Online Appendices For "Decompositions and Policy Consequences of an Extraordinary Decline in Air Pollution from Electricity Generation"

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Online Appendices

A Supplementary Information for Section 1

app-dam

AP3 Updates

The primary difference between the updated AP3 model (Clay et al 2018) and the prior AP2 model lies in the NO_X-ammonium nitrate calculations. The contribution of emitted NO_X to ambient $PM_{2.5}$ is dictated by the atmospheric transformation of NO_X first to gas phase nitrate (NO_3), gaseous nitric acid (HNO_3), and then to particulate ammonium nitrate (NH_4NO_3). AP2 relied on a discrete-form computation of ammonium nitrate. Using predicted ambient levels of NH_4, SO_4, and NO_3, AP2 assumed that NH_4 reacted first with SO_4 to form $(NH_4)_2SO_4$, and then any remaining NH_4 reacted with ambient NO_3 to form NH_4NO_3. In AP3, the model still relies on estimated ambient levels of NH_4, SO_4, and NO_3, but then, after NH_4 and SO_4 form $(NH_4)_2SO_4$, formation of NH_4NO_3 is dictated by a polynomial fit to predictions from the PM-CAMx model—a state of the art chemical transport model. The polynomial is linear in gaseous nitric acid (HNO_3), NH_4, and it includes an interaction term between HNO_3 and NH_4. The model also includes ambient temperature, humidity, and their interaction as well. A range of polynomial functional forms were tested with the corresponding predictions evaluated against those from PM-CAMx (Sergi et al 2018). The selected function outperformed the others according to the following criteria: mean squared error, mean proportional error, mean fractional bias, and mean fractional error. To estimate marginal changes in ambient NH_4NO_3, two additional polynomials are fit. Each is linear in HNO_3 and were calibrated from PM-CAMx output. One polynomial estimates incremental changes when conditions are HNO_3 limited, the other when conditions are NH_4 limited.

Independence of Damage Valuations and Emissions

Atmospheric chemistry is one reason that damages may not be independent of aggregate emissions. There are at least two additional reasons. First, the function that links exposure to ambient $PM_{2.5}$ to adult mortality risk may exhibit thresholds or nonlinearities.

The function used herein, which is also widely used in federal government policy analyses (EPA 2010) and academic research (Holland et al 2016) is essentially linear in ambient $PM_{2.5}$ concentrations, with no threshold. Second, the willingness-to-pay to avoid mortality risk (the underlying conceptual metric of the VSL) may vary with the risk level. In accord with the literature that estimates the VSL and subsequently applies it to value environmental risk, we do not vary the VSL according to ambient $PM_{2.5}$, and hence, risk, levels. If compelling empirical evidence were presented on such a relationship, the AP3 model is able to accommodate a functional relationship between the VSL and risk.

To provide an upper bound on the actual reduction in damages if the independence assumption does not hold, consider an alternative procedure in which all valuations are fixed at the highest values. If damage valuations are V_i in the initial period and V_f in the final period, i.e., are independent of the aggregate level of emissions of power plants, Figure A-1 shows how to calculate the decline in damages. If emissions in the initial period are e_i and in the final period are e_f, total damages in the initial period are given by the sum of areas A and B. Total damages in the final period are given by $B + C$. Thus the actual decline in damages is $A - C$. If we instead evaluate damages in both periods using V_f, this gives the decline in damages equal to $A + D_1 + D_2$, which significantly overstates the decline, but is an upper bound on the decline.

Next suppose that damage valuations are not independent of the aggregate level of emissions from power plants. In this case, Eq. 1 is inappropriate for assessing total damages, which can instead be found by integrating under the marginal valuation curve. Figure A-1 shows how to calculate the decline in damages if the marginal valuation curve is constant over time but decreasing in emissions as indicated by the line V. The actual decline in damages is equal to $A + D_1$. Our main procedure using Eq. 1 determines the decline in damages in the same manner as before, but now we are inappropriately using V_i and V_f rather than V. Thus our main procedure determines the decline in damages to be $A - C$, which understates the decline in damages. The upper-bound procedure determines the decline in damages to be $A + D_1 + D_2$, which overstates the decline in damages, but to a lesser degree than in the independent case.

Figure A-1: Decline in Damages: Not Independent Case

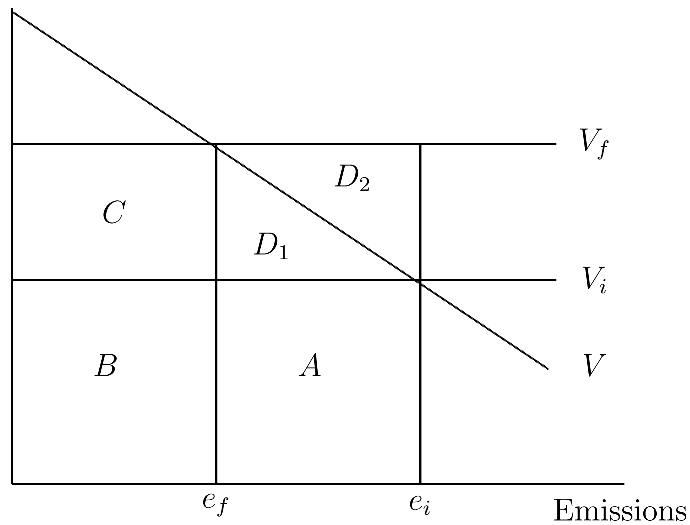

fig-indepB

If we hold all damage valuations fixed at the final year for a given plant, then the decline in damages turns out to be $167 billion. This provides an upper bound on the actual reduction in damages.

Distributional Effects: Geography

Here we supplement the information presented in Figure 2 and Figure 3 with additional details. Figure A-2 shows local damages received by each county for each of the individual years from 2010-2017. Taking the difference between the first and last of these figures gives the reduction in local damages (not per capita) in Figure A-3. Aggregating the county data to the state level gives the results in Table A-1. In addition to the per capita values, the table also shows the reduction in total damages received as well as damages received in 2010. West Virginia has the greatest per capita reduction in damages, but it has only the 19th greatest reduction in total damages due to its smaller population. Pennsylvania, New York, and Ohio have the greatest reductions in total damages due to the high per capita damages and large populations.

Table A-1: Damages Received by State

State	Reduction in Damages Received	Reduction per Capita	Damages Received in 2010	per Captia in 2010	per Capita in 2017
Pennsylvania	12.51	988	17.1	1350	362
New York	10.75	557	14.99	777	220
Ohio	8.93	775	13.23	1148	373
New Jersey	5.64	644	7.73	883	239
Virginia	5.1	644	6.99	882	238
Michigan	5.04	508	7.79	785	277
North Carolina	5.01	532	7.04	748	216
Illinois	4.88	382	7.92	619	238
Maryland	3.72	649	5.18	902	254
Georgia	3.7	385	5.15	537	151
Florida	3.66	196	6.07	325	129
Indiana	3.6	558	5.97	924	367
Tennessee	3.47	550	5.3	842	291
Massachusetts	3.43	526	4.51	692	166
Kentucky	3.06	708	4.69	1087	379
Alabama	2.54	536	3.67	774	238
South Carolina	2.48	542	3.32	725	183
West Virginia	2.31	1253	3.22	1746	492
Connecticut	2.14	603	2.81	790	187
Texas	2.04	82	6.98	282	199
Missouri	1.81	305	3.46	581	276
Wisconsin	1.75	310	2.89	510	201
Mississippi	1.17	397	1.89	640	243
Louisiana	1.04	232	1.97	440	208
Arkansas	.89	308	1.77	612	304
Iowa	.86	283	1.48	488	205
New Hampshire	.79	599	1.01	766	167
Oklahoma	.75	201	1.67	448	247
Minnesota	.71	134	1.25	237	103
Delaware	.65	731	.89	1001	270
Maine	.63	476	.83	628	152
Rhode Island	.61	575	.8	760	185
Kansas	.56	198	1.08	382	185
California	.4	11	1.21	33	22
District of Columbia	.36	614	.51	852	238
Colorado	.34	68	.78	157	89
Vermont	.31	502	.43	683	180
Nebraska	.28	155	.56	310	155
Arizona	.14	22	.39	62	40
South Dakota	.1	130	.2	243	113
New Mexico	.1	49	.26	129	80
Washington	.1	15	.22	33	18
Utah	.08	31	.22	80	49
North Dakota	.06	96	.12	181	85
Oregon	.06	16	.13	34	18
Nevada	.06	21	.15	55	33
Idaho	.05	30	.1	66	36
Montana	.04	44	.09	91	47
Wyoming	.04	66	.08	149	82

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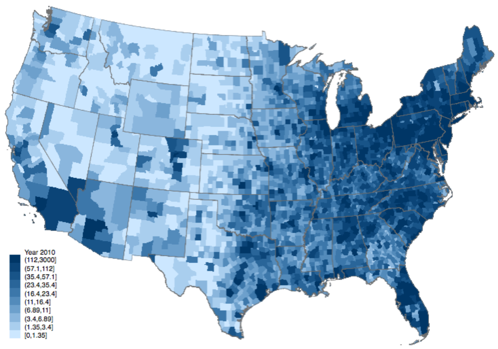
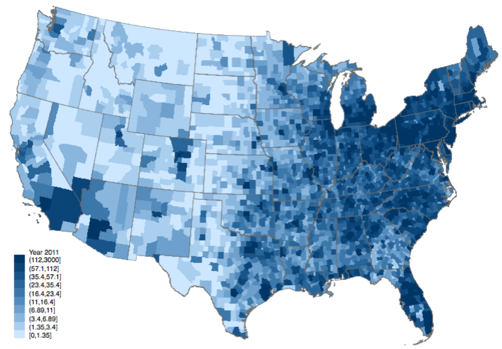
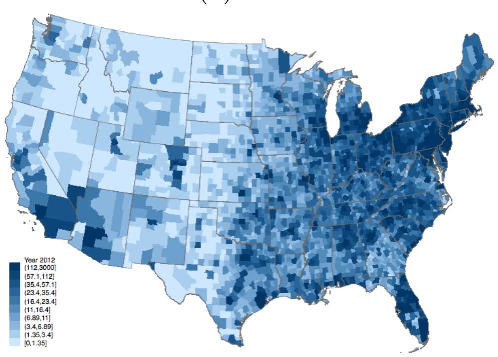
Notes: Damages and reduction in damages are in billions of 2014$.



