CESifo WORKING PAPERS

8483
2020

August 2020

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
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CESifo *Working Paper No. 8483*

Congestion in the Electricity Transmission System Redistributes Pollution across Long Distances

Abstract

Electricity transmission redistributes environmental impacts across space. We exploit episodes of high electricity transmission system congestion to explore changes in ambient concentrations of air pollutants in the eastern United States. Reducing electricity system congestion decreases ozone and PM2.5 concentrations in New England and New York and increases them in the western portions of the Pennsylvania-New Jersey-Maryland electricity market and much of the Midwestern states. We quantify the health impacts of changes in environmental pollution induced by a reduction in congestion and find overall health losses in central states such as Illinois, Indiana, and Ohio and health gains in Atlantic.

JEL-Codes: Q510, Q520, Q530.

Keywords: electricity congestion, air quality, electricity transmission, health impacts.

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July 27, 2020
We want to thank without implicating David Laband, Shatakshee Dhongde and seminar participants at Georgia Tech, Morehouse College and Carnegie Mellon University. Moreno-Cruz acknowledges support from the Canada Research Chairs program.

The electricity transmission system in the United States expands more than 200,000 miles of high-voltage power lines, allowing the cheaper sources of electricity generation in a vast region to meet demand across very long distances. From an environmental perspective, this long-distance connectivity implies that the environmental impacts associated with electricity generation may occur far from the locations where electricity is demanded. For example, electricity demand in Ridgefield, New Jersey, could be supplied by their local power plant fueled with natural gas, or it could supplied by a power plant powered by coal in Manchester, Ohio, more than 600 miles away utilizing these high-voltage power lines. In this paper, we are interested in understanding the role that electricity transmission plays in redistributing environmental impacts across space. We are particularly interested in how the transmission system affects the spatial distribution of air pollutant concentrations and health impacts of electricity generation in the United States. To do this, we exploit the physical constraints of the transmission system that, from time to time, force power generation to be re-dispatched to satisfy electricity demand.

Typically in wholesale electricity markets, electricity service providers and electricity generators submit demand and supply bids to an independent system operator that aggregates the bids into supply and demand curves. Under ideal system operation the intersection of these supply and demand curves determines the electricity price across the entire market. Electricity transmission lines, however, are subject to capacity constraints that limit the amount of electricity they can transfer between nodes. For the system to operate safely and reliably, operators curtail power along the lines that are at full capacity or *constrained*. When a transmission line is constrained, local demand must be sourced by local power instead of more distant — possibly cheaper— sources. When multiple lines are constrained the system is said to be *congested*.

Electricity system congestion also affects the environmental outcomes. Electricity generation from fossil fuels like coal, natural gas, and petroleum releases air pollutants that significantly affect human health such as sulfur dioxide and nitrogen oxides. The emissions profiles of the plants that would have been dispatched under ideal system operation are not the same as the emissions profiles of the plants that are *actually* dispatched due to system congestion. For instance, according to EPA's eGRID database, an average coal-fired power plant emits approximately 13.0 pounds of sulfur dioxide and 6.0 pounds of nitrogen oxides per megawatt hour of electricity produced while an average natural gas-fired power plant emits 0.1 pounds of sulfur dioxide and 1.7 pounds of nitrogen oxides per megawatt hour of electricity produced. Different emission patterns result in a spatial redistribution of air pollutant concentrations due to different electricity generators being dispatched in different locations. Our specific goal is to quantify the spatial redistribution of pollution and damages in the eastern United States that results from transmission system congestion.

We proceed in three steps. First, we define a measure of congestion that captures the capacity of the electricity system to deliver power across space at any time. In order to quantify congestion within a market, we need a measurement that i.) is broad enough to capture system wide congestion, and ii.) effectively discriminates between hours with many minor constraints and hours with maybe fewer but more disruptive bottlenecks. We use congestion prices to construct our measure of congestion. Congestion prices are determined at every node in an electricity market by calculating the difference in the cost of generating an additional unit of electricity given the current transmission constraints in the system and what the price at that node would be in a system that does not have physical constraints. Therefore, congestion prices send signals about the value of transmission capacity at each of the nodes in the electricity grid. We measure congestion as the sum of the square of these congestion prices to differentiate hours of low dispersion and high average congestion from hours of high dispersion and low average congestion.

