Something in the Air: How Policy Affects Air Quality and How Air Quality Affects Markets

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Contents

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1 Introduction

Sustainability is a defining issue that governments must face in the twenty-first century. The climate crisis, environmental degradation, and biodiversity loss all pose serious threats to human flourishing and to the well-being of the planet in the long run. Air quality is a particularly important subdomain of sustainability for human health, so it is important to understand its interactions with systems of policies and markets. This paper comprises two parts, the first addressing the extent to which policy affects air quality and the second addressing the extent to which markets respond to changes in air quality.

2 Measuring the Effect of Air Quality Policy

2.0.1 The Importance of Policy

Government policy has a uniquely important role in addressing sustainability since "business as usual" market mechanisms cannot effect the necessary changes with enough speed or thoroughness to prevent catastrophic environmental outcomes. Individual economic agents like firms and households do not fully bear the costs of their unsustainable actions, so governments must design incentives and implement regulations to resolve these externalities. Moreover, governments must intervene with forward looking policy that overcomes the tendency for individual agents to act without considering the costs of their unsustainable actions on future generations' well-being. Finally, governments must coordinate their policy responses and act in concert in order to overcome the collective-action problem.

Policies set at the national and international level are particularly important in addressing sustainability. Climate change is global in scope, so it is incumbent upon national governments, the largest fundamental unit of interpersonal and social organization, and intergovernmental organizations to implement policies that promote sustainability.

Given the importance of government policy in addressing sustainability, it is crucial that governments implement effective policies to make real progress on important outcomes. But how should governments allocate scarce resources toward policies in this uncertain environment? The evaluation of policy efficacy is challenging. The causal analysis approach to economic research, which has become accepted as the gold-standard of a published study, has trouble recovering a significant, unbiased effect when the sample size is small (bounded by the number of countries) and when the number of omitted variables is large (the policy system is highly interconnected and complex). But this difficulty in setting up well-controlled natural experiments to evaluate the efficacy of these policies cannot stand in the way of decisive policy action: the situation is too urgent.

2.0.2 Ambient Air Quality: A Pressing Concern

By the mid-twentieth century, ambient air quality, especially in urban areas, became a domain of policy concern in many high-income countries. A slate of pollutants including NOX, SOX, NMVOCs, PM2.5, PM10, and Carbon Monoxide are emitted by various consumer facing and industrial sources. For decades it has been known that ambient sulfur and nitrogen oxides produce acid rain (Likens et al., 1972), which can devastate ecosystems (Schindler, 1988). Recent research consistently shows that these pollutants large negative health and environmental consequences; particulate matter, especially PM2.5, “pose[s] a hazard to public health even at low levels” (Feng et al., 2016). Given the threats the pollutants pose to human and environmental well-being and the near-invisibility of their action, it is incumbent upon governments to regulate the emissions of these pollutants through policy.

2.1 Literature Review

The ideation for what became this paper began with a look at nitrogen management policies, so a number of papers in that domain were influential in setting up this analysis. The work of Dalgaard et al. reviews in detail the nitrogen management policies which Denmark implemented in the period from 1985 to 2011. Their paper provides a model of the time series analysis of the response of a set of outcome variables of interest to the implementation of specific policies. The authors bring their specific institutional knowledge of Denmark agriculture and policy to bear on the subject, hand coding and classifying policies according to a schema which distinguishes between input and output based policies; command and control, market based, and information/voluntary action polices; and geographically targeted policies versus general regulations. The rich coding schema allows for the authors to distinguish between the effects of different kinds of policy at a granular level, providing useful feedback to policymakers (Dalgaard et al., 2014).

One limitation of the paper is the limited geographic scope, which poses challenges for external validity and generalizability. The institutional knowledge that makes the paper so compelling is also a limitation for generalizability in the sense that their approach requires expert knowledge of the policies and institutions of a particular country in a particular subdomain.

Kanter et al. take a different from Dalgaard et al., relying less on institutional knowledge and more on data mining. They gather nitrogen management policy data around the world from the ECOLEX database using keywords searches, collecting the country, year, name, keywords, and abstract of a policy (Kanter et al., 2020). We follow their approach to policy data collection by collecting the same variables from ECOLEX instead relating to air quality. One problem they encounter that we also address below in my analysis is how to account for the number of policies passed by a country. Certain countries tend to pass more policies on average, and it is difficult to tell the extent to which this represents a greater commitment to reducing pollution rather than certain institutional factors in the legislation or regulation process of the country.

Kanter et al. take the number of policies passed as a "unit of analysis," which is a step we are more wary of taking about because of concern about the potential for institutional differences across countries: see my discussion below of the relationship between the average size or scope of a policy and the number of laws passed in a given country. The ECOLEX data are rich in keywords, but this richness cannot completely account for the lack of specific institutional knowledge, which poses challenges for both Kanter et al. and this paper.

There are relatively few available cross-country analyses of the effects of air policy. Kodjak provides an analysis of a few fuel efficiency standards policies across the G20 countries, concluding that a focus on heavy-duty vehicle emissions is the most effective approach to reducing the emissions of vehicles (Kodjak, 2015). The OECD reports the Environmental Policy Stringency Index constructed by Botta and Koźluk, which represents the best effort I have found at compiling a set of quantitative standards, tax levels, and other policy variables. They aggregate these quantitative standards into a single score reflecting the degree of stringency of a country's policy (Botta and Koźluk, 2014). Unfortunately, the most recent data stop in 2012 and there appears to be no plan for updating the work. Both of these papers represent attempts to project a complex policy package down to a few key quantitative metrics.

This paper pulls together an original dataset from the ECOLEX database in the spirit of Kanter et al. described above and matches these policy variables with a rich set of air pollution outcome variables and controls at the country-year level, organizing the analysis in an original framework inspired by a "systems approach" to air quality and air pollution.

2.2 Theory of Air Quality Policy: A Systems Approach

2.2.1 Setting Up the Structural Equation

Consider a set of n pollutants (e.g. $PM_{2.5}$, SO_2, CO, etc.) stored in the $n \times 1$ vector p and a set of d possible sources (e.g. vehicle emissions, construction, power generation, etc.)

stored in the $d \times 1$ vector s. Let each component of s represent a proxy of the amount of a source behavior over a given period (e.g. average number of miles driven per year for vehicle emissions). The two vectors are related by an $n \times d$ matrix A, so that the equation $As = p$ holds. We assume that each source of pollution adds some linear contribution to the overall amount of each pollutant and that there are no interaction terms, so that each row of A encodes the relative weights on each source for a particular pollutant. Hence, the matrix equation above encodes a system of n equations of the form

$$p_j = A_{j1}s_1 + A_{j2}s_2 + \ldots + A_{jd}s_d.$$

Each coefficient A_{ji} corresponds to the rate at which increasing the source behavior increases the amount of pollutant in the air. For example, the coefficient on the number of miles driven corresponds to the rate.

The linearity assumption seems reasonable on the surface: driving twice as much should cause approximately twice as much pollution, with a rough doubling of, say, the $PM_{2.5}$, SO_2, and CO emissions from vehicles. This simple story that the linearity assumption suggests may be leaving out important details. Perhaps an increase in the amount of driving requires the use of older, less efficient vehicles which would be left, so that increasing the amount of driving produces nonlinear increases in pollution. It is possible to extend this model by adding polynomial features to the vector s to account for such nonlinearities, but without compelling evidence of nonlinear behavior, the linearity should be sufficient if we assume that source variables vary somewhat smoothly.

The equation $As = p$ has nd coefficients contained in the matrix A to be estimated and represents the structural equation encoding the pathways through which air pollution occurs. Since we are assuming that the pollutants do not interact with one another, we treat the structural matrix equation as a set of n independent linear equations. These coefficients are not estimated via linear regression; instead, we can back out the coefficients contained in

A from widely reported data which breaks down air pollution by source. For pollutant j, a source i contributes a known share $A_{ji}s_i$, so dividing this share by s_i allows us to estimate A_{ji}. Hence, the units of A_{ji} are quantity of pollutant p_j per amount of source behavior s_i. The structural equation can be thought of as a useful form of organizing the accounting for the sources of emissions.

