Measuring the Environmental Benefits from Transportation Electrification: Urban Electric Buses*

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Abstract

We determine the environmental benefit of using electric buses rather than diesel for urban transit. For diesel we calculate air pollution damages using an integrated assessment model (AP3). For electric buses we initially use marginal damage estimates from the literature. The environmental benefit of operating an electric bus fleet (rather than diesel) is about $70 million per year in Los Angeles and above $9 million per year in five other MSA's. Thirteen MSA's have benefits which exceed 10¢ per mile, and the benefit in Los Angeles exceeds 60¢ per mile. We also explore three methods for determining more spatially disaggregated estimates of marginal damages from electricity consumption. Two of the methods use OLS, and one uses a machine learning technique (Lasso). Using data from Texas, which allows for a rich set of controls, we show these methods provide similar estimates for the three largest regions. Moreover, two of the methods may work reasonably well in other parts of the country for which detailed controls have not been available.

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1 Introduction

Economies rely on the transportation sector to move people, raw materials, and intermediate and final goods throughout the supply chain. The energy and emission consequences of transportation have long-made this sector a target of environmental regulations. In the United States, traditional measures to mitigate pollution from the transportation sector applied a mix of technology and performance standards. The earliest policies focused on the light-duty vehicle fleet. Subsequent rules applied to heavy-duty vehicles including highway diesel trucks and urban buses. In both cases, the regulatory apparatus focuses on tailpipe emissions. In parallel with policies levied on the transportation sector were regulations applied to stationary point sources. Primary among the traditionally-regulated point sources were the fossil fuel-fired power stations. While these early and extant policies cover local air pollution, meaningful efforts to mitigate future climate change are also likely to affect both sectors.

Against this regulatory mosaic, and very much in the context of policy options for managing climate change, electrification of the transportation sector is proceeding. If environmental policy efficiently managed externalities from both transportation and electricity generation, then adoption and use of electric and internal-combustion vehicles would be socially optimal. That is, the incentives presented by policy would ensure that the mix of electric and internal combustion transportation would reflect both private and social costs. Of course, policies are not efficient. One size fits all standards applied to internal combustion engine vehicle design cannot reflect the heterogeneous impacts (per vehicle mile traveled) that depend on where and how the vehicle is driven. In parallel, power plants are not regulated according to plant-specific marginal damages - the theoretical first-best. And, as shown in prior work, the uniform subsidies applied to purchases of electric vehicles do not embody variation in net environmental impact (Holland et al 2016.) This imperfect regulatory framework, within which electrification is occurring, necessitates second-best policies that can improve the efficiency of transportation electrification. Carefully designed second-best policy requires estimates of benefits and costs.

To date, much of the innovation and market penetration of electrification has occurred with light-duty vehicles. Accordingly, the literature focuses on relative environmental impacts of internal combustion and electric light-duty vehicles.[1] However, cars are only one aspect of our transportation infrastructure that could be electrified. Recently, Elon Musk unveiled plans for a Tesla long-haul semi-truck. Some buses and trains have long been electrified, using overhead power lines or electrified rails, but advances in battery technology, wireless charging, and autonomous driving may open new possibilities for buses and trains as well as for short-haul delivery, commercial and heavy-duty trucking, and other transportation modes.

In light of these emerging possibilities for electrification into the transportation sector, the present analysis examines buses used for mass-transit.[2] We focus on this case for three reasons. First, proponents of mass-transit claim that it is a means to reduce individual vehicle use (and hence, total energy use and emissions). We offer a comparison between traditional diesel-powered and electric buses that could affect the merits of this claim moving forward. Second, buses are relied on heavily in cities where local pollution causes large damages. Third, this vehicle class lies at the electrification frontier. Thus, guidance in the form of a comparative policy analysis between internal combustion buses and electric buses may help states and metropolitan areas prioritize investment in electrification.

The environmental benefit of electrification is the difference between the damages of the forgone non-electrified transport and the damages from the electrified transport. In theory, it is straightforward to calculate the environmental benefit of switching from gasoline or diesel powered mode of transportation to the corresponding electric powered mode of transportation. One simply compares the damages from emissions from the tailpipe to the damages from the emissions from the smokestack. In practice, there are several difficulties to carrying out this calculation, some of which have not been satisfactorily addressed by the previous literature. First, both electrified and non-electrified transportation cause emissions of a variety of pollutants. A complete assessment must analyze multiple pollutants. This

[1]Prior analyses include Archsmith et al. 2015, Graff Zivin et al. 2014, Holland et al. 2016, Holland et al. 2019, Li et al. 2017, and Michalek et al. 2011.

[2]See Tong et al 2017 for a review of previous studies of air pollution from various alternative fuel buses. Tong et al 2017 analyze electric buses but use average damages from electric power plants rather than marginal damages.

multipollutant framework necessitates a modeling apparatus that tracks both local air pollutants and greenhouse gases (GHGs). For local air pollution, we employ the AP3 model (Clay et al., 2019; Holland et al., 2019) which is an updated version of the AP2 model (Muller, 2014; Holland et al., 2016). For GHGs, we use the social cost of carbon from the federal government inter-agency working group meta-analysis (USIAWG, 2016).

This distinction among pollution types raises the second empirical challenge; transportation emissions occur at different locations. While greenhouse gases have the same effects regardless of their location, the effects of emissions of local pollutants, e.g., particulate matter, depend on where they are emitted. Thus, we use AP3 to calculate impacts ($/vmt) by county using spatially tailored estimates of the marginal damage of emissions.[3] These values reflect heterogeneity in exposure (whether emissions occur in cities or rural locations) and variation in atmospheric conditions which dictate the fate and transport of emissions. Relatedly, and third, emissions of electrified transportation are difficult to assess. Emissions of a diesel bus occur directly from the tailpipe of the bus. However, an electric bus has no tailpipe, but causes emissions from the power plants which are generating the electricity. Assessing emissions from electric transportation requires assigning emissions at power plants to electricity use at various locations. Fourth, the increasing use of renewables is fundamentally changing the dispatch of power plants in the electricity grid.

The third and fourth challenges listed above have led to issues with the measurement of the environmental benefits of transportation electrification. The difficulty in matching electricity use to power plants creates a mis-match between spatial scales. The damages from the direct emissions from internal combustion-powered automobiles, buses, and trains are typically measured at the county level. This yields approximately 3100 different values.[4] In contrast, the damages from emissions of electrified transportation are typically measured in a handful of regions such as the three interconnections or the nine North American Electric Reliability Corporation (NERC) regions. Increasing precision of the estimates of emissions from electric vehicle charging (to align with the spatial precision for internal combustion-powered vehicle emissions) creates the impetus to drill down at finer spatial scales. However, reducing

[3]See the Appendix for details on AP3.
[4]See Michalek et al., 2011 and Holland et al., 2016.

the spatial scales at which the damages from electricity are estimated introduces econometric concerns including multicollinearity and spatio-temporal correlation in generation. The increasing use of renewables can create an additional statistical problem if renewables are correlated with load, in which case estimates may suffer from omitted variable bias.

The present analysis starts by employing existing methodologies and parameter estimates to calculate the environmental benefit of electric buses relative to diesel buses for each county in the contiguous U.S. For electric buses, we multiply electricity per mile by marginal damages from electricity use in each of the three interconnections (East, West, and Texas). For diesel buses, we multiply emissions per mile for each pollutant by AP3 damage valuations in each county. The resulting environmental benefit is positive on average and large in some areas: above $9 million per year in six MSA's from operating the bus fleet with electric buses instead of diesel buses.

We then move to a more detailed analysis within the jurisdiction of the Electricity Reliability Council of Texas. This tack facilitates working at a finer geographic scale than previous studies (Holland et al., 2016) because Texas is a nearly self-contained electricity grid. That is, the limited ties to generation and load outside Texas uniquely enable estimation of the load-generation-emission-damage relationship at smaller geographic scales. We also have detailed data on wind, solar, and nuclear generation for Texas, which we use as control variables in our regressions. We use three different methods to attempt to determine marginal damage estimates at eight load regions within Texas. The first is based on OLS regressions augmented with data on non-fossil generation as control variables. The second uses a Lasso machine learning approach to select which region's load shocks affect generation and emissions at each power plant. The third uses the geographic location of each power plant and OLS regressions to estimate marginal damages for each region. The three methods provide similar estimates for the three largest regions but not necessarily for the remaining regions. Moreover, our results give preliminary evidence that the second and third method may work reasonably well even without the controls and thus may be of use in the other interconnections (East and West) in which these controls have been unavailable.

2 Environmental benefits of electric buses: Baseline results

To calculate the environmental benefits of bus electrification, we calculate air pollution damages from electric buses and then subtract those from the corresponding damages from the forgone diesel bus. We first detail our calculations of fuel use and emissions rates (grams per mile) of pollutants from diesel and electric buses. We then describe the valuation of the pollutants (dollars per gram). Multiplying emission rates by valuations and then aggregating over pollutants gives the damages by bus type and hence the environmental benefits.

2.1 Non Electric Bus fuel use, emissions, and damages

To provide a valid comparison across electric and diesel buses, we utilize data from the Larson Transportation Institute's Bus Research and Testing Center, located in Altoona, Pennsylvania. This testing center was established in 1989 with funding provided by the Federal Transit Administration under the the Surface Transportation and Uniform Relocation Assistance Act (STURAA; Public Law 100-17) of 1987. The facility tests safety, structural integrity, durability, performance, maintainability, noise, and fuel economy on a test track. It also tests emissions while operating the vehicle over a simulated transit duty cycle on a dynamometer. The tests are detailed and accurate and are likely to well represent fuel use and emissions from actual driving.

Lowell (2013) reports emission test results for three types of buses: "Diesel," "Diesel Hybrid," and compressed natural gas "CNG" buses. All buses met the latest federal emissions standards (last revised in 2010) and thus are reflective of emissions of current buses. For comparison, we also collect data on emissions from the existing bus fleet from the meta analysis in Cooper et al. (2012) which we refer to as "Old Diesel". The emissions rates for NO_X, $PM_{2.5}$, and VOCs (volatile organic compounds) come directly from emissions tests. For SO_2 and CO_2, emissions per mile are based on the fuel used and hence calculated from the fuel economy of the appropriate bus. For the SO_2 calculation, we assume ultra low sulfur diesel which has 15 parts per million sulfur content. For CO_2, we assume 22.38 lbs of CO_2 per gallon of diesel fuel. The resulting average emissions rates (g per mile) for the four types of buses are shown in Table 1. The table shows the dramatic improvements in emissions rates due to the 2010 emissions standards. Although we use the Diesel bus for the environmental benefit calculation, the Diesel Hybrid and CNG bus have lower baseline emissions for at least some pollutants.

Table 1: Emissions rates for non-electric buses

	MPGe	NO_X	$PM_{2.5}$	VOCs	SO_2	CO_2
Diesel	4.68	1.178	0.0065	0.0258	0.020	2171
Diesel Hybrid	5.42	1.125	0.0037	0.0078	0.0174	1873
CNG	4.62	0.465	NR	0.0283	NR	2197
Old Diesel	3.79	19.619	0.493	0.659	0.0249	2678

Notes: Emissions rates in grams per mile calculated from Lowell (2013) and Cooper et al. (2012). "MPGe" is miles per gallon equivalent to a diesel bus. Although natural gas has lower carbon content than diesel fuel this advantage is offset by lower fuel economy leading to similar MPGe and CO_2 per mile for CNG and Diesel. "NR" is not reported.

Damages are determined as the product of emission rates and damage valuations of the various pollutants. We use the AP3 integrated assessment model to determine the damage valuations (Clay et al 2019). AP3 uses air flow modeling to map the flow of emissions over space, chemistry to specify how primary pollutants interact in the atmosphere to create ambient concentrations of secondary pollutants, epidemiology to map pollution concentrations into increased mortality, and finally economics to assign dollar values of damages using the value of a statistical life. For each of the 3109 counties in the contiguous U.S., we take the AP3 valuation for each pollutant ($ per gram) and multiply by the emission rates in Table 1. For CO_2, we use the social cost of carbon adjusted to 2017 of $43.50 per ton of CO_2. Aggregating across pollutants gives damages (dollars per mile) for each non-electric bus type.

2.2 Electric Bus fuel use and damages

Our electric bus is the Proterra Catalyst FC battery electric bus which used an average of 2.185 kWh per mile in the Altoona test facility in 2018.[5] Proterra is the largest manufacturer

[5]The test procedure is based on simulated driving routes. Two NREL studies analyze Proterra electric bus use over actual transit routes over longer time frames in southern California (Eudy and Jeffers, 2017)

of electric buses in the US. Like electric cars, it is expected that electric buses will consume more electricity per mile in very hot and very cold weather.[6] We apply the same temperature correction used by Holland et al. (2016) to adjust the electricity consumption per mile according to the average monthly temperature in each county.[7]

To determine damages from an electric bus, we need to know the *marginal damages* from consuming a unit of electricity ($ per kWh). Holland et al. (2018) estimate marginal damages separately for the three interconnections in the U.S. electricity grid: East, West, and Texas. They analyze the large decline in damages from 2010 to 2017 and find that marginal damages decreased dramatically in the East but increased slightly in the West and Texas. Using their trend estimates, marginal damages per kWh in 2017 are $0.060 in the East; $0.029 in the West; and $0.036 in Texas.[8] Multiplying the county-specific electricity consumption per mile by the interconnection-specific marginal damage per kWh gives the damage from an electric bus mile in each county.

2.3 Results

Figure 1 shows the air pollution damages from driving a diesel bus one mile in each county. Damages are largest in counties that contain large urban areas, and there is significant spatial heterogeneity despite the fact that a large share of the damages are from CO_2, a global pollutant. Figure 2 shows the air pollution damages from driving an electric bus one mile in each county. This figure shows significant differences across the interconnections. In particular, damages per mile from electric buses are substantially lower in the West and

and Seattle, WA (Eudy and Jeffers, 2018) and find efficiencies of 2.15 to 2.36 kWh per mile. Other buses tested in the test facility (and their efficiencies) include: Gillig (2.268 kWh per mile) in 2018; Nova L920 (2.024 kWh per mile) in 2018; Proterra Cat E2 (2.203 kWh per mile) in 2017; Proterra BE40 (1.70 kWh per mile) in 2015; Proterra BE35 (1.73 kWh per mile) in 2012, BYD K7 (1.36 kWh per mile for a 30 ft. bus) in 2017, and BYD Ebus (1.99 kWh per mile) in 2014.

[6]The test facility holds temperature constant at 73°. The NREL studies report slightly higher kWh per mile in Seattle than in southern California, possibly due to temperature differences.

[7]The temperature correction assumes no penalty at an average daily temperature of 68°. For each month, the kWh per mile is penalized based on the difference between 68°and the average daily temperature of the month. We then average across months.

[8]All valuations are in 2014 dollars. Holland et al. (2018)'s methodology is to first calculate damages from the emissions of pollution at each power plant in the contiguous U.S. using the AP3 model. They then regress aggregate damages within an electricity interconnection on electricity usage in the interconnection and a time trend. For example, the East is $0.060 =(0.08644-7*0.00377) based on their reported coefficients.

Texas relative to the East. However, the figure also shows an important limitation of this calculation: There is limited spatial heterogeneity within an interconnection. In particular, the only spatial variation within an interconnection arises from the temperature correction. Comparing the two figures shows that benefits of bus electrification are likely to be most significant in the West and Texas and will be negative in some counties.

Summary statistics for data in these figures is given in the first two rows of Table 2. The statistics are weighted by estimated bus miles for each county from the US EPA MOVES model.[9] The mean damage per mile for the Diesel bus ($0.151) is larger than the mean damage for the Electric bus ($0.125). Diesel bus damages range from a minimum of $0.106 per mile, which largely reflects the CO_2 damages, to a maximum of $0.696 per mile, which reflects the high damage cost of local air pollution in Los Angeles. The range of Electric bus damages is much smaller ranging from $0.064 per mile in temperate California to $0.159 per mile in the north of the East interconnection. The third row of the table shows the environmental benefit per mile of an electric bus, which is the difference between the diesel and electric bus damages. Although there are counties in which the environmental benefit is negative, on average electric buses generate a positive environmental benefit. In a few counties this benefit is quite large (up to 63 cents per mile). The table also shows summary statistics for the damages from the other three types of buses. The Diesel Hybrid and CNG buses are cleaner on average than the baseline Diesel bus. The range of damage from the CNG bus is also smaller reflecting the lower damages from local pollutants particularly NO_X. The CNG bus is cleaner on average than the Electric bus although the minimum and maximum damages are lower for the Electric bus. For comparison, the table includes the Old Diesel bus which is on average five times more damaging than the other bus types and has a maximum damage of a remarkable ten dollars per mile.