Second, we use variation in congestion over time to empirically examine the impacts of electricity system congestion on the environment. Environmental externalities are not fully priced into the cost of electricity generation and therefore congestion prices do not reflect the differential environmental costs of using alternative electricity generation sources. Fossil fuel generation emits sulfur dioxide (SO_2) and nitrogen oxide (NO_x) that are precursors to particulate matter and ozone formation. Particulate matter and ozone, in turn, have large health and environmental impacts. Due to air-transportation dynamics and atmospheric chemistry, these impacts occur in areas away from where the pollutants are emitted. We use data from the Environmental Protection Agency (EPA)'s detailed Air Quality System data (AQS) to examine how concentrations of small particulate matter ($PM_{2.5}$) and ground level ozone change in response to congestion in the electricity grid. We regress pollution concentrations on grid congestion for each air quality monitor in our sample, to estimate the marginal change in pollutant concentrations due to changes in congestion.

Third, using our estimates of pollution concentration changes due to congestion, we quantify the impacts in terms of health outcomes. Health outcomes depend quite delicately on the timing and location of point sources and the magnitude of the changes in concentrations. We use BenMAP, the tool that EPA uses to conduct portions of regulatory impact analyses, to estimate damages from pollution. We simulate counterfactual pollution distributions with less congestion in the electricity grid. Lower electricity system congestion allows for the use of electricity generating plants further from where the electricity is consumed. Due to the original design of the electricity system, more distant plants are more likely to be coal-fired and thus cause more health damages from higher emission rates than alternative plants with higher marginal costs of generation but also lower emission rates. We find an overall net health benefit of reduced congestion, but there are clear winners and losers based on geographic location.

Many studies have assessed the general impact of electricity *generation* on the environment (Cullen; 2013; Denny and O'Malley; 2006; Graff Zivin et al.; 2014; Kerl et al.; 2015; Tschofen et al.; 2019). The spatial distribution of environmental and health impacts of electricity *transmission*, however, have received little attention; Hitaj (2015) is a notable exception. We show a sizable amount of pollution changes due to congestion and the effects are likely to be time, area, and pollutant specific. Our results suggests a role for environmental considerations during the electricity grid planning and expansion. For example, distributed generation such as solar PV may have environmental value in addition to producing no marginal air pollution since it indirectly reduces pollution in population centers (Siler-Evans et al.; 2013) while also likely reducing congestion within the grid changing the distribution of pollution.

Our paper contributes to the literature on the value of transmission and electricity market integration (e.g. Mansur and White (2012) in Eastern US, Wolak (2015) in Alberta, and Ryan (2017) in India). A more directly related study estimates the value of electricity transmission using a natural experiment generated by the closure of the San Onofre Nuclear

Generating Station (SONGS) in February 2012 (Davis and Hausman; 2016). The authors find that because of limits in the transmission system, SONGS closure could not be met by low cost alternatives. They also find an increase in CO_2 emissions, incurring extra environmental costs of $320 million, in 2013 dollars. Unlike in our study, they focus on emissions and do not analyze the spatial distribution of air pollution impacts.

Previous studies have also integrated air pollution impacts in the analysis of energy systems. The Air Pollution Emission Experiments and Policy analysis model (APEEP) of Muller and Mendelsohn (2006) and Muller et al. (2011) links air emissions data to monetary and non-monetary damages. Using this model, Muller and Mendelsohn (2006) and Muller et al. (2011) find that there is substantial heterogeneity in the distribution of economic damages across space. While we do not make use of the APEEP model, our study similarly finds a previously unexplored empirical relationship between electricity systems and environmental outcomes that varies across space and time.

A link between air pollution and mortality and morbidity has been identified before, e.g. Chay and Greenstone (2003); Currie and Neidell (2005); Currie et al. (2014). While over 90% of the monetized health impacts are related to mortality, other morbidity impacts are also accounted for in the literature, such as ER visits, doctor visits, respiratory symptoms and lung function reductions (Pope III et al.; 2002). We expand this literature with our work by linking the effects of electricity transmission restrictions to mortality and morbidity by showing that electricity system integration can have unexpected environmental impacts. This clearly expands beyond the electricity system and our study highlight that seemingly innocuous infrastructure can have large impacts in daily health outcomes.

We organize our paper as follows. We begin in section 1 with a brief overview of electricity markets in the United States to provide context for our data sources and then introduce our measure of system congestion. In section 2 we introduce the data we use to construct our measure of congestion, and then introduce data on pollutant concentrations. In section 3 we present our empirical approach and the main regression equation we use to estimate the impacts of electricity congestion on pollutant concentrations. In section 4 we present our results. The best way for understanding our results is via counterfactual exercise where we artificially change congestion and calculate the changes in pollutant concentrations and health outcomes. We close with a discussion of our results in section 5.