We postulate that there exists a structural equation of the form $A_t s_t = p_t$ at each t in some set of observation times—these will be annual observations for us. Over time, we observe variation in the quantities of pollutants in the air, which we see as variation in the components of p_t. We can use the structural equation to decompose the observed differences: $p_{t+1} - p_t = A_{t+1}s_{t+1} - A_t s_t$. By tracking the evolution of A and s in time, we are able to untangle the extent to which observed changes in pollution levels over time are attributable to changes in the levels of source behavior (the difference $s_i^{(t+1)}$ - $s_i^{(t)}$) and which changes are attributable to changes in how much pollution the source behavior generates (the difference $A_{ji}^{(t+1)} - A_{ji}^{(t)}$).

2.2.2 The Interaction of Policy with the Structural Equation

The time dependent set of structural equations provides a rich framework for understanding the channels by which national policy acts. By thinking about the air pollution system in terms of its sources s, their relative contributions A, and the outcomes p, we can then imagine three distinct mechanisms for policy to bring about changes in the amount of air pollution.

1. **Direct Capture of Pollutants:** This type of policy aims to decrease the stock of pollutants p in the air by acting directly on the pollutants in the environment. This is not modeled explicitly because it is more a proposed idea than a widespread policy, but such a policy could be incorporated into the structural model by a measure of the amount of removal behavior (e.g. cumulative energy put into "air scrubbers" or something of that kind) and computing a negative coefficient for the matrix A

associated with this source. Since these policies are not widely implemented, this extension of the model will not be warranted for analysis of policy data, but it could be used to account for natural sinks for air pollutants.

2. **Level of Source Behavior:** A policy might discourage certain high pollution behaviors by changing incentives, requiring permits, spreading information, or through other mechanisms. A gasoline tax is a canonical example of a policy which acts to reduce pollution from vehicle emissions by reducing the amount of driving (the source behavior) that occurs inside a country.

3. **Pollution Generation Intensity of Source Behavior:** A policy might change the rate at which engaging in the source behavior contributes to air pollution. A policy which sets and enforces more stringent emissions standards for vehicles will decrease the amount of pollution due to driving without necessarily decreasing the amount of driving that occurs.

It is natural to ask why we might want to group policies according to this framework. One answer is conceptual: we understand the the sources as components within the system and the generation intensities as the interrelations between the components. A second and more tangible answer concerns the political salience and intrusiveness of policy. Policies that aim to decrease source behavior might feel more intrusive to constituents; after all, the raison d'être of the policy is to reduce the polluting behavior of the constituents, and constituents tend to notice when the government is trying to change their behavior. Policies which target the generation intensity have the potential to feel less intrusive because they do not necessarily demand behavioral change. Hence, policymakers might be concerned with distinction between sources and generation intensities when designing policy.

2.2.3 Modularity of the Structural Equation

Our ability to set up the structural model as described depends on the form of the available data and the particular definitions of the categories of pollution sources, since certain source variables are more suited toward the selection of a single proxy measure than others. For example, the variable "Pollution from Road Transit" has a fairly natural source proxy of "Total Passenger-Kilometers Travelled", allowing us to perform the division to obtain an estimate of the associated coefficient in the matrix A. A variable like "Pollution from Industrial Processes" admits no easy proxy measure, however, because it is difficult to imagine a single variable that captures the notion of the level of industrial processing that occurs in a country.

Fortunately, the structural model is modular in the sense that we are able to select which sources we model and which we leave as observed values. In this setting, the we have a structural model which looks something like $p = As + v$, where v is an $d \times 1$ vector of pollution amounts from unmodelled sources. Hence, the structural model allows for domain specific research to be contextualized in the larger air quality system as available instead of requiring the full modeling of the system, which would likely prove to be unmanageably complex.

2.2.4 Modeling the Source Behavior and Generation Intensity

The structural provides a roadmap for organizing and aggregating the outcome variables A and s, but it imposes no constraints on the way that A and s are modeled. Let s_{it} indicate the level of some source variable, for example total passenger kilometers driven, in country i in year t, and let A_{jit} denote the pollution generation intensity for pollutant j of the associated source in country i in year t.

We use a fixed effects linear model with appropriate time-dependent controls x_{it} for each source variable as available along with a set of time-dependent dummies π_{it} which turn on when various policy keywords are implemented. Writing out the models, we have

$$s_{it} - \overline{s}_i = x_{it}^T \beta + \pi_{it}^T \delta + \epsilon,$$
$$A_{jit} - \overline{A}_{ji} = x_{it}^T \beta + \pi_{it}^T \delta + \epsilon.$$

There are a number of important subtleties associated with setting up these models. One choice concerns whether or not to tally the keywords or to use a simple dummy. Below we will try the model both ways and compare the results. Another potential subtlety concerns correlations in pollution from drift between neighboring countries. The potential for spatial autocorrelation is real and requires some sophisticated modeling to overcome, so we assume that spillovers across borders are not important for this analysis and we proceed with caution.

2.3 Policy Data by Country

The policy data come from the ECOLEX database, which catalogs information on environmental law and policy across countries. In order to narrow down the scope of policies considered, we use an initial keyword search of 'air quality' to find only the laws which contain text directed toward addressing air quality. The ECOLEX database contains the type of law (Legislation, Regulation, Decision, Treaty), the name of the law, the year of implementation, and, most importantly, a keyword description. Below I reproduce a typical entry in the database:

Country: Argentina

Type: Legislation

Name: Decreto 3970/90 - Reglamentación de la Ley 5965.

Year: 1990

Keywords: Pollution control, Air quality/air pollution, Emissions, Environmental standards, Offences/penalties, Waste disposal, Effluent waste water/discharge, Sewerage, Freshwater quality/freshwater pollution, Water quality standards

The data were collected via a web-scraping script. A total of 5232 policies are in sample across 141 countries in the period from 1990 to 2019. Below we produce a frequency table, which shows the count of the top 40 keywords and the the proportion of the laws in the sample which contain the keyword. We see that the keyword frequency drops quickly below 5%, highlighting the diversity of policy packages passed.

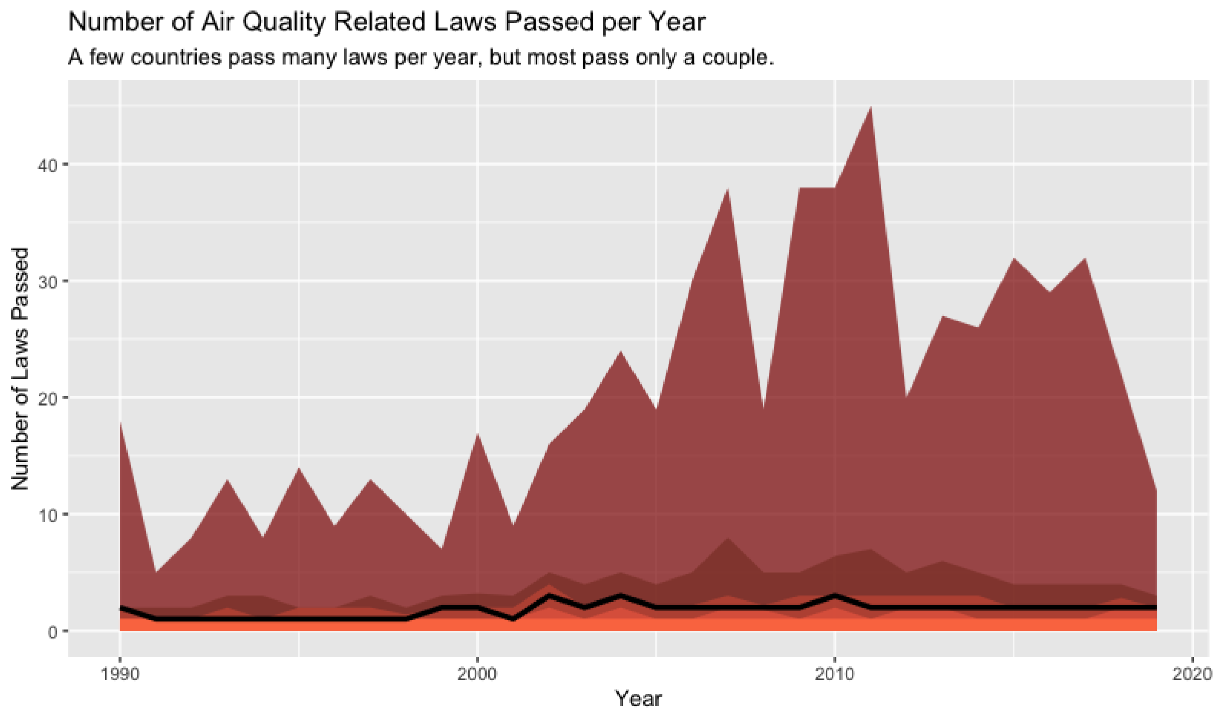
For the further analysis below, we will be subsetting down to the OECD countries, for which the pollution data and the available controls are much more available. Hence, we will analyze the characteristics of both the full policy dataset and the subsetted dataset in what follows.