Table 3 shows damages aggregated to the MSA level based on estimated bus miles from the MOVES model. The top twenty MSAs are ranked by the annual benefit, which is the difference between damages from all bus miles in the MSA using new diesel buses and all bus miles using electric buses. This benefit is highest in the Los Angeles MSA. In Los Angeles,

[9] The MOVES model estimates VMT for each US county for a variety of vehicle categories. The bus miles category includes both transit and school buses.

Figure 1: Diesel Bus Air Pollution Damages ($ per mile)

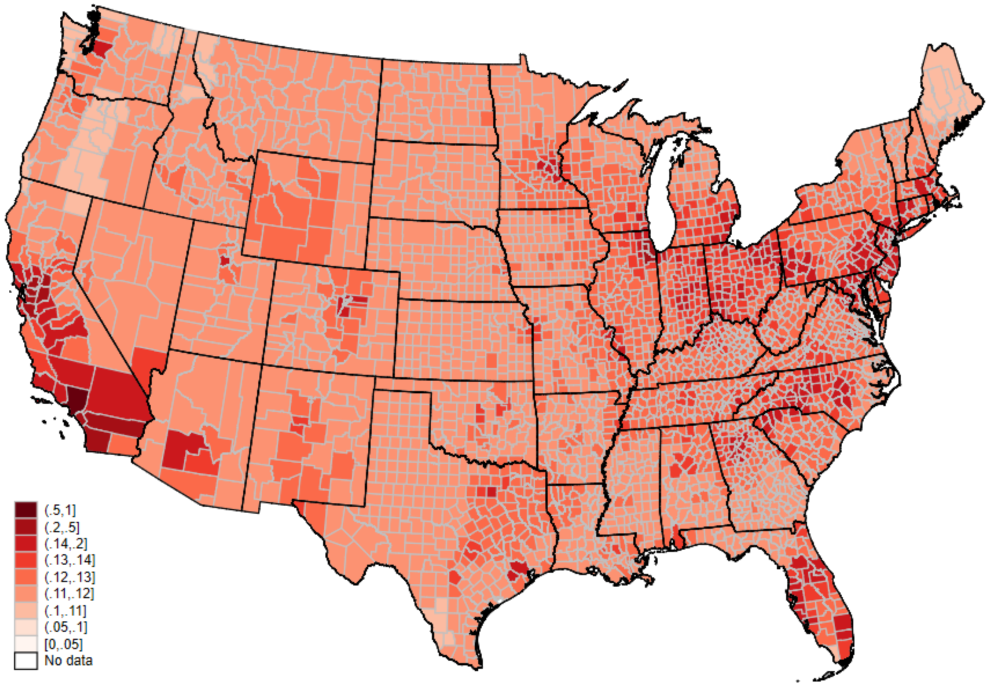


Figure 2: Electric Bus Air Pollution Damages ($ per mile)

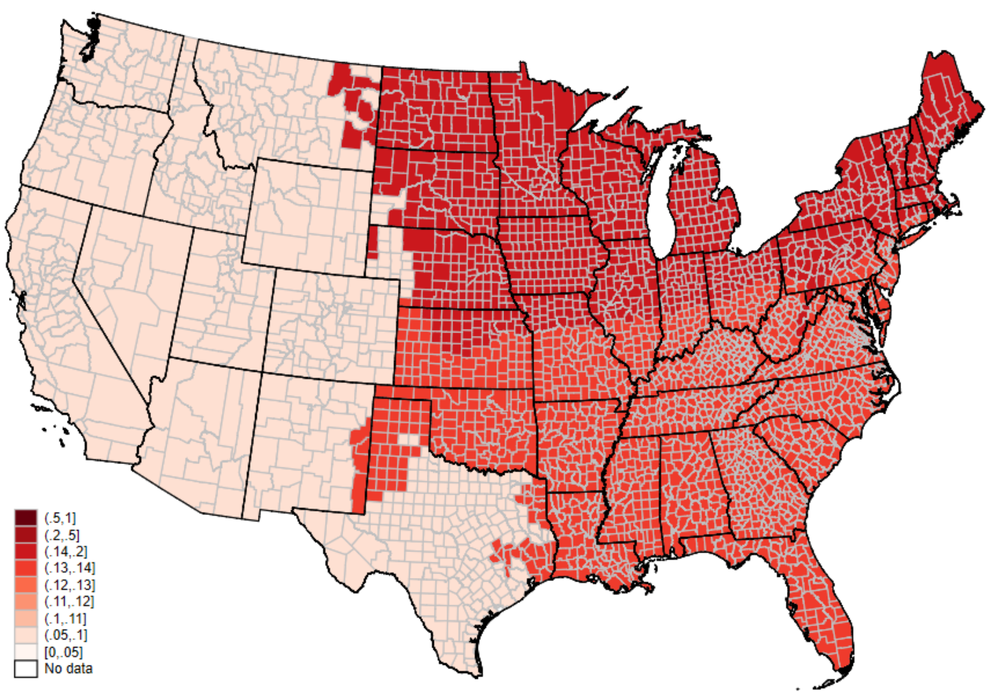


Table 2: Damages By Bus Type and Environmental Benefit of Electric Buses ($)

	Mean	Std. Dev.	Min	Max
Diesel	0.151	0.067	0.106	0.696
Electric	0.125	0.029	0.064	0.159
Benefit	0.026	0.078	-0.046	0.632
Diesel Hybrid	0.134	0.063	0.092	0.648
CNG	0.123	0.025	0.106	0.330
Old Diesel	1.003	1.194	0.167	10.381

Notes: Weighted by bus VMT from MOVES.

if the entire bus fleet were new diesel buses, air pollution damages from the buses would be $71.4 million per year. However, if the entire bus fleet were new electric buses, damages would be reduced to $6.6 million which is an annual benefit of $64.7 million. This large benefit is driven by the large benefit per mile of $0.632, which is the largest in the country. Other MSAs in the West also have large benefits per mile, e.g., Santa Ana, CA and San Diego, CA, and thirteen MSA's have benefits which exceed $0.10 per mile.[10] Cities in the East tend to have smaller benefit per mile but can still have substantial annual benefits. For example, New York, NY has a benefit of $0.111 per mile and has an annual benefit of $15.0 million from adopting an electric bus fleet relative to a new diesel fleet. For comparison, the table also reports damages from Old Diesel buses and shows substantial damages from old diesels and hence substantial benefits from replacing pre-2010 buses. Table I in the Online Appendix shows a similar table for all 376 MSAs in the contiguous U.S.

The results in Tables 2 and 3 calculate damages from electric buses based on the marginal damages reported in Holland et al. (2018). While these estimates are quite robust, they have limited spatial heterogeneity because they are determined at the interconnection level.[11] In particular, the results assume that the marginal damage from electricity use is the same within each interconnection. In the West, this assumption implies that marginal damages are the same in Los Angeles, CA as they are in Seattle, WA or Phoenix, AZ. In the East,

[10]In addition to the MSAs in Table 3, this includes Stockton, CA ($0.16 per mile), San Francisco, CA ($0.12 per mile), Modesto, CA ($0.12 per mile), Vallejo, CA ($0.14 per mile), and Santa Cruz, CA ($0.11 per mile).

[11]The estimates change smoothly across time periods as would be expected. The results are also robust to endogeneity concerns and are little changed by instrumenting or by assuming fossil generation is always marginal.

Table 3: Damages and benefits (in millions) by MSA

MSA	Diesel	Electric	Annual Benefit	Benefit per mile	Bus VMT	Old Diesel
Los Angeles, CA	71.4	6.6	64.7	0.632	102.5	1064.0
New York, NY	33.8	18.8	15.0	0.111	135.1	426.4
Chicago, IL	41.5	28.7	12.8	0.064	200.2	424.2
Phoenix, AZ	18.9	8.3	10.6	0.087	122.0	126.0
Riverside, CA	15.5	5.7	9.8	0.115	85.2	124.7
Santa Ana, CA	12.5	3.0	9.5	0.205	46.6	142.1
Newark, NJ	29.7	20.9	8.8	0.059	149.6	302.8
San Diego, CA	11.1	2.6	8.6	0.216	39.7	125.8
Atlanta, GA	48.8	40.4	8.4	0.028	298.7	379.8
Dallas, TX	19.7	11.7	8.0	0.057	140.5	113.2
Edison, NJ	25.3	19.7	5.6	0.040	141.8	226.7
Oakland, CA	6.5	1.9	4.6	0.160	28.8	66.6
Houston, TX	11.5	7.2	4.3	0.051	84.3	62.8
Seattle, WA	7.7	3.5	4.2	0.081	52.0	49.2
Washington, DC	27.4	23.3	4.1	0.024	169.8	212.8
Sacramento, CA	5.8	2.2	3.7	0.113	32.6	47.3
Fort Worth, TX	9.2	5.6	3.6	0.054	67.1	50.5
San Jose, CA	5.1	1.6	3.5	0.139	24.9	47.6
Detroit, MI	21.9	18.6	3.4	0.026	129.8	178.9
Philadelphia, PA	11.6	8.4	3.2	0.053	60.4	114.9

Notes: “Diesel” is multiple post-2010 buses and “Electric” is the Proterra Catalyst FC battery electric bus using 2.185 kWh per mile. VMT is bus vehicle miles traveled from MOVES in millions.“Old Diesel” uses emission rates from meta-analysis of pre-2010 buses.

this implies marginal damages are the same in New York, NY as in Atlanta, GA, Miami, FL, New Orleans, LA, and Minneapolis, MN. Although it is technically feasible for electricity to flow freely throughout each interconnection, it is likely that congestion in the transmission network would lead marginal damages to differ across locations within an interconnection at least during some hours of the day. In theory a regionally disaggregated approach should be superior because it nests the aggregated model.[12] However, the regionally disaggregated approaches have been criticized and may not be robust due to the high level of correlation between load in different regions. (Callaway et al. Forthcoming). To explore the regionally disaggregated models more carefully, we focus on the Texas interconnection.

3 A closer look at the Texas Interconnection

We focus on the Texas for three reasons. First, the market authorities governing the Texas electricity market (commonly called ERCOT) make extensive data available. Holland et al. (2018) utilize hourly data on load and on fossil generation at power plants regulated by the U.S. EPA under the Clean Air Act Air Markets. In addition to this data, Texas makes available data on hourly generation of all small fossil power plants not regulated by the U.S. EPA., as well as all non-fossil units including renewables (wind, solar, and hydropower) and all nuclear units. Texas also makes available data on electricity load in all of ERCOT as well as load for eight smaller load regions. This extensive data makes Texas ideal for our analysis. Second, the Texas electricity market is isolated from the rest of the country. In fact, only five relatively small direct current power lines (DC ties), for which we have some data on hourly flows, connect Texas with the rest of the US and with Mexico. This isolated system means that power flows can be analyzed more completely than in other regions. Finally, electric buses in Texas are of independent interest because three Texas MSAs are in our top twenty MSAs for benefit from electric bus adoption.

We first begin by describing the Texas data in more detail. We then analyze three methods for estimating marginal damages across the electricity load regions within Texas. All

[12] More precisely, if the true coefficients are equal across regions, they should be equal in the disaggregated model. Hence, the disaggregated model can be used to test whether or not the aggregate model is appropriate.

three methods utilize the additional data available in Texas (renewable generation, nuclear generation, and DC ties) as control variables. Unfortunately, these controls have not been available nationally. The first method simply adds the controls to the standard estimation procedure used by previous work (Holland et al. 2016 and Holland et al. 2018). The second method utilizes machine learning techniques to let the data determine the correct regions to include for estimating marginal damages. The third method estimates a parsimonious model based on the geographic location of the power plant.

We apply two criteria for assessing the models. Any model for predicting marginal damages should also reliably predict *marginal generation*. Because electricity cannot be stored economically at scale, electricity generation should equal electricity load in each hour. Therefore a regression with generation as the dependent variable and load as the independent variable should, in theory, have a coefficient of one. Another criteria is that the estimated marginal damages should not be changing dramatically from year to year. While the electricity grid does change over time, investment is often a multi-year process so changes in the grid should occur gradually.

3.1 Texas Data

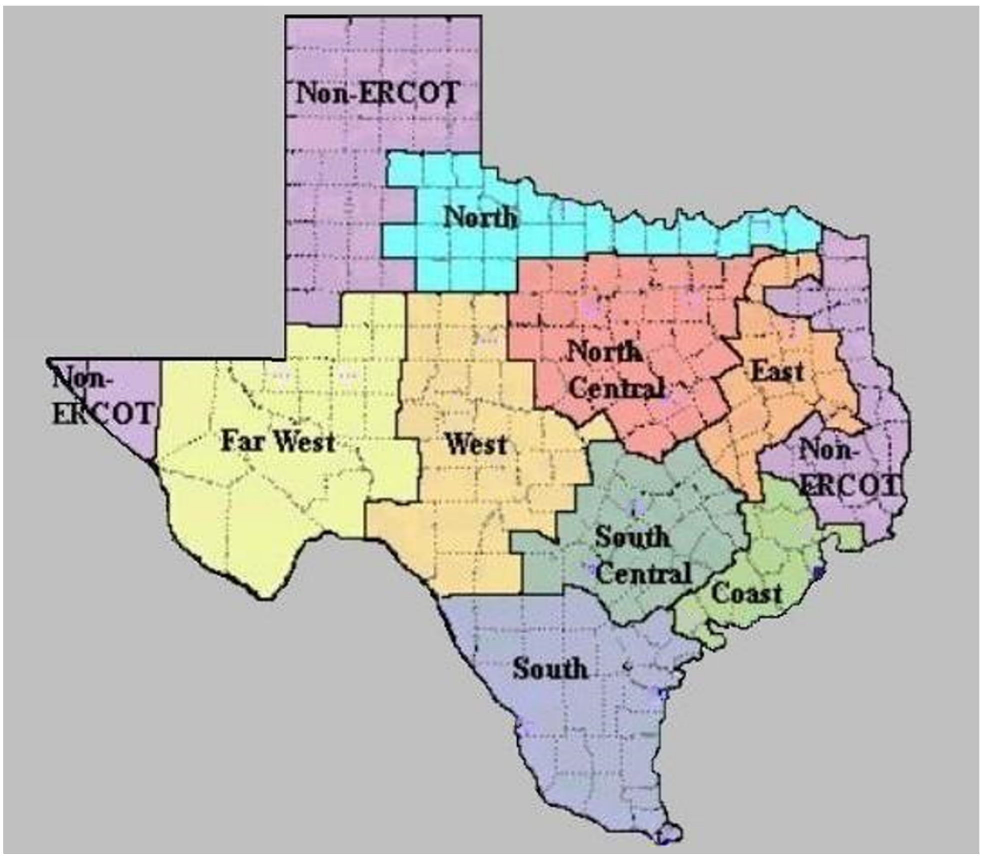
To estimate marginal damages in Texas, we utilize three sources of data: data on load, data on generation from all sources, and data on emissions and generation from plants regulated by the EPA.[13] The sample covers six years from 2012 through 2017.

ERCOT reports hourly aggregate electricity load to the Federal Energy Regulatory Commission (FERC) on Form 714. We refer to this aggregate quantity as *Texas Load*. Separately, ERCOT posts hourly load data for eight load regions. These load regions are illustrated in Figure 3. Summary statistics for hourly load are presented in Panel A of Table 4. The three largest regions, North Central, Coast, and South Central, contain Dallas, Houston, and San Antonio respectively. Electricity load is highly seasonal (highest in summer, lowest in winter) and has predictable hourly patterns (e.g., peaks at 6pm in the summer months). These seasonal and hourly patterns are illustrated in Online Appendix Figure A. For our purposes, the most important characteristic of load is that it highly correlated across the eight load

[13]The first two datasets are from ERCOT, and the third is from EPA air markets

regions. The correlation coefficients are presented in Table 5. Of the 28 correlation coefficients, 13 are above 90% and an additional seven coefficients are between 80% and 90%. The least correlated region is the Far West, for which correlation coefficients range from 0.48 to 0.63. These high correlations across load regions may cause problems from multicollinearity when load from various regions are used in the same regression.