1 Electricity markets and congestion

In this section we briefly introduce how the electricity system works from an economic point of view. Using this parsimonious understanding of electricity markets, we then introduce our working definition of electricity system congestion.

1.1 Electricity Market Overview

Electricity transmission in the United States is separated into three largely independent "grids" or interconnections: the Eastern Interconnection, Western Interconnection, and the Texas Interconnection. The Eastern interconnection spans roughly all of the United States east of the Rocky Mountains excepting Texas, while the Western Interconnection spans all of the other continental United States, excepting Texas, while nearly all of Texas is covered by its own interconnection. The electricity flows between each interconnection are small, which means that each interconnection can be modeled as operating independently from the other interconnections.

Within each interconnection there are possibly many regional transmission organizations (RTOs) or independent system operators (ISOs) that operate the electricity transmission system in their geographic region. For instance, the Eastern Interconnection has six RTOs/ISOs. Electricity flows much more readily across RTO/ISO boundaries than across interconnection. RTOs and ISOs facilitate open-access to electricity transmission within a region and foster competition for electricity generation among wholesale market participants. They operate transparent wholesale markets for electricity in which electricity generators submit prices at which they are willing to supply a particular amount of electricity and order these bids from lowest to highest to dispatch the lowest cost electricity generators until demand is met. The market clearing price at every point in time is then paid to all generators and published publicly. We use these wholesale electricity prices to gain insight into congestion within the electricity system, as we discuss below.

1.2 Measuring congestion

We define a system-wide measure of congestion using publicly available electricity prices provided by different system operators. The energy price allows for the electricity market to balance the demand and the supply bids from the generating units across the entire market. Without constraints on the transmission system, the energy price is the electricity price. In practice, there are often constraints that cause deviations at particular locations from this energy price. These constraints are either due to particular transmission lines having a capacity constraint such that more electricity cannot be safely transmitted over them (congestion) or due to the loss of electricity due to transmission distance (line losses). The total price of electricity is the energy price plus the congestion and line loss prices. Transmission constraints may cause a reordering of dispatch to ensure grid stability.

Given the market clearing energy price, the congestion and line loss prices are set such that supply and demand are balanced at every node within the wholesale market. With congestion, a different dispatch order is required. Higher marginal cost units are dispatched closer to congested areas to relieve the congestion. Congestion and line loss prices vary widely and can cause potentially large deviations in the total price of electricity within the wholesale market. During particularly congested hours it is possible for local electricity prices to vary by over an order of magnitude. For instance, the price of electricity on the northern edge of New Jersey near New York City might be as high as $500 while prices for electricity in southern New Jersey might be as low as $20 in a particular hour.

In the empirical approach we adopt below, we analyze how air pollution concentrations change with system wide congestion. With that in mind, we need a measure of system congestion that captures the capacity of the system to respond to changes in demand at any given point in time. In particular, our measure of congestion at time t is given by:

$$Congestion_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(P_{it}^{c}\right)^2} \tag{1}$$

where P_{it}^{c} is the congestion price at location i at time t and N is the number of nodes in the system. The square term in this measure allows effective differentiation between hours with low levels of congestion in many areas of the grid from hours with high levels on congestion in a few areas of the grid.

2 Data

We next turn to describing the various data sets used in our analysis, how we aggregate these data sets, give background and context for the interpretation of our results.

2.1 Data on System Congestion

Ideally, we would like to have congestion data for all of the three electric interconnections within the United States to accurately measure congestion and how that congestion affects environmental outcomes across the country. However, since large sections of both the Eastern and Western Interconnections do not have transparent, competitive wholesale electricity markets with publicly available pricing data, we restrict our attention to the four markets in the Eastern Interconnection that have transparent market data. These markets are the Independent System Operator of New England (ISO-NE), the New York Independent System Operator (NYISO), the PJM Regional Transmission Organization (PJM), and the Mid-continent Independent System Operator (MISO). ISO-NE market includes all of the states in New England. The NYISO market covers the state of New York. The PJM Interconnection covers all of Pennsylvania, New Jersey, Maryland, Delaware, Virginia, West Virginia, and Ohio, as well as parts of Kentucky, Indiana, Illinois, and Michigan. The MISO market covers the remaining portions of Indiana, Illinois, and Michigan as well as Arkansas, Iowa, Louisiana, Minnesota, Wisconsin, and portions of Kentucky, Mississippi, Missouri, and North and South Dakota. We are excluding the states in the Southwest Power Pool (Kansas, Nebraska, portions of North and South Dakota, and Oklahoma) and the Southeast (Alabama, Florida, Georgia, North Carolina, South Carolina, and Tennessee) because there are not transparent wholesale electricity markets in these regions and thus congestion prices are not publicly available.