2.3.1 How Many Policies?

Across the full dataset ($N = 141$), we see that an average of 1.24 laws relating to air quality are enacted per country per year. In the OECD ($N = 38$), this figure climbs to 2.62 laws per country per year. Given the frequency with which laws are passed, one concern for a time series analysis is untangling the effect of one policy from another. The design of this paper attempts to account for this potential issue by considering only the policies which fall into the particular subdomains which would be expected to have an effect on the particular source being considered. For instance, only laws which relate to automobile or vehicle emissions policy are considered in the time series analysis of road transport emissions data.

Table 1: Frequency Table for Keywords in the Policy Dataset (All Countries)

Keyword	Keyword Count	Keyword Frequency
pollution.control	2391	0.801542072
air.quality.air.pollution	2068	0.693261817
emissions	1271	0.426081126
standards	1135	0.380489440
environmental.standards	1029	0.344954744
hazardous.substances	472	0.158229970
ozone.layer	467	0.156553805
enforcement.compliance	415	0.139121690
climate.change	412	0.138115991
data.collection.reporting	412	0.138115991
offences.penalties	411	0.137780758
monitoring	385	0.129064700
oil	374	0.125377137
freshwater.quality.freshwater.pollution	362	0.121354341
waste.management	359	0.120348642
authorization.permit	350	0.117331545
institution	331	0.110962119
oil.pollution	296	0.099228964
inspection	293	0.098223265
environmental.planning	234	0.078444519
eia	225	0.075427422
waste.disposal	219	0.073416024
energy.conservation.energy.production	217	0.072745558
soil.pollution.quality	216	0.072410325
legal.proceedings.administrative.proceedings	213	0.071404626
policy.planning	210	0.070398927
access.to.information	203	0.068052296
transport.storage	203	0.068052296
basic.legislation	170	0.056989608
food.quality.control.food.safety	170	0.056989608
registration	162	0.054307744
sustainable.development	154	0.051625880
noise.pollution	151	0.050620181
ecosystem.preservation	143	0.047938317
protected.area	143	0.047938317
renewable.energy	140	0.046932618
hazardous.waste	138	0.046262152
certification	134	0.044921220
indigenous.peoples	117	0.039222259
radiation	117	0.039222259
land.use.planning	115	0.038551793
subsidy.incentive	113	0.037881328



To accomplish this subsetting, the data were filtered by an expansive but coherent set of keywords:

$$\text{Keyword} = (\text{“automobile”} OR \text{“automotive”} OR \text{“vehicle”} OR \text{“mobile source”}) AND (\text{“emissions”} OR \text{“air quality”})$$

. This keyword search returned $N = 141$ laws, which were then subsetted down to the OECD countries and hand coded as in or out of sample by title. The hand coding process eliminated laws which were obviously not in sample: in particular, around 40 laws which related to NMVOC pollution attributable to automobile manufacturing and painting were removed from the sample. A similar subsetting procedure will be performed when the energy generation series is analyzed. In the regression equations below, a total of $N = 50$ laws are in sample implemented across 19 out of 28 of in sample countries at various times.

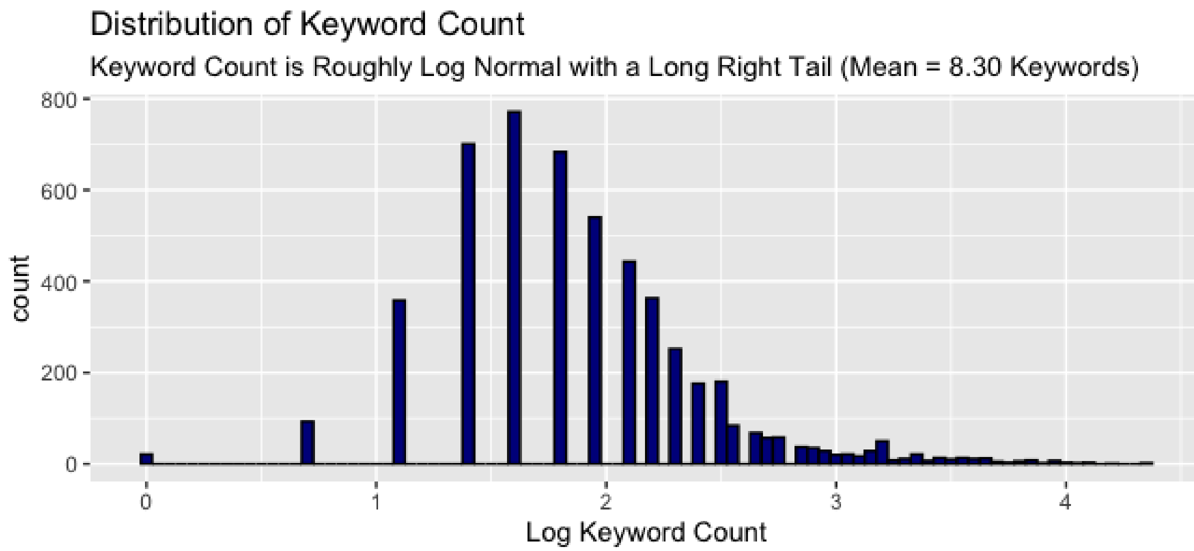
2.3.2 Big Packages or Targeted Policies?

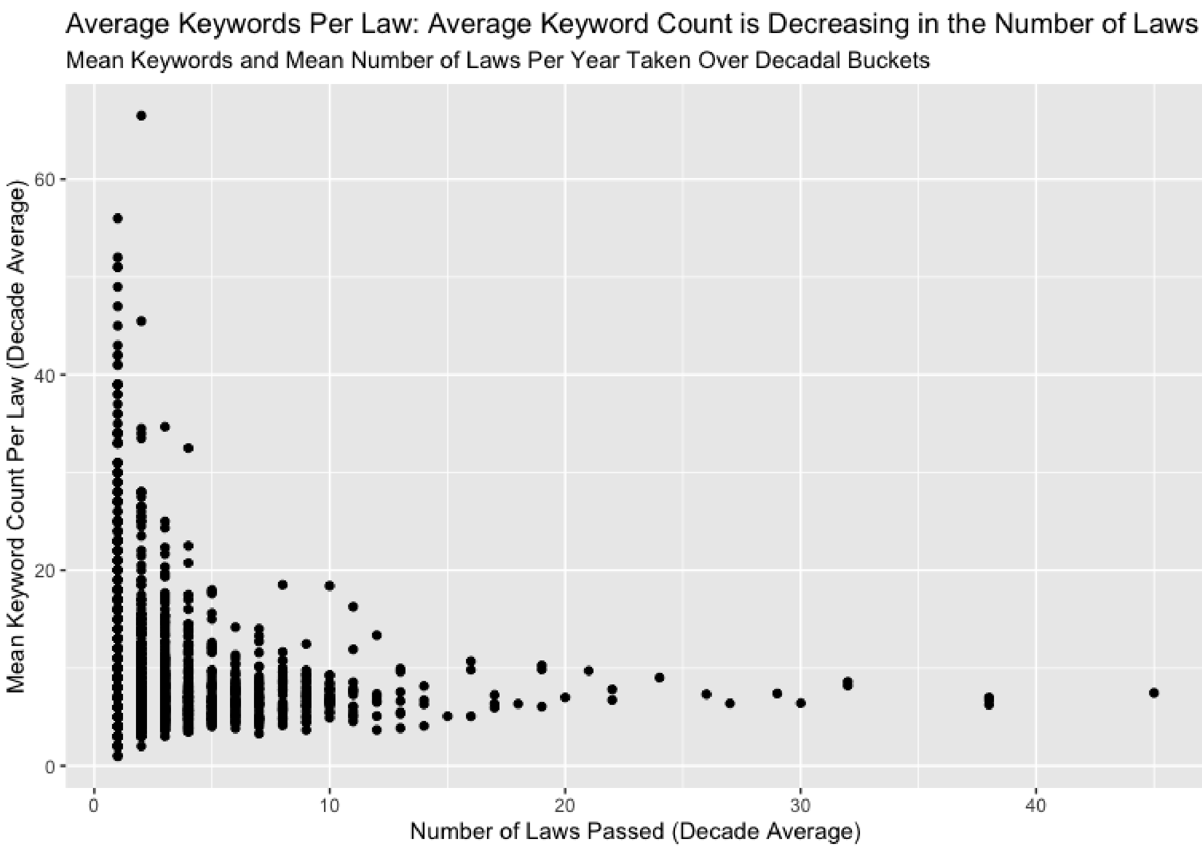
We use the number of keywords (coded as `nkeywords`) as a proxy measure for the scope or size of a piece of legislation. A policy package with many keywords spanning a diversity of environmental topics may be structurally different from a more targeted piece of policy. We consider the means across the decade buckets of 1990s, 2000s, and 2010s of the number of laws passed in the period and the average number of keywords per law. Across the automotive emissions subsample described above, the story is much the same, with a few big laws in some countries and many smaller policy packages in others. In the OECD subsample, Canada and the United Kingdom consistently pass many more laws than all of the other countries, likely because of the parliamentary structure of the government and the institutional culture. Because of this pattern, we take some issue with the methodology used in the Kanter et al. paper mentioned in the literature review above because Canada and the United Kingdom are clear outliers when it comes to the number of laws passed, skewing any result that depends on a roughly consistent amount of policy being passed across countries (Kanter et al. 2020).