Figure 3: Texas load regions



ERCOT also reports hourly net generation data at each generating unit. Summary statistics by fuel type are presented in Panel B of Table 4, and generation by month is shown in Online Appendix Figure B. Gas accounts for the largest generation share with mean hourly generation of over 16,000 MWh and coal is the second largest generation share (12,000 MWh). These fuels are the most correlated with load. Generation from nuclear has limited variation over time and has held steady throughout this time period while hourly generation from wind power is quite volatile but has increased steadily and in recent years

Table 4: Summary statistics of Texas data

Panel A. Electricity Load				
	Mean	Std. Dev.	Min	Max
Texas	39,025	9,160	22,528	71,093
N. Central	12,899	3,446	7,124	25,282
Coast	11,220	2,574	6,457	20,101
S. Central	6,387	1,693	3,525	12,345
South	3,241	804	1,666	5,845
Far West	1,948	375	1,134	3,164
East	1,388	322	762	2,494
West	1,111	228	632	1,902
North	831	176	509	1,559
Panel B. Electricity generation				
	Mean	Std. Dev.	Min	Max
Gas	16,468	7,258	3,094	42,673
Coal	12,259	3,480	1,771	18,992
Nuclear	4,486	789	1,347	5,188
Other	740	214	19	1,365
Wind	4,848	3,179	5	15,994
Solar	78	170	0	1,052
Hydro/Bio	117	70	27	488
Panel C. Regulated generation and damages				
	Mean	Std. Dev.	Min	Max
Generation	30,589	9,322	10,134	61,913
Damage	1,690	461	490	3,074

Notes: Generation in Panel B is net of electrictiy used within the plant. Regulated generation in Panel C is gross of electricity used within the plant. 52,608 observations.

Table 5: Correlation coefficients for Texas load regions

	N. Central	Coast	S. Central	South	Far West	East	West	North
N. Central	1							
Coast	0.875	1						
S. Central	0.950	0.936	1					
South	0.854	0.942	0.938	1				
Far West	0.540	0.619	0.574	0.603	1			
East	0.966	0.908	0.956	0.879	0.533	1		
West	0.953	0.835	0.936	0.846	0.629	0.924	1	
North	0.976	0.804	0.899	0.782	0.480	0.931	0.940	1

Notes: 52,608 observations.

has a higher generation share than nuclear. Solar and Hydro/Biomass generation is relatively limited in Texas.

Emissions and gross generation data for all power plants regulated under the Air Markets program of the Clean Air Act are from the EPA CEMS database. We refer to this generation from these plants as *regulated generation*. This data reports hourly emissions of SO_2, NO_X, and CO_2 as well as gross generation from the power plant, which we use to estimate hourly $PM_{2.5}$ emissions. The AP3 model gives us dollar values of damages per unit from each power plant for the local pollutants. For the global pollutant CO_2, we use the social cost of carbon of $41 per ton of CO_2. Summary statistics of damages and gross generation are presented in Panel C of Table 4.[14]

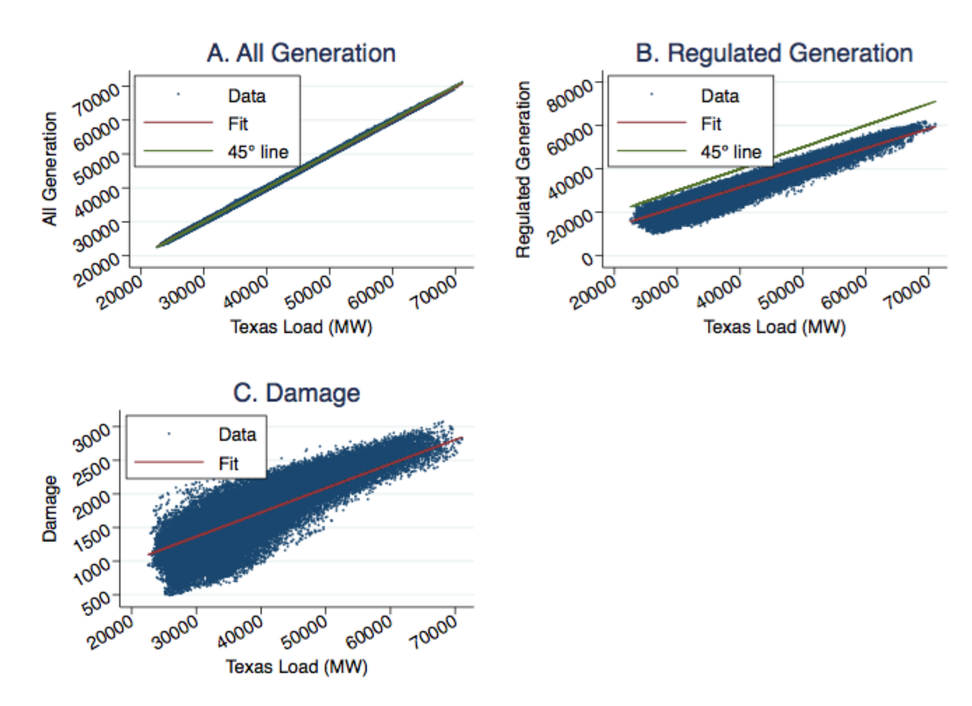
A final source of data is hourly electricity flows on the DC ties. We collect hourly flows from the Southwest Power Pool (SPP) beginning in 2014 for the two lines connecting ERCOT and the SPP. Adding the DC ties data to the hourly generation data should give us a very close match to the hourly load data. Indeed this is the case. Panel A of Figure 4 shows that aggregate hourly load and aggregate hourly net generation match almost exactly in our data.[15] The regression of generation on load with month of sample by hour of day fixed effects (not shown) yields a slope of 0.989 with an R^2 of 0.9995. Adjusting for the DC flows into SPP increases the R^2 further and increases the estimated coefficient from 0.989 to 0.994.

Panel B of Figure 4 shows the relationship between Texas load and regulated generation. As with Panel A, the regression has month of sample and hour of day fixed effects (not shown). A one kWh increase in load is associated with an increase of 0.902 kWh of regulated generation with an R^2 of 0.928. If regulated generation were always marginal then this estimated coefficient would be close to one, as it was in panel A. However, regulated generation differs in two ways from net generation. First, it only includes fossil generation above a certain size threshold. Thus it does not incllude non-fossil generation, such as wind, nuclear, and solar, and may also exclude small fossil generation. Second, it is gross generation which includes electricity used within the plant.

[14]Unfortunately, the CEMS data on gross generation cannot be directly merged with the ERCOT data on net generation at the unit level.

[15]More detailed versions of Figure 4 are shown in Online Appendix Figures C, D, and E.

Figure 4: Hourly load v. generation, regulated generation, and damage



Panel C of Figure 4 shows the relationship between load and damages.[16] This relationship shows that a one kWh increase in load is associated with a \$0.036 increase in damages, *i.e.,* the marginal damage is \$0.036 per kWh. The R^2 in this regression is 0.898.

[16]Once again the fitted relationship is based on a regression with fixed effects but the fixed effects are not shown.

3.2 Method 1: Non-fossil controls

Although the fitted relationship in Panel C of Figure 4 is based on month of sample by hour of day fixed effects, it may still suffer from omitted variable bias. Table 6 tests this relationship for robustness to omitted variables using our controls and an instrumental variables model. Model (1) in Table 6 corresponds to the fitted result in Panel C. In this regression there are 1,728 fixed effects (= 6 years * 12 months * 24 hours) which should capture many confounding variables. But, because Texas has data on non-regulated generation, we assess any remaining omitted variable bias by directly controlling for non-fossil generation and imports through DC lines. Model (2) shows that the estimated marginal damage only increases to \$0.038 when including our controls.

Table 6: Marginal damage estimates for Texas interconnection: OLS v. IV with controls

	OLS		OLS		IV	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Texas Load	0.0360***	0.0380***				
	(0.001)	(0.001)				
Generation			0.0414***	0.0409***	0.0399***	0.0403***
			(0.000)	(0.001)	(0.001)	(0.001)
Wind Gen.		-0.0409***		-0.0024***		-0.0029***
		(0.001)		(0.001)		(0.001)
Solar Gen.		-0.0905***		-0.0522**		-0.0522**
		(0.025)		(0.022)		(0.022)
Hydro/Bio		-0.1004**		-0.0945**		-0.0881**
		(0.042)		(0.039)		(0.039)
Nuclear Gen.		-0.0380***		-0.0023		-0.0027
		(0.005)		(0.005)		(0.005)
DC-East		-0.0267**		-0.0015		0.0009
		(0.012)		(0.011)		(0.011)
DC-North		-0.1089***		-0.0683***		-0.0666***
		(0.018)		(0.017)		(0.017)
DC Indicator		27.7810*		22.5736*		22.3319*
		(14.976)		(13.120)		(13.102)

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

Notes: Damage is dependent variable. Newey-West standard errors with 48-hour lags. Each regression has 52,608 observations and 1,728 fixed effects (=6 years * 12 months * 24 hours). The IV estimates use load as an instrument for regulated generation.

Table 6 also tests an alternative method for estimating marginal damages. Namely, if we assume that regulated generation is always marginal and that there are no imports (both reasonable assumptions for Texas) then marginal damages can in principle be estimated from the relationship between regulated generation and damages. Estimating this relationship directly likely suffers from endogeneity bias so we instrument for regulated generation with Texas load. Models (3)-(6) of Table 6 show both the OLS and IV results. The OLS estimates for regulated generation in (3) and (4) are larger than those for load in (1) and (2) and are also larger than the IV estimates in (5) and (6) which correct for endogeneity. Overall, Table 6 has four broad lessons. First, the interconnection results are robust to the omitted non-fossil generation. Controlling for non-fossil generation changes the main OLS result by about 5% but only changes the IV estimate by about 1%. Second, the marginal damages are robust to the different methods. The largest difference, between (1) and (3) is about 15%. Controlling for non-fossil generation reduces the difference to about 8%. Third, conditioning on our controls affects the coefficients as anticipated. In particular, conditioning the OLS regressions on the controls moves the estimates closer to the IV estimates. Finally, if we assume that fossil generation is the only marginal generation, the estimates in (1) and (2) should be scaled by the estimates for how regulated generation responds to load. Scaling the estimates implies effects quite close to the IV estimates.[17]

The interconnection level results in Table 6 are robust to method and to additional controls. We now ask whether we can estimate the marginal damages at smaller geographic regions. First, we note that the relationship between regulated generation and damages (and hence the IV strategy) cannot be estimated meaningfully at the region level since the method assumes no imports between regions. This assumption is not realistic for Texas regions. However, we can regress damages on load in each of the eight regions. The estimated coefficient for a region would then be the damage from an additional kWh of electricity used in the region conditional on the load in all the other regions. In theory, this should yield precisely the marginal damage estimate of interest. The results from regressing damages on load in each of the eight regions are shown in (3) and (4) of Table 7 and illustrate the problem

[17]The coefficients for how regulated generation responds to load are shown in Online Appendix Table A. Using these estimates the result in (1) becomes \$0.0399 (=0.036/0.902) and the result in (2) becomes \$0.040 (=0.038/0.943) which are very close to the IV estimates.

Table 7: Marginal generation and marginal damage estimates for Texas regions: All

	Generation		Damage	
Variables	(1)	(2)	(3)	(4)
N. Central	0.766***	0.938***	0.039***	0.048***
	(0.081)	(0.016)	(0.005)	(0.004)
Coast	0.655***	0.974***	0.035***	0.049***
	(0.076)	(0.014)	(0.005)	(0.003)
S. Central	0.847***	0.958***	0.040***	0.047***
	(0.147)	(0.026)	(0.009)	(0.006)
South	0.765***	0.955***	0.018	0.025***
	(0.202)	(0.037)	(0.012)	(0.009)
Far West	-7.222***	1.543***	-0.297***	0.087***
	(0.835)	(0.132)	(0.047)	(0.034)
East	2.356***	0.611***	-0.005	-0.087***
	(0.634)	(0.110)	(0.039)	(0.027)
West	10.436***	0.505***	0.310***	-0.121**
	(0.988)	(0.183)	(0.058)	(0.048)
North	0.379	1.185***	0.054	0.081
	(1.317)	(0.245)	(0.084)	(0.063)
Controls	No	Yes	No	Yes

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

Notes: Damage is dependent variable. Newey-West standard errors with 48-hour lags. Each regression has 52,608 observations and 1,728 fixed effects. Controls are generation from wind, solar, hydro/biomass and nuclear and power flows on two DC ties plus an indicator for the availability of the DC flow data.

of multi-collinearity arising from the high correlation of the load in the regions. In (3), the estimate for the Far West is large and negative (!) while the estimate for the West is large and positive. Conditioning on our controls in (4) mitigates the problem somewhat, but there are still large negative coefficients (in East and West) offset by large positive coefficients (in Far West and North). The same issue arises when we try to predict fossil generation instead of damages, as shown in (1) and (2). In theory, the coefficients in (1) and (2) should all be one. However in (1) without controls, an increase in load in the Far West predicts a decrease (!) in fossil generation. With controls in (2), the effect is positive for all regions but is statistically different than one for some regions. High or low marginal generation in (1) or (2) leads to high or low marginal damages in (3) or (4).[18]

One solution to the problem of multicollinearity is to use more data. The analysis in Table 7 aggregates the data to the hour. However, we have data on hourly emissions and generation at each power plant. Using this disaggregated data allows us to incorporate more fixed effects in the models to better capture unobserved heterogeneity. Using the disaggregated data, Online Appendix Table C has 4.9 million observations and 160,344 fixed effects, and Online Appendix Table D, which aggregates the hourly data to the region, has 420,864 observations and 13,824 fixed effects. The results are quite similar to those in Table 6 and 7. In particular, the interconnection estimates are robust, but the estimates for the regions still show unrealistically large or small (negative) marginal damage estimates.

Another possibility is to estimate effects for only a subset of the load regions. To avoid omitted variable bias, we regress damages or generation on Texas load and on load for a subset of the regions. The marginal damage for any region is either the Texas load coefficient or the sum of the Texas load coefficient and the coefficient for the individual region.[19] Online Appendix Table B adds one additional region (ordered by load size) in each additional regression model. Models (1)-(3) of Online Appendix Table B give reasonable results. However in Model (4), the coefficient on Load is negative, which implies negative marginal damages in the Far West, East, West, and North. Models (5) -(7) give similar unrealistic estimates. For this reason we focus on the Big Three regions, which each contain major metropolitan

[18]The marginal damage estimates cannot be simply scaled by the marginal generation estimates if the marginal damage estimate is negative.

[19]This is equivalent to aggregating all the omitted regions into one region.

areas: N. Central (Dallas and Fort Worth), Coast (Houston), and S. Central (San Antonio and Austin). Moreover, as seen in Table 4, these regions contain the vast majority of the overall Texas load.

Table 8 shows results from regressing regulated generation and damages on Texas load and load in the three biggest regions. The table shows that the controls are again important. Column (2) shows that the marginal generation (0.981) of Texas load is not statistically different than one and the marginal generation estimate for each of three regions is not statistically different from the marginal generation of Texas load. In the preferred specification (4), marginal damage is \$0.042 per kWh in N. Central, \$0.048 per kWh in Coast, \$0.035 per kWh in S. Central, and \$0.017 per kWh in all other regions.

Table 8: Marginal generation and marginal damage estimates for Texas regions: Big Three

	Generation		Damage	
Variables	(1)	(2)	(3)	(4)
Texas Load	0.711***	0.981***	0.007	0.017**
	(0.178)	(0.031)	(0.010)	(0.007)
N. Central	0.229	-0.049	0.036***	0.025***
	(0.204)	(0.037)	(0.012)	(0.008)
Coast	-0.199	-0.015	0.022*	0.031***
	(0.214)	(0.037)	(0.012)	(0.009)
S. Central	0.797***	-0.071	0.052***	0.018
	(0.281)	(0.046)	(0.016)	(0.011)
Controls	No	Yes	No	Yes

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

Notes: Regulated generation or damage is dependent variable. Newey-West standard errors with 48-hour lags. Each regression has 52,608 observations and 1,728 fixed effects. Controls are generation from wind, solar, hydro/biomass and nuclear and power flows on two DC ties plus an indicator for the availability of the DC flow data.

To test the robustness of these Big Three estimates, we estimate the effects separately for each year of data. The smaller sample size implies that the estimates will be less precisely estimated. The yearly marginal effects are shown in Appendix Figure F. The yearly effects are reasonably robust for the three large regions, but are noisy for the residual Texas regions.

3.3 Method 2: Machine learning

The methods used thus far have aggregated the data across all power plants. This assumes that power plants all respond to load in all the regions. However, some power plants may respond to load shocks in some regions while other power plants may respond to load shocks in different regions. We use machine learning to let the data select which region's load shocks predict damages or generation at each power plant.

We use the Lasso estimator (Least Absolute Shrinkage and Selection Operator) for variable selection. For each power plant, we perform a Lasso regression with generation or damage as the dependent variable and the load regions, controls, and fixed effects as our independent variables. In general, machine learning is only concerned with prediction, but we are interested in the estimated effects and must be concerned with omitted variable bias. Therefore we "force" the Lasso regression to include Texas load and calculate marginal effects for a region as the coefficient for Texas load plus the coefficient (or zero if not selected) of the region. The Lasso estimator is known to produce biased estimates, so we use Lasso for variable selection and then use linear regression to calculate the marginal effects. The estimates for a given plant show how the plant responds to an increase in load in a region. The marginal effect then sums the effects across all power plants.