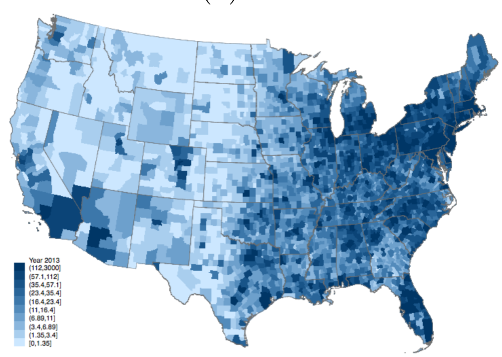
(a) 2010



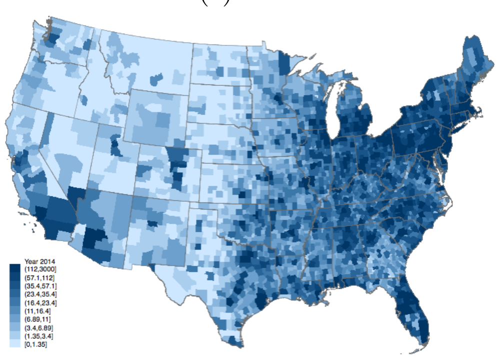
(b) 2011



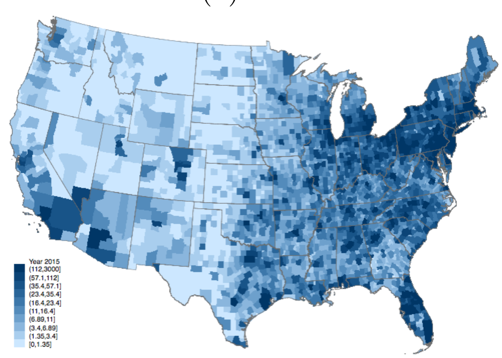
(c) 2012



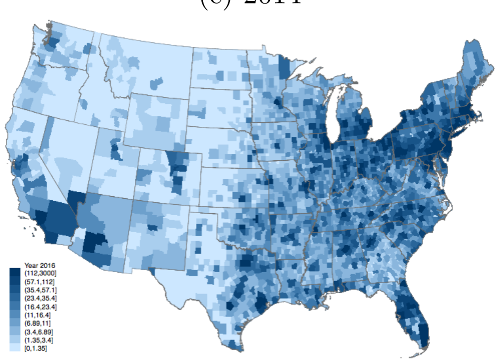
(d) 2013



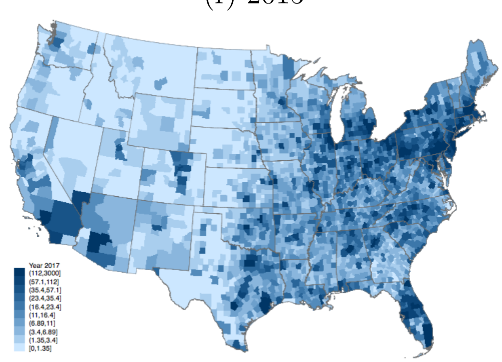
(e) 2014



(f) 2015



(g) 2016



(h) 2017

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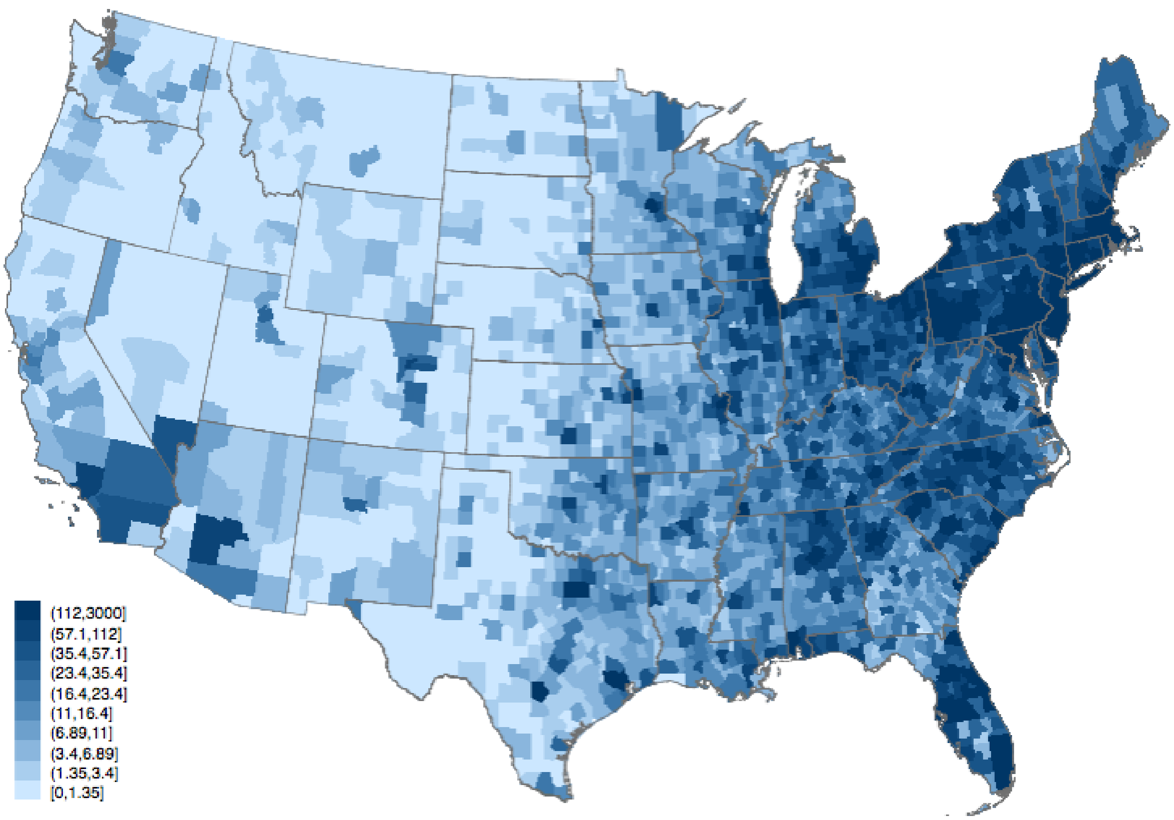
Figure A-2: Local Damages Received by County and Year (millions of 2014$)

Figure A-3: Reduction in Local Damages Received by County 2010-2017 (millions of 2014$)

m-received



B Supplementary Information for Section 2

app-decomp

Decompositions

Here we give more details about the decomposition in the main text and provide a number of additional decompositions as sensitivity analysis. To understand our decomposition formula, consider first the product rule from differential calculus. Suppose we have two variables $x(t)$ and $y(t)$ that are multiplied together to form a third variable $a(t) = x(t)y(t)$. We have

$$\frac{da}{dt} = \frac{dx}{dt}y + \frac{dy}{dt}x.$$

The first term on the right hand side is the effect of changing x with y kept fixed.

With discrete data, we need to make assumptions about what it means to keep the variables fixed. In other words, we need to determine base quantities.[1] And this decision has implications for the error term in the decomposition. To see this, start with with a two variable decomposition in discrete time. Suppose at time 0 we have $a_0 = x_0 y_0$ and at time 1 we have $a_1 = x_1 y_1$. In the main paper, we use a base that is analogous to the Marshall-Edgeworth price index. This gives

$$\Delta a = \Delta x \bar{y} + \bar{x} \Delta y.$$

In this case the error is zero because the left hand side is algebraically equivalent to the right hand side. In contrast, using a base that is analogous to the Laspeyres price index gives

$$\Delta a = \Delta x y_0 + x_0 \Delta y + Error,$$

where $Error = \Delta x \Delta y$. We see that the Marshall-Edgeworth base gives lower error than the Laspeyres base.[2]

[1] Oaxaca (1973) calls this the "index number problem".

[2] To derive the decomposition formulas, one uses two expressions repeatedly. First, the variable decomposition formula is $\Delta a = \Delta x \bar{y} + \bar{x} \Delta y$. Second, note that $\overline{xy} = \overline{x} \cdot \overline{y} + \Delta x \Delta y / 4$.

Table B-1: Decomposition Summary Stats

table-decomp-full-stats

	2010	2011	2012	2013	2014	2015	2016	2017
Generation								
Always Coal	1,645.2	1,564.3	1,404.4	1,465.4	1,466.8	1,279.9	1,215.7	1,190.3
Switch Coal	225.3	195.0	152.9	157.2	151.3	126.7	98.1	93.4
Always Gas	824.2	834.9	994.2	880.4	870.0	1,005.6	1,032.8	934.3
Other	55.1	56.3	90.0	110.5	130.6	166.6	179.3	196.6
Total Generation	2,749.9	2,650.6	2,641.6	2,613.5	2,618.7	2,578.8	2,525.9	2,414.6
Damage								
Always Coal	168.12	158.49	137.32	146.15	150.82	124.73	107.22	101.85
Switch Coal	56.51	48.10	31.25	29.75	30.83	16.64	4.94	3.28
Always Gas	18.06	17.98	21.12	19.34	19.51	22.67	23.41	21.36
Other	2.11	2.01	2.98	3.93	4.71	5.37	5.79	6.17
Total Damage	244.80	226.57	192.67	199.17	205.88	169.41	141.36	132.66
Plants								
Always Coal	293	293	293	293	293	293	293	293
Switch Coal	169	163	151	138	126	115	92	78
Always Gas	750	750	750	750	750	750	750	750
Other	214	211	223	230	226	246	246	236
Total Plants	1426	1417	1417	1411	1395	1404	1381	1357

Notes: Generation in billions of megawatt-hours (MWh). Damages in billions of 2014$. Total damages do not exactly match the damages in Table 1 because the decomposition requires that we drop plants that report zero generation. Fuel types are from EPA's Emissions & Generation Resource Integrated Database (eGRID, EPA 2009-2016). "Always Coal" denotes plants with coal as primary fuel type in all years. "Switch Coal" denotes plants that start with coal but switch to gas or other fuels or exit. "Always Gas" denotes plants with gas as primary fuel type in all years. "Other" denotes the residual category.

Next consider a three variable decomposition with $a_0 = x_0 y_0 z_0$ and $a_1 = x_1 y_1 z_1$. The Marshall-Edgeworth base gives

$$\Delta a = \Delta x \bar{y} \bar{z} + \bar{x} \Delta y \bar{z} + \bar{x} \bar{y} \Delta z + Error$$

where $Error = \Delta x \Delta y \Delta z / 4$. The Laspeyres base gives

$$\Delta(xyz) = \Delta x y_0 z_0 + x_0 \Delta y z_0 + x_0 y_0 \Delta z + Error$$

where $Error = \Delta x \Delta y z_0 + \Delta x y_0 \Delta z + x_0 \Delta y \Delta z + \Delta x \Delta y \Delta z$. Once again error is clearly larger with the Laspeyres base.

In the main paper, we have a four variable decomposition. The error terms in this case are given in the Appendix to the main paper. In Table 3 in the main paper, we use the Marshall-Edgeworth base, which keeps the other variables fixed at the average of the initial and final values. Our decomposition does not seem to have been used before, although it is numerically equivalent to the decomposition in Sun (1998) in the two variable case. In the three and four variable case, our decomposition is slightly different than the one in Sun (1998). For example, in the three variable case, if we take the error term in our decomposition, divide it by 3, add the resulting value to each of the remaining terms in the decomposition, then our formula is equivalent to the formula in Sun (1998). Thus our scale effect plus one third of the error term is equal to Sun (1998)'s scale effect. Table B-1 shows the summary statistics, broken down by plant category, for the variables q and e used in the decomposition as well as the number of plants in various categories.

In the main paper, Table 3 shows the decompositions from 2010-2017. We give the yearly decompositions in Table B-2. Standard errors for these decompositions are given in Table B-3. We calculate the standard errors by regressing each plant's contribution to the given effect on a constant with standard errors clustered by power plant. We use the number of plants to rescale the coefficient and standard errors to match the main results. The standard errors inform whether the reductions are similar across plants. If they are large, then this is consistent with the declines coming from a small share of the plants. Conversely, if they are small, then this is consistent with many plants reducing damages by similar amounts. The decompositions for the East, West, and Texas interconnections are given in Table B-4.