Within each of the markets in our sample, we collect electricity prices at every location available within the system after the market introduced locational marginal pricing. The price of electricity at each location is the sum of an energy price that is common across the entire market and two location specific prices: a price for line losses and a price for congestion. These data are taken from each Independent System Operator (ISO) or Regional Transmission Organization (RTO) that operates the wholesale electricity market. In addition to collecting the hourly locational price, we also collect data on the total hourly load (demand) within the wholesale electricity market.

Our data from these four market begin in the middle of 2007 and run through the end of 2015 leaving us with a total of 75,262 hourly observations of congestion. We combine the data across the four electricity markets into an aggregate measure of hourly congestion given in Equation (1). This allows us to capture potentially important changes in generation across markets due to congestion in an adjacent market. The distribution of congestion is skewed with many hours having low levels of congestion while some hours, typically in the afternoon, having very high congestion. The average amount of congestion is approximately 15 with a standard deviation of approximately 20. While some hours have zero congestion as we measure it, our measure ranges up to nearly 600.

2.2 Data on Pollution Concentrations

In order to relate our measure of changes in congestion to pollution concentrations and health outcomes, we collect data from the EPA Air Quality System's over 5,000 individual pollution monitors distributed across the United States. These monitors are used to measure pollution concentrations across the country and determine if each county is in compliance with the Clean Air Act Amendments' National Ambient Air Quality Standards. Specifically we use data from the Air Quality System on the ambient concentration of ground level ozone (O_3) and fine particulate matter ($PM_{2.5}$). According to the EPA's 2011 National Emissions Inventory electricity generators are responsible for 39.6% of national emissions of $PM_{2.5}$ and for 51.5% of national emissions that are precursors to ground level ozone formation (nitrogen oxides and volatile organic compounds).

Ground level ozone can cause major health impacts and has been linked to asthma incidence (Muller and Mendelsohn; 2006). However, ozone is not directly emitted into the atmosphere. Instead, ground level ozone is formed through a reaction of nitrogen oxides

(NO_x) and volatile organic compounds (VOCs) with heat and sunlight.[1] NO_x and VOCs are therefore considered the primary precursors to ground level ozone and are monitored at stationary sources and regulated to influence ground level ozone. Electricity generation is one of the major sources of nitrogen oxides emissions.

$PM_{2.5}$ concentrations are emitted directly into the atmosphere, but often include a large contribution from secondary aerosols formed by their precursors SO_x and NO_x (Grosjean and Seinfeld; 1989; Muller and Mendelsohn; 2006). Increased $PM_{2.5}$ concentrations are associated with increases in mortality, asthma rates, non-fatal heart attacks, emergency room (ER) visits, and hospital visits (Pope III et al.; 2002).

We restrict our sample to air quality monitors within states that have any portion of their borders included in the wholesale electricity markets described above. When overlapped with the time period over which we have electricity congestion data discussed above, this gives us with over 500,000 daily monitor observations for $PM_{2.5}$ and over 27,000,000 hourly monitor observations for ozone.

3 Empirical Approach

Our empirical strategy relies on the observation that while the system is congested, the electricity system needs to alter its operation in response to momentary changes in its capacity to transmit power along long distances. We use our measure of electricity system congestion to estimate how the spatial distribution of air pollution depends on the electricity transmission grid.

Since our measure of congestion is system-wide, spanning a majority of the eastern United States, it is unlikely that it will be correlated with any other factors that affect pollution concentrations at any one particular pollution monitor. Yet, is is possible that system operation could respond to pollution concentrations, which could impede us from interpreting our results a causal. The most plausible mechanism by which local pollution concentrations could affect congestion is through the electricity generators changing their bidding behavior

[1] The necessity of heat and sunlight for ozone formation leads to seasonal patterns in ground-level ozone that we will account for in our regression specifications.

in response to local pollution concentrations in order to avoid additional future regulatory costs related to environmental performance. While generators can exert some control over emissions, they are unlikely to have an effect on pollution concentrations. First, each generator only contributes a small amount to pollution concentrations in any particular location. Second, high smokestacks disperse pollutants over a significant region around their source. The exact region over which the pollutants disperse is a function of weather conditions such as winds and local temperatures, arguably outside the control of electricity generator operators. Third, the National Ambient Air Quality Standards use an annual average for $PM_{2.5}$ and the annual fourth-highest daily maximum 8-hour concentration, averaged over 3 years, for ozone to levy warnings and penalties. It is unlikely that generators have sufficient knowledge and certainty over these measures to change their behavior contemporaneously and affect regulatory outcomes.