Table 9 shows the marginal damages for nine different Lasso models each of which includes our fixed effects. The first model "All" forces Lasso to include Texas load and allows Lasso to select from all eight regions, but does not include our controls. Models (1) to (8) force Lasso to include Texas load and allow Lasso to select from the controls and from the largest region in (1), from the two largest regions in (2), etc. The preferred model (8) forces Texas load and selects variables from among the controls and all eight regions.[20] The preferred estimates range from \$0.018 per kWh in the South to \$0.058 per kWh in the West.[21]

Table 10 shows summary statistics for the estimated coefficients for each of the 100 plants for the preferred Model (8). The Texas load coefficient is forced (so it is selected for all 100 plants) and ranges from a small negative at one plant to \$0.0071 at one plant. This implies

[20] All eight regions are never selected, because it would result in perfect collinearity.

[21] Standard errors can be calculated for these estimates by stacking the data and running a single regression with the selected coefficients.

Table 9: Marginal damage estimates for Texas load regions using Lasso

Region	All	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N. Central	0.042	0.043	0.042	0.043	0.041	0.041	0.041	0.041	0.040
Coast	0.033	0.036	0.037	0.039	0.042	0.042	0.042	0.043	0.042
S. Central	0.032	0.036	0.036	0.032	0.036	0.038	0.038	0.037	0.038
South	0.018	0.036	0.036	0.038	0.019	0.018	0.018	0.017	0.018
Far West	-0.101	0.036	0.036	0.038	0.040	0.021	0.022	0.019	0.020
East	0.074	0.036	0.036	0.038	0.040	0.040	0.041	0.041	0.041
West	0.148	0.036	0.036	0.038	0.040	0.040	0.040	0.059	0.058
North	0.036	0.036	0.036	0.038	0.040	0.040	0.040	0.039	0.045
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is damage with 52,608 observations and 1,728 fixed effects for each of 100 plants. Each Lasso requires Texas load but selects variables from among the smaller load regions and controls. Model (n) allows Lasso to select variables from the n largest load regions. Reported marginal effect sums Texas load and region estimates from linear regressions with hour and month by year fixed effects across all plants. Controls include generation from wind, solar, hydro/biomass and nuclear and power flows on two DC ties plus an indicator for the availability of the DC flow data.

that almost 20% of the entire effect results from damages at a single plant responding to all Texas load.[22] The most selected load region is the Coast which is selected for 22 plants and has a total additional effect of $0.002 per kWh. Among our controls, wind is selected most (for 88 plants). Other controls are also frequently selected by Lasso which indicates the importance of these controls.

Table 11 shows Lasso results when regulated generation, rather than damages, is the dependent variable. The model labeled (All) has no controls and allows Lasso to select from all regions, and has unreasonable results. Models (1) to (8) allow Lasso to select from more load regions. Although estimates are not all unity, as they should be in theory, they are not wildly implausible again highlighting the importance of our controls. The summary statistics for Model (8) are presented in Online Appendix Table E.

We also test the robustness of the marginal damages by estimating the effects annually. Appendix Figure G shows the marginal damages for the preferred model with controls estimated for each year in the sample. The variation of the estimates across the years is quite small for the largest regions but increases as the regions get smaller so that some estimates

[22]This is the WA Parish power plant which is a coal and gas-fired power plant near Houston. It is the second largest conventional power plant in the US.

Table 10: Summary statistics of variables selected by Lasso: damage

	Sum	Min	Max	N
Texas Load	0.0397	-0.0001	0.0071	100
N. Central	0.0008	-0.0001	0.0006	8
Coast	0.0020	-0.0007	0.0017	22
S. Central	-0.0018	-0.0009	0.0007	10
South	-0.0217	-0.0126	0.0012	20
Far West	-0.0200	-0.0138	0.0014	5
East	0.0017	-0.0040	0.0040	18
West	0.0184	0.0009	0.0038	7
North	0.0048	-0.0037	0.0035	8
Wind	-0.0399	-0.0082	-0.0000	88
Solar	-0.0676	-0.0771	0.0196	18
Hydro/Bio	0.0325	-0.0303	0.0368	18
Nuclear	-0.0156	-0.0171	0.0082	24
DC-East	0.0086	-0.0025	0.0023	29
DC-North	-0.0576	-0.0773	0.0046	41
DC Indicator	-0.8151	-0.8151	-0.8151	1

Notes: Dependent variable is damage. 52,608 observations for each of 100 plants. Lasso selects from all load regions and controls.

Table 11: Marginal regulated generation for Texas load regions using Lasso

Region	All	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
N. Central	0.88	0.98	0.98	0.99	0.99	1.00	0.97	0.95	0.95
Coast	0.72	1.00	1.03	1.06	1.09	1.09	1.08	1.09	1.08
S. Central	0.98	1.00	0.96	0.92	0.95	0.96	0.93	0.89	0.91
South	0.63	1.00	0.96	0.95	0.74	0.73	0.71	0.67	0.68
Far West	-2.25	1.00	0.96	0.95	0.96	0.68	0.70	0.65	0.66
East	2.51	1.00	0.96	0.95	0.96	0.96	1.51	1.56	1.57
West	5.06	1.00	0.96	0.95	0.96	0.96	0.94	1.52	1.44
North	0.68	1.00	0.96	0.95	0.96	0.96	0.94	0.91	0.83
Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is regulated generation with 52,608 observations and 1,728 fixed effects for each of 100 plants. Each Lasso requires Texas load but selects variables from among the smaller load regions and controls. Model (n) allows Lasso to select variables from the n largest load regions. Reported marginal effect sum Texas load and region estimates from linear regressions with hour and month by year fixed effects across all plants. Each Lasso allows controls for generation from wind, solar, hydro/biomass and nuclear and for power flows on two DC ties plus an indicator for the availability of the DC flow data.

for the smallest region are rather noisy and implausible. Overall, the results for all the regions are quite robust across the years of the sample.

Although we have confirmed the importance of the controls, the analogous data have not been available in other interconnections. So it is worthwhile to see what happens with the Lasso procedure when the controls are not used. These results are shown in Online Appendix Table F. Although Model (All) is unrealistic, Models (1) to (4) of Online Appendix Table F are plausible estimates of marginal damages. The corresponding Online Appendix Table G, which shows the estimates for marginal generation, are also reasonable for Models (1) to (4). This suggests a possible approach for estimating marginal damages outside of Texas where we cannot control for non-fossil generation.

Lasso uses the data to identify which load regions are most relevant to a given power plant. This flexibility is appealing since, for example, it can choose multiple regions or no regions based on the data. However, this flexibility can be problematic since it may identify unlikely load regions. For example, a power plant located in the Far West is unlikely to be responding to load shocks in the East, but Lasso may select the East if it is spuriously correlated. Since the location of each power plant is known, we next use the plant's location to define which load regions might affect its damages or generation.

3.4 Method 3: Own region interaction

We next use the geographic location of each power plant to estimate marginal damages for each load region. We identify the *own region* for each power plant based on the county in which it is located and the map in Figure 3.[23] Generation or damages at any power plant is then allowed to be affected by load in the own region as well as Texas load.

To be more precise, we estimate the following equation:

$$y_{it} = \sum_{j \in Reg} I_j(i)[\beta_j * Load_{jt} + \gamma_j * Texas_t] + \delta * Control_t + FE_{if(t)} + \epsilon_{it}$$

where y_{it} is damage or generation at power plant i in hour t; Reg is the set of eight load regions; $I_j(i)$ is an indicator function which equals one iff plant i is in region j; $Load_{jt}$ is load in region j in hour t; $Texas_t$ is load in Texas in hour t; $Control_t$ is a vector of our controls in hour t; $FE_{if(t)}$ is the fixed effect for plant by month of sample by hour; and ϵ_{it} is the error term. An increase in load in a region also increases the Texas load so the marginal effect of an increase in load in region k is

$$\beta_k + \sum_{j \in Reg} \gamma_j,$$

which can then be scaled so the effect is per kWh. These marginal effects are presented in Table 12.[24] The marginal generation estimates, without controls (1) and with controls (2), are not unreasonable and are improved by including the controls. The marginal damage estimates in (3) and (4) are all positive and not implausible. Thus the own region method provides another possible alternative to estimating disaggregated marginal damages in other interconnections in which the controls are not available.

Appendix Figure H shows the yearly marginal damages for the preferred model with controls estimated for each year in the sample. The estimates are noisier than the Lasso estimates, but are reasonably robust across the years.

[23]ERCOT does not designate power plants as located in load regions. Some power plants are located on load region borders and hence likely serve both regions. We simply assign the own region based on the county.

[24]Standard errors will be calculated for these estimates.

Table 12: Marginal generation and damages on own region

	Generation		Damage	
	(1)	(2)	(3)	(4)
N. Central	1.016	1.026	0.039	0.040
Coast	0.884	1.094	0.039	0.048
S. Central	1.014	0.968	0.041	0.039
South	0.952	1.036	0.036	0.040
Far West	0.542	0.839	0.030	0.043
East	1.167	0.909	0.039	0.028
West	0.830	0.794	0.035	0.033
North	0.971	0.947	0.036	0.036
Controls	No	Yes	No	Yes

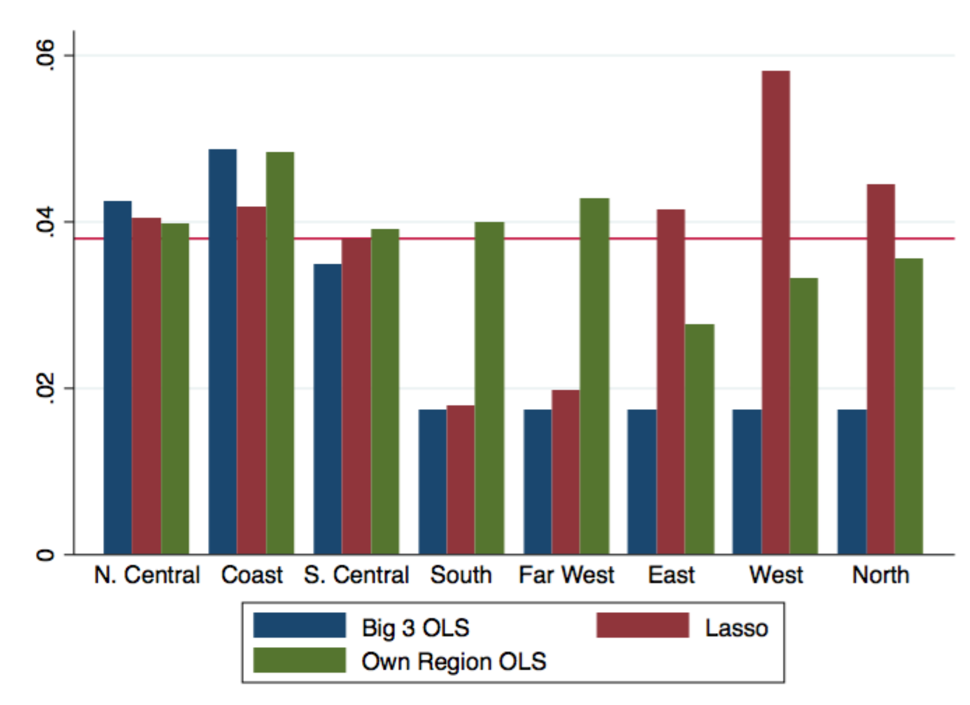
Notes: Dependent variable is regulated generation or damage. Plant-level analysis with 4,881,696 observations and 160,344 fixed effects.

Because the relevant variation in the independent variables is at the region level, the model can be estimated with the data aggregated to the region if the fixed effects are also aggregated to the region. Online Appendix Table H presents the results from estimating the model aggregated to the region with the coarser set of fixed effects. The results are generally robust to the aggregation although the disaggregated model fits slightly better and is our preferred model.

3.5 Comparing the results

We have presented multiple methods for estimating marginal damages for each region. In theory they all should give the same results, and there is no reason to prefer one to another *a priori*. Figure 5 compares the results from our three preferred methods: OLS using only the largest three regions, Lasso selecting from all eight regions, and OLS allowing each power plant to be separately affected by load in its own geographic region. Each method controls for non-fossil generation. There are several things to note from the comparison. First, the three methods all give quite similar results for the three largest regions: N. Central (Dallas), Coast (Houston), and S. Central (San Antonio). These three regions account for approximately 80% of the Texas load, so it is reassuring to see that the methods work well for the main three regions.[25] These results suggest that all three regions are close to the average damage for Texas of $0.038 per kWh with the Coast being perhaps slightly dirtier. Second, the methods are not consistent for the other five regions. The two methods with independent estimates for the regions (Lasso and Own Region OLS) do not agree on which regions are relatively clean or relatively dirty. The other method, which treats these regions as the residual, implies surprisingly low estimates for these five regions.

Figure 5: Comparing marginal damages across models



Notes: "Big Three OLS" shows estimates from Table 8 Model (4). "Lasso" shows estimates from Table 9 Model (8). "Own Region OLS" shows estimates from Table 12 Model (4). The horizontal line is the average Texas effect from Table 6 Model (2). All models include controls.

Online Appendix Figure I adds the OLS results with all regions to the comparison. This comparison emphasizes how poorly the simplest OLS model performs when applied to the highly correlated load regions.

Finally, we circle back to the substantive issue of the environmental benefit from electric buses. Table 13 shows the environmental benefit (annual and per mile) for each MSA in Texas

[25] The results should on average give the same result as the overall marginal damage for Texas. Weighted by load, the three methods have average marginal damages of $0.037, $0.038, and $0.042 per kWh respectively.

using each of the methods considered in this paper.[26] The benefits reflect the estimates in Figure 5: higher marginal damage estimates imply lower benefits. Within the largest three regions, the greatest variation across the three methods (OLS Big 3, Lasso, and OLS Own) is for Houston. The largest estimate of the environmental benefit for Houston is about one million dollars per year greater than the smallest estimate. This highlights implications of the variation in the estimates. MSAs in the smaller regions show substantial variation across methods.

Table 13: Comparing environmental benefit across models

	Annual Benefit			Benefit per mile		
	Big 3	Lasso	Own	Big 3	Lasso	Own
Dallas (N. Central)	5.921	6.526	6.785	0.042	0.046	0.048
Fort Worth (N. Central)	2.630	2.919	3.043	0.039	0.043	0.045
Killeen (N. Central)	0.245	0.284	0.300	0.027	0.032	0.033
Waco (N. Central)	0.149	0.173	0.184	0.026	0.031	0.033
Houston (Coast)	2.234	3.562	2.299	0.026	0.042	0.027
Victoria (Coast)	0.006	0.050	0.008	0.002	0.018	0.003
Austin (S. Central)	1.278	1.100	1.025	0.050	0.043	0.040
San Antonio (S. Central)	1.753	1.486	1.374	0.046	0.039	0.036
Brownsville (South)	0.398	0.390	0.132	0.077	0.076	0.026
Corpus Christi (South)	0.545	0.534	0.178	0.077	0.076	0.025
Laredo (South)	0.203	0.198	0.045	0.068	0.067	0.015
McAllen (South)	0.664	0.651	0.207	0.077	0.076	0.024
Midland (Far West)	0.258	0.240	0.064	0.078	0.073	0.019
Odessa (Far West)	0.206	0.192	0.051	0.078	0.072	0.019
College Station (East)	0.367	0.119	0.260	0.082	0.027	0.058
Tyler (East)	0.390	0.142	0.283	0.087	0.031	0.063
Abilene (West)	0.339	-0.077	0.176	0.076	-0.017	0.040
San Angelo (West)	0.161	-0.036	0.084	0.077	-0.017	0.040
Sherman (North)	0.187	0.045	0.092	0.082	0.020	0.040
Wichita Falls (North)	0.216	0.043	0.100	0.079	0.015	0.036

Notes: "Big 3" uses estimates from Table 8. "Lasso" uses estimates from Table 9. "Own" uses own region estimates from Table 12. "Annual Benefit" in millions of dollars, and "Benefit per mile" in dollars. All estimates include controls.

[26] The results are not directly comparable to the results in Table 3 due to a different sample and constant valuation of pollution damages.

4 Conclusion

Advances in electric motors, battery technology, wireless charging, and autonomous driving open new possibilities for electrification of transportation. Whether market forces can result in efficient electrification depends on the extent to which pollution can be adequately regulated. Understanding the benefits and costs of regulation is thus crucial to assessing public policy toward electrification.