2.4 Air Pollution Data

The best available data source for yearly pollution data broken down by emissions source is OECD statistics. The OECD categorizes air pollution according to the classification schema depicted in Figure 1. To map the data onto the structural equation described in Section 3, we take the leaves of the tree as the categories of source types, which would give a vector s of length nine. From the discussion of modularity in Section 3.3, we know that we can select a subset of these nine categories to model as a function of policy and some controls. We select two sources to model in this paper: "Road Transport" and "Power Stations." The availability of data and the ability to proxy the source behavior of Road Transport by Passenger Kilometers and Power Stations by Total Energy Consumption motivates these selections. The other sources in this dataset do not readily admit the single variable proxy demanded by the structural equation, so we represent these as the unmodeled factors in the vector v.

The OECD Pollution Dataset tracks six types of air pollution: Carbon Monoxide (CO), Non-Methane Volatile Organic Compounds (NMVOCs), Nitrogen Oxides (NOX), Coarse


Distribution of Keyword Count
Keyword Count is Roughly Log Normal with a Long Right Tail (Mean = 8.30 Keywords)
count
800
600
400
200
0
0
1
2
3
4
Log Keyword Count

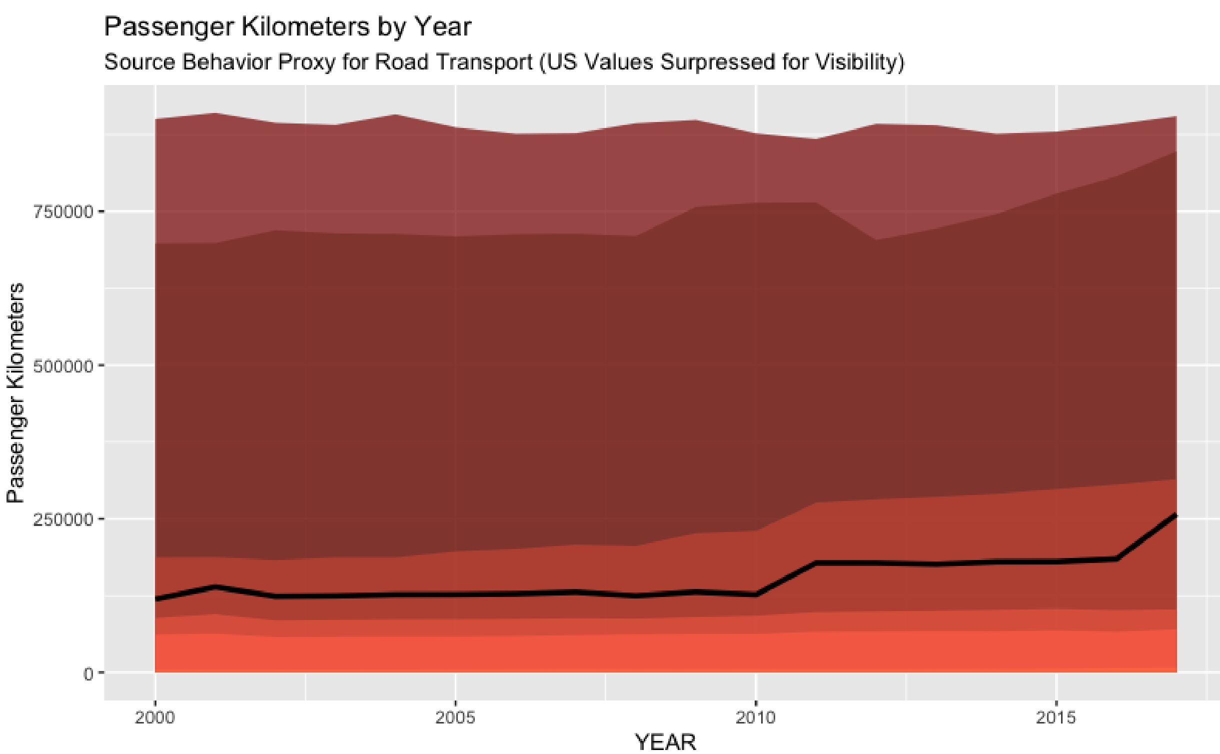

Average Keywords Per Law: Average Keyword Count is Decreasing in the Number of Laws
Mean Keywords and Mean Number of Laws Per Year Taken Over Decadal Buckets
Mean Keyword Count Per Law (Decade Average)
60
40
20
0
0
10
20
30
40
Number of Laws Passed (Decade Average)

Particulates (PM10), Fine Particulates (PM2.5), and Sulfur Oxides (SOX). This gives the following form for the structural equation:

$$\begin{bmatrix} p_{\text{CO}} \\ p_{\text{NMVOC}} \\ p_{\text{NOX}} \\ p_{\text{PM10}} \\ p_{\text{PM25}} \\ p_{\text{SOX}} \end{bmatrix} = \begin{bmatrix} A_{\text{CO, RT}} & A_{\text{CO, PS}} \\ A_{\text{NMVOC, RT}} & A_{\text{NMVOC, PS}} \\ A_{\text{NOX, RT}} & A_{\text{NOX, PS}} \\ A_{\text{PM10, RT}} & A_{\text{PM10, PS}} \\ A_{\text{PM25, RT}} & A_{\text{PM25, PS}} \\ A_{\text{SOX, RT}} & A_{\text{SOX, PS}} \end{bmatrix} \begin{bmatrix} s_{\text{RT}} \\ s_{\text{PS}} \end{bmatrix} + \begin{bmatrix} v_{\text{CO}} \\ v_{\text{NMVOC}} \\ v_{\text{NOX}} \\ v_{\text{PM10}} \\ v_{\text{PM25}} \\ v_{\text{SOX}} \end{bmatrix},$$

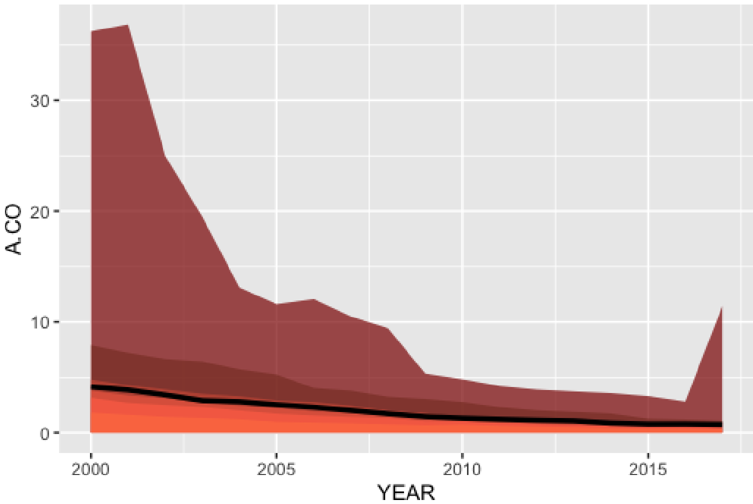
where s_{RT} denotes the total passenger kilometers travelled per year, s_{PS} denotes total energy consumption by country, and the quantities $A_{\text{i,RT}}s_{\text{RT}}$ and $A_{\text{i,PS}}s_{\text{PS}}$ are the observed totals in the OECD data for pollutant i.