With this in mind, we identify the causal relationship of congestion on pollution concentrations, using variation that comes from within month and day of the week changes in hourly congestion. That is, we compare pollution concentrations days in January of a particular year with high system congestion to days in January with low system congestion while allowing each day of the week in our sample to have a different mean level of congestion. We also expect congestion to have different impacts across space and for different seasons; thus, we estimate a separate effect of congestion at each monitor during each quarter of the year. Thus, our strategy allows congestion to have a different effect on pollution concentrations in New York City during winter than on pollution concentrations in rural Pennsylvania in winter or pollution concentrations in New York City during the summer.

We regress the ambient concentration registered at each monitor in every hour on the system congestion, allowing the marginal effect of congestion to vary for each pollution monitor. The estimating equation takes the form

$$c_{it} = \sum_{q=1}^{4} \beta_{iq} \times \mathbf{1}_q \times Congestion_t + \gamma_i X_t + \alpha_i + \phi_{im} + \psi_{id} + \nu_{it} \tag{2}$$

where c_{it} is the concentration of either ground level ozone or $PM_{2.5}$ at monitor i at time t, $Congestion_t$ is the amount of congestion in the electricity system at time t during quarter q,

α_i is a monitor fixed effect, ϕ_{im} is a monitor×month fixed effect and ψ_{id} is a monitor×day of week fixed effect. High demand periods tend to have high levels of congestion and also tend to be hot and sunny. These periods are also more likely to have high ozone concentrations and could pose a threat to the validity of our estimates without conditioning on load. We, therefore, also control for system load at time t, X_t.

4 Results

After estimating the empirical model in equation (2), we are left with approximately 2200 coefficients of interest for each pollutant. Each coefficient captures a marginal effect of congestion for each pollution monitor for each pollutant for each quarter of the year. We present summary statistics for these coefficients in Table 1. We should expect some monitors to have a positive marginal effect while others would have a negative marginal effect as the result of the spatial redistribution of pollution. Moreover, we should not expect all coefficients to be significant as for many monitors the changes induced by congestion could be statistically indistinguishable from zero. To capture these differences, we present the summary statistics of the monitor coefficient separately by their sign and by significance. All coefficients have the interpretation of how the ambient concentration of the pollutant changes for a one unit change in congestion on the electricity grid.

In order to give our coefficient estimates a practical interpretation and to illustrate the spatial pattern of pollution changes due to congestion in the transmission system, we simulate a counterfactual pollution concentration scenario from a decrease in congestion. Before we construct our counterfactual scenario, we establish a baseline level of pollution by averaging the pollution level in each hour of the year across all of the complete years of data in our data set (2008-2015). We also construct the average level of congestion in each hour of the year the same way. This methodology naturally reduces extreme congestion observations from particularly high congestion days and gives us a baseline expectation of congestion for each hour. In our counterfactual scenario we simulate a shock equivalent to a one unit reduction

Table 1: Summary statistics monitor coefficients

Variable	Mean	Std. Dev.	Min.	Max.	N
		PM 2.5 (μg/m^3)			
All coef.	-0.001	0.009	-0.199	0.099	2273
Positive coef.	0.006	0.007	0.000	0.099	968
Negative coef.	-0.005	0.008	-0.199	-0.000	1305
All sig. coef.	-0.002	0.013	-0.199	0.099	682
Positive sig. coef.	0.009	0.008	0.002	0.099	240
Negative sig. coef.	-0.008	0.011	-0.199	-0.002	442
		Ozone (parts per billion)			
All coef.	-0.015	0.052	-0.261	0.287	2245
Positive coef.	0.035	0.032	0.000	0.287	839
Negative coef.	-0.044	0.036	-0.261	-0.000	1406
All sig. coef.	-0.023	0.064	-0.261	0.287	1217
Positive sig. coef.	0.053	0.032	0.014	0.287	414
Negative sig. coef.	-0.062	0.035	-0.261	-0.014	803

in congestion in every hour of the year in which congestion is non-zero.

$$Counterfactual\ Congestion_t = Congestion_t - 1 \tag{3}$$

Since our measure of congestion has a standard deviation of 20, we are subtracting 1/20 of a standard deviation of congestion to each hour in our sample.