In the main text, we derived the decomposition formula by dividing emissions by total fossil production Q. It would be more in line with previous literature (e.g. Levinson (2009)) to divide by electricity load L instead. With this procedure, Eq. (1) becomes

$$D_t = \sum_i \sum_p v_{ipt} e_{ipt} = \sum_i \sum_p v_{ipt} \frac{e_{ipt}}{q_{it}} \frac{q_{it}}{L_t} L_t = \sum_i \sum_p v_{ipt} r_{ipt} \theta_{it} L_t, \tag{A-1}$$

where $r_{ipt} = \frac{e_{ipt}}{q_{it}}$ is the emissions rate for pollutant p and $\theta_{it} = \frac{q_{it}}{L_t}$ is the share of electricity generated. The results for this decomposition are shown in Table B-5. Much of the scale effect is shifted into the composition effect.

Table B-2: Decomposition of Change in Damages by Year (billions of 2014$)

table-decomp-full2-1

	2011	2012	2013	2014	2015	2016	2017
Scale (Total Fossil Generation)							
Load	–2.4	–5.6	–5.3	–2.2	–5.1	–0.3	–3.6
Renewables	–2.3	–4.0	–6.9	–9.1	–9.7	–12.7	–15.9
Nuclear	1.5	3.1	1.5	0.9	0.8	0.1	0.2
Hydroelectric	–5.2	–1.3	–0.7	0.1	0.9	–0.6	–3.0
Other	–0.3	–1.0	–0.3	–1.2	–0.8	–3.6	–2.9
Total Scale	–8.7	–8.9	–11.6	–11.5	–14.0	–17.1	–25.2
Composition (Generation Shares)							
Coal	–4.4	–21.9	–12.9	–14.0	–33.1	–37.6	–32.0
Switch from Coal	–5.4	–22.7	–21.1	–18.6	–21.2	–13.9	–5.3
Gas	0.8	4.1	1.5	1.2	4.0	6.0	4.5
Entry of Coal	0.2	0.9	1.7	1.8	1.8	2.1	2.4
Entry of Gas	0.1	0.5	0.6	0.9	1.6	2.0	2.7
Exit of Coal	–0.9	–2.1	–7.1	–9.2	–14.9	–26.3	–31.1
Exit of Gas	–0.1	–0.1	–0.1	–0.1	–0.2	–0.2	–0.4
Other	–0.3	–0.2	–0.0	–1.8	–3.1	–3.4	–0.7
Total Composition	–9.9	–41.7	–37.4	–39.8	–65.1	–71.5	–60.0
Technique(Emissions Rate)							
Coal - New SO_2 Control Tech.	–4.8	–14.2	–19.5	–24.3	–26.7	–32.9	–35.7
Coal - No New Tech.	2.1	0.3	–1.0	1.4	–1.0	–5.4	–8.9
Switch from Coal	–1.1	–2.0	–1.8	–3.2	–7.1	–12.3	–15.9
Gas	–0.7	–1.4	–1.0	–1.2	–1.2	–2.4	–2.5
Other	–0.0	–0.2	–0.4	1.7	3.1	3.3	0.4
Total Technique	–4.5	–17.5	–23.7	–25.6	–32.8	–49.7	–62.6
Valuation							
SO_2	2.0	9.6	17.2	24.9	21.0	16.9	15.7
NO_X	0.2	1.1	2.1	3.0	2.8	2.6	2.4
$PM_{2.5}$	0.3	0.7	1.0	1.4	1.3	1.3	1.2
CO_2	2.3	4.5	7.0	9.6	11.9	14.1	16.0
Total Valuation	4.8	15.9	27.3	38.9	37.0	35.0	35.3
Error	0.0	–0.0	–0.3	–0.8	–0.5	–0.1	0.3
Total	–18.2	–52.1	–45.6	–38.9	–75.4	–103.4	–112.1

Notes: Total changes do not exactly match the aggregate decline in damages in Table 1 because the decomposition requires that we drop plants that report zero generation. Fuel types are from eGRID (EPA 2009-2016). "Coal" and "Gas" denotes whose primary fuel type did not change over time. "Switch from Coal" denotes plants that start with coal but switch to gas or other fuels. "Entry" denotes plants that were not in the 2010 sample and "Exit" denotes plants that were not in the 2017 sample. "Other" denotes plants not categorized by one of the above distinctions. "New SO_2 Control Tech" denotes plants that installed SO_2 emissions control technology between 2010 and 2017.

Table B-3: Standard Errors of Decomposition

e-decomp-se

Year	(1) Total	(2) Scale	(3) Composition	(4) Technique	(5) Valuation	(6) Error
2011	−18.23***	−8.69***	−9.90***	−4.45	4.80***	0.01
	(3.60)	(0.54)	(2.80)	(3.08)	(0.27)	(0.01)
2012	−52.13***	−8.87***	−41.67***	−17.53***	15.95***	−0.01
	(6.56)	(0.53)	(5.87)	(4.83)	(1.01)	(0.04)
2013	−45.63***	−11.61***	−37.37***	−23.71***	27.33***	−0.27*
	(7.21)	(0.69)	(7.12)	(6.52)	(1.77)	(0.15)
2014	−38.92***	−11.54***	−39.82***	−25.64***	38.92***	−0.85***
	(8.03)	(0.69)	(8.06)	(8.38)	(2.55)	(0.32)
2015	−75.39***	−13.99***	−65.09***	−32.84***	37.05***	−0.52
	(9.10)	(0.81)	(9.38)	(8.50)	(2.33)	(0.32)
2016	−103.44***	−17.11***	−71.47***	−49.74***	34.97***	−0.09
	(10.69)	(0.94)	(9.78)	(9.10)	(2.10)	(0.32)
2017	−112.14***	−25.19***	−59.98***	−62.58***	35.28***	0.33
	(11.26)	(1.40)	(9.04)	(8.93)	(2.16)	(0.21)
Observations	10,434	10,434	10,434	10,434	10,434	10,434

*** p<0.01, ** p<0.05, * p<0.1
Standard errors clustered by plant

Table B-4: Decomposition of Change in Damages by Interconnection (billions of 2014$)

	East	West	Texas
Scale (Total Fossil Generation)			
Load	–10.0	1.5	2.3
Renewables	–9.1	–2.7	–2.3
Nuclear	–1.2	0.6	0.2
Hydroelectric	–0.5	–1.5	0.0
Other	–3.3	–0.4	0.7
Total Scale	–24.1	–2.6	0.8
Composition (Generation Shares)			
Coal	–28.8	–1.1	–2.0
Switch from Coal	–5.0	0.0	0.0
Gas	4.3	0.2	–0.1
Entry of Coal	1.9	0.2	0.3
Entry of Gas	2.1	0.2	0.3
Exit of Coal	–30.5	–0.3	0.0
Exit of Gas	–0.2	–0.1	–0.1
Other	–0.7	0.0	0.0
Total Composition	–56.9	–0.8	–1.6
Technique (Emissions Rate)			
Coal- New SO_2 Control Tech.	–33.8	–1.0	–0.9
Coal - No New Tech.	–6.9	–0.9	–1.1
Switch from Coal	–16.0	0.0	0.0
Gas	–2.3	–0.2	0.0
Other	0.4	0.0	0.0
Total Technique	–58.6	–2.1	–2.0
Valuation			
SO_2	13.8	0.5	1.4
NO_X	1.8	0.4	0.1
$PM_{2.5}$	1.0	0.1	0.1
CO_2	12.4	2.2	1.5
Total Valuation	28.9	3.2	3.1
Error	0.4	0.0	0.0
Total	–110.2	–2.3	0.4

e-decomp-inters-appendix

Notes: Fuel types are from eGRID (EPA 2009-2016). "Coal" and "Gas" denotes whose primary fuel type did not change over time. "Switch from Coal" denotes plants that start with coal but switch to gas or other fuels. "Entry" denotes plants that were not in the 2010 sample and "Exit" denotes plants that were not in the 2017 sample. "Other" denotes plants not categorized by one of the above distinctions. "New SO_2 Control Tech" denotes plants that installed SO_2 emissions control technology between 2010 and 2017.

Table B-5: Decomposition of Change in Damages by Year (billions of 2014$): Electricity Load Rather than Fossil Generation

e-Ldecomp-full-1

Type	2011	2012	2013	2014	2015	2016	2017
Effect							
Scale	−1.6	−3.7	−3.5	−1.5	−3.4	−0.2	−2.3
Composition	−17.0	−46.8	−45.5	−49.9	−75.7	−88.4	−82.9
Technique	−4.4	−17.5	−23.5	−25.3	−32.5	−49.3	−62.2
Valuation	4.8	16.0	27.4	39.0	37.2	35.2	35.5
Error	−0.0	−0.1	−0.5	−1.3	−1.0	−0.7	−0.3
Total	−18.2	−52.1	−45.6	−38.9	−75.4	−103.4	−112.1

Next we consider several alternative ways to define the base in the decompositions. The Laspeyres base keeps the other variables fixed at the initial value. The results for the Laspeyres base are given in Table B-6. The Laspeyres based has a much bigger error (equal to about 20 percent of the total decline in damages). As a consequence, the magnitudes of the other effects are different, although their relative importance stays the same. The main advantage of the Laspeyres base is that the base in the same in all time periods, which makes it easier to interpret changes in effects across time. For the average base, we take the average value of the variable across all years, not just the comparison year. For example, the value of $\bar{Q}$ used to calculate the time period t entry in Table 2 is equal to $\frac{1}{2}(Q_t + Q_{2010})$, but the value of $\bar{Q}$ used in Table B-6 is equal to $\frac{1}{8}(Q_{2010} + Q_{2011} + \ldots + Q_{2017})$. This lowers the error relative to the Laspeyres base, but it still large in comparison to the Marshall-Edgeworth base. As with the Laspeyres base, the base is the same in each year. The last base we consider is the Paasche base. Here all of the other variables fixed at their final value. Again the error is large compared to the Marshall-Edgeworth base. The Laspeyres base, the Paasche, and the Average base show much smaller declines in valuations after 2014. Even for these bases, though, the valuation effect is not constant after 2014 due to entry and exit.

The next decomposition eliminates valuation entirely and just focuses on 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). A summary of these decompositions over 2010-2017 is given in Table iv in the Appendix. Here we give results for each individual year.

Table B-6: Decomposition of Change in Damages 2010-2017 (billions of 2014$)

e-decomp-all-appendix

	Baseline	Laspeyres	Average Base	Paasche
Effect				
Scale	−25.2	−29.9	−27.1	−18.4
Composition	−60.0	−54.2	−72.4	−66.0
Technique	−62.6	−53.6	−67.3	−71.3
Valuation	35.3	47.1	35.0	23.3
Error	0.3	−21.6	19.6	20.3
Total	−112.1	−112.1	−112.1	−112.1

Notes: Total changes do not exactly match the aggregate drop in damages in Table 1 because the decomposition requires that we drop plants that report zero generation.