Other data from the OECD include Road Transport, GDP per Capita, Rail Transport, and Population. Historical gas price data was sourced from the World Bank. All of these control variables were subsetted and matched to the observations at the Country-Year Level.


Passenger Kilometers by Year
Source Behavior Proxy for Road Transport (US Values Surpressed for Visibility)
Passenger Kilometers
750000
500000
250000
0
2000
2005
2010
2015
YEAR

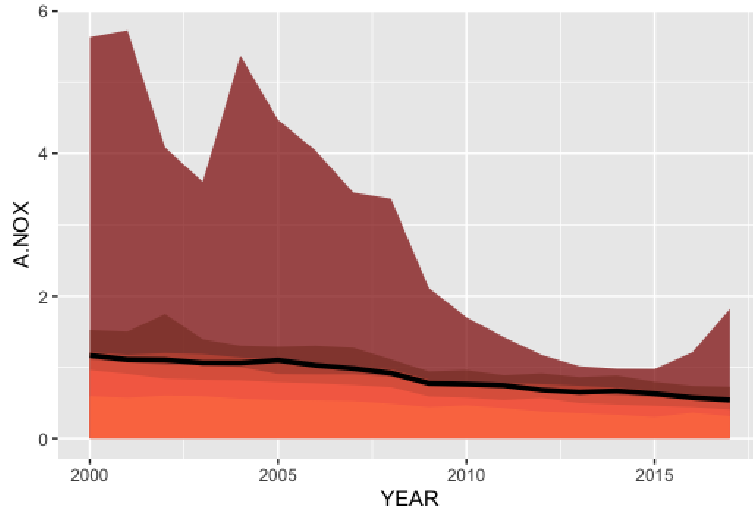
Carbon Monoxide Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black



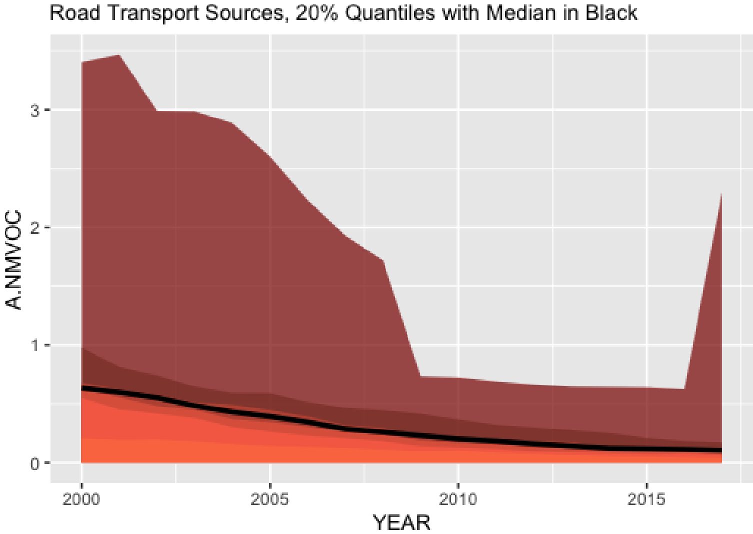
Nitrogen Oxide Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black



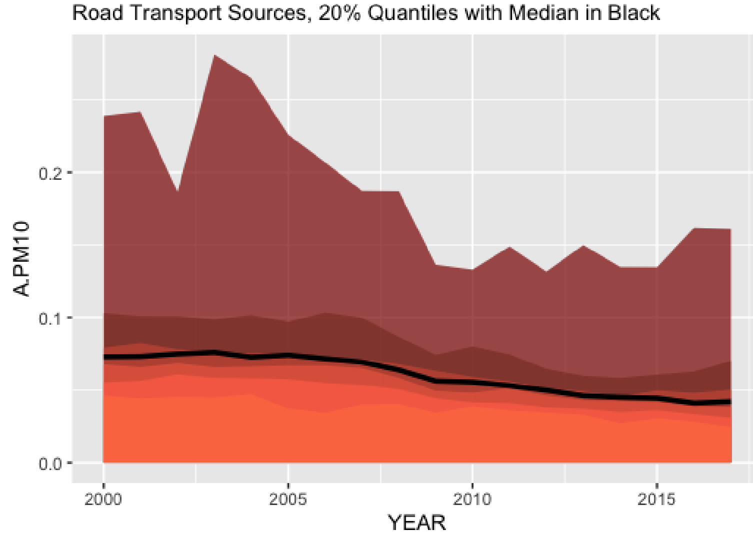
NMVOC Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black



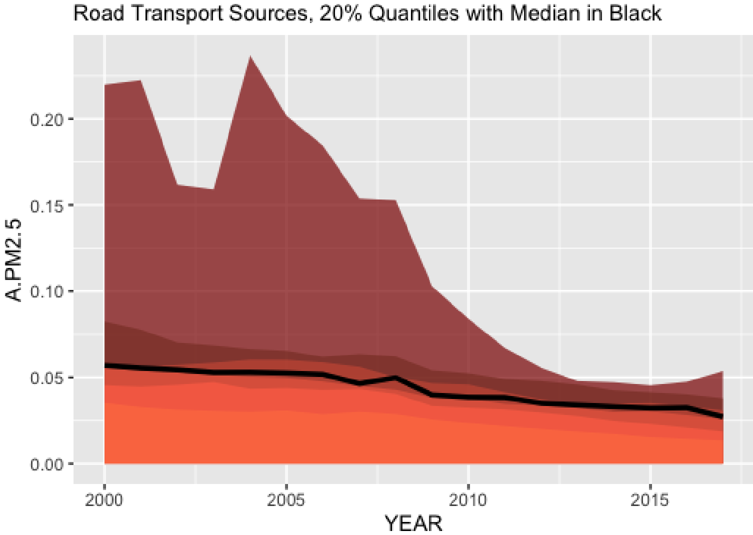
Particulate Matter (PM10) Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black



Particulate Matter (PM2.5) Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black



