each county.

Table 9 shows the annual environmental benefit across all counties in the contiguous United States for an electric versus gasoline Ford Focus driving 15,000 miles per year.[38] For 2010, the annual environmental benefit has a substantial range across counties (from −\$390 to \$781) and weighted mean (weighted by

[38] Figure C-5 in online Appendix C maps these data.

Table 8—Heterogeneous Marginal Damage Estimates

	East		West		Texas		
	Level	Trend	Level	Trend	Level	Trend	Observations
Main results	8.64	−0.38	2.03	0.12	2.83	0.11	70,128
	(0.10)	(0.02)	(0.05)	(0.01)	(0.08)	(0.02)	
Electric vehicle charging	9.18	−0.42	2.13	0.13	3.09	0.06	70,128
	(0.11)	(0.03)	(0.06)	(0.01)	(0.10)	(0.03)	
Daytime hours	8.27	−0.34	1.96	0.12	2.45	0.17	29,220
(8:01AM to 6:00PM)	(0.11)	(0.03)	(0.05)	(0.01)	(0.10)	(0.03)	
Nighttime hours	9.03	−0.42	2.13	0.12	3.17	0.06	40,908
(6:01PM to 8:00AM)	(0.12)	(0.03)	(0.06)	(0.01)	(0.11)	(0.03)	
Summer	8.68	−0.46	2.06	0.12	2.67	0.09	35,328
(May–October)	(0.11)	(0.02)	(0.06)	(0.01)	(0.11)	(0.03)	
Winter	8.63	−0.28	1.98	0.12	2.93	0.15	34,800
(November–April)	(0.16)	(0.04)	(0.08)	(0.02)	(0.13)	(0.03)	
Summer day time	8.12	−0.39	1.99	0.12	2.41	0.15	14,720
	(0.13)	(0.03)	(0.06)	(0.01)	(0.13)	(0.04)	

Notes: Newey-West standard errors (48-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. Estimates are in cents per kWh. "Level" refers to β and "Trend" refers to γ in equation (4).

Table 9—Environmental Benefit of an Electric Vehicle ($ per Year)

Interconnection	Year	Mean	Standard deviation	Min	Max
East	2010	−192	128	−390	657
	2017	13	143	−186	939
West	2010	233	225	20	781
	2017	258	267	0	910
Texas	2010	75	41	−24	183
	2017	107	51	−14	246
National	2010	−81	234	−390	781
	2017	72	201	−186	939

Note: Vehicle miles traveled are weighted across all counties in the contiguous United States.

vehicle miles traveled) that is slightly negative (−$81 per year). In 2017, the environmental benefit is higher by about $150 across all counties, and the weighted mean is now positive. The increase is largest in the East (about $200 across the distribution) so electric vehicles are now cleaner than gasoline vehicles on average in the East. Even though marginal damages from electricity use increased in both the West and Texas, the environmental benefit of electric vehicles increased in these regions because damages from gasoline vehicles increased even more. To provide context for these benefits, Holland et al. (2016) show that the optimal purchase subsidy for an electric vehicle is equal to the lifetime environmental benefit. Electric vehicles in the United States 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 percent discount rate, the net present value of the lifetime environmental benefit at the mean is only \$630, but at the maximum value is \$8,250. Thus, even with the cleaner grid in 2017 the air pollution benefits cannot justify the magnitude of the federal subsidy for the mean of the counties although the benefit exceeds the federal subsidy in some counties due to the considerable heterogeneity in the benefit.

Turning to household solar adoption, the electricity from solar panels reduces the demand for grid electricity and thus reduces air pollution damages. Under the assumption that electricity generated from solar panels is a one-for-one replacement for grid-generated electricity, 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) and Sexton et al. (2018), we combine annual solar insolation data with marginal damage estimates from the "Daytime hours" row in Table 8.[39] Table 10 shows the summary statistics for the distribution of environmental benefit per year for a 6-kilowatt system across approximately 83,000 unit areas in the contiguous United States.[40] Overall, the mean benefit is \$418 in 2010 with a range across locations from \$94 to \$825. 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 percent, which implies a subsidy \$5,652 for the average system.[41] Using the 2017 environmental benefits and assuming a 20-year lifetime and a 3 percent discount rate, the average environmental benefit (\$5,455) is approximately equal to the subsidy.