Table B-7: SO_2 Emissions Decompositions (percent of 2010 total emissions)

e-decomp-SO2MASS

Type	2011	2012	2013	2014	2015	2016	2017
Effect							
Scale	−3.3	−3.3	−4.2	−4.0	−4.5	−5.2	−7.7
Composition	−4.5	−19.6	−15.7	−13.9	−25.1	−27.5	−24.4
Technique	−4.3	−12.9	−17.6	−21.2	−27.6	−38.3	−41.9
Error	0.0	0.0	0.1	0.1	0.1	−0.1	−0.1
Total	−12.1	−35.8	−37.3	−39.0	−57.1	−71.2	−74.0

Table B-7 shows the results for SO_2 (expressed in percentage of total SO_2 emissions in 2010). We see the technique effect reduces emissions monotonically throughout the sample. Results for the other pollutants are shown in Tables B-8 to B-10.

The final decomposition calculation considers a different way of treating damage valuations in 2015-2017. In the main text, we kept these valuations equal to the 2014 values. Here we consider a linear extrapolation of the trend from 2011-2014 to determine the valuations in 2015-2017. For example, the valuation in 2017 is equal to the valuation in 2014 plus the difference between the valuation in 2014 and the valuation in 2011. The results are shown in Table B-11 and Figure B-1. Because valuations are generally increasing from 2011 to 2014, the extrapolation obviously increases the valuation effect, but it does not alter the relative importance of the other effects.

Table B-8: NO_x Emissions Decompositions (percent of 2010 total emissions)

e-decomp-NOXMASS

Type	2011	2012	2013	2014	2015	2016	2017
Effect							
Scale	−3.5	−3.7	−4.7	−4.4	−5.3	−6.7	−9.7
Composition	−3.1	−13.5	−10.8	−13.0	−21.0	−24.9	−23.3
Technique	0.6	−1.3	−2.6	−3.4	−8.2	−11.2	−16.8
Error	0.0	0.0	0.1	0.1	0.1	0.2	0.2
Total	−6.0	−18.5	−18.0	−20.8	−34.3	−42.7	−49.6

Table B-9: CO_2 Emissions Decompositions (percent of 2010 total emissions)

e-decomp-CO2MASS

Type	2011	2012	2013	2014	2015	2016	2017
Effect							
Scale	−3.5	−3.8	−4.9	−4.7	−5.9	−7.7	−11.5
Composition	−0.9	−6.2	−4.3	−3.9	−9.7	−12.0	−10.1
Technique	0.0	−0.1	0.1	−0.4	0.7	0.7	−0.7
Error	0.0	0.0	0.0	0.0	0.1	0.1	0.1
Total	−4.3	−10.2	−9.1	−9.0	−14.7	−18.9	−22.2

Table B-10: $PM_{2.5}$ Emissions Decompositions (percent of 2010 total emissions)

-decomp-PM25MASS

Type	2011	2012	2013	2014	2015	2016	2017
Effect							
Scale	−3.4	−3.7	−4.6	−4.4	−5.5	−7.2	−10.7
Composition	−0.7	−5.8	−4.9	−4.9	−12.6	−15.3	−14.8
Technique	−5.3	−7.2	−7.3	−9.5	−7.4	−7.5	−8.2
Error	0.0	0.0	0.0	−0.0	0.1	0.1	0.1
Total	−9.4	−16.7	−16.8	−18.8	−25.5	−29.8	−33.5

Table B-11: Decomposition of Change in Damages from 2010-2017: Linear Extrapolation for 2015-2017 Valuations (billions of 2014$)

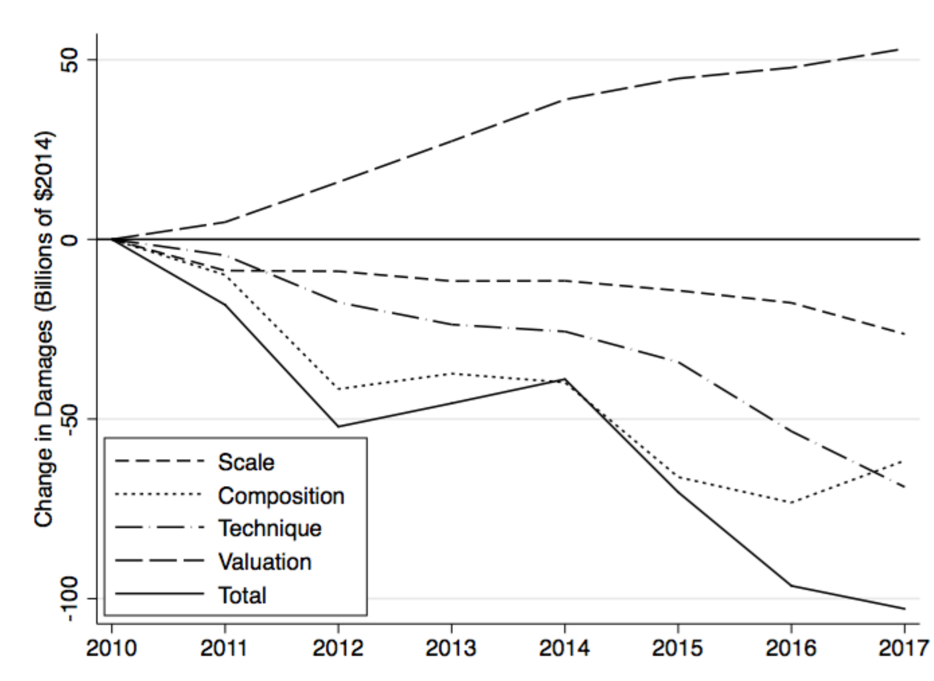
	v_{ipt} Spatial Temporal
Scale (Total Fossil Generation)	
Load	–3.7
Renewables	–16.6
Nuclear	0.2
Hydroelectric	–3.1
Other	–3.1
Total Scale	–26.4
Composition (Generation Shares)	
Coal	–33.9
Switch from Coal	–5.3
Gas	4.6
Entry of Coal	2.5
Entry of Gas	2.7
Exit of Coal	–31.1
Exit of Gas	–0.4
Other	–0.7
Total Composition	–61.6
Technique (Emissions Rate)	
Coal - New SO_2 Control Tech.	–39.1
Coal - No New Tech.	–9.9
Switch from Coal	–17.7
Gas	–2.6
Other	0.4
Total Technique	–68.9
Valuation	
SO_2	30.3
NO_X	4.6
$PM_{2.5}$	2.2
CO_2	16.0
Total Valuation	53.1
Error	0.9
Total	–102.8

e-decomp-final-interp1-small-1

Notes: Total changes do not exactly match the aggregate decline in damages in Table 1 because the decomposition requires that we drop plants that report zero generation. Fuel types are from eGRID (EPA 2009-2016). "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.

Figure B-1: Decomposition of Change in Damages by Year: Linear Extrapolation for 2015-2017 Valuations

fig-decomp-mono1



Notes: All changes relative to 2010.

Scale Effect

Table iii in the Appendix shows generations by fuel type. Here we show this information for each of the interconnections (see Tables B-12 to B-14). In the East, total generation is down slightly from 2010-2017. Fossil generation is down, and renewable generation (primarily wind) is up about 200%. Nuclear and Hydro are up slightly. In the West, generation actually increases slightly from 2010-2017. Fossil generation down and renewable generation is up, with approximately equal magnitude increases in wind and solar. Nuclear is down and hydro is up (after a marked decline in 2015 due to drought). In Texas, both total generation and fossil generation have increased. Wind has more than doubled, though there is very little solar or hydro.

Table B-12: Total Electricity Generation by Fuel Type: East Interconnection

s-eastinter

Fuel	2010	2011	2012	2013	2014	2015	2016	2017
Fossil								
Coal	1,503.7	1,392.0	1,201.9	1,243.8	1,251.2	1,058.6	968.3	918.8
Gas	624.8	687.1	842.2	738.9	738.6	898.4	981.1	932.3
Oil	25.6	18.7	12.2	17.4	21.7	19.3	15.7	13.0
Total Fossil	2,154.1	2,097.8	2,056.3	2,000.1	2,011.5	1,976.2	1,965.2	1,864.1
Renewable								
Wind	45.3	57.3	70.5	88.1	96.2	105.4	121.7	142.4
Solar	0.1	0.3	0.8	1.5	2.4	3.5	7.2	12.8
Total Renew	45.5	57.6	71.3	89.6	98.7	109.0	128.9	155.2
Other								
Nuclear	693.0	677.8	671.1	692.9	699.1	698.6	702.7	708.0
Hydro	94.5	98.4	83.5	102.4	93.8	97.4	91.2	100.1
OtherGen	50.7	51.3	52.9	55.8	56.8	57.4	56.5	56.1
Total Other	838.2	827.6	807.5	851.1	849.7	853.4	850.4	864.1
Grand Total	3,037.7	2,983.0	2,935.1	2,940.8	2,959.8	2,938.6	2,944.4	2,883.4

Notes: Annual net generation from all power plants (in millions of megawatt-hours) and fuel type as reported in in EIA form 923 (EIA 2010-2017a).

Table B-15 shows three measures of total electricity consumption from three different data sources. The first measure, annual retail sales from EIA form 861 (EIA 2010-2017c), comes from utility-level data on metered electricity sales, e.g., from residential household meters. The second measure, hourly load from FERC from 714 (FERC 2010-2017), comes from

Table B-13: Total Electricity Generation by Fuel Type: West Interconnection

e-fuels-westinter

Fuel	2010	2011	2012	2013	2014	2015	2016	2017
Fossil								
Coal	221.1	209.8	199.5	213.3	205.0	188.6	167.7	168.5
Gas	215.2	173.5	221.9	231.2	226.6	236.0	222.1	202.9
Oil	1.8	1.7	1.0	0.8	0.7	0.8	0.9	0.7
Total Fossil	438.1	385.0	422.3	445.3	432.3	425.4	390.6	372.1
Renewable								
Wind	24.7	33.6	39.2	46.5	48.0	44.7	51.1	49.2
Solar	1.0	1.5	3.3	7.3	14.8	20.8	28.0	38.0
Total Renew	25.8	35.1	42.4	53.8	62.8	65.5	79.1	87.2
Other								
Nuclear	72.6	72.7	59.8	57.8	58.8	59.2	60.9	58.4
Hydro	163.1	218.7	190.4	164.2	163.6	149.3	173.7	197.6
OtherGen	25.9	25.8	26.7	27.2	27.6	27.5	26.3	26.5
Total Other	261.6	317.2	276.9	249.3	250.0	235.9	260.9	282.5
Grand Total	725.5	737.3	741.7	748.3	745.1	726.9	730.6	741.8

Notes: Annual net generation from all power plants (in millions of megawatt-hours) and fuel type as reported in in EIA form 923 (EIA 2010-2017a).