Sulfur Oxide Generation Intensity by Year

Road Transport Sources, 20% Quantiles with Median in Black

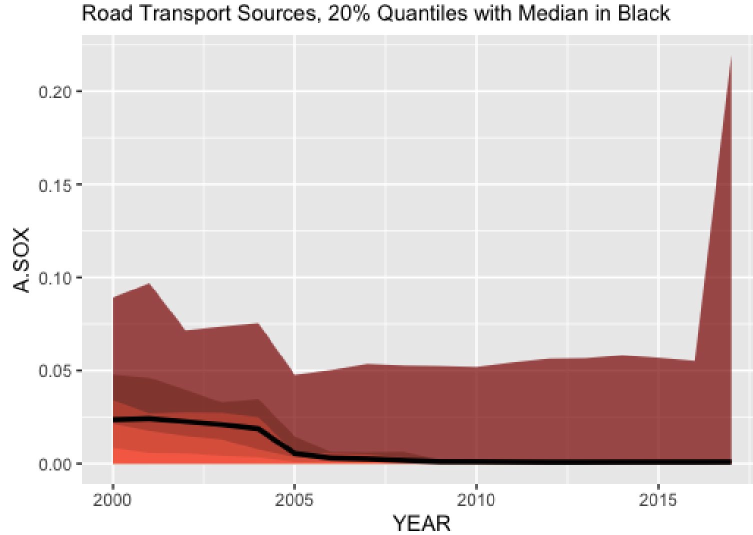


Figure 1: OECD Statistics Classification of Air Pollution

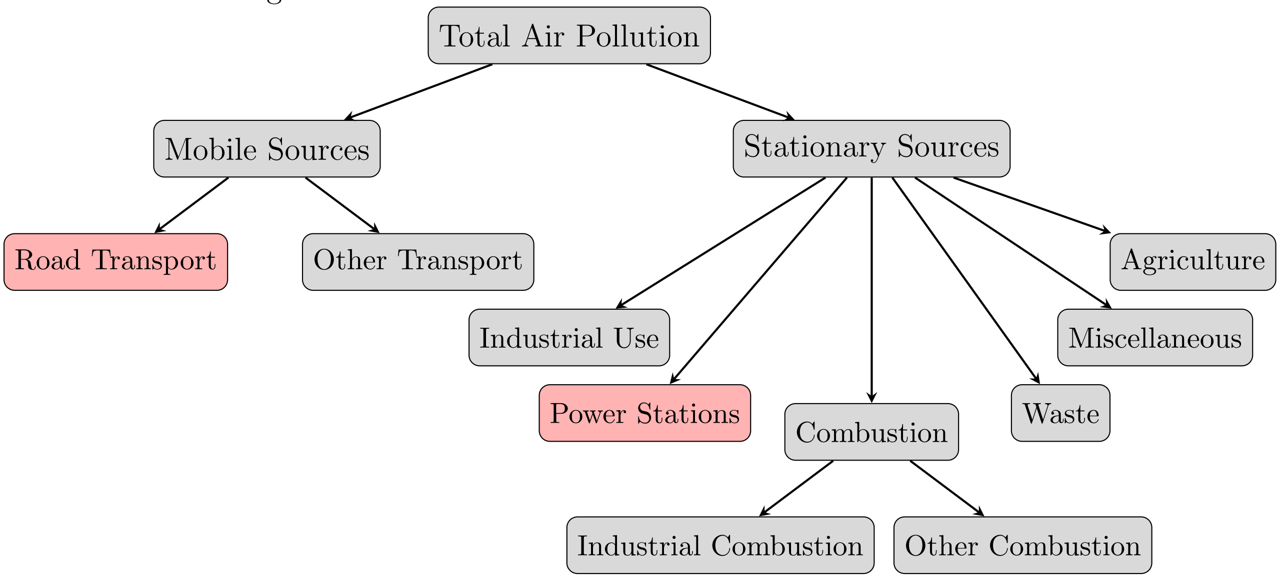


Table 2: Mobile Source Air Pollution from Road Transit, 2000-2019, OECD Countries

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
YEAR	727	2009	5.696	2000	2005	2014	2019
CO	725	1,632.453	5,930.237	3.939	80.545	644.321	61,744.890
NMVOC	719	175.822	520.748	0.594	10.810	109.699	4,831.200
NOX	725	374.567	1,014.831	2.112	42.253	337.695	9,377.977
PM10	637	39.463	465.517	0.367	2.322	21.578	11,701.000
PM2-5	606	15.094	36.381	0.248	1.759	13.868	298.980
SOX	707	6.349	24.197	0.003	0.077	1.574	259.292

Table 3: Stationary Source Air Pollution from Power Generation, 1990-2019, OECD Countries

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
YEAR	1,075	2004	8.572	1990	1997	2012	2019
CO	1,064	55.304	176.699	0.001	2.564	34.511	1,318.000
NMVOC	1,040	3.161	7.062	0.000	0.293	2.979	56.111
NOX	1,064	220.961	685.327	0.002	10.507	205.896	6,044.674
PM10	887	21.427	80.398	0.000	0.597	8.514	1,109.000
PM2-5	845	13.698	55.219	0.000	0.411	4.903	563.540
SOX	1,064	460.267	1,547.191	0.001	5.171	268.573	14,432.650

2.5 Describing the Models

We now turn to estimating the fixed effects models described above. We run the models in six different configurations for each outcome variable of interest. Configurations (1) and (2) use the variable `any_policy_implemented`, which is a dummy which turns on and stays on once a policy has been implemented in sample.

Configurations (3) and (4) use a cumulative step variable called `policy_cumulative` to model the passage of multiple policies over the course of the sample period. For example, Australia passes automotive emissions laws in 2002, 2004, and 2013, so the `policy_cumulative` variable increases from 0 to 1 in 2002, 1 to 2 in 2004, and 2 to 3 in 2013, holding its value in the intermediate years. This setup gives equal weighting to all policies in sample, which seems to be the most sensible way of attempting to compute an average effect of a policy.

Configurations (5) and (6) represent the richest models, in which we are separately evaluating the effects of different policy keywords in the sample. Unfortunately, we are unable to estimate the interaction term effects of these policy keywords because of the limited sample size. The keywords selected here were chosen from a frequency list of in-sample keywords as some of the more interesting potential options. Further analysis of the potential keywords and the sensitivity of the analysis to which subset of keyword variables are used will be added in the final version of this paper.

For each pair of models described above, the first model includes only country fixed effects, while the second includes both country and year fixed effects. The year fixed effects may help account for the effect of improved technologies unrelated to policy among other things, so we believe that the models which include the year fixed effects probably reflect the true effects of policy better by accounting for some unobserved omitted variables.

2.6 Analyzing the Results

The results of the regressions are described in Table 4 through Table 10 below. The results for the Passenger Kilometers regressions show that we are likely omitting some variables, as the effect of implementing a policy is estimated to be of the order of magnitude of a one USD per liter increase in the price of gasoline. This is a very large effect, which makes us question what the models are picking up.

The positive coefficients on population and the negative coefficients on gasoline price line up with our expectations, giving us some confidence that we are measuring something real in the data.

Interestingly, in models (5) and (6) the effects of enforcement/compliance policies are estimated to be positive and significant, which is surprising because we would expect policies with an enforcement mechanism to have strong negative effects. The perverse sign on enforcement/compliance policy is also observed across most of the generation intensity regressions and requires further investigation.

For the emissions standards variable, we obtain an interesting result: standards-based policies seem to be important for the CO and NMVOC generation intensities but have no statistically observable effect on the NOX, PM2.5, PM10, and SOX generation intensities. The public health variable has a relatively large negative effect across all of the generation intensities. This pattern is one of the most robust findings in the paper. Investigating further, it turns out that dropping the public health variable makes all of the standards variables significant across all of the pollutant generation intensities. Since the public health variable is highly correlated with the standards variable (almost all policies which have a public health keyword also have an emissions standards keyword), introducing the public health variable is picking up the effect of the standards variable. This suggests that policies which implement standards with a focus on public health have the largest effects on reducing generation intensity of all policies considered.

Turning our attention toward the generation intensity regressions, we observe a negative and significant coefficient on gas prices and total population, which is somewhat surprising. The graphs of the generation intensities depicted above shed a bit of light on what may be happening here. In general, the generation intensities for most pollutants are decreasing in time, while in general gas prices and population are increasing in time. As such, regression the generation intensities on these variables produces a negative coefficient to account for this trend. If we believe that policy and technology are the main variables that are accounting for the decrease in generation intensity, which seems sensible, and we believe that the year fixed effects are a reasonable proxy for technological progress outside of policy, then the negative coefficients on population and gas price may be masking some of the effect of either policy or technological progress in the regressions.

The results for the electricity generation dataset are forthcoming and will be included in an updated version of this paper.

Table 4: Regression Estimates of the Effect of Policy on Passenger Kilometers, the Source Behavior Proxy for Road Transport

	Dependent variable:					
	Passenger.Kilometers (s_{RT})					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	$-106{,}515.500^{***}$	$-83{,}323.340^{***}$				
	(18,232.090)	(18,628.050)				
policy_cumulative			$-63{,}420.160^{***}$	$-59{,}653.240^{***}$		
			(6,400.635)	(6,472.450)		
enforcement.compliance					$169{,}695.100^{***}$	$144{,}858.300^{***}$
					(31,601.910)	(31,591.940)
offences.penalties					$-143{,}920.400^{***}$	$-120{,}796.000^{***}$
					(39,505.020)	(39,378.150)
standards					$-38{,}908.130^{**}$	$-31{,}873.840^{**}$
					(15,372.860)	(15,347.720)
public.health					$-281{,}541.400^{***}$	$-288{,}643.200^{***}$
					(22,878.620)	(22,501.440)
gas.price.usd.per.liter	$-51{,}183.620^{***}$	$-145{,}592.900^{***}$	$-52{,}048.240^{***}$	$-172{,}244.700^{***}$	$-74{,}262.450^{***}$	$-229{,}823.600^{***}$
	(10,236.910)	(30,377.280)	(9,786.373)	(28,912.060)	(9,458.541)	(28,224.140)
TotPop	53.142^{***}	53.270^{***}	54.184^{***}	53.952^{***}	55.620^{***}	55.305^{***}
	(1.005)	(1.031)	(0.978)	(0.996)	(0.957)	(0.960)
GDPperCAP	-0.214	1.183	0.627	1.506^{**}	0.682	1.568^{**}
	(0.614)	(0.753)	(0.601)	(0.725)	(0.580)	(0.689)
Total.Rail.Transport	-2.155^{***}	-1.664^{***}	-2.520^{***}	-2.445^{***}	-2.486^{***}	-2.710^{***}
	(0.567)	(0.642)	(0.549)	(0.626)	(0.527)	(0.598)
Observations	840	840	840	840	840	840
R^2	0.995	0.995	0.995	0.995	0.995	0.996
Adjusted R^2	0.995	0.995	0.995	0.995	0.995	0.996
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 5: Regression Estimates for the Effect of Policy on Carbon Monoxide Generation Intensity from Road Transport