After constructing these pollution concentration counterfactuals, we calculate the health impacts of this new distribution of pollution using the Benefits Mapping and Analysis Program - Community Edition (BenMAP). BenMAP includes information on baseline health and population data calibrated using data from 2010, concentration-response relationships drawn from published epidemiological literature, economic valuation and estimates health outcomes. BenMAP translates pollution monitor concentration readings into local damages based on the selected concentration-response functions and then converts these health impacts into economic damages using common valuations from the literature. Following EPA's calibrated valuations, our simulations in BenMAP use a distribution of the value of a statistical life with a mean of $5.5 million in year 2000 dollars. This translates to approximately $8.2 million in year 2020 dollars.

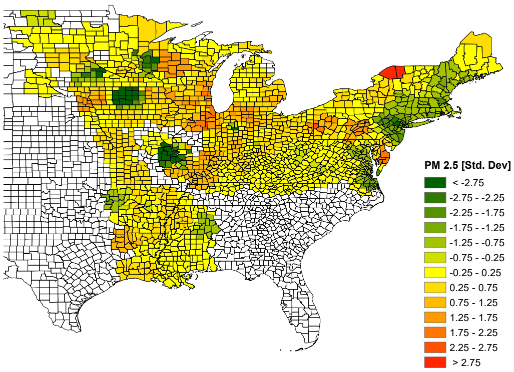
In addition to the software, EPA makes configuration setup files available for both ozone and $PM_{2.5}$ that allow users to conduct similar analyses to EPA using the same epidemiological studies and weighting of estimated concentration-response functions across studies. We use both of these configuration files to estimate the value of reducing congestion in the electricity grid. Since every county does not have a pollution monitor in it for every pollutant, we construct pollution concentrations for each pollutant by interpolating between monitors, weighting each monitor reading by the inverse of its distance to the interpolated point. We also extrapolate monitor readings by creating a 100 kilometer buffer around the monitors within the wholesale markets. Even with this extrapolation, there are relatively small zones within our general area of study that we cannot observe. Increasing the buffer, however, affects the accuracy of the interpolation process. We resolve this trade-off in favor of accuracy over coverage.

There is uncertainty built into the damage estimates for each county that stems from uncertainty in the damage functions in BenMAP for each pollutant. BenMAP reports a distribution of damage estimates for each level of pollution exposure. In the spirit of including economically significant damage estimates, we assume that if the range of damage estimates between the 2.5th percentile and the 97.5th percentile includes a damage of zero for a county the actual damage for that county is zero. Additionally, we set the monitor coefficients to zero if they are not statistically different from zero in the regression. In principle these choices reduce the magnitude of our estimated impacts, but in practice the effects do not change substantially if we instead use all of the point estimates regardless of their economic or statistical significance.

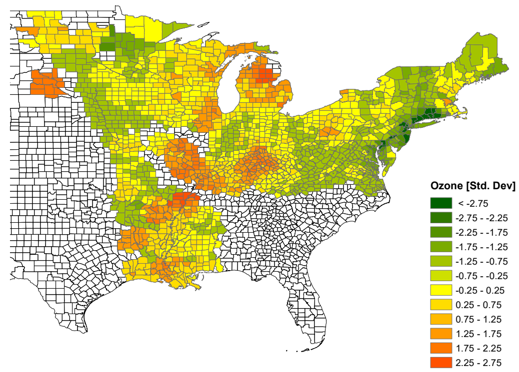
We present our results in Figure 1. Panel 1a displays the changes in $PM_{2.5}$ concentrations in our counterfactual scenario. The figure shows a distinct spatial pattern of areas that on average have an increase in pollution and areas that have a decrease in pollution levels. A decrease in congestion causes an increase in $PM_{2.5}$ levels in the western portions of our region of study, with the exception of population centers in in the Midwest, while $PM_{2.5}$ levels are decreased substantially along the Atlantic Ocean and in Midwestern population centers. A similar pattern emerges when examining changes in ozone though with slightly less pronounced reductions in the western portion of the study area, as shown in Panel 1b.