Table B-14: Total Electricity Generation by Fuel Type: Texas Interconnection

e-fuels-texasinter

Fuel	2010	2011	2012	2013	2014	2015	2016	2017
Fossil								
Coal	120.3	128.8	109.8	122.0	122.8	97.6	101.0	115.0
Gas	154.5	159.4	169.8	162.3	166.5	195.4	184.0	169.3
Oil	0.7	0.4	1.5	0.9	0.3	0.2	0.2	0.2
Total Fossil	275.5	288.6	281.0	285.2	289.6	293.2	285.2	284.5
Renewable								
Wind	24.0	28.1	29.4	32.5	36.3	39.7	53.3	62.0
Solar	0.0	0.0	0.1	0.1	0.3	0.4	0.7	2.2
Total Renew	24.0	28.2	29.5	32.6	36.5	40.1	54.0	64.1
Other								
Nuclear	41.3	39.6	38.4	38.3	39.3	39.4	42.1	38.6
Hydro	1.1	0.5	0.5	0.4	0.3	0.7	1.2	1.0
OtherGen	1.2	1.3	1.4	1.4	1.6	1.9	1.7	1.5
Total Other	43.6	41.5	40.3	40.1	41.2	41.9	45.0	41.0
Grand Total	343.1	358.3	350.9	357.9	367.3	375.2	384.2	389.7

Notes: Annual net generation from all power plants (in millions of megawatt-hours) and fuel type as reported in in EIA form 923 (EIA 2010-2017a).

Balancing Authority Area and Planning Areas.[3] The third measure, annual net generation from EIA form 923 (EIA 2010-2017a), is the same as the last row in Table iii. It comes from all generating units from all types of power plants.[4] The three measures can differ due to transmission losses, reporting differences, and imports.[5]

Table B-15: Retail Sales, Load, and Generation

table-sales

	2010	2011	2012	2013	2014	2015	2016	2017
Retail Sales	3,712	3,695	3,615	3,627	3,676	3,683	3,686	3,634
Electricity Load	4,094	4,067	4,026	4,032	4,069	4,031	4,090	4,047
Generation	4,106	4,079	4,028	4,047	4,072	4,041	4,059	4,015

Notes: "Retail Sales" is from EIA form 861 (EIA 2010-2017c) and is the sum of annual retail sales at all utilities. "Electricity Load" is from FERC form 714 (FERC 2010-2017) and is the sum of hourly load across non-overlapping respondents. "Generation" is from EIA form 923 (EIA 2010-2017a) and is the sum of annual net generation across all power plants. These data are for the contiguous United States. All figures in millions of MWh.

The distributions of load and fossil generation provide further evidence for renewables being the primary driver of the scale effect. Figure B-2 shows kernel density estimates for load and fossil generation for the early years (2010-12) and late years (2015-17) of our sample. The distribution of load (the left panel) is virtually identical across the two time periods.[6] However, the distribution of fossil generation (the right panel) has shifted left (the mean has decreased) and has become more variable (it has relatively more weight in the tails) which is consistent with fossil generation being required to support intermittent renewables.[7]

[3]Form 714 respondents (Balancing Authority and Planning Areas) range from small municipalities (e.g., Eugene Water & Electric Board with mean hourly load of about 250 MWhs) to large utilities (e.g., Duke Energy Carolinas with mean hourly load of about 11,000 MWhs) to independent system operators (ISO) (e.g., California Independent System Operator with mean hourly load of about 25,000 MWhs). We drop some respondents in order to avoid double counting, e.g., reporting utilities whose load is also reported by an ISO.

[4]At the interconnection level, electricity generation must equal electricity consumption. At a disaggregated level, e.g., NERC region level, load equals generation plus net imports.

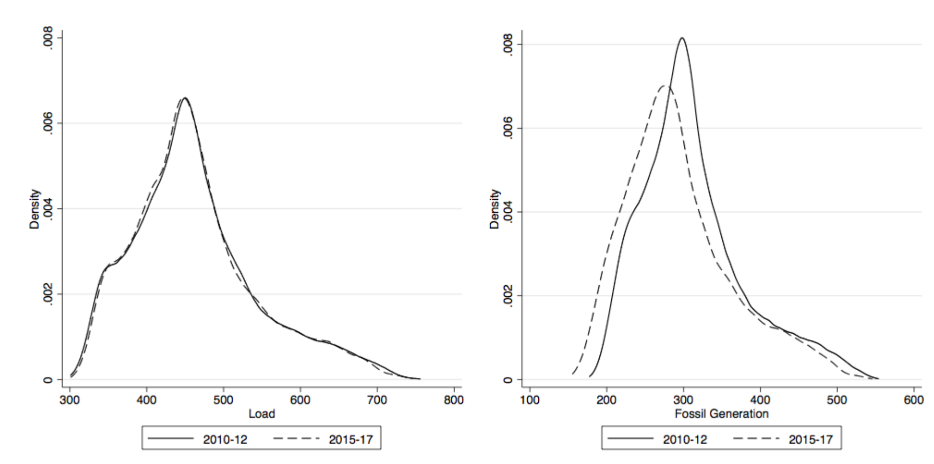
[5]With transmission losses, aggregate generation should exceed aggregate load, which should exceed retail sales.

[6]This is evidence for the limited role of efficiency, which would likely change the shape of the density.

[7]Figures C-1, C-2, and C-3 in Online Appendix C show that this pattern also holds for the East and West interconnection, but not for Texas.

Figure B-2: Kernel density estimates of Load and Fossil Generation

fig-LoadGen



Notes: Kernel density estimates for hourly load and hourly fossil generation

Composition Effect

The exit of coal plants is an important component of the composition effect. Additional data on entry and exit of plants from the CEMS data is given in Table B-16. Plants may enter or exit the CEMS data over time for several reasons. An existing power plant may actually be shut down, or a new power plant may be built. But it is also possible that an existing power plant may be required to start reporting emissions to the EPA. Between 2010 and 2017, 80 coal plants, 55 gas plants, and 29 other plants exited. The exiting coal plants generated less electricity than the average coal plant and had much higher damages per MWh. Exiting gas plants also generated less than average with higher damages per MWh. Between 2010 and 2017, 10 coal plants, 78 gas plants, and 20 other plants entered. The coal plants that entered generated less than the average coal plant but were cleaner. These 10 plants are listed in Table B-17. The first three plants were producing power well before 2010 and report generation in EIA form 923 (EIA 2010-2017a), so they must have been omitted from the CEMS data for some reason. The other entering coal plants were built between 2011 and 2014. The entering gas plants have higher than average generation and lower than average damages per MWh.

As a consistency check, we examined the entry and exit of plants using EIA form 860 (EIA 2010-2017b) as well. The results are shown in Table B-18. The EIA data generally shows a greater number of plants, both entering and exiting, than than the CEMS data.

Tables B-19-B-21 show the entry and exit of plants by interconnection. Each of the interconnections has at least one coal plant enter during 2010-2017.

Table B-16: Entry and Exit of Plants Between 2010-2017

ble-plant-entry4

	2010			2017		
	N	Average Generation	Damages per MWh	N	Average Generation	Damages per MWh
Coal						
Exit	80	1,234	308			
Enter				10[a]	3,273	69
Always Coal	306	5,701	98	306	4,151	80
Gas						
Exit	55	170	32			
Enter				78	1,461	21
Always Gas	776	1,021	23	776	1,192	23
Other						
Exit	29	44	138			
Enter				20	265	42
Always Other	86	32	154	86	26	111

Notes: Primary fuel type of plants from eGRID (EPA 2009-2016). "N" is number of power plants. "Average Generation" is average annual gross generation from CEMS (EPA 2010-2017) in 1000 MWhs. "Damages per MWh" is average annual damages in 2014$ per MWh.
[a]Three of these ten plants do not report emissions in CEMS (EPA 2010-2017) for 2010 but report generation in EIA form 923 (EIA 2010-2017a) and earlier operating years in EIA form 860 (EIA 2010-2017b). The remaining seven plants are newly constructed coal power plants.

Table B-17: Coal Plants Entering CEMS Data Between 2010-2017

table-coal-entry2

ORIS code	Plant Name	State	Entry Year
10671	AES Shady Point, LLC[a]	OK	1990
10849	Northshore Mining Silver Bay Power[a]	MN	1955
50951	Sunnyside Cogeneration Associates[a]	UT	1993
55856	Prairie State Generating Station	IL	2012
56564	John W. Turk Jr. Power Plant	AR	2012
56609	Dry Fork Station	WY	2011
56611	Sandy Creek Energy Station	TX	2013
56671	Longview Power	WV	2011
56786	Spiritwood Station	ND	2014
56808	Virginia City Hybrid Energy Center	VA	2012

Notes: "Entry Year" from EIA form 860 (EIA 2010-2017b). Plants denoted [a] enter the CEMS data after 2010 but report generation in EIA form 923 (EIA 2010-2017a) and earlier Entry Years. Four additional coal plants report Entry Year of 2010 but are not classified as entering in our decompositions.

Table B-18: Entry and Exit of Plants 2010-2017: from EIA form 860

table-plant-entry-eia

	Enter		Exit	
Fuel	Number	Capacity	Number	Capacity
Coal	12	790	116	322
Gas	169	248	181	132
Other	239	13	212	34

Table B-19: Entry and Exit of Plants Between 2010-2017: East

lant-east-entry4

	2010			2017		
	N	Average Generation	Damages per MWh	N	Average Generation	Damages per MWh
Coal						
Exit	75	1,272	316			
Enter				7	3,142	78
Always Coal	252	5,470	106	252	3,844	83
Gas						
Exit	36	188	33			
Enter				47	1,860	21
Always Gas	532	942	25	532	1,211	24
Other						
Exit	28	28	136			
Enter				15	327	39
Always Other	86	32	154	86	26	111

Notes: Primary fuel type of plants from eGRID (EPA (2009-2016). "N" is number of power plants. "Average Generation" is average annual gross generation from CEMS (EPA 2010-2017) in 1000 MWhs. "Damages per MWh" is average annual damages in 2014$ per MWh.

Table B-20: Entry and Exit of Plants Between 2010-2017: West

	2010			2017		
	N	Average Generation	Damages per MWh	N	Average Generation	Damages per MWh
Coal						
Exit	5	666	102			
Enter				2	2,015	43
Always Coal	38	6,121	57	38	4,812	59
Gas						
Exit	13	153	28			
Enter				23	430	22
Always Gas	172	1,006	19	172	919	21
Other						
Exit	0	0	0			
Enter				4	73	84
Always Other	0	0	0	0	0	0

lant-west-entry4

Notes: Primary fuel type of plants from eGRID (EPA 2009-2016). “N” is number of power plants. “Average Generation” is average annual gross generation from CEMS (EPA 2010-2017) in 1000 MWhs. “Damages per MWh” is average annual damages in 2014$ per MWh.

Table B-21: Entry and Exit of Plants Between 2010-2017: Texas

	2010			2017		
	N	Average Generation	Damages per MWh	N	Average Generation	Damages per MWh
Coal						
Exit	0	0	0			
Enter				1	6,709	52
Always Coal	16	8,350	88	16	7,406	92
Gas						
Exit	6	97	34			
Enter				8	2,087	19
Always Gas	72	1,638	20	72	1,706	23
Other						
Exit	1	502	142			
Enter				1	100	60
Always Other	0	0	0	0	0	0

lant-texas-entry4

Notes: Primary fuel type of plants from eGRID (EPA 2009-2016). “N” is number of power plants. “Average Generation” is average annual gross generation from CEMS (EPA 2010-2017) in 1000 MWhs. “Damages per MWh” is average annual damages in 2014$ per MWh.

Technique Effect

In the main text, Figure 4 shows the installations of SO_2 emissions control. Figure B-3a show the installations of scrubbers, which are one specific technology. Figure B-3b shows the installation of scrubbers starting from 1970. A significant number of scrubbers were installed during the 1980's. Also shown are the spot price of SO_2 permits from the allowance auction in EPA's Acid Rain Program. Figure B-3c shows the break down of scrubbers that were installed for State and Federal regulations. The majority of scrubbers were installed for state regulations. Figure B-3d shows the break down of scrubbers that were installed for New Source Review.[8] Since 2000, only a small percentage of scrubbers were installed for New Source Review.