	Dependent variable:					
	A.CO					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	-6.117^{***}	-5.742^{***}				
	(0.400)	(0.403)				
policy_cumulative			-2.267^{***}	-2.160^{***}		
			(0.145)	(0.144)		
enforcement.compliance					3.869^{***}	3.375^{***}
					(0.789)	(0.773)
offences.penalties					-2.679^{***}	-2.251^{**}
					(0.986)	(0.964)
standards					-1.486^{***}	-1.192^{***}
					(0.384)	(0.376)
public.health					-5.664^{***}	-5.960^{***}
					(0.571)	(0.551)
gas.price.usd.per.liter	-2.469^{***}	-4.081^{***}	-2.701^{***}	-5.708^{***}	-3.273^{***}	-6.894^{***}
	(0.225)	(0.657)	(0.222)	(0.643)	(0.236)	(0.691)
TotPop	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}	-0.0003^{***}
	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
GDPperCAP	-0.0001^{***}	-0.00001	-0.00004^{***}	0.00000	-0.00005^{***}	-0.00000
	(0.00001)	(0.00002)	(0.00001)	(0.00002)	(0.00001)	(0.00002)
Total.Rail.Transport	0.00002^{**}	0.00004^{***}	0.00002	0.00002	0.00003^{**}	0.00003^{**}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Observations	840	840	840	840	840	840
R^2	0.791	0.807	0.793	0.811	0.768	0.794
Adjusted R^2	0.783	0.795	0.785	0.800	0.758	0.781
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression Estimates for the Effect of Policy on Nitrogen Oxide Generation Intensity from Road Transport

	Dependent variable:					
	A.NOX					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	-0.605^{***}	-0.546^{***}				
	(0.073)	(0.073)				
policy_cumulative			-0.349^{***}	-0.338^{***}		
			(0.025)	(0.025)		
enforcement.compliance					0.721^{***}	0.560^{***}
					(0.118)	(0.116)
offences.penalties					-0.779^{***}	-0.622^{***}
					(0.147)	(0.144)
standards					0.001	0.042
					(0.057)	(0.056)
public.health					-1.585^{***}	-1.593^{***}
					(0.085)	(0.083)
gas.price.usd.per.liter	-0.273^{***}	-0.334^{***}	-0.280^{***}	-0.503^{***}	-0.405^{***}	-0.789^{***}
	(0.041)	(0.120)	(0.038)	(0.110)	(0.035)	(0.104)
TotPop	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}	-0.0001^{***}	-0.00005^{***}	-0.00004^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPperCAP	-0.00001^{***}	-0.00000	-0.00001^{**}	0.00000	-0.00001^{***}	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total.Rail.Transport	-0.00001^{**}	0.00000	-0.00001^{***}	-0.00000	-0.00001^{***}	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	840	840	840	840	840	840
R^2	0.804	0.818	0.830	0.842	0.853	0.869
Adjusted R^2	0.797	0.807	0.823	0.833	0.847	0.860
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression Estimates for the Effect of Policy on Non Methane Volatile Organic Compounds Generation Intensity from Road Transport

	Dependent variable:					
	A.NMVOC					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	−0.511***	−0.446***				
	(0.041)	(0.039)				
policy_cumulative			−0.182***	−0.157***		
			(0.015)	(0.014)		
enforcement.compliance					0.420***	0.340***
					(0.078)	(0.073)
offences.penalties					−0.270***	−0.196**
					(0.097)	(0.091)
standards					−0.139***	−0.079**
					(0.038)	(0.035)
public.health					−0.544***	−0.557***
					(0.056)	(0.052)
gas.price.usd.per.liter	−0.333***	−0.441***	−0.354***	−0.566***	−0.405***	−0.654***
	(0.023)	(0.064)	(0.023)	(0.064)	(0.023)	(0.065)
TotPop	−0.00002***	−0.00002***	−0.00002***	−0.00002***	−0.00002***	−0.00002***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPperCAP	−0.00001***	0.00000	−0.00001***	0.00000	−0.00001***	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total.Rail.Transport	0.000	0.00000***	−0.00000	0.00000*	0.00000	0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	840	840	840	840	840	840
R^2	0.862	0.883	0.861	0.882	0.857	0.884
Adjusted R^2	0.857	0.876	0.856	0.875	0.851	0.876
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 8: Regression Estimates for the Effect of Policy on Particulate Matter ($PM_{2.5}$) Generation Intensity from Road Transport

	Dependent variable:					
	A.PM2.5					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	−0.028***	−0.021***				
	(0.004)	(0.004)				
policy_cumulative			−0.015***	−0.014***		
			(0.001)	(0.001)		
enforcement.compliance					0.040***	0.028***
					(0.006)	(0.005)
offences.penalties					−0.046***	−0.034***
					(0.006)	(0.006)
standards					0.001	0.004
					(0.004)	(0.003)
public.health					−0.070***	−0.070***
					(0.004)	(0.003)
gas.price.usd.per.liter	−0.013***	−0.026***	−0.014***	−0.033***	−0.019***	−0.049***
	(0.002)	(0.006)	(0.002)	(0.005)	(0.002)	(0.005)
TotPop	−0.00000***	−0.00000***	−0.00000***	−0.00000***	−0.00000***	−0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPperCAP	−0.00000***	0.00000	−0.00000***	0.00000	−0.00000**	0.00000**
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total.Rail.Transport	−0.00000***	0.00000	−0.00000***	−0.00000	−0.00000***	−0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	746	746	746	746	746	746
R^2	0.793	0.820	0.814	0.842	0.851	0.883
Adjusted R^2	0.785	0.808	0.806	0.832	0.844	0.875

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Regression Estimates for the Effect of Policy on Particulate Matter (PM_{10}) Generation Intensity from Road Transport

	Dependent variable:					
	A.PM10					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	-0.039^{***}	-0.034^{***}				
	(0.004)	(0.005)				
policy_cumulative			-0.018^{***}	-0.018^{***}		
			(0.002)	(0.002)		
enforcement.compliance					0.040^{***}	0.026^{***}
					(0.008)	(0.007)
offences.penalties					-0.050^{***}	-0.036^{***}
					(0.009)	(0.008)
standards					0.007	0.010^{**}
					(0.005)	(0.005)
public.health					-0.083^{***}	-0.084^{***}
					(0.005)	(0.005)
gas.price.usd.per.liter	-0.016^{***}	-0.020^{***}	-0.017^{***}	-0.031^{***}	-0.023^{***}	-0.048^{***}
	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)	(0.006)
TotPop	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}	-0.00000^{***}
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPperCAP	-0.00000^{***}	0.00000	-0.00000	0.00000	-0.00000	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total.Rail.Transport	-0.00000^{**}	0.00000	-0.00000^{***}	-0.00000	-0.00000^{***}	-0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	766	766	766	766	766	766
R^2	0.805	0.821	0.819	0.837	0.843	0.863
Adjusted R^2	0.798	0.810	0.812	0.826	0.837	0.854
Note:						$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 10: Regression Estimates for the Effect of Policy on Sulfur Oxide Generation Intensity from Road Transport

	Dependent variable:					
	A.SOX					
	(1)	(2)	(3)	(4)	(5)	(6)
any_policy_implemented	0.012***	0.013***				
	(0.002)	(0.002)				
policy_cumulative			−0.00003	0.001**		
			(0.001)	(0.001)		
enforcement.compliance					−0.019***	−0.017***
					(0.004)	(0.004)
offences.penalties					0.013**	0.012**
					(0.005)	(0.005)
standards					0.001	0.004**
					(0.002)	(0.002)
public.health					0.007**	0.009***
					(0.003)	(0.003)
gas.price.usd.per.liter	−0.015***	0.011***	−0.014***	0.014***	−0.014***	0.014***
	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)	(0.003)
TotPop	−0.00000***	−0.00000***	−0.00000***	−0.00000***	−0.00000***	−0.00000***
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
GDPperCAP	−0.00000***	0.00000	−0.00000***	0.00000	−0.00000***	0.00000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Total.Rail.Transport	−0.00000***	0.000	−0.00000***	−0.000	−0.00000***	−0.000
	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
Observations	840	840	840	840	840	840
R^2	0.771	0.838	0.762	0.830	0.775	0.836
Adjusted R^2	0.762	0.828	0.753	0.820	0.766	0.825
Note:						*p<0.1; **p<0.05; ***p<0.01

3 Estimating the Effect of Air Quality on Housing Price

3.1 Introduction

Economists have long understood housing prices as a hedonic function of various amenities offered by a housing unit and its surroundings. These amenities take many forms, including among them employment opportunities, neighborhood characteristics, cultural amenities, local school quality, proximity to friends and family, idiosyncratic locational preferences, and environmental amenities. Hedonic modeling allows us to infer the market valuation of non-market goods like environmental amenities from market prices, yielding important information about preferences and valuations that are difficult to see directly from market values.