C. *Robustness*

The regression in equation (4) estimates the damage function as the relationship between electricity load and damages. This may underestimate marginal damages if load is correlated with omitted nonfossil generation. An alternative specification that estimates damages as a function of fossil generation may have endogeneity bias, which can be large if interregional trading is not modeled.[42] 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 shows similar estimates across all specifications.

[39] Details on solar insolation data from the National Renewable Energy Lab are given in online Appendix C.

[40] See Figure C-6 in online Appendix C for a graphical display of these data.

[41] See https://www.energystar.gov/about/federal_tax_credits/2017_renewable_energy_tax_credits. The average cost of a 6-kilowatt system is \$18,840.

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

Table 10—Environmental Benefit of a Solar Panel System ($ per Year)

Interconnection	Year	Mean	Standard deviation	Min	Max
East	2010	622	57	488	825
	2017	443	41	348	588
West	2010	170	23	94	213
	2017	242	33	134	305
Texas	2010	213	18	184	252
	2017	316	26	274	375
National	2010	418	227	94	825
	2017	356	103	134	588

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

Table 11—Marginal Damage Estimates: Sensitivity

Variables	Base (1)	Fixed value (2)	High SCC (3)	Low SCC (4)	High VSL (5)	Low VSL (6)
East						
Load (β)	8.64	10.29	9.17	8.12	12.05	4.59
	(0.1)	(0.11)	(0.10)	(0.09)	(0.14)	(0.04)
Load trend (γ)	−0.38	−0.65	−0.36	−0.40	−0.62	−0.10
	(0.02)	(0.03)	(0.03)	(0.02)	(0.03)	(0.01)
West						
Load (β)	2.03	2.48	2.36	1.70	2.39	1.61
	(0.05)	(0.05)	(0.05)	(0.04)	(0.06)	(0.04)
Load trend (γ)	0.12	0.06	0.15	0.10	0.13	0.11
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Texas						
Load (β)	2.83	3.49	3.23	2.42	3.44	2.10
	(0.08)	(0.1)	(0.09)	(0.08)	(0.11)	(0.05)
Load trend (γ)	0.11	0.01	0.13	0.09	0.13	0.08
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.01)
Observations	70,128	70,128	70,128	70,128	70,128	70,128

Notes: Newey-West standard errors (48-hour lag). Dependent variable is hourly damages in the interconnection. Coefficient estimates are in cents per kWh. Regressions are unweighted and include month of sample by hour fixed effects—i.e., 2,304 ($= 8 \times 12 \times 24$) fixed effects. Baseline VSL is $8.7, high VSL is $13.3, and low VSL is $3.9 million. Baseline SCC starts at $35.36 in 2010, high SCC starts at $44.00, and low SCC starts at $26.74.

Table 11 explores the sensitivity of the marginal damage estimates to assumptions about key 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.[43] Under the fixed valuations, the 2010 point estimates are higher and marginal damages fall more or increase less. In particular, the Texas trend is statistically

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

insignificant instead of positive. The other columns in Table 11 use the high and low values for the SCC and the VSL defined earlier. The high SCC value increases the marginal damages and the low value decreases the marginal damages. The trends are more positive for the higher SCC values reflecting the higher growth of the SCC. The high and low VSL has the greatest effect on the results in the East, where damages are higher. Overall, the results are largely robust to these different modeling assumptions.

IV. Conclusion

From 2010 to 2017, the US population grew by over five percent and real gross domestic product expanded by more than 15 percent. Despite these trends, electric power consumption remained effectively unchanged and emissions of important pollutants fell. We translate emissions into monetary damage and find that total annual damages from emissions of local and global pollutants fell by $112 billion, or 46 percent, over eight years. The benefits of these reduced damages from local pollutants were particularly concentrated among households in the Mid-Atlantic and Northeast.