We find that diesel buses built before 2010 are quite dirty. Calculation of air pollution damages from these buses shows that about 15 MSA's have annual damages greater than $100 million. Relative to this benchmark, both new diesel buses and electric buses generate significant decreases in damages. But electric buses are generally cleaner: Electric buses generate an environmental benefit relative to new diesel buses on average in the U.S. The greatest environmental benefit per mile, as well as the greatest environmental benefit for the entire bus fleet, occurs in Los Angeles.

Using the rich data available for Texas, we explore three different methods for determining marginal damages of electricity consumption at a spatially disaggregated level. At this level of spatial disaggregation, electricity consumption is highly correlated across regions. Our three methods generally yield similar estimates for the three largest regions in Texas. For all three methods, the results are most plausible when using control variables that are available for Texas but have not been for other parts of the country. It may be reasonable to use the Lasso method and the own region method without controls to obtain spatially disaggregated estimates of marginal damages in these other interconnections.

Appendix

AP3 Model Details

This paper uses the AP3 integrated assessment model (IAM), (see Clay et al., 2019; Holland et al., 2018 for recent applications) which is an updated version of the AP2 model (Muller, 2014; Jaramillo and Muller, 2016; Holland et al., 2016). The model links emissions of local air pollutants to concentrations, population exposure, physical health effects (premature mortality risk), and monetary damages. To monetize emissions of GHGs we use the social cost of carbon reported in the U.S. federal government's interagency working group report (USIAWG, 2016).

The AP3 model begins by using the 2014 National Emissions Inventory (NEI) which is the most recent comprehensive inventory of air pollution emissions for the U.S. economy. AP3 matches reported emissions to the location of release. So-called area source emissions (vehicles, residences, and small businesses) are allocated to the county in which they are reported to have occurred. AP3 attributes point source emissions to facility location for nearly 700 large industrial emission sites (many of which are power stations). Discharges from other point sources are allocated to the county in which the NEI reports that they occurred.

A reduced complexity air quality model then links emissions to annual average concentrations. Crucially, for releases of nitrogen oxides (NOx), sulfur dioxide (SO2), ammonia (NH3), and volatile organic compounds (VOCs), AP3 models their contribution to ambient fine particulate matter (PM2.5). AP3 also models the dispersion of primary (emitted) PM2.5. Central to the formation of secondary PM2.5 are the processes associated with the nitrate-sulfate-ammonium equilibrium. While formation of ammonium sulfate is modeled in the same fashion as in AP2, AP3 employs a new regression-based approach to estimating the formation of ammonium nitrate from NOx emissions. Specifically, in a series of offline regression analyses, a polynomial is fitted to the process linking nitrate, free ammonia, along with controls for temperature and humidity, to ambient ammonium nitrate (which is a constituent of PM2.5). The model is fit to daily predictions from the CAMx chemical transport model. The resulting fit of PM2.5 predicted by the AP3 model, by major species, is reported in Sergi et al., (2019).

Population and mortality rate data is gathered from the U.S. Census and the Centers for Disease Control and Prevention by age-group and county to estimate exposures in 2014. Then, peer-reviewed concentration-response functions linking exposure to changes in adult mortality rates are used to estimate the mortality risk consequences of emissions (Krewski et al., 2009; Lepeule et al., 2012). These studies comprise the most recent updates to the two most widely used epidemiological studies on the air pollution-mortality linkage in the policy analysis literature. Changes in mortality risk are valued using the Value of a Statistical Life (VSL) approach (Viscusi and Aldy, 2013). In this study, we employ the USEPA's preferred VSL of $7.4 million ($2006) which we inflate to year-2014 USD.

As in prior applications, AP3 is used to calculate the marginal ($/ton) damage from emissions of the five pollutants listed above. This computation is made by county (or source) of emission. The process of making this tabulation begins by running AP3 with baseline emissions (as reported by the USEPA in the 2014 NEI) to estimate associated baseline damages. Then, one (U.S. short) ton of emissions of a particular pollutant, perhaps NOx, is added to reported emissions at a given site. AP3 is used to calculate the change in concentrations, exposure, physical health effects, and monetary damage. This change, of course, manifests across many locations receiving pollution. The total' marginal damage is the spatial sum across receptor counties resulting from this additional emission of NOx. Emissions at the chosen site are reset to baseline, and AP3 moves to the next source and repeats this calculation. This algorithm is repeated over all sources and pollutants.

This process yields estimates of the ($/ton) marginal damage for all source locations and pollutants covered by AP3. To compute the damages from vehicles (buses, in the present application), we match the ($/ton) damages to emission rate data provided by the USEPA (check?) for a given vehicle type and vintage. Emission rates are typically expressed in physical units, per distance travelled (grams/mile). Unit conversion yields a ($/VMT) estimate. Similarly, for power stations, AP3 provides marginal damage estimates, also in ($/ton). Using USDOE (check?) data on the emission rates from power stations (emission totals (tons) are reported along with net generation (kwh)) we analogously tabulate damages per unit output ($/kwh). Data on the electricity use per VMT thus yields the $/VMT figure for electric buses.

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Online Appendices

Additional Figures and Tables

Supplementary material for Subsection 3.1

Figure A: Hourly load by hour for each month

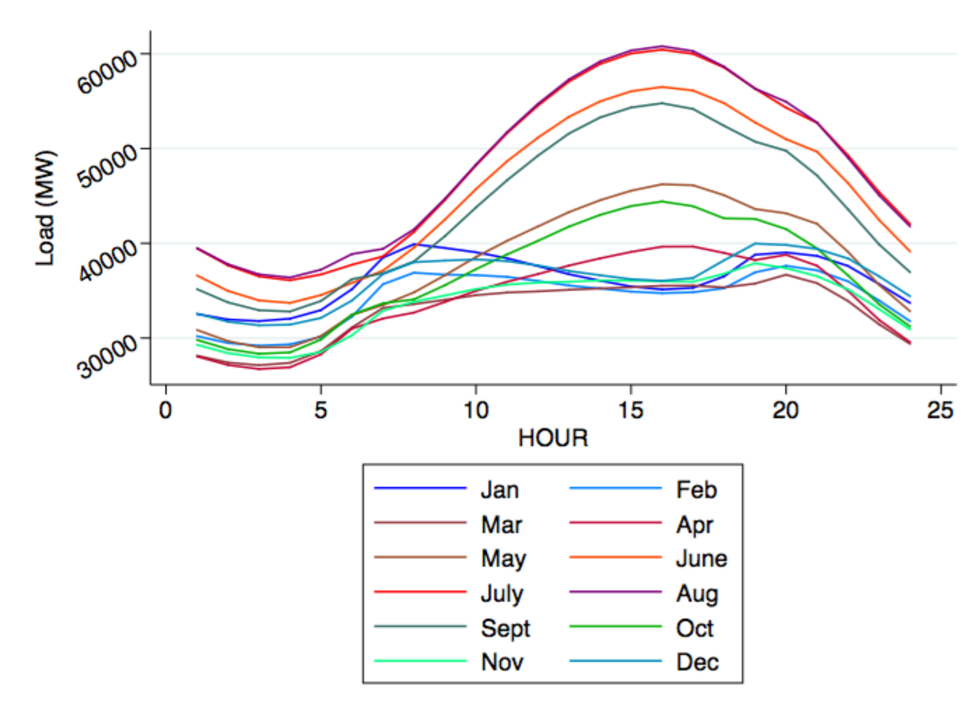


Figure B: Hourly generation by month by fuel type

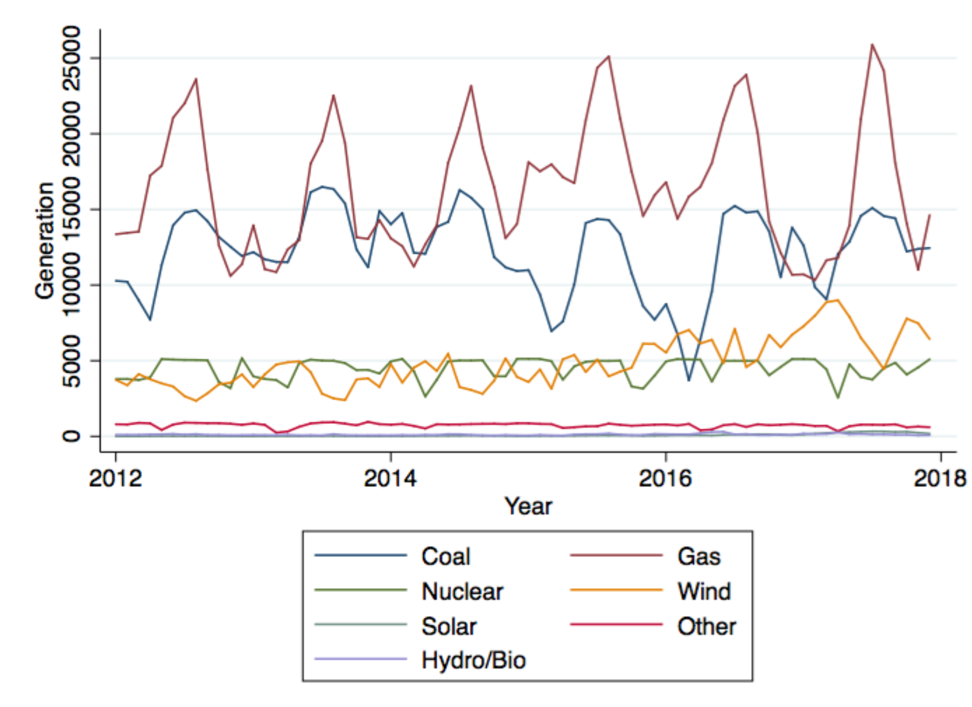


Figure C: Hourly load v. hourly generation

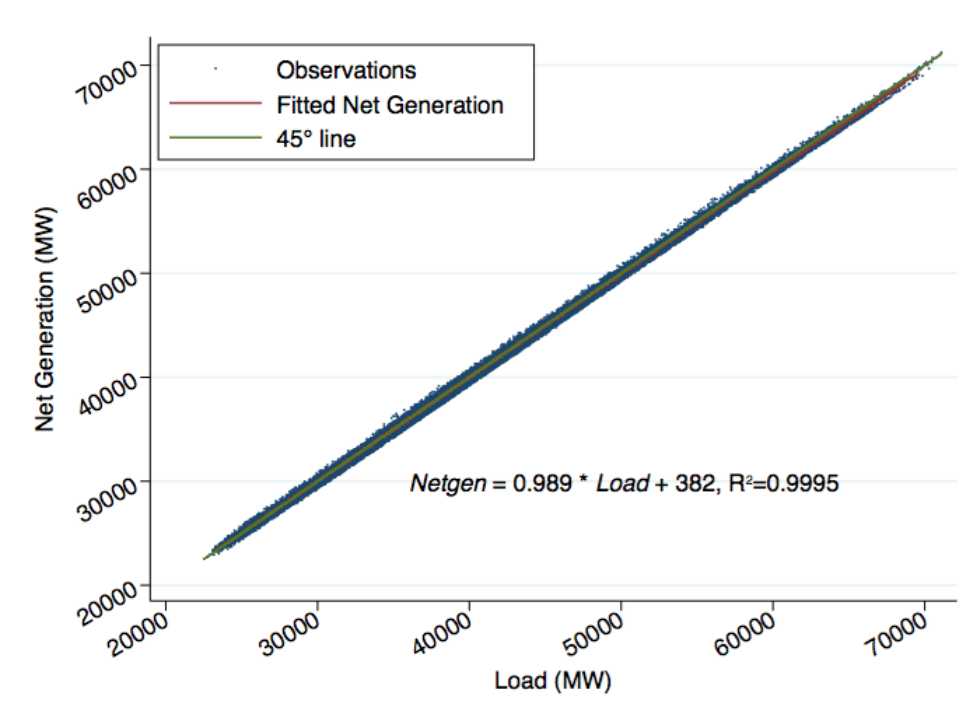


Figure D: Hourly load v. hourly regulated fossil generation

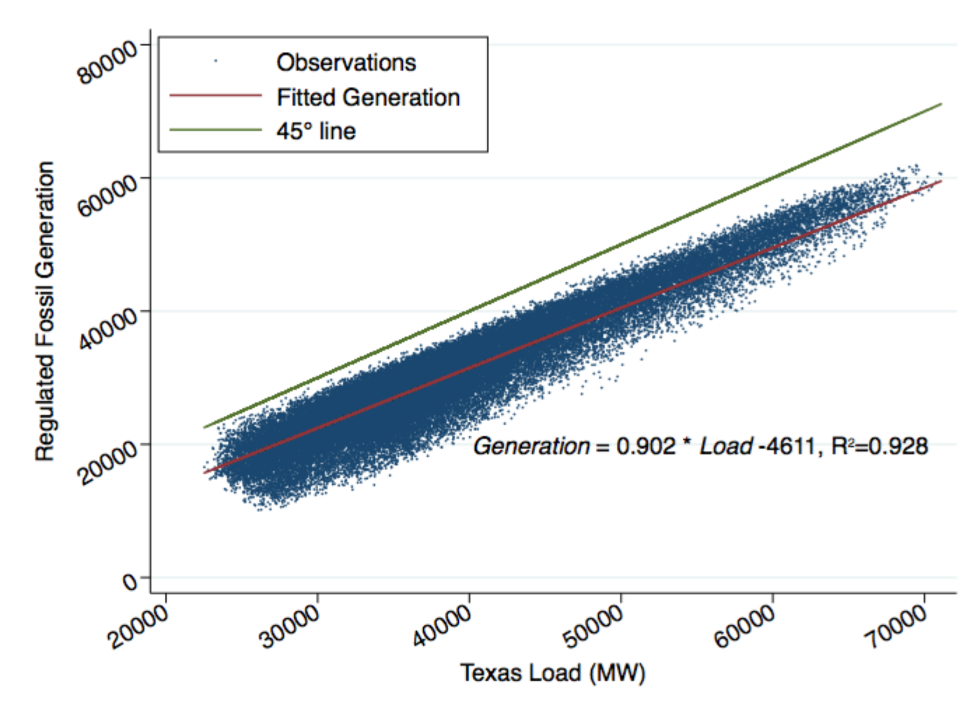
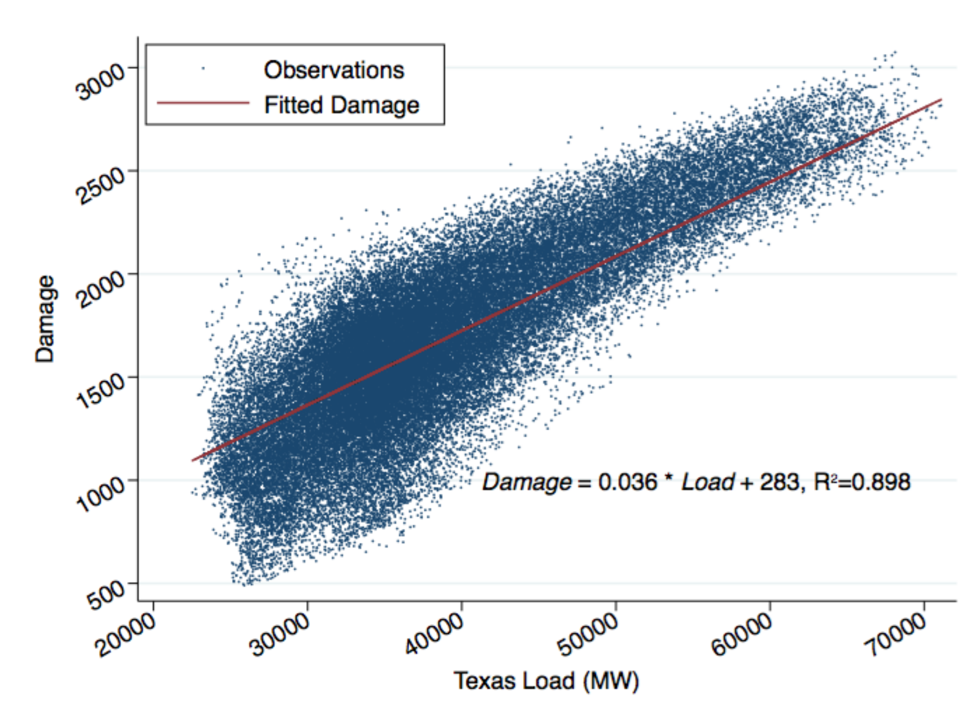