We show in Panel 1c the health impacts resulting from the counterfactual changes in the

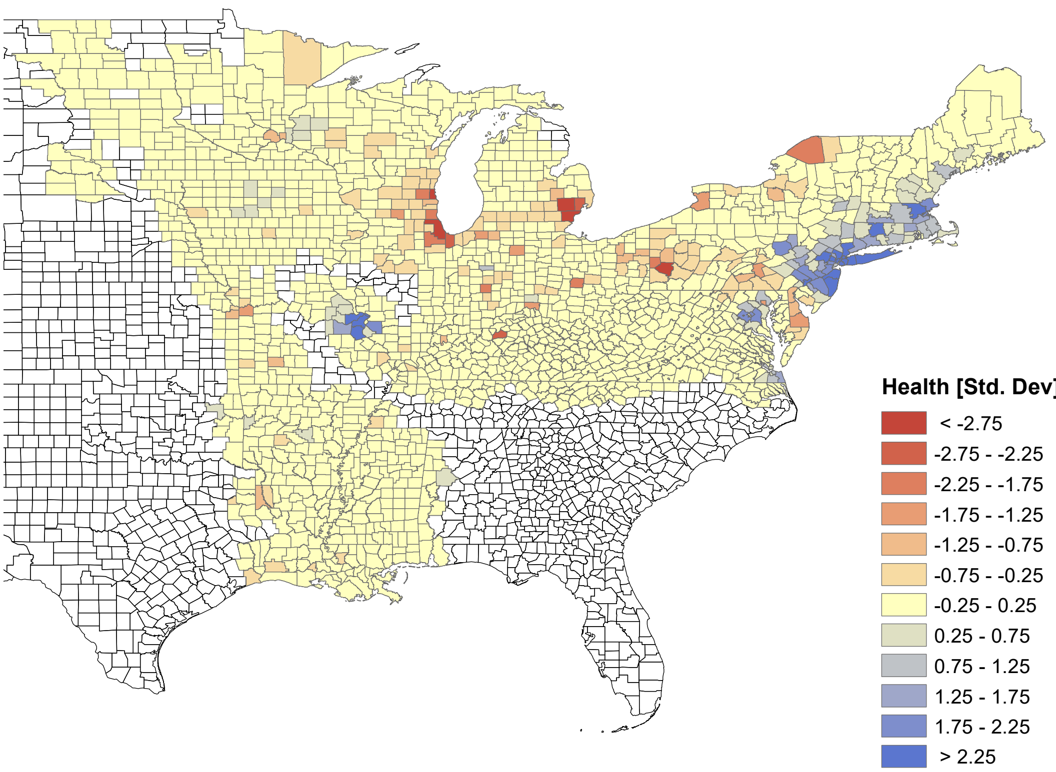
Figure 1: Changes in Pollution and Health Outcomes Due to a Simulated Reduction in Congestion



(a) Changes in PM 2.5



(b) Changes in Ozone



(c) Health Changes due to a Reduction in Congestion distribution of pollutant concentrations. The health damage estimates we present are the present discounted value of the stream of health benefits the population receives from this one year change in congestion when the benefits accrue over a period of years. We use a discount rate of 3% to value the stream of future benefits and costs. While the the discount rate will affect the monetary valuation of the benefits and costs, the choice of discount rate will not affect the spatial distribution of those costs and benefits. The light orange to red counties in Panel 1c are the counties that experience health costs from decreased transmission congestion in the electricity grid. Those counties see an increase in $PM_{2.5}$ and/or ozone levels and corresponding health damages. The counties shown in shades of blue are counties that experience a decrease in health costs due to a transmission congestion decrease, with many areas along the Atlantic Ocean observing significant benefits from congestion reduction.

In Table 2 we show the sum of the valuation of the change in congestion for each state in our sample region. The first column, labeled benefits, displays the estimated health benefits in each state under the counterfactual scenario where one unit (one twentieth of a standard deviation) of electricity congestion is subtracted in every hour of the year. The second column, labeled damages, displays the estimated health costs in each state under the same counterfactual scenario. The table reports the net sum of the benefits or damages in each state. For instance, the damages of reduced congestion in western Pennsylvania outweigh be benefits of reduced congestion in eastern Pennsylvania for an overall net damage from congestion and thus Pennsylvania appears in the damages column. The overall benefits from reduced congestion are larger than the damages only by 1%, suggesting a redistribution of pollution that creates winners and losers without overall gains.