Our decomposition of the decline in damages quantifies the relative importance of four effects. The technique effect measures within-plant changes in emission rates and 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 reduction in fossil generation contributed an effect 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 increase was driven by changes in the composition of the atmosphere, population growth and demographic change, and increases in the social cost of carbon.

The decline in total damages need not imply a decline in marginal damages. Our econometric analysis of the relationship between load and damages reveals that marginal damages did fall in the East but at a much slower rate than total damages or average damages. Despite lower overall emissions in the West and Texas, marginal damages increased in these markets. Grid-powered electric vehicles are now cleaner than gasoline vehicles, on average, though substantial heterogeneity remains. The benefits of solar power decreased in the East but increased in the West and Texas.

Although the paper demonstrates an extraordinary reduction in damages from the US power generation sector, we offer the following caveats. First, this is not a causal analysis of which policies and market forces drove these changes. 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. We explore these plausible explanations, but do not disentangle them causally. 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

A. *Details on Emissions Data*

The CEMS (Continuous Emissions Monitoring System) database is part of EPA's Air Markets Program (EPA 2010–2017.) CEMS power plants do not include nonfossil power plants, small fossil plants (capacity < 25 megawatt), and plants in Hawaii or Alaska. CEMS 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, for the 248 largest CEMS plants that are modeled at the plant level in AP3, we calculate each plant's $PM_{2.5}$ emissions rate as the ratio of $PM_{2.5}$ emissions from the National Emissions Inventory (NEI 2008, 2011, 2014) over the annual gross generation from CEMS (Winsorizing at the second and ninety-eighth percentile). For the remaining plants that are modeled at the county level in AP3, we assign the average $PM_{2.5}$ emission rate of NEI plants with the same fuel type. Because the NEI is only available in 2008, 2011, and 2014, we approximate $PM_{2.5}$ emissions rates for other years with linear interpolation. Second, we calculate $PM_{2.5}$ emissions at each plant as the product of this $PM_{2.5}$ emissions rate and the plant's gross generation from CEMS.[44]

Table A1 shows annual emissions of the pollutants. These emissions correspond closely with annual emissions reported in the National Tier I summary data from EPA.[45] Figure 1 illustrates this same data normalized to 2010 emissions.

For a historical perspective, we illustrate emissions from 1990–2016 in Figure A1.[46] 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

[44] Additional information on $PM_{2.5}$ emissions rates is available from EIA form 923 (EIA 2010–2017) (at the control technology level) or from EPA (at the annual sector level). These sources are less comprehensive than the NEI.

[45] See https://www.epa.gov/air-emissions-inventories/air-pollutant-emissions-trends-data.

[46] The data source for this figure is EIA (1990–2016).

Table A1—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: This table presents total emissions from all CEMS power plants. SO_2, NO_x, and $PM_{2.5}$ emissions are in billion pounds. CO_2 emissions are in billion tons.