Figure E: Hourly load v. hourly damage



Supplementary material for Subsection 3.2

Figure F: Yearly estimates for Big 3 marginal damages

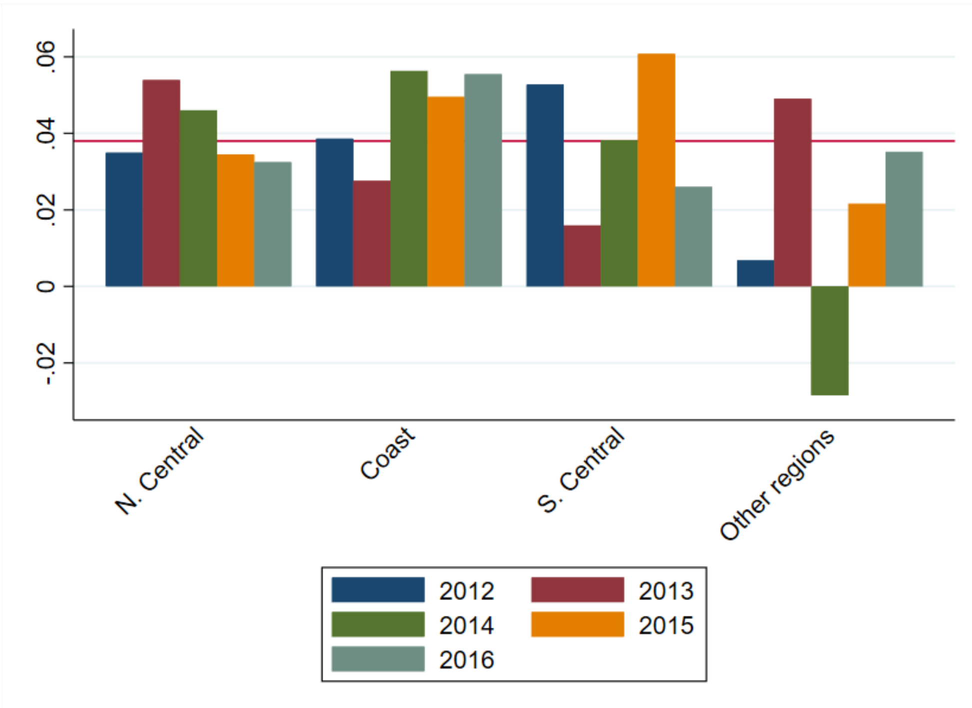


Table A: Estimates for regulated fossil generation by subregions

	Gross Generation				Damages			
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Load	0.902***	0.943***		0.980***	0.036***	0.038***		0.017**
	(0.011)	(0.002)		(0.031)	(0.001)	(0.001)		(0.007)
Coast			0.972***	-0.016			0.048***	0.031***
			(0.014)	(0.038)			(0.003)	(0.009)
N. Central			0.937***	-0.051			0.047***	0.025***
			(0.016)	(0.037)			(0.004)	(0.008)
S. Central			0.959***	-0.069			0.047***	0.018
			(0.026)	(0.046)			(0.006)	(0.011)
East			0.610***				-0.087***	
			(0.109)				(0.027)	
Northern			1.166***				0.074	
			(0.244)				(0.062)	
Southern			0.956***				0.025***	
			(0.037)				(0.009)	
West			0.496***				-0.125***	
			(0.184)				(0.048)	
Far West			1.543***				0.087***	
			(0.132)				(0.033)	
Wind Gen.		-0.941***	-0.944***	-0.941***		-0.041***	-0.041***	-0.041***
		(0.003)	(0.003)	(0.003)		(0.001)	(0.001)	(0.001)
Solar Gen.		-0.947***	-0.972***	-0.925***		-0.090***	-0.092***	-0.087***
		(0.116)	(0.113)	(0.113)		(0.024)	(0.024)	(0.024)
Nuclear Gen.		-0.883***	-0.884***	-0.882***		-0.040***	-0.040***	-0.040***
		(0.021)	(0.020)	(0.020)		(0.005)	(0.006)	(0.005)
Other Gen.		0.108**	0.109**	0.112**		0.044***	0.045***	0.045***
		(0.047)	(0.047)	(0.047)		(0.013)	(0.013)	(0.013)
DC-East		-0.683***	-0.695***	-0.684***		-0.026**	-0.028**	-0.026**
		(0.043)	(0.043)	(0.043)		(0.011)	(0.011)	(0.011)
DC-North		-1.048***	-1.041***	-1.042***		-0.109***	-0.109***	-0.108***
		(0.077)	(0.077)	(0.077)		(0.018)	(0.018)	(0.018)
DC Indicator		136.796	134.909	127.293		28.725*	27.114*	26.274*
		(94.989)	(92.663)	(94.851)		(14.706)	(14.179)	(14.818)

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

Notes: Newey-West standard errors with 48-hour lags. Each regression has 52,608 observations and 1,728 fixed effects.

Table B: Marginal damage estimates for Texas regions: Adding load regions

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Texas Load	0.0384***	0.0270***	0.0173**	-0.0042	-0.0695***	-0.0495	0.0813
	(0.001)	(0.003)	(0.007)	(0.013)	(0.021)	(0.033)	(0.063)
N. Central	-0.0008	0.0147***	0.0250***	0.0508***	0.1227***	0.1019***	-0.0337
	(0.003)	(0.005)	(0.008)	(0.015)	(0.023)	(0.035)	(0.065)
Coast		0.0214***	0.0313***	0.0523***	0.1188***	0.0998***	-0.0321
		(0.006)	(0.009)	(0.014)	(0.021)	(0.032)	(0.063)
S. Central			0.0176	0.0392**	0.1093***	0.0891***	-0.0345
			(0.011)	(0.016)	(0.023)	(0.034)	(0.061)
South				0.0297*	0.0941***	0.0734**	-0.0564
				(0.017)	(0.023)	(0.034)	(0.063)
Far West					0.1581***	0.1258**	0.0059
					(0.040)	(0.059)	(0.075)
East						-0.0348	-0.1678**
						(0.043)	(0.068)
West							-0.2028**
							(0.088)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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

Notes: Damage is dependent variable. Newey-West standard errors with 48-hour lags. Each regression has 52,608 observations and 1,728 fixed effects. Controls are generation from wind, solar, hydro/biomass and nuclear and power flows on two DC ties plus an indicator for the availability of the DC flow data. Northern is omitted in all models.

Table C: Main regressions with plant fixed effects

	Generation			Damage		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Load	0.9728***	1.0189***		0.0388***	0.0411***	
	(0.002)	(0.002)		(0.000)	(0.000)	
N. Central			1.0031***			0.0510***
			(0.017)			(0.001)
Coast			1.0332***			0.0524***
			(0.013)			(0.001)
S. Central			1.0395***			0.0507***
			(0.029)			(0.002)
Southern			1.0355***			0.0271***
			(0.036)			(0.003)
Far West			1.3796***			0.0826***
			(0.126)			(0.011)
East			0.7271***			-0.0904***
			(0.112)			(0.010)
West			0.8042***			-0.1208***
			(0.179)			(0.015)
Northern			1.4176***			0.0933***
			(0.259)			(0.022)
Controls	No	Yes	Yes	No	Yes	Yes

Notes: Dependent variable is regulated generation or damage. 4,881,696 observations with 160,344 fixed effects. No standard error correction.

Table D: Main regressions with zonal fixed effects

	Generation			Damage		
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Load	0.9020***	0.9440***		0.0360***	0.0380***	
	(0.002)	(0.002)		(0.000)	(0.000)	
N. Central			0.9378***			0.0476***
			(0.018)			(0.001)
Coast			0.9739***			0.0492***
			(0.013)			(0.001)
S. Central			0.9583***			0.0468***
			(0.031)			(0.002)
Southern			0.9546***			0.0249***
			(0.038)			(0.003)
Far West			1.5429***			0.0872***
			(0.134)			(0.010)
East			0.6114***			-0.0865***
			(0.119)			(0.009)
West			0.5049***			-0.1215***
			(0.190)			(0.014)
Northern			1.1849***			0.0813***
			(0.275)			(0.021)
Controls	No	Yes	Yes	No	Yes	Yes

Notes: Dependent variable is regulated generation or damage. 420,864 observations with 13,824 fixed effects. No standard error correction.

Supplementary material for Subsection 3.3

Table E: Summary statistics for estimates for variables selected by lasso: regulated generation

	Sum	Min	Max	N
Texas Load	0.9144	-0.0081	0.0471	100
N. Central	0.0356	-0.0061	0.0208	9
Coast	0.1683	-0.0284	0.0748	23
S. Central	-0.0059	-0.0329	0.0401	10
South	-0.2296	-0.1057	0.0917	22
Far West	-0.2535	-0.1312	0.0362	4
East	0.6570	-0.1113	0.2333	21
West	0.5257	-0.2100	0.1906	7
North	-0.0815	-0.2110	0.1706	8
Wind	-0.9407	-0.0586	-0.0000	89
Solar	0.9635	-0.4496	0.5615	16
Hydro/Bio	-0.3197	-1.0205	0.3266	17
Nuclear	-0.5663	-0.1163	0.0438	25
DC-East	0.2358	-0.1324	0.0676	30
DC-North	0.1393	-0.3887	0.1504	41
DC Indicator	-341.3611	-298.3783	-42.9828	2

Notes: Dependent variable is regulated generation. 52,608 observations for each of 100 plants. Lasso selects from all load regions and controls.

Table F: Marginal damage estimates for Texas load regions using lasso: No controls

Region	(1)	(2)	(3)	(4)	(5)	(6)	(7)	All
N. Central	0.046	0.046	0.045	0.044	0.046	0.045	0.042	0.042
Coast	0.032	0.028	0.029	0.031	0.033	0.032	0.033	0.033
S. Central	0.032	0.034	0.036	0.039	0.041	0.040	0.032	0.032
South	0.032	0.034	0.034	0.018	0.021	0.019	0.017	0.018
Far West	0.032	0.034	0.034	0.036	-0.075	-0.084	-0.101	-0.101
East	0.032	0.034	0.034	0.036	0.038	0.070	0.073	0.074
West	0.032	0.034	0.034	0.036	0.038	0.037	0.150	0.148
North	0.032	0.034	0.034	0.036	0.038	0.037	0.034	0.036
Controls	No	No	No	No	No	No	No	No

Notes: 52,608 observations for each of 100 plants. Lasso used for variable selection; estimates from linear regression with hour and month by year fixed effects.

Table G: Marginal regulated generation for Texas load regions using lasso: No controls

Region	(1)	(2)	(3)	(4)	(5)	(6)	(7)	All
N. Central	1.04	1.06	1.01	1.00	1.06	0.98	0.86	0.88
Coast	0.88	0.69	0.66	0.69	0.69	0.65	0.70	0.72
S. Central	0.88	0.99	1.20	1.24	1.28	1.26	1.00	0.98
South	0.88	0.99	0.94	0.75	0.78	0.72	0.61	0.63
Far West	0.88	0.99	0.94	0.95	-1.30	-1.03	-2.18	-2.25
East	0.88	0.99	0.94	0.95	1.04	2.43	2.50	2.51
West	0.88	0.99	0.94	0.95	1.04	0.95	5.26	5.06
North	0.88	0.99	0.94	0.95	1.04	0.95	0.83	0.68
Controls	No	No	No	No	No	No	No	No

Notes: 52,608 observations for each of 100 plants. Lasso used for variable selection; estimates from linear regression with hour and month by year fixed effects.

Figure G: Yearly estimates for lasso marginal damages

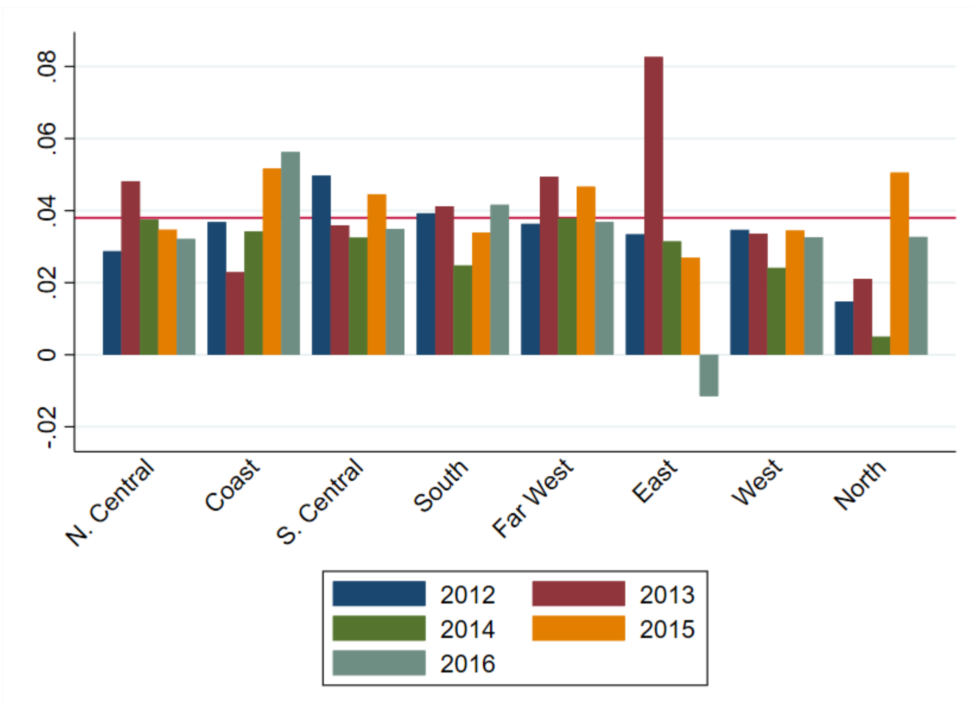
Supplementary material for Subsection 3.4

Table H: Marginal generation and damages based on own region

	Generation		Damage	
	(1)	(2)	(3)	(4)
N. Central	0.939	0.984	0.036	0.038
Coast	0.818	0.956	0.036	0.042
S. Central	0.956	0.955	0.038	0.039
South	0.894	0.990	0.034	0.038
Far West	0.534	1.130	0.028	0.054
East	1.095	0.857	0.036	0.026
West	0.763	0.193	0.032	0.008
North	0.852	0.677	0.033	0.025
Controls	No	Yes	No	Yes

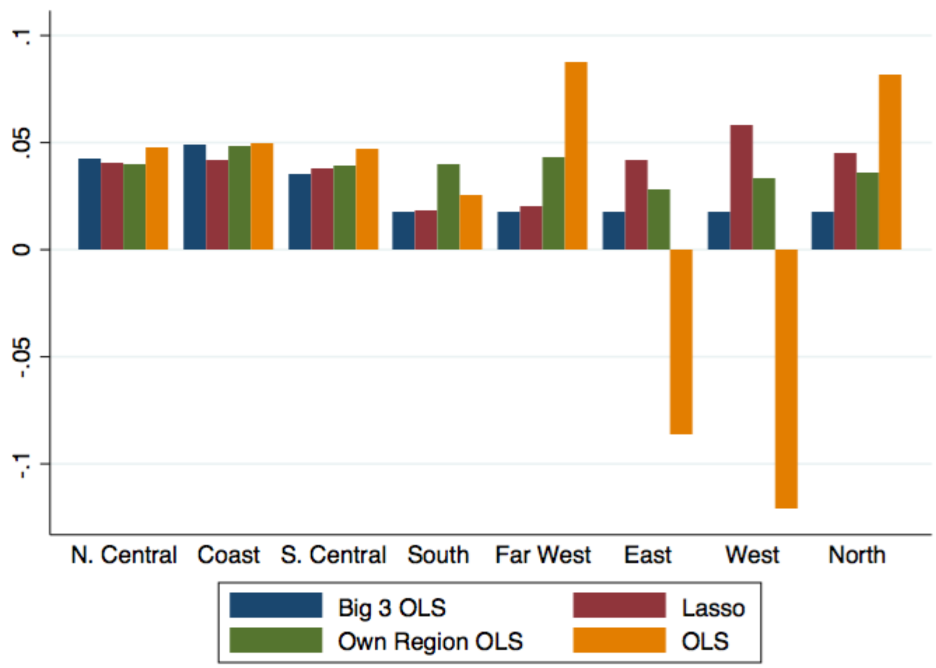
Notes: Dependent variable is regulated generation or damage. Region-level analysis with 420,864 observations and 13,824 fixed effects.