Moving from SO_2 to NO_X, one technology for removing the latter is called Selective Catalytic Reduction (SCR). The installations of SCR over time is given in Figure B-4. The majority of these were installed prior to 2010.

Table B-22 shows annual average fossil fuel shares across plants. In particular, for each power plant, we calculate the fossil generation share of each of the three fossil fuels. The table then reports the mean across all the plants reporting non-zero shares. In 2010, we see that across all plants reporting coal-fired generation, the mean coal share was 89%. By 2017, the mean coal share had fallen to 65% indicating that plants with some coal-fired generation had reduced their share of generation from coal by 22 percentage points.[9] Conversely, the share of gas-fired generation (at plants reporting gas-fired generation) increased from 76% in 2010 to 84% in 2017.

[8] The figure is based on a dataset of New Source Review lawsuits and settlement data that was generously provided to us by Sam Krumholz.

[9] This could occur either by converting existing coal-fired boilers to gas-fired boilers or by increasing generation at (existing or new) gas-fired boilers and/or by decreasing generation at (or retiring) coal-fired boilers.

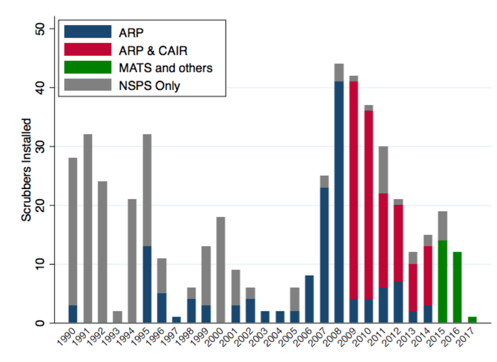
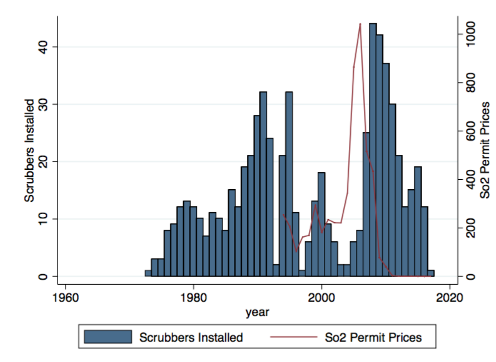
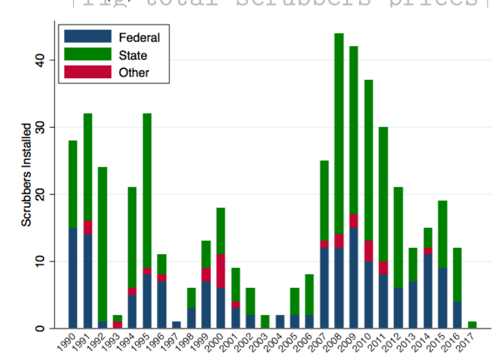


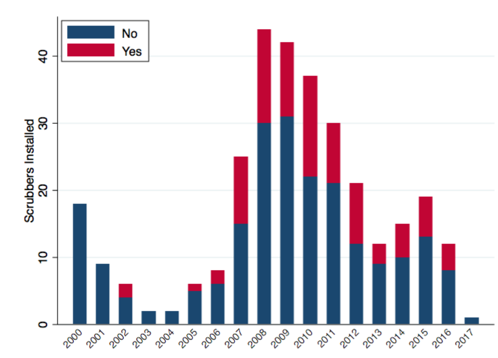
fig-scrubbers (a) Scrubbers 1990-2017 fig-total-scrubbers-prices



(b) Scrubbers: 1970-2017



scrubbers-fedstate (c) Scrubbers Federal and State Regs fig-scrubbers-nsr



(d) Scrubbers New Source Review

rubber-all

Figure B-3: Scrubber Regulations

Notes: Source EIA form 860 (EIA 2010-2017b). The year is the first year a scrubber is active. "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. SO_2 prices are in \$2014. Price data from EPA (1994-2017).

Table B-22: Average Within-Plant Generation Shares

table-fuelshares

Fuel	2010	2011	2012	2013	2014	2015	2016	2017
Coal	0.89	0.87	0.82	0.80	0.78	0.74	0.68	0.65
Gas	0.76	0.77	0.80	0.80	0.79	0.81	0.83	0.84
Oil	0.41	0.40	0.39	0.39	0.39	0.38	0.38	0.38

Notes: Source EIA (2010-2017a). The mean is across non-zero generation shares at the power plants. The number of plants with each non-zero share is approximately 600 coal, 2,000 gas, and 2,000 oil.

Figure B-4: Installation of Selective Catalytic Reduction (SCR)

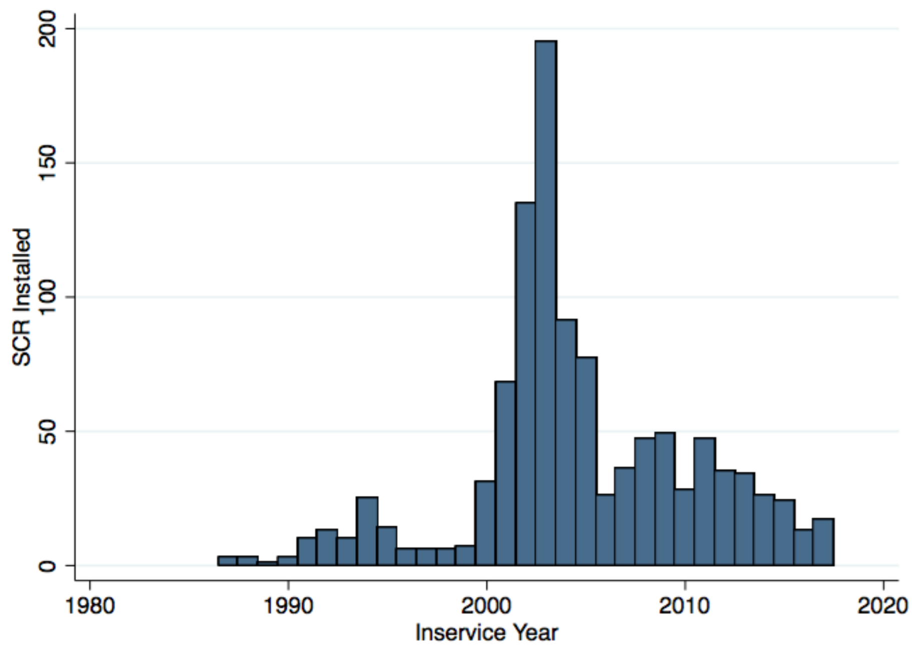


fig-scr

Table B-23: Decomposition of Damages Into Change In Emissions and Change in Valuations : 2011-2014

table-decomp-pollutant

	Total	MD Effect	Emission Effect
SO_2	-19.1%	17.3%	-36.3%
NO_x	-2.0%	14.9%	-16.9%
CO_2	3.9%	8.9%	-5.0%
$PM_{2.5}$	-0.8%	11.3%	-12.1%

Notes: Decomposition at the plant level. Number are expressed at percentage of total damages in 2011.

Valuation Effect

The valuation effect in the main paper shows how changes in valuations have effected damages, keeping other variables fixed. Here we do a different decomposition to provide a complementary look at the valuation effect. Let D_{pt} be the total damage from pollutant p at time t. We have

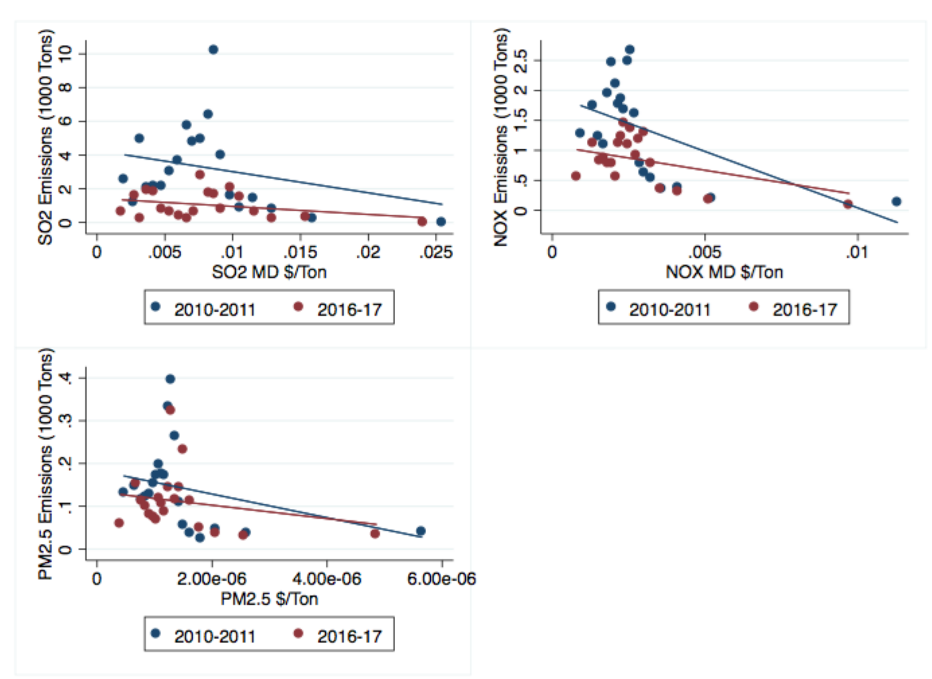
$$D_{pt} = \sum_i v_{ipt} e_{ipt},$$

where, as in the main text, e_{ipt} and v_{ipt} are the emissions and damage valuation per unit of emissions of pollutant p from plant i at time t. Decomposing this equation gives us a valuation effect and an emission effect.[10] As before, we account for entry and exit of plants as well. The results are shown in Table B-23. This decomposition compares the year 2014 to the year 2011 because these years correspond to years in which we have direct data from AP3. As we know from above, emissions are decreasing over this period. The emission effect shows a 33% decline in emissions of SO_2 and a 13% decline in emissions of NO_X. The valuation effect show that damage valuations are increasing over this period. For example, damage valuations from SO_2 have increased 17%.

The relationship between damage valuations and emissions is shown in Figure B-5. Emissions are larger in low damage valuation locations, but this relationship is becoming less strong over time.

[10] When there are only two variables in the decomposition, the error is zero.

Figure B-5: Damage Valuations and Emissions



scatter_v_and_e

C Supplementary Information for Section 3

app-policy

The local polynomial regressions based on both load and fossil generation are given in Figures C-1 to C-3. The damage function is very similar for both load and fossil generation.