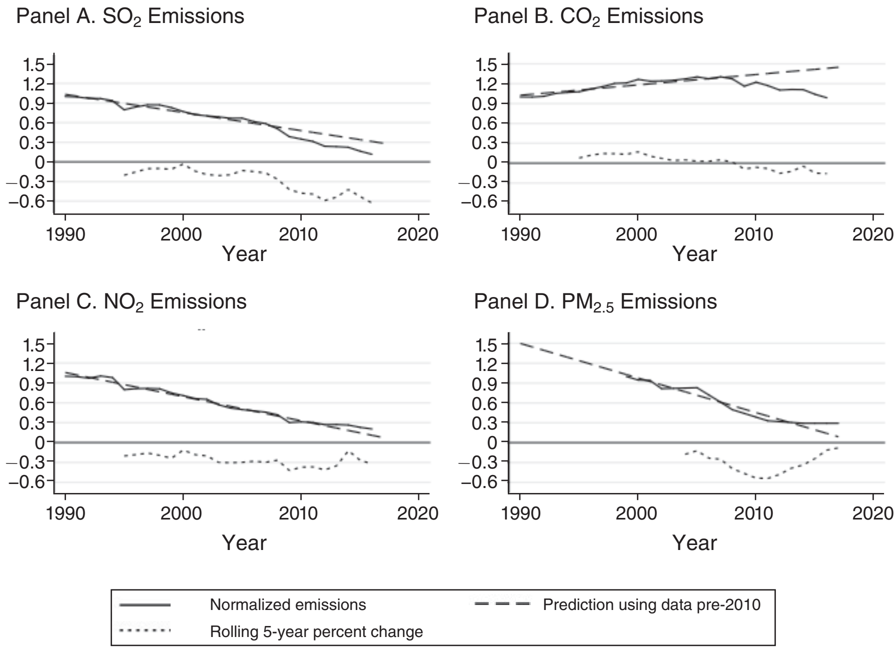

Figure A1. Power Plant Emissions from 1990 to 2016

Source: Data are from EIA US Electric Power Industry Estimated Emissions by State (EIA 1990–2016).

change in emissions. For SO_2 and CO_2, emissions from 2010 to 2017 clearly deviate below trend.

B. *Details on AP3*

AP3 reports damage valuations by location and stack height in each NEI year. We interpolate valuations in non-NEI years and assign relevant valuations to each CEMS power plant. Table A2 shows the mean damage valuations across the unbalanced panel of power plants. Reflecting our assumptions, local pollutant damages are flat after 2014, and CO_2 damage valuations increase throughout the sample period.

Equation (1) assumes 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 $PM_{2.5}$.

Table A2—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 dollars 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 dollars per metric ton.

In particular, damage valuations in AP3 are generally increasing over time from 2008 to 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 $PM_{2.5}$. 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.

C. *Details on Electricity Generation*

Table A3 shows electricity generation by fuel type over time. Gas, solar, and wind generation are increasing over time, coal is decreasing over time, and nuclear and hydro vary but show no dominant pattern.

D. *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 we can write ΔD in equation (3) as $\sum_i \sum_p \Delta\left(v_{ip} r_{ip} \theta_i Q\right)$. Ignoring the summations and subscripts we can write the decomposition as[47]

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

[47] 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 $\overline{xy} \;=\; \bar{x}\cdot\bar{y} + \Delta x\Delta y/4$. Repeatedly applying these formulas to the product $vr\theta Q$ yields the decomposition and error.

Table A3—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
Other gen	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

Note: This table presents annual net generation from all power plants (in millions of megawatt-hours) and fuel type as reported in EIA form 923 (EIA 2010–2017).

Table A4—Decomposition of Change in Emissions from 2010 to 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

where

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

The *Error* for equation (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 equation (3) and calculate the decomposition for each pollutant separately (rather than summing over p). The results are given in Table A4 (expressed in percentage of total emissions in 2010).

REFERENCES

Andaloussi, Mehdi Benatiya. 2018. "Clearing the Air: The Role of Technology Adoption in the Electricity Generation Sector." Columbia University Working Paper.

Ang, B.W., and F.Q. Zhang. 2000. "A Survey of Index Decomposition Analysis in Energy and Environmental Studies." *Energy* 25 (12): 1149–76.

Antweiler, Werner, Brian R. Copeland, and M. Scott Taylor. 2001. “Is Free Trade Good for the Environment?” *American Economic Review* 91 (4): 877–908.

Borenstein, Severin, and James B. Bushnell. 2018. “Do Two Electricity Pricings Wrongs Make a Right? Cost Recovery, Externalities, and Efficiency.” NBER Working Paper 24756.

Callaway, Duncan S., 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.

Clay, Karen, Akshaya Jha, Nicholas Z. Muller, and Randy Walsh. 2019. “The External Costs of Shipping Petroleum Products by Pipeline and Rail: Evidence of Shipments of Crude Oil from North Dakota.” *Energy Journal* 40 (1): 55–72.

Coglianese, John, Todd D. Gerarden, and James H. Stock. 2018. “The Effects of Fuel Prices, Environmental Regulations, and Other Factors on U.S. Coal Production, 2008–2016.” Cornell University Working Paper.