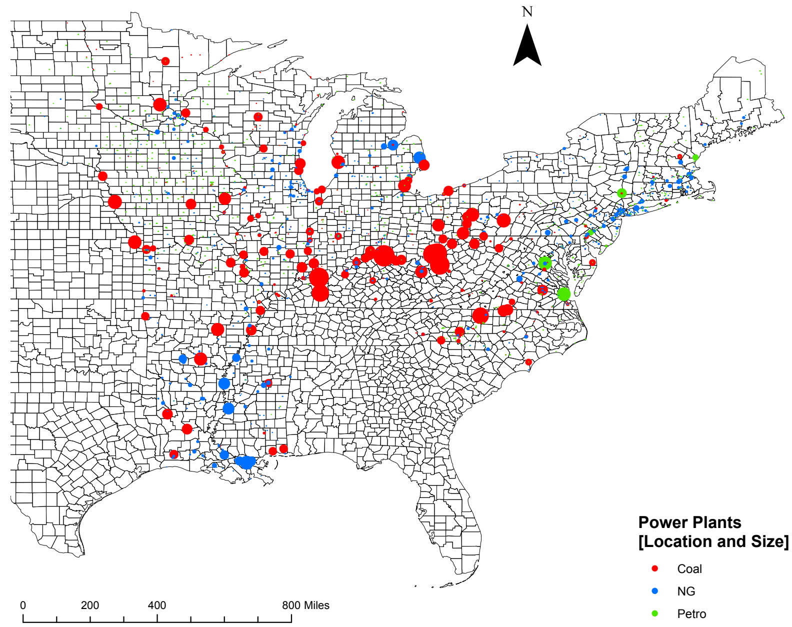
Our results are indicative of substitution pattern in generation due to congestion in the electricity transmission system. Figure 2 displays the locations of fossil-fired electricity generators located in the geographic footprint of the four electricity markets in our sample by the type of fuel that is used for generation. Coal-fired electricity generation produces more nitrogen oxides and $PM_{2.5}$ than natural gas-fired generation. Coal-fired electricity generation is concentrated in the Midwest and western-portions of Virginia and Pennsylvania, while natural gas-fired units are located in the eastern portion of the United States. Given this emission pattern across fuel sources, we can infer a generation substitution pattern.

Table 2: Benefit and Damage Estimates from a Decrease in Congestion

	Benefits		Damages
AL	6,042	AR	10,691
CT	85,046	DE	33,907
DC	19,532	IA	107
MA	180,022	IL	402,298
MD	19,555	IN	168,623
ME	23,706	KS	19,144
MO	127,200	KY	56,689
NC	7,147	LA	40,454
ND	353	MI	210,200
NH	25,973	MN	21,991
NJ	388,415	MS	8,595
NY	370,193	NE	3,800
OK	8,656	OH	154,680
RI	28,303	PA	48,780
VA	111,983	SD	3,228
		TN	10,987
		TX	20,828
		VT	1,345
		WI	164,016
		WV	7,254
Total	**1,402,126**	**Total**	**1,387,617**

Benefits and damages are listed in thousands of 2000 USD.

Figure 2: Location of Fossil-fuel fired Power Plants in Sample Region



The size of the dot is proportional to the size of the power plant.

This means that due to transmission congestion, pollution from the western half of our sample where there are large, coal-fired generating units, is reallocated the eastern half of our sample where smaller natural gas-fired generators are producing more electricity to ease grid congestion and meet local demand. Overall, states in the western portion of our data are damaged by a decrease in congestion since congestion tends to increase pollution concentrations in those states while states in the eastern portion benefit from a decrease in congestion since electricity generation (and therefore emissions) is far away when congestion is low but shifts to local sources when congestion is high.

5 Conclusions

We examined the effect of congestion on pollution concentrations and found a clear geographic pattern. Using empirical estimates of the effects of congestion on concentrations, we constructed a counterfactual estimate of pollution levels with less congestion in the electricity grid. In this counterfactual, counties in the western portion of our study area showed a large and significant increase in the amount of ground level ozone and $PM_{2.5}$ while counties in the eastern portion of our study area showed a large and significant decrease in the amount of ground level ozone and $PM_{2.5}$ from a decrease in congestion. We then estimated the net benefit to society measured in terms of monetized reduction in mortality and morbidity of the current average level of transmission congestion compared to reduction in congestion by one unit from the current level would result in redistribution of pollution, with the benefits in the eastern US \$1.40 billion being slightly higher that the damages to central US approximately equal to \$1.38 billion.

The electricity transmission system not only transfers electricity across regions, it also determines who benefits and who incurs damages from pollution. When planning for the expansion of the electricity transmission system, it is therefore important to account for the spatial heterogeneity of environmental externalities associated with electricity generation. In particular, it is useful to calculate the social cost of generating electricity at existing power plants and electricity transmission jointly. Changes in electricity system transmission are able to amplify or dampen the effects of changes in electricity generation. More generally, the benefits of any environmental policy aimed at reducing pollution and health impacts from electricity generation needs to account for the current and future electricity transmission infrastructure.

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