Figure C-1: Local polynomial and kernel density estimates: Texas

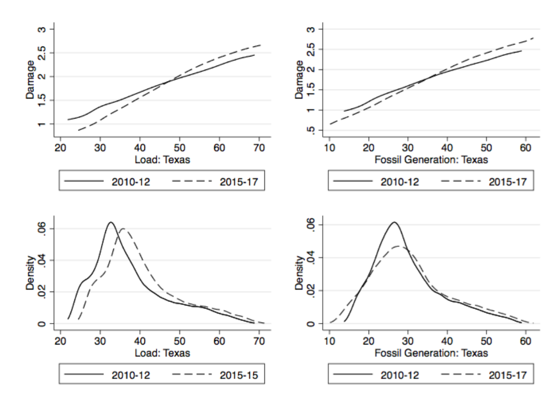


fig-fourErcot

Notes: Top graphs are local polynomial regressions of hourly damages on hourly load and on hourly fossil generation. Bottom graphs are kernel density estimates for hourly load and for hourly fossil generation.

Figure C-2: Local polynomial and kernel density estimates: Eastern Interconnection

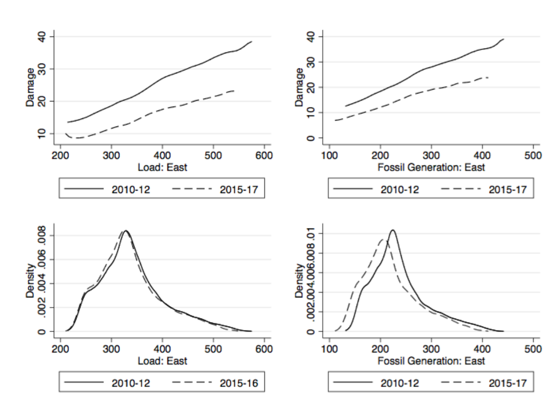


fig-fourEast

Notes: Top graphs are local polynomial regressions of hourly damages on hourly load and on hourly fossil generation. Bottom graphs are kernel density estimates for hourly load and for hourly fossil generation.

The regression results used to create the annual estimates of marginal damage shown in Figure 8 are given in Table C-1.

Figure C-3: Local polynomial and kernel density estimates: Western Interconnection

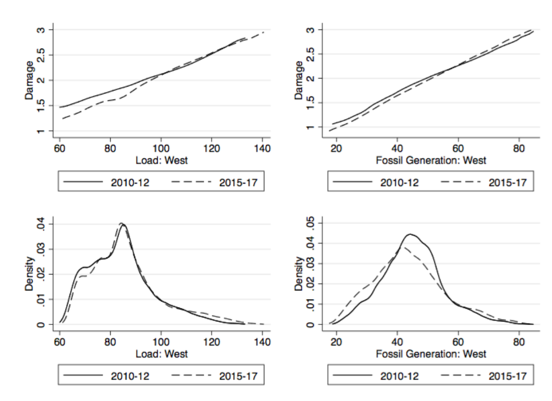


fig-fourWest

Notes: Top graphs are local polynomial regressions of hourly damages on hourly load and on hourly fossil generation. Bottom graphs are kernel density estimates for hourly load and for hourly fossil generation.

Table C-1: Marginal Damage Estimates: Annual

table-reg-annual

Sample Year	2010	2011	2012	2013	2014	2015	2016	2017
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
East								
Load	8.31***	8.37***	7.59***	7.46***	7.86***	7.40***	6.18***	5.34***
	(0.14)	(0.15)	(0.16)	(0.17)	(0.18)	(0.19)	(0.14)	(0.17)
West								
Load	1.91***	2.28***	2.23***	2.44***	2.50***	2.64***	2.91***	2.79***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.09)	(0.07)	(0.08)	(0.07)
Texas								
Load	2.97***	2.70***	2.76***	3.58***	3.09***	3.93***	3.16***	3.54***
	(0.13)	(0.11)	(0.11)	(0.15)	(0.11)	(0.14)	(0.16)	(0.17)
Observations	8,760	8,760	8,784	8,760	8,760	8,760	8,784	8,760

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

Newey-West Standard errors (48 hour lag)

Notes: Dependent variable is hourly damages in the interconnection. Coefficient estimates in ¢ per kWh. Regressions include month of sample by hour fixed effects.

As with the decompositions, we consider an alternative specification in which local damages are fixed at 2014 values. The results are shown in Table C-2. Relative to Table 6 in the main text, the trend line starts greater in each interconnection, but the slope is very small in the West and statistically insignificant in the West.

Table C-2: Marginal Damage Estimates: Fixed Valuations

Variables	(1)	(2)
East		
Load (β)	7.995***	10.288***
	(0.088)	(0.112)
Load Trend (γ)		−0.653***
		(0.026)
West		
Load (β)	2.697***	2.485***
	(0.030)	(0.054)
Load Trend (γ)		0.056***
		(0.013)
Texas		
Load (β)	3.518***	3.494***
	(0.054)	(0.099)
Load Trend (γ)		0.007
		(0.025)
Observations	70,128	70,128

table-reg-main-sens

*** p<0.01, ** p<0.05, * p<0.1
Newey-West Standard errors (48 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.

Next we consider sensitivity to using generation vs load in our main regression. Our main regressions may understate marginal damages if load, conditional on fixed effects, is positively correlated with omitted generation. For example, large-scale hydropower that produces during high priced hours forgoes the opportunity to produce in other hours if reservoirs are constrained. Similarly, when small fossil generators not in CEMS meet peak load, we miss these marginal damages. An alternative approach is to regress damages on fossil generation. If this is done at an electricity region and does not account for trading with other regions, then this approach will be biased with the direction of bias determined by electricity imports and exports. In addition, regressing one input (e.g., pollution) on a plant's output, as in the productivity literature, may result in biased estimates.

Table C-3, which shows the three specifications for levels and annual trend models, is consistent with these sources of bias, but show that the bias is not extreme. In each case the 2010 coefficient on load (Model 2) is smaller than the coefficient on fossil generation (Model 6) and the IV coefficient (Model 4) lies between the two OLS results. However the results are quite similar across the three models, likely due to our aggregation to the interconnection level. In particular, both levels and trends are quite similar across the three specifications.

Next we look at more dissaggregated marginal damage estimates at the NERC level. The results are shown in Table C-4.

As described in the main text, we supplement the univariate non-parametric regressions with an additional regression on the residuals of regressions of damage and load on hour hour of day by month of sample fixed effects. The results are shown in Figure C-4.

Table C-3: Marginal Damage Estimates: Generation vs. Load

	(1)	(2)	(3)	(4)	(5)	(6)
Variables	OLS		IV		OLS	
East						
Load	7.32***	8.64***				
	(0.07)	(0.10)				
Load Trend		−0.38***				
		(0.02)				
Fossil Gen			8.11***	9.72***	8.11***	9.77***
			(0.07)	(0.09)	(0.07)	(0.09)
Fossil Gen Trend				−0.46***		−0.46***
				(0.02)		(0.02)
West						
Load	2.49***	2.03***				
	(0.03)	(0.05)				
Load Trend		0.12***				
		(0.01)				
Fossil Gen			3.06***	2.76***	3.09***	2.79***
			(0.02)	(0.03)	(0.02)	(0.03)
Fossil Gen Trend				0.08***		0.08***
				(0.01)		(0.01)
Texas						
Load	3.23***	2.83***				
	(0.05)	(0.08)				
Load Trend		0.11***				
		(0.02)				
Fossil Gen			3.66***	3.16***	3.86***	3.38***
			(0.05)	(0.08)	(0.04)	(0.07)
Fossil Gen Trend				0.14***		0.12***
				(0.02)		(0.02)
Observations	70,128	70,128	70,128	70,128	70,128	70,128

eg-genvload

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

Newey-West Standard errors (48 hour lag)

Notes: Dependent variable is hourly damages in the interconnection. Coefficient estimates in ¢ per kWh. The IV estimates in (3) & (4) report second stage estimates using load as an instrument for fossil generation. Regressions include month of sample by hour fixed effects.

Table C-4: Marginal Damage Estimates for Electricity Regions

table-reg-nerc

	(1)	(2)	
Variables	level	2010 base	Annual change
Florida	2.823***	4.763***	-0.714***
	(0.776)	(1.129)	(0.241)
Midwest	8.223***	4.957***	0.034
	(0.653)	(0.955)	(0.241)
Northeast	5.334***	2.888*	-0.165
	(1.053)	(1.622)	(0.350)
MidAtlantic	8.672***	15.645***	-1.063***
	(0.681)	(1.117)	(0.244)
Southeast	7.338***	7.643***	-0.212**
	(0.282)	(0.427)	(0.097)
South Central	4.976***	9.436***	-0.607
	(1.016)	(1.576)	(0.391)
California	2.303***	1.764***	0.138***
	(0.074)	(0.109)	(0.026)
West (ROW)	2.668***	2.275***	0.110***
	(0.073)	(0.117)	(0.029)
Observations	70,128	70,128	

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

Newey-West Standard errors (48 hour lag)

Notes: Dependent variable is hourly damages in the interconnection. Coefficient estimates in ¢per kWh. Regressions include month of sample by hour fixed effects. 'Florida" is the NERC region denoted FRCC; "Midwest" is MRO & MISO; "Northeast" is NPCC; "MidAtlantic" is RFC; "Southeast" is SERC; "South Central" is SPP; and "West (ROW)" is the Western Interconnection excluding California.

Figure C-4: Non Linear Marginal Effects

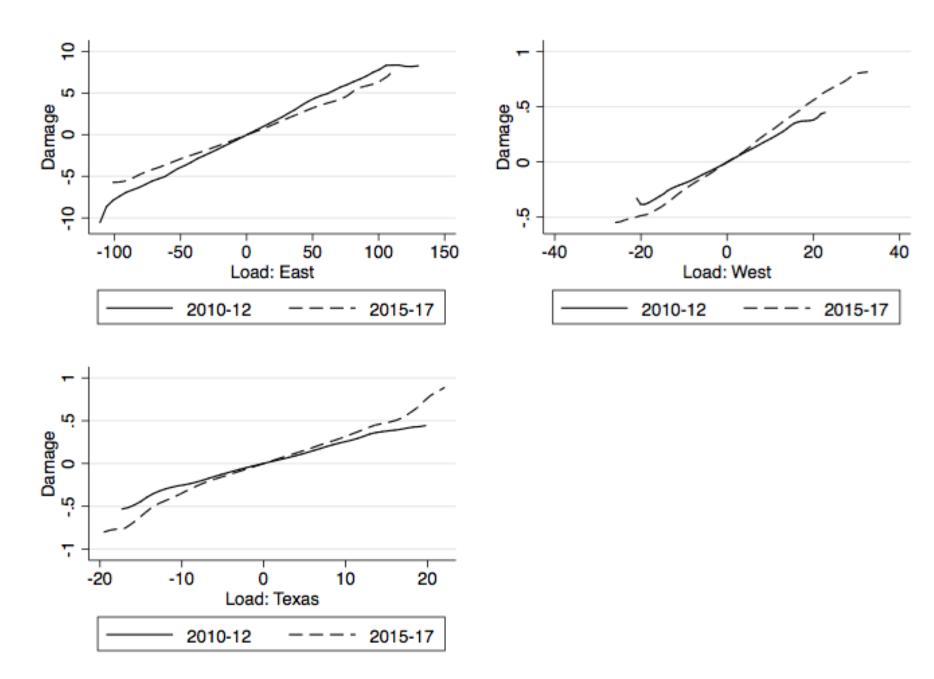


fig-DamageFcn-Resid

Table C-5 shows the average damages (damages divided by load).