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.

Denhom, Paul, Michael Kuss, and Robert M. Margolis. 2013. “Co-benefits of Large Scale Plug-in Hybrid Electric Vehicle and Solar PV Deployment.” *Journal of Power Sources* 236: 350–56.

Energy Information Administration (EIA). 1990–2016. “U.S. Electric Power Industry Estimated Emissions by State (EIA-767, EIA-906, EIA-920, and EIA-923).” United States Department of Energy. https://www.eia.gov/electricity/data/state/emission_annual.xls (accessed September 16, 2018).

Energy Information Administration (EIA). 2010–2017. “Form EIA-923 Detailed Data with Previous Form Data (EIA-906/920).” https://www.eia.gov/electricity/data/eia923/.

Environmental Protection Agency (EPA). 1994–2017. “SO2 Allowance Auctions.” Clean Air Markets. https://www.epa.gov/airmarkets/so2-allowance-auctions (accessed October 8, 2018).

Environmental Protection Agency (EPA). 2009–2016. “Emissions & Generation Resource Integrated Database (eGRID).” Energy and the Environment. https://www.epa.gov/sites/production/files/2018-02/egrid2016_all_files_since_1996.zip (accessed July 9, 2018).

Environmental Protection Agency (EPA). 2010. *Guidelines for Preparing Economic Analyses.* Washington DC: National Center for Environmental Economics, Office of Policy. https://www.epa.gov/environmental-economics/guidelines-preparing-economic-analyses.

Environmental Protection Agency (EPA). 2010–2017. “Air Markets Program Data.” https://ampd.epa.gov/ampd/.

Federal Energy Regulatory Commission (FERC). 2010–2017. “Form No. 714 - Annual Electric Balancing Authority Area and Planning Area Report.” https://www.ferc.gov/industries-data/electric/general-information/electric-industry-forms/form-no-714-annual-electric/data.

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* 10 (2): 90–116.

Feng, Kuishuang, Steven J. Davis, Laixiang Sun, and Klaus Hubacek. 2015. “Drivers of the US CO2 Emissions 1997–2013.” *Nature Communications* 6: Article 7714.

Fortin, Nicole, Thomas Lemieux, and Sergio Firpo. 2011. “Chapter 1—Decomposition Methods in Economics.” In *Handbook of Labor Economics*, Vol. 4A, edited by Orley Ashenfelter and David Card, 1–102. Amsterdam: Elsevier.

Graff Zivin, Joshua S., Matthew J. Kotchen, and Erin T. 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): 248–68.

Henneman, Lucas R.F., Christine Choirat, and Corwin M. Zigler. 2019. “Accountability Assessment of Health Improvements in the United States Associated with Reduced Coal Emissions between 2005 and 2012.” *Epidemiology* 30 (4): 477–85.

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.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates. 2016. “Are There Environmental Benefits from Driving Electric Vehicles? The Importance of Local Factors.” *American Economic Review* 106 (12): 3700–729.

Holland, Stephen P., Erin T. Mansur, Nicholas Z. Muller, and Andrew J. Yates. 2020. “Replication Data for: Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation." American Economic Association [publisher], Inter-university Consortium for Political and Social Research [distributor]. https://doi.org/10.3886/E112172V1.

Knittel, Christopher, Konstantinos Metaxoglou, and Andre Trindade. 2015. "Natural Gas Prices and Coal Displacement: Evidence from Electricity Markets." NBER Working Paper 21627.

Kochi, Ikuho, Bryan Hubbell, and Randall Kramer. 2006. "An Empirical Bayes Approach to Combining and Comparing Estimates of the Value of a Statistical Life for Environmental Policy Analysis." *Environmental and Resource Economics* 34 (3): 385–406.

Kotchen, Matthew J., and Erin T. Mansur. 2016. "Correspondence: Reassessing the Contribution of Natural Gas to US CO2 Emission Reductions since 2007." *Nature Communications* 7: Article 10648.