Figure H: Yearly estimates for own region marginal damages



Supplementary material for Subsection 3.5

Figure I: Comparing marginal damages across models



Notes: "Big Three OLS" shows estimates from Table 8 Model (4). "Lasso" shows estimates from Table 9 Model (8). "Own Region OLS" shows estimates from Table 12 Model (4). "OLS" shows estimates from Table 7 Model (4). All models include controls

Damages and benefits for all MSAs

MSA	Diesel	Electric	Aggregate Benefit	Benefit per mile	Bus VMT	Old Diesel
Los Angeles, CA	71.4	6.6	64.7	0.632	102.5	1064.0
New York, NY	33.8	18.8	15.0	0.111	135.1	426.4
Chicago, IL	41.5	28.7	12.8	0.064	200.2	424.2
Phoenix, AZ	18.9	8.3	10.6	0.087	122.0	126.0
Riverside, CA	15.5	5.7	9.8	0.115	85.2	124.7
Santa Ana, CA	12.5	3.0	9.5	0.205	46.6	142.1
Newark, NJ	29.7	20.9	8.8	0.059	149.6	302.8
San Diego, CA	11.1	2.6	8.6	0.216	39.7	125.8
Atlanta, GA	48.8	40.4	8.4	0.028	298.7	379.8
Dallas, TX	19.7	11.7	8.0	0.057	140.5	113.2
Edison, NJ	25.3	19.7	5.6	0.040	141.8	226.7
Oakland, CA	6.5	1.9	4.6	0.160	28.8	66.6
Houston, TX	11.5	7.2	4.3	0.051	84.3	62.8
Seattle, WA	7.7	3.5	4.2	0.081	52.0	49.2
Washington, DC	27.4	23.3	4.1	0.024	169.8	212.8
Sacramento, CA	5.8	2.2	3.7	0.113	32.6	47.3
Fort Worth, TX	9.2	5.6	3.6	0.054	67.1	50.5
San Jose, CA	5.1	1.6	3.5	0.139	24.9	47.6
Detroit, MI	21.9	18.6	3.4	0.026	129.8	178.9
Philadelphia, PA	11.6	8.4	3.2	0.053	60.4	114.9
Denver, CO	5.3	2.5	2.9	0.077	37.0	33.1
Portland, OR	5.6	3.0	2.7	0.059	45.5	23.0
Warren, MI	30.0	27.4	2.6	0.014	190.6	218.8
Stockton, CA	3.1	0.9	2.2	0.164	13.3	30.9
San Francisco,CA	3.2	1.1	2.1	0.119	17.4	27.4
Charlotte, NC	18.2	16.1	2.0	0.017	118.8	123.9
Salt Lake City, UT	3.7	1.7	2.0	0.081	24.9	24.5
Camden, NJ	10.1	8.1	2.0	0.034	58.8	86.3
Las Vegas, NV	3.5	1.8	1.8	0.068	26.2	17.6
San Antonio, TX	4.8	3.2	1.7	0.043	38.4	20.9
Cincinnati-Middletown, OH-KY-IN	9.9	8.3	1.6	0.027	59.8	78.4
Baltimore-Towson, MD	12.2	10.6	1.6	0.021	76.5	91.5
Tampa, FL	7.4	5.8	1.6	0.037	42.5	61.1
Pittsburgh, PA	9.4	7.9	1.5	0.027	56.0	73.6
Bakersfield, CA	2.7	1.2	1.5	0.078	18.7	15.8
Minneapolis-St. Paul, MN	14.6	13.2	1.4	0.016	88.0	113.7
Fresno, CA	2.2	1.0	1.2	0.083	14.8	13.2
Austin-Round Rock, TX	3.3	2.1	1.2	0.047	25.7	15.7
Albuquerque, NM	2.5	1.3	1.2	0.063	19.0	11.0
Raleigh-Cary, NC	13.8	12.6	1.2	0.013	92.9	86.8
Oxnard-Thousand Oaks-Ventura, CA	1.9	0.8	1.1	0.096	11.9	13.2
Nassau-Suffolk, NY	3.9	2.8	1.1	0.056	19.9	39.3
Modesto, CA	1.6	0.6	1.0	0.116	8.9	13.2
Cleveland-Elyria-Mentor, OH	7.8	6.9	1.0	0.020	48.5	59.9
Orlando, FL	6.8	5.9	1.0	0.022	43.0	49.9
Vallejo-Fairfield, CA	1.3	0.4	0.9	0.135	6.7	12.5
Tacoma, WA	1.9	1.0	0.9	0.058	14.9	7.9
Tucson, AZ	1.8	0.9	0.9	0.061	14.2	7.6
Boise City-Nampa, ID	1.8	1.0	0.8	0.058	14.3	7.4
Columbus, OH	8.7	8.0	0.7	0.013	56.9	59.1
Flagstaff, AZ	1.6	0.9	0.7	0.053	13.5	5.3
El Paso, TX	1.3	0.6	0.7	0.069	9.7	6.6
Provo-Orem, UT	1.4	0.8	0.6	0.055	11.5	5.5
Santa Rosa-Petaluma, CA	1.1	0.4	0.6	0.092	6.9	7.1
Wilmington, DE-MD-NJ	8.9	8.3	0.6	0.010	59.8	59.0
Ft Lauderdale, FL	3.9	3.3	0.6	0.026	24.0	29.1
Reno-Sparks, NV	1.4	0.8	0.6	0.052	11.7	4.6
Salem, OR	1.3	0.7	0.6	0.060	10.1	5.2
Bethesda-Frederick-Gaithersburg, MD	4.6	4.0	0.6	0.021	28.9	34.2
Las Cruces, NM	1.2	0.6	0.6	0.061	9.3	4.9
Greensboro-High Point, NC	5.9	5.3	0.6	0.015	39.0	38.5
Dayton, OH	4.7	4.2	0.6	0.019	30.0	34.4
Colorado Springs, CO	1.0	0.5	0.5	0.059	8.2	4.3
Akron, OH	3.9	3.5	0.5	0.020	24.5	29.5
Indianapolis, IN	6.4	5.9	0.5	0.012	42.1	42.8
Louisville, KY-IN	4.4	3.9	0.5	0.016	28.3	30.6
Merced, CA	0.8	0.3	0.4	0.086	5.2	5.0
Visalia-Porterville, CA	0.9	0.5	0.4	0.062	7.2	3.9
Santa Barbara-Santa Maria-Goleta, CA	0.8	0.3	0.4	0.080	5.3	4.2
Salinas, CA	0.9	0.4	0.4	0.060	7.0	3.3
Prescott, AZ	0.9	0.5	0.4	0.054	7.7	3.0
Eugene-Springfield, OR	1.0	0.6	0.4	0.045	9.0	2.2
Spokane, WA	1.0	0.6	0.4	0.047	8.4	2.8

Killeen-Temple-Fort Hood, TX	1.1	0.7	0.4	0.042	9.0	4.6
Santa Cruz-Watsonville, CA	0.6	0.2	0.4	0.114	3.2	4.8
Ogden-Clearfield, UT	0.8	0.5	0.4	0.053	6.7	3.1
El Centro, CA	0.8	0.5	0.4	0.052	6.8	2.9
Greeley, CO	0.7	0.4	0.3	0.062	5.3	3.1
San Luis Obispo-Paso Robles, CA	0.6	0.3	0.3	0.069	4.7	2.9
Trenton-Ewing, NJ	2.8	2.5	0.3	0.017	17.7	20.0
Farmington, NM	0.7	0.4	0.3	0.051	5.8	2.1
Coeur d'Alene, ID	0.7	0.4	0.3	0.050	5.8	2.3
Olympia, WA	0.7	0.4	0.3	0.050	5.7	2.0
McAllen-Edinburg-Pharr, TX	1.0	0.7	0.3	0.033	8.6	3.3
Madera, CA	0.5	0.3	0.3	0.070	4.1	2.7
Santa Fe, NM	0.6	0.3	0.3	0.054	5.1	2.1
Hanford-Corcoran, CA	0.5	0.2	0.3	0.077	3.5	2.9
Deltona, FL	1.4	1.1	0.3	0.031	8.3	10.8
Allentown-Bethlehem-Easton, PA-NJ	4.5	4.3	0.3	0.008	30.7	29.6
Canton-Massillon, OH	1.9	1.7	0.2	0.021	12.0	14.4
Medford, OR	0.6	0.3	0.2	0.046	5.3	1.4
Corpus Christi, TX	0.8	0.6	0.2	0.034	7.0	2.6
Kennewick-Richland-Pasco, WA	0.6	0.4	0.2	0.046	5.3	1.5
Waco, TX	0.7	0.5	0.2	0.041	5.6	2.8
Fort Collins-Loveland, CO	0.5	0.3	0.2	0.053	4.4	2.0
Idaho Falls, ID	0.5	0.3	0.2	0.052	4.3	1.9
Redding, CA	0.5	0.3	0.2	0.046	4.7	1.2
Yuma, AZ	0.5	0.3	0.2	0.049	4.2	1.5
Bremerton-Silverdale, WA	0.5	0.3	0.2	0.051	4.1	1.5
Tyler, TX	0.6	0.4	0.2	0.044	4.5	2.4
Yakima, WA	0.5	0.3	0.2	0.043	4.5	1.1
Longview, WA	0.4	0.2	0.2	0.057	3.2	1.5
St. George, UT	0.4	0.2	0.2	0.048	3.8	1.1
Brownsville-Harlingen, TX	0.6	0.4	0.2	0.035	5.1	1.9
Yuba City, CA	0.4	0.2	0.2	0.060	3.0	1.5
Cambridge-Newton-Framingham, MA	1.7	1.5	0.2	0.015	10.9	12.6
Boulder, CO	0.4	0.2	0.2	0.057	2.8	1.4
Chico, CA	0.4	0.2	0.2	0.053	3.1	1.1
Pueblo, CO	0.3	0.2	0.2	0.058	2.8	1.4
Greenville, SC	2.2	2.0	0.2	0.011	14.8	13.5
Bend, OR	0.4	0.2	0.2	0.042	3.7	0.8
Mount Vernon-Anacortes, WA a	0.4	0.2	0.2	0.044	3.5	1.0
Bellingham, WA	0.4	0.3	0.1	0.039	3.8	0.7
Abilene, TX	0.5	0.4	0.1	0.034	4.4	1.5
Napa, CA	0.2	0.1	0.1	0.096	1.5	1.7
Fayetteville, NC	3.3	3.2	0.1	0.006	23.5	18.8
Billings, MT	0.3	0.2	0.1	0.048	2.8	1.0
Winston-Salem, NC	3.7	3.6	0.1	0.005	26.1	21.2
Pocatello, ID	0.3	0.2	0.1	0.045	2.8	0.9
Worcester, MA	1.2	1.0	0.1	0.017	7.3	8.4
Midland, TX	0.4	0.3	0.1	0.035	3.3	1.3
Sarasota, FL	1.9	1.8	0.1	0.008	13.2	11.8
Atlan City, NJ	4.3	4.2	0.1	0.004	30.2	25.1
Grand Junction, CO	0.3	0.1	0.1	0.051	2.1	0.8
Reading, PA	1.4	1.3	0.1	0.011	9.4	9.4
York-Hanover, PA	1.2	1.1	0.1	0.013	7.9	8.1
Wenatchee, WA	0.3	0.2	0.1	0.044	2.4	0.7
West Palm Beach, FL	2.8	2.7	0.1	0.005	20.1	16.5
Cheyenne, WY	0.2	0.1	0.1	0.050	2.1	0.7
Lancaster, PA	1.0	0.9	0.1	0.015	6.7	7.1
Wichita Falls, TX	0.3	0.2	0.1	0.035	2.7	1.1
Odessa, TX	0.3	0.2	0.1	0.035	2.6	1.0
Sherman-Denison, TX	0.3	0.2	0.1	0.039	2.3	1.0
Missoula, MT	0.2	0.1	0.1	0.045	2.0	0.6
Spartanburg, SC	1.2	1.1	0.1	0.011	8.2	7.4
Victoria, TX	0.3	0.2	0.1	0.031	2.7	0.8
Lewiston, ID-WA	0.2	0.1	0.1	0.044	1.8	0.5
Corvallis, OR	0.2	0.1	0.1	0.048	1.6	0.5
Miami, FL	4.3	4.3	0.1	0.003	31.2	24.6
Durham, NC	6.0	5.9	0.1	0.002	43.5	32.5
Youngstown-Warren-Boardman, OH-PA	2.7	2.6	0.1	0.004	18.5	16.5
Laredo, TX	0.3	0.3	0.1	0.025	3.0	0.6
San Angelo, TX	0.2	0.2	0.1	0.034	2.1	0.7
Bridgeport-Stamford-Norwalk, CT	1.1	1.1	0.1	0.009	7.6	7.6
Hickory-Lenoir-Morganton, NC	3.2	3.1	0.1	0.003	23.1	17.6
Casper, WY	0.1	0.1	0.1	0.052	1.2	0.5
Ocala, FL	1.2	1.2	0.1	0.007	8.6	7.2
Logan, UT-ID	0.2	0.1	0.1	0.047	1.3	0.5
Lake County-Kenosha County, IL-WI	4.1	4.0	0.1	0.002	27.7	25.6
Rapid City, SD	0.2	0.2	0.1	0.027	2.1	0.6
Great Falls, MT	0.1	0.1	0.1	0.045	1.2	0.4
Anderson, SC	0.8	0.7	0.1	0.010	5.4	4.8

Carson City, NV	0.1	0.1	0.0	0.059	0.8	0.4
Richmond, VA	10.8	10.8	0.0	0.001	79.2	58.5
Gainesville, GA	1.0	0.9	0.0	0.005	6.9	5.5
Palm Bay, FL	1.4	1.3	0.0	0.003	9.9	7.7
Springfield, OH	0.8	0.8	0.0	0.006	5.5	5.0
Punta Gorda, FL	0.5	0.4	0.0	0.008	3.1	2.8
Knoxville, TN	3.0	3.0	0.0	0.001	22.0	16.2
Anderson, IN	0.5	0.5	0.0	0.006	3.6	3.2
Milwaukee-Waukesha-West Allis, WI	4.3	4.3	0.0	0.001	29.2	27.7
Cape Coral, FL	1.4	1.4	0.0	0.002	10.0	7.6
Lebanon, PA	0.6	0.6	0.0	0.002	4.0	3.4
Danville, VA	0.6	0.6	0.0	0.002	4.2	3.1
Weirton-Steubenville, WV-OH	0.4	0.4	0.0	0.002	2.9	2.4
Muncie, IN	0.4	0.4	-0.0	-0.000	2.8	2.2
Lexington-Fayette, KY	1.0	1.0	-0.0	-0.001	7.5	5.4
Altoona, PA	0.3	0.3	-0.0	-0.004	1.9	1.4
Rome, GA	0.5	0.5	-0.0	-0.002	3.5	2.3
Columbus, IN	0.3	0.3	-0.0	-0.004	2.2	1.5
Kokomo, IN	0.2	0.3	-0.0	-0.006	1.8	1.2
Johnson City, TN	0.5	0.5	-0.0	-0.004	3.7	2.4
Mansfield, OH	0.6	0.6	-0.0	-0.003	4.6	3.4
Burlington, NC	1.1	1.2	-0.0	-0.002	8.5	5.8
Hartford-West Hartford-East Hartford, C	1.9	1.9	-0.0	-0.001	13.7	11.1
Johnstown, PA	0.5	0.6	-0.0	-0.004	4.0	2.9
Morristown, TN	0.5	0.5	-0.0	-0.004	4.0	2.5
Monroe, MI	2.2	2.2	-0.0	-0.001	15.4	12.6
Kankakee-Bradley, IL	0.6	0.6	-0.0	-0.004	4.2	3.2
Toledo, OH	3.1	3.1	-0.0	-0.001	21.7	17.8
Poughkeepsie-Newburgh-Middletown, NY	1.4	1.4	-0.0	-0.002	10.1	7.9
Goldsboro, NC	0.9	0.9	-0.0	-0.003	6.5	4.2
Fort Wayne, IN	1.3	1.3	-0.0	-0.002	9.4	7.2
Lima, OH	0.5	0.5	-0.0	-0.005	3.8	2.7
Hot Springs, AR	0.2	0.2	-0.0	-0.014	1.4	0.6
Lawrence, KS	0.1	0.1	-0.0	-0.019	1.0	0.4
Wheeling, WV-OH	0.6	0.7	-0.0	-0.004	4.8	3.3
New Haven-Milford, CT	1.1	1.2	-0.0	-0.003	8.3	6.4
Norwich-New London, CT	0.5	0.5	-0.0	-0.007	3.5	2.4
Racine, WI	0.5	0.5	-0.0	-0.007	3.6	2.8
Cleveland, TN	0.4	0.4	-0.0	-0.008	3.1	1.7
Dalton, GA	1.0	1.0	-0.0	-0.004	7.3	4.7
Kingsport-Bristol-Bristol, TN-VA	1.2	1.2	-0.0	-0.003	8.8	5.8
Roanoke, VA	1.9	1.9	-0.0	-0.002	14.2	9.9
Elizabethtown, KY	0.4	0.4	-0.0	-0.009	2.9	1.6
Chattanooga, TN-GA	2.3	2.4	-0.0	-0.002	17.5	11.8
Boston-Quincy, MA	1.7	1.7	-0.0	-0.002	12.3	10.0
Owensboro, KY	0.3	0.3	-0.0	-0.014	2.1	1.0
Gadsden, AL	0.4	0.5	-0.0	-0.008	3.4	1.9
Anniston-Oxford, AL	0.4	0.5	-0.0	-0.008	3.4	1.9
Michigan City-La Porte, IN	0.6	0.6	-0.0	-0.007	4.3	3.1
Dubuque, IA	0.2	0.2	-0.0	-0.024	1.3	0.6
Bowling Green, KY	0.4	0.4	-0.0	-0.010	3.0	1.6
Bloomington, IN	0.5	0.5	-0.0	-0.009	3.6	2.1
Vero Beach, FL	0.3	0.3	-0.0	-0.015	2.1	0.9
Janesville, WI	0.6	0.6	-0.0	-0.008	4.1	3.0
Jonesboro, AR	0.3	0.3	-0.0	-0.015	2.2	1.0
Pittsfield, MA	0.2	0.3	-0.0	-0.019	1.8	0.9
Morgantown, WV	0.5	0.5	-0.0	-0.009	3.8	2.3
Ames, IA	0.2	0.2	-0.0	-0.026	1.3	0.5
Elmira, NY	0.2	0.2	-0.0	-0.022	1.6	0.7
Parkersburg-Marietta, WV-OH	0.7	0.7	-0.0	-0.007	5.0	3.1
Sumter, SC	0.3	0.4	-0.0	-0.013	2.6	1.2
Hagerstown-Martinsburg, MD-WV	2.1	2.1	-0.0	-0.002	15.4	11.3
Lynchburg, VA	1.4	1.5	-0.0	-0.004	10.8	7.1
Vineland-Millville-Bridgeton, NJ at	2.4	2.4	-0.0	-0.002	17.7	12.6
Decatur, AL	0.6	0.7	-0.0	-0.008	4.8	2.7
Huntington-Ashland, WV-KY-OH	0.9	1.0	-0.0	-0.006	7.1	4.4
Ithaca, NY	0.2	0.3	-0.0	-0.023	1.8	0.8
Pine Bluff, AR	0.3	0.3	-0.0	-0.018	2.4	0.9
Sheboygan, WI	0.2	0.3	-0.0	-0.023	1.8	0.9
Florence-Muscle Shoals, AL	0.5	0.5	-0.0	-0.011	3.9	1.9
Sandusky, OH	0.5	0.6	-0.0	-0.011	3.9	2.4
Fond du Lac, WI	0.3	0.3	-0.0	-0.019	2.3	1.3
Elkhart-Goshen, IN	0.5	0.6	-0.0	-0.012	3.9	2.4
Danville, IL	0.4	0.5	-0.0	-0.013	3.5	1.9
Williamsport, PA	0.4	0.4	-0.0	-0.016	2.8	1.4
Athens-Clarke County, GA	0.9	0.9	-0.0	-0.007	6.9	4.0
Huntsville, AL	1.3	1.3	-0.0	-0.005	9.7	5.9
Harrisburg-Carlisle, PA	1.6	1.7	-0.0	-0.004	11.9	8.5
Lafayette, IN	0.5	0.5	-0.0	-0.013	3.7	2.0