Table C-5: Average Damages by Region (¢ per kWh)

table-region-ave

Region	2010	2011	2012	2013	2014	2015	2016	2017
East								
Florida	3.1	2.8	2.9	3.0	3.2	2.8	2.6	2.6
Midwest	2.7	2.5	2.6	2.6	2.5	2.2	2.0	2.0
Northeast	2.5	2.1	1.5	1.5	1.5	1.3	1.2	1.1
MidAtlantic	15.7	14.0	10.6	10.8	11.3	9.5	6.4	5.8
Southeast	6.9	6.6	5.6	5.7	5.7	4.6	4.0	3.8
South Central	5.0	5.1	4.8	5.0	5.0	4.0	3.5	3.3
Total East	7.0	6.6	5.6	5.7	5.8	4.8	3.8	3.5
West								
California	0.6	0.5	0.7	0.7	0.8	0.8	0.7	0.6
West (ROW)	3.4	3.1	3.0	3.4	3.3	3.1	2.8	2.7
Total West	2.3	2.1	2.1	2.4	2.3	2.2	2.0	1.9
Texas	4.4	4.3	3.9	4.4	4.4	3.9	3.7	4.0
Total	6.0	5.6	4.8	4.9	5.1	4.2	3.5	3.3

Notes: Damages created in billions of 2014$ aggregated across all CEMS power plants using AP3 damage estimates. "Florida" is the NERC region denoted FRCC; "Midwest" is MRO & MISO; "Northeast" is NPCC; "MidAtlantic" is RFC; "Southeast" is SERC; "South Central" is SPP; and "West (ROW)" is the Western Interconnection excluding California.

A graphical depiction of the data in Table 9 is given in Figures C-5.

Next we describe the data sources for the solar panel calculation. From NREL we obtain the solar insolation values.[11] These data are described as:

> The insolation values represent the resource available to a flat plate collector, such as a photovoltaic panel, oriented due south at an angle from horizontal equal to the latitude of the collector location. This is typical practice for PV system installation, although other orientations are also used (NREL 2018b).

Each data point describes annual average value of solar insolation (in kWh per meter squared per day) for a unit area of size 0.1 degree in latitude and longitude (about 10km by 10km). There are 83,376 observations in the contiguous U.S. Each observation is mapped to a county

[11] Data from NREL (2018a). Table labelled as "Geographic Coordinate System Name: WGS_1984". Entry in table labelled as "Lower 48 and Hawaii PV 10-km Resolution 1998-2009". Zip file labelled as "us9808_atilt_updated.zip".

Figure C-5: Enviromental Benefit of an Electric Vehicle in 2010 and 2017 ($ per year)

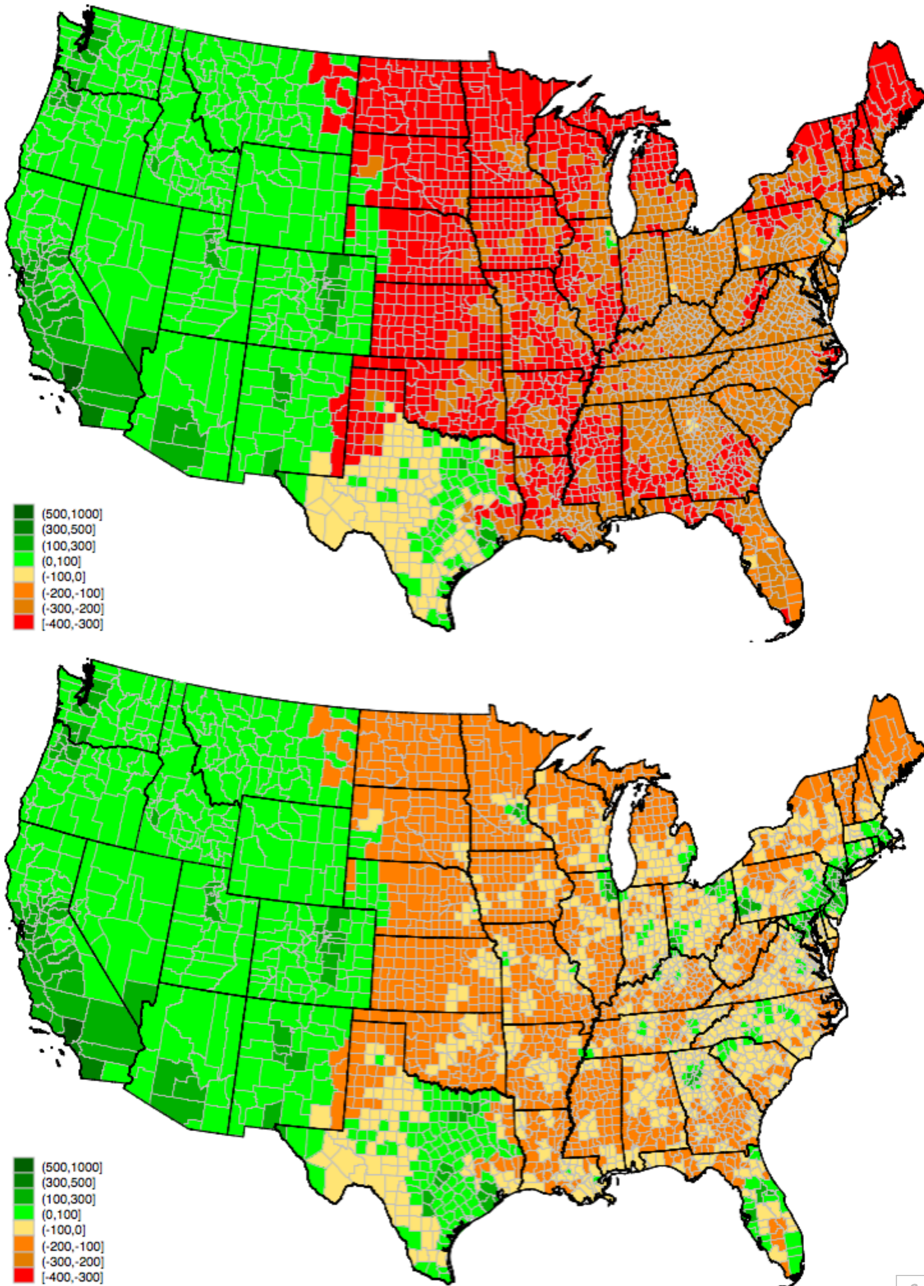


fig-subsidy-county-2010

using a Census Bureau GIS database (Census Bureau 2018). The counties are then mapped into interconnection. The marginal damages for each interconnection are constructed from the estimates in the Day Time Hour rows of Table 8 . Following Siler-Evans at al (2013), we assume 13% efficiency. We also assume that the panels cover a 27 by 13 foot area (32 square meters) which is the average size for a 6kW system.

A graphical depiction of the data in Table 10 is given in Figure C-6. The quantity for each county is the mean over all unit areas within the county.

References

[1] Census Bureau. 2018. Cartographic Boundary Shapefiles. United States Department of Commerce. https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html (accessed on October 12, 2018).

[2] Energy Information Administration. 2010-2017c. "Form EIA-861." United States Department of Energy. https://www.eia.gov/electricity/data/eia861/ (accessed October 15, 2018).

[3] National Renewable Energy Laboratory. 2018b. "Solar Maps Development: How the Maps Were Made." https://www.nrel.gov/gis/solar-map-development.html (accessed on October 12, 2018).

[4] 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.

Figure C-6: Enviromental Benefit of an Solar Panel System in 2010 and 2017 ($ per year)

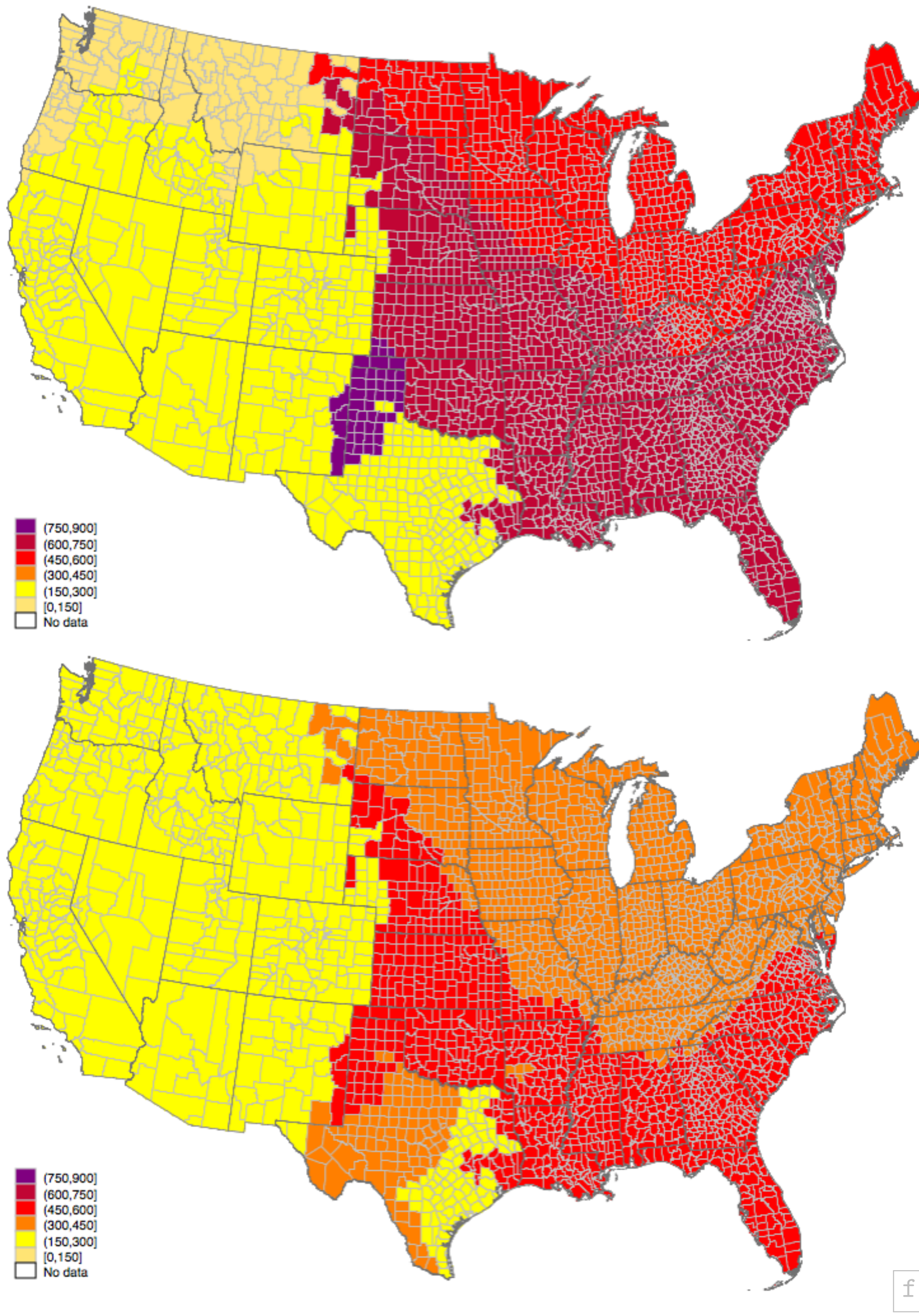


fig-solar-county