Krumholz, Sam. 2018. "What Caused the US Coal-Fired Sulfur Dioxide Decline? An Examination of Causes, Costs, and Market Interactions." University of California, San Diego Working Paper.

Levinson, Arik. 2009. "Technology, International Trade, and Pollution from US Manufacturing." *American Economic Review* 99 (5): 2177–92.

Levinson, Arik. 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 (1): 43–56.

Linn, Joshua, and Kristen McCormack. 2019. "The Roles of Energy Markets and Environmental Regulation in Reducing Coal-Fired Plant Profits and Electricity Sector Emissions." *RAND Journal of Economics* 50 (4): 733–67.

Mansur, Erin T. 2008. "Measuring Welfare in Restructured Electricity Markets." *Review of Economics and Statistics* 90 (2): 369–86.

McLaren, Joyce, John Miller, Eric O'Shaughnessy, Eric Wood, and Evan Shapiro. 2016. "CO2 Emissions Associated with Electric Vehicle Charging: The Impact of Electricity Generation Mix, Charging Infrastructure Availability and Vehicle Type." *Electricity Journal* 29 (5): 72–88.

Melitz, Marc, and Saso Polanec. 2015. "Dynamic Olley-Pakes Productivity Decomposition with Entry and Exit." *RAND Journal of Economics* 46 (2): 362–75.

Metcalf, Gilbert E. 2008. "An Empirical Analysis of Energy Intensity and Its Determinants at the State Level." *Energy Journal* 29 (3): 1–26.

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." *PNAS* 108 (40): 16554–58.

Muller, Nicholas Z. 2014. "Toward the Measurement of Net Economic Welfare: Air Pollution Damage in the U.S. National Accounts—2002, 2005, 2008." In *Measuring Economic Sustainability and Progress*, edited by Dale W. Jorgensen, J. Steven Landefeld, and Paul Schreyer, 429–59. Chicago: University of Chicago Press.

Muller, Nicholas Z., Robert Mendelsohn, and William Nordhaus. 2011. "Environmental Accounting for Pollution in the United States Economy." *American Economic Review* 101 (5): 1649–75.

National Emissions Inventory (NEI). 2008. "2008 National Emissions Inventory Data." https://www.epa.gov/air-emissions-inventories/2008-national-emissions-inventory-nei-data.

National Emissions Inventory (NEI). 2011. "2011 National Emissions Inventory Data." https://www.epa.gov/air-emissions-inventories/2011-national-emissions-inventory-nei-data.

National Emissions Inventory (NEI). 2014. "2014 National Emissions Inventory Data." https://www.epa.gov/air-emissions-inventories/2014-national-emissions-inventory-nei-data.

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

Nealer, Rachael, David Reichmuth, and Don Anair. 2015. *Cleaner Cars from Cradle to Grave—How Electric Cars Beat Gasoline Cars on Lifetime Global Warming Emissions*. Cambridge, MA: Union of Concerned Scientists.

Reguant, Mar. 2014. "Complementary Bidding Mechanisms and Startup Costs in Electricity Markets." *Review of Economic Studies* 81 (4): 1708–42.

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 (9): 3170–76.

Sexton, Steven, A. Justin Kirkpatrick, Robert Harris, and Nicholas Z. Muller. 2018. "Heterogeneous Environmental and Grid Benefits from Rooftop Solar and the Costs of Inefficient Siting Decisions." NBER Working Paper 25241.

Shapiro, Joseph S., and Reed Walker. 2018. "Why Is Pollution from US Manufacturing Declining? The Roles of Environmental Regulation, Productivity, and Trade." *American Economic Review* 108 (12): 3814–54.

Siler-Evans, Kyle, Inês Azevedo, M. Granger Morgan, and Jay Apt. 2013. "Regional Variations in the Health, Environmental, and Climate Benefits of Wind and Solar Generation." *PNAS* 110 (29): 11768–73.

Sun, J.W. 1998. "Changes in Energy Consumption and Energy Intensity: A Complete Decomposition Model." *Energy Economics* 20 (1): 85–100.