Auburn-Opelika, AL	0.5	0.5	-0.1	-0.014	3.7	1.6
Jackson, TN	0.4	0.5	-0.1	-0.015	3.6	1.6
Iowa City, IA	0.3	0.4	-0.1	-0.021	2.5	1.1
Charleston, WV	1.4	1.5	-0.1	-0.005	10.8	6.8
Longview, TX	0.6	0.7	-0.1	-0.011	4.8	2.5
Kingston, NY	0.5	0.6	-0.1	-0.014	3.9	2.2
Gary, IN ivision	2.2	2.2	-0.1	-0.004	15.6	12.1
Asheville, NC	3.7	3.8	-0.1	-0.002	27.7	18.7
Houma-Bayou Cane-Thibodaux, LA	0.4	0.5	-0.1	-0.016	3.7	1.5
State College, PA	0.6	0.6	-0.1	-0.013	4.6	2.6
Lawton, OK	0.3	0.4	-0.1	-0.021	2.7	1.0
Barnstable Town, MA	0.3	0.3	-0.1	-0.024	2.4	0.9
Providence-New Bedford-Fall River, RI-M	1.7	1.7	-0.1	-0.005	12.5	9.4
Tuscaloosa, AL	1.0	1.1	-0.1	-0.008	7.9	4.5
Terre Haute, IN	0.5	0.6	-0.1	-0.014	4.2	2.1
South Bend-Mishawaka, IN-MI	0.9	0.9	-0.1	-0.009	6.7	4.4
Winchester, VA-WV	0.8	0.8	-0.1	-0.010	6.0	3.4
Harrisonburg, VA	0.7	0.8	-0.1	-0.011	5.8	3.1
Clarksville, TN-KY	0.6	0.7	-0.1	-0.013	5.1	2.5
Decatur, IL	0.6	0.6	-0.1	-0.015	4.4	2.3
Waterloo-Cedar Falls, IA	0.3	0.4	-0.1	-0.025	2.6	1.1
La Crosse, WI-MN	0.3	0.4	-0.1	-0.027	2.4	1.0
Fort Walton Beach-Crestview-Destin, FL	0.5	0.5	-0.1	-0.017	3.8	1.4
Florence, SC	0.7	0.8	-0.1	-0.012	5.9	2.9
Hinesville-Fort Stewart, GA	0.5	0.5	-0.1	-0.018	3.9	1.5
Rocky Mount, NC	1.6	1.7	-0.1	-0.006	12.3	7.4
Panama City-Lynn Haven, FL	0.4	0.5	-0.1	-0.019	3.6	1.3
Essex County, MA	0.7	0.8	-0.1	-0.012	5.8	3.6
College Station-Bryan, TX	0.5	0.6	-0.1	-0.016	4.5	2.0
Texarkana, TX-Texarkana, AR	0.6	0.7	-0.1	-0.015	4.8	2.1
Port St. Lucie, FL	1.1	1.2	-0.1	-0.008	8.7	4.9
Lubbock, TX	0.4	0.5	-0.1	-0.020	3.6	1.3
Mobile, AL	1.3	1.4	-0.1	-0.007	10.3	5.8
Oshkosh-Neenah, WI	0.4	0.5	-0.1	-0.023	3.2	1.6
Appleton, WI	0.4	0.5	-0.1	-0.022	3.3	1.7
Myrtle Beach-Conway-North Myrtle Beach,	0.9	1.0	-0.1	-0.010	7.5	3.7
Bay City, MI	0.4	0.5	-0.1	-0.021	3.5	1.7
Lakeland, FL	1.8	1.9	-0.1	-0.005	13.6	8.5
Cedar Rapids, IA	0.4	0.5	-0.1	-0.022	3.5	1.6
Sioux City, IA-NE-SD	0.3	0.4	-0.1	-0.029	2.6	0.9
Cumberland, MD-WV	0.7	0.8	-0.1	-0.014	5.7	3.0
Warner Robins, GA	0.7	0.8	-0.1	-0.014	5.5	2.5
Bismarck, ND	0.3	0.4	-0.1	-0.033	2.3	0.8
Salisbury, MD	1.0	1.1	-0.1	-0.010	8.1	4.3
Hattiesburg, MS	0.5	0.6	-0.1	-0.019	4.2	1.5
Scranton–Wilkes-Barre, PA	1.6	1.7	-0.1	-0.007	11.7	8.3
Springfield, MA	0.8	0.9	-0.1	-0.013	6.5	4.0
Dothan, AL	0.5	0.6	-0.1	-0.019	4.4	1.6
Grand Forks, ND-MN	0.3	0.4	-0.1	-0.038	2.2	0.8
Glens Falls, NY	0.3	0.4	-0.1	-0.029	3.0	1.0
Amarillo, TX	0.6	0.7	-0.1	-0.018	4.9	1.7
Topeka, KS	0.5	0.6	-0.1	-0.021	4.4	1.8
Saginaw-Saginaw Township North, MI	0.9	1.0	-0.1	-0.013	6.8	4.2
Pensacola-Ferry Pass-Brent, FL	1.4	1.5	-0.1	-0.008	11.0	6.0
Pascagoula, MS	0.7	0.8	-0.1	-0.015	6.2	2.6
Holland-Grand Haven, MI	1.0	1.1	-0.1	-0.012	7.7	4.8
Naples, FL	0.8	0.9	-0.1	-0.015	6.4	2.9
Ocean City, NJ	1.6	1.7	-0.1	-0.008	12.7	7.7
Nashville-Davidson–Murfreesboro, TN	5.3	5.4	-0.1	-0.002	39.6	26.9
Bloomington-Normal, IL	0.8	0.9	-0.1	-0.015	6.3	3.3
Jackson, MI	1.8	1.9	-0.1	-0.007	13.2	9.4
Eau Claire, WI	0.5	0.6	-0.1	-0.023	4.3	2.3
Evansville, IN-KY	1.1	1.2	-0.1	-0.011	9.0	4.9
Erie, PA	0.7	0.8	-0.1	-0.018	5.4	2.8
Gainesville, FL	0.8	0.9	-0.1	-0.015	6.8	3.0
Blacksburg-Christiansburg-Radford, VA	1.2	1.3	-0.1	-0.011	9.5	5.0
Rochester, MN	0.6	0.7	-0.1	-0.021	4.8	2.6
Wausau, WI	0.4	0.5	-0.1	-0.029	3.6	1.5
Ann Arbor, MI	4.3	4.4	-0.1	-0.003	30.9	24.5
St. Louis, MO-IL	15.1	15.2	-0.1	-0.001	109.3	83.2
Alexandria, LA	0.6	0.7	-0.1	-0.020	5.4	1.8
Albany, GA	0.8	0.9	-0.1	-0.017	6.6	2.6
Springfield, IL	1.1	1.2	-0.1	-0.013	8.4	4.5
Columbus, GA-AL	1.4	1.5	-0.1	-0.010	10.8	5.6
Sioux Falls, SD	0.5	0.6	-0.1	-0.030	3.9	1.5
Champaign-Urbana, IL	1.0	1.1	-0.1	-0.014	7.9	4.2
Lincoln, NE	0.6	0.7	-0.1	-0.024	4.8	1.9
Lafayette, LA	0.9	1.0	-0.1	-0.016	7.5	3.2
Monroe, LA	0.7	0.9	-0.1	-0.019	6.3	2.4

St. Joseph, MO-KS	0.6	0.8	-0.1	-0.022	5.4	2.2
Binghamton, NY	0.8	0.9	-0.1	-0.020	6.1	2.9
Jacksonville, FL	4.0	4.1	-0.1	-0.004	30.3	19.3
Augusta-Richmond County, GA-SC	2.5	2.7	-0.1	-0.006	19.6	11.6
Muskegon-Norton Shores, MI a	1.2	1.3	-0.1	-0.014	9.0	5.4
Columbia, MO	0.8	0.9	-0.1	-0.020	6.6	2.7
Greenville, NC	1.2	1.3	-0.1	-0.013	9.8	4.4
Valdosta, GA	0.8	1.0	-0.1	-0.018	7.2	2.6
Charlottesville, VA	1.3	1.5	-0.1	-0.012	10.7	5.3
Joplin, MO	0.9	1.0	-0.1	-0.018	7.5	3.0
Lake Charles, LA	0.9	1.0	-0.1	-0.018	7.3	2.7
Memphis, TN-MS-AR	3.5	3.6	-0.1	-0.005	26.4	16.9
Fort Smith, AR-OK	0.9	1.1	-0.1	-0.018	7.8	3.1
Gulfport-Biloxi, MS	0.9	1.1	-0.1	-0.018	7.9	2.9
Jefferson City, MO	0.9	1.1	-0.1	-0.019	7.7	3.2
Green Bay, WI	0.7	0.9	-0.1	-0.024	6.0	2.9
Fayetteville-Springdale-Rogers, AR-MO	1.1	1.3	-0.1	-0.016	9.3	4.0
Rockford, IL	1.7	1.8	-0.1	-0.012	12.6	8.3
Brunswick, GA	0.9	1.1	-0.1	-0.018	8.1	2.8
Des Moines, IA	0.8	1.0	-0.2	-0.022	6.8	3.1
Beaumont-Port Arthur, TX	1.2	1.4	-0.2	-0.015	10.0	4.3
U a-Rome, NY	0.8	0.9	-0.2	-0.025	6.3	2.7
St. Cloud, MN	0.8	0.9	-0.2	-0.025	6.3	3.3
Davenport-Moline-Rock Island, IA-IL	1.3	1.5	-0.2	-0.015	10.2	5.7
Dover, DE	4.2	4.4	-0.2	-0.005	31.7	20.6
Fargo, ND-MN	0.6	0.7	-0.2	-0.036	4.7	1.8
Shreveport-Bossier City, LA	2.1	2.3	-0.2	-0.010	16.6	8.9
Tallahassee, FL	1.1	1.3	-0.2	-0.018	9.3	3.4
Buffalo-Niagara Falls, NY	1.7	1.9	-0.2	-0.013	13.0	8.1
Wichita, KS	1.0	1.2	-0.2	-0.020	8.7	3.5
Columbia, SC	2.9	3.1	-0.2	-0.008	22.8	13.0
Macon, GA	2.3	2.4	-0.2	-0.010	18.0	9.6
Montgomery, AL	1.4	1.6	-0.2	-0.016	11.7	4.9
Birmingham-Hoover, AL	4.7	4.8	-0.2	-0.005	35.7	21.7
New Orleans-Metairie-Kenner, LA	2.9	3.1	-0.2	-0.009	22.8	12.7
Charleston-North Charleston, SC	2.0	2.2	-0.2	-0.012	16.5	7.5
Syracuse, NY	1.3	1.5	-0.2	-0.020	10.4	5.3
Jackson, MS	1.8	2.0	-0.2	-0.014	14.8	6.7
Little Rock-North Little Rock, AR	2.2	2.4	-0.2	-0.012	17.9	9.0
Lewiston-Auburn, ME	0.8	1.0	-0.2	-0.032	6.8	2.0
Peoria, IL	2.0	2.3	-0.2	-0.014	15.9	8.8
Jacksonville, NC	1.5	1.7	-0.2	-0.018	12.7	4.4
Wilmington, NC	2.7	2.9	-0.2	-0.011	21.9	10.6
Madison, WI	2.2	2.4	-0.2	-0.015	16.5	10.3
Savannah, GA	2.0	2.2	-0.2	-0.015	16.2	7.0
Baton Rouge, LA	2.9	3.2	-0.2	-0.011	23.3	12.3
Battle Creek, MI	2.8	3.1	-0.3	-0.012	21.4	13.5
Omaha-Council Bluffs, NE-IA	1.7	1.9	-0.3	-0.019	13.5	7.0
Grand Rapids-Wyoming, MI	3.4	3.7	-0.3	-0.011	25.6	16.9
Niles-Benton Harbor, MI	2.9	3.2	-0.3	-0.013	22.1	13.0
Rochester, NY	1.7	2.0	-0.3	-0.020	14.1	6.9
Springfield, MO	2.2	2.5	-0.3	-0.016	18.0	7.9
Duluth, MN-WI	1.0	1.2	-0.3	-0.035	8.1	3.0
Tulsa, OK	3.3	3.6	-0.3	-0.011	26.0	14.5
Albany-Schenectady-Troy, NY	1.7	2.0	-0.3	-0.021	14.2	6.9
Rockingham County, NH	3.1	3.4	-0.3	-0.014	23.7	14.3
Manchester-Nashua, NH	3.2	3.5	-0.3	-0.013	24.4	15.1
Kalamazoo-Portage, MI	3.2	3.5	-0.3	-0.013	24.5	14.6
Flint, MI	5.9	6.2	-0.3	-0.008	43.2	31.4
Kansas City, MO-KS	7.8	8.2	-0.3	-0.006	58.6	41.2
Virginia Beach-Norfolk-Newport News, VA	8.2	8.6	-0.4	-0.006	63.2	38.1
Lansing-East Lansing, MI	5.5	5.9	-0.4	-0.011	41.1	27.2
Oklahoma City, OK	4.8	5.3	-0.5	-0.012	38.3	21.2
Bangor, ME	1.2	1.6	-0.5	-0.040	11.2	2.0
Burlington-South Burlington, VT	1.8	2.3	-0.6	-0.035	15.7	4.3
Portland-South Portland-Biddeford, ME	4.3	5.3	-1.0	-0.027	36.9	13.2

Table I: Damages and benefits (in millions) by MSA