In this paper, we explore the value that homeowners place on air quality by estimating the causal effect of declines in air quality due to wildfire increased smoke exposure. Wildfire smoke contains a number of pollutants, most salient for health outcomes is PM 2.5 (EPA). Chronic exposure to PM 2.5 can lead to significant declines in life expectancy, on the order of -0.35 years for a 10 $\mu g/m^3$ reduction in particulate matter (Apte).

Under the logic of a hedonic model, homebuyers are sophisticated agents who take into account these potentially significant effects of air quality on life expectancy and health outcomes among all other factors, suggesting a potentially large effect of air quality on housing prices. On the other hand, the consequences of living amid chronic air quality are temporally delayed and difficult to quantify, so homeowners may not be considering these effects fully when choosing housing. Moreover, the market for clean air may also suffer from information problems, since light pollution is not often visible directly to homeowners who do not seek out AQI information directly.

3.2 Relationship to the Literature

This paper attempts to contribute to the existing literature on estimating the causal effect of multi-year air quality shocks on housing prices, and explores the concept of thresholding nonlinearities in preferences about housing prices. In particular, it may be that homeowners do not respond to air quality inside a certain band of acceptability, but begin to respond once the air quality moves outside that band.

A 2005 paper by Chay and Greenstone uses a spatial hedonic approach based on a United States Clean Air Act policy which implemented stricter regulations on counties which failed to meet pre-specified particulate pollution targets. They estimate that a 1% increase in particulate matter pollution concentration decreases home values by approximately 0.2% to 0.35% (Chay and Greenstone, 2005). The fundamental idea of Chay and Greenstone's study is to use an instrument for air quality, namely non-attainment status under the Clean Air Act, to get plausibly exogenous variation in air quality; my strategy is similar in that wildfire smoke introduces plausibly exogenous variation in air quality that I will use in my estimation strategy. My wildfire smoke instrument represents an improvement on the non-attainment status instrument for a few reasons. Non-attainment status is a dummy, while wildfire smoke is a continuously valued variable, which offers more variability to exploit in estimation of coefficients. Furthermore, one must treat selection bias arguments very seriously in the non-attainment case: perhaps there are systematic unobserved factors which simultaneously affect whether a county is a non-attainment county and which also affect housing quality, potentially introducing omitted variables bias. Wildfire smoke, treatment by which is largely determined by wind patterns, admits fewer compelling arguments of this nature.

Kim et al. use a spatial hedonic approach at a very local level to estimate the effects of air pollution on housing prices in Seoul, South Korea, associating a 4% air quality increase with a 1.4% housing price increase (Kim et al., 2003). They use a relatively small sample of households with detailed housing price data across all of the major districts of Seoul, controlling for neighborhood income and housing characteristic factors, along with a spatially interpolated local air pollution dataset. Their estimates use spatially lagged variables as instruments, which is an econometric technique to overcome the lack of exogenous variation present in the cross-sectional price data but which is subject to many technical challenges (*ibid*). Zabel and Kiel employ a similar strategy in four U.S. cities, gathering data about individual housing units' prices and characteristics, controlling for neighborhood factors, and estimating a hedonic model for housing prices in Chicago, Denver, Philadelphia, and Washington D.C. They find a small, significant negative relationship between air pollution and housing prices in two of them (Zabel and Kiel, 2000). Instead of relying on sophisticated econometric techniques to overcome endogeneity in a cross-sectional sample as in both of these papers, my paper uses plausibly exogenous variation in air quality measured over multiple periods, which I believe is a stronger design. My design applies to a more general setting than the estimates of these papers, which are city specific and may therefore lack the external validity that estimates generated from county-level data from across the U.S. would carry.

Borgschulte et al. use wildfire smoke to instrument for air quality in their 2018 working paper estimating the causal effect of air quality on the labor market, particularly on employment and adaptation costs. Although their outcome variable of interest is unrelated to housing prices, the machinery of their research design, which they claim is novel in their paper, is quite similar to the design I propose to use. They use daily air quality data from the EPA, a wildfire smoke dataset based on satellite imagery to instrument for air quality, and identify their observations at the county level (Borgschulte et al., 2018). Their paper is focused on estimating the effect of short term shocks of bad air quality on the labor market, which is different from my medium to long-run focus on housing prices as effected by changing trends in wildfire smoke.

In summary, my paper can be understood as applying the research design using wildfire data similar to that deployed by Borgschulte et al. to the domain of housing prices. Previous estimates of the causal effect of air quality housing prices have often been local, identified at the housing-unit level within a city or collection of cities, as in the cases of Kim et al. and Zabel and Kiel. These estimates are clearly useful in the context of these cities, but they are open to external validity and generalizability critiques that my paper attempts to address by identifying observations across the United States at the county level. The county-level identification of air quality and housing prices follows in the footsteps of Chay and Greenstone.

3.3 Wildfire Smoke Data

The data take the form of panel data, with monthly observations at the US county level of the number of days in each month in which the county is covered by wildfire smoke plumes, the mean air quality index (AQI) over the month, and the level of the Zillow housing price index in that month. I also have associated to each observation a set of controls for unemployment level and population density.

3.4 Wildfire Smoke

The wildfire smoke data used in this paper was produced from an incredibly detailed dataset put together by Vargo in 2019, which included daily satellite observations of light, medium, and heavy smoke plumes at the census block level (Vargo). In order to use this data, a few important aggregation decisions were made:

1. The smoke exposure "dummy" at the county level on a given day is a population-weighted continuous variable with values on $[0, 1]$. For example, suppose a county contains ten census blocks, three of which contain 50% of the population of the county. If these three blocks receive light smoke exposure on a given day, then the county level smoke exposure for that day is 0.5, the population weighted dummy for exposure in the county.

2. In order to capture all of the smoke data in a single variable, we compute a weighted sum of the light smoke, medium smoke, and heavy smoke exposure variables for each

day. The weights in the sum follow from the NOAA definitions of smoke plume intensity, which tracks the density.[1] Hence, the "smoke score" for each day approximately measures the total exposure to smoke in micrograms.

3. Finally, we aggregate to the monthly level by summing daily scores over the months to obtain monthly estimates for smoke exposure.

The data exclude all counties in geographic west of the United States, as such counties may suffer from potentially significant confounding effects because wildfire events are heavily correlated with smoke events and may also affect housing prices.

3.5 Zillow Home Value Index

The Zillow Home Value Index is a smoothed metric of housing prices which accounts. It can be roughly interpreted as a smoothed dollar value for the 35th to 65th percentile of home values in a county (Zillow).

3.6 Variable Descriptions

- $\text{price}_{c,t}$ (*numeric variable*): The Zillow Home Value Index value, a smoothed indicator of housing prices in county d and time period t.
- $\text{smoke}_{c,t}$ (*dummy variable*): A time-dependent treatment variable determined from the smoke score, which a weighted sum of the number of light, medium and heavy smoke days over the month within each county. The dummy is one if we are in the post treatment period (beginning 2015) and the county experiences a change in mean monthly smoke score above a threshold value across the pre- and post-treatment period.
- D_c (*dummy variable*): A set of dummy variables for the county fixed effects.
- T_t (*dummy variable*): A set of dummy variables for the time fixed effects.
- $\text{Unemp}_{c,g(t)}$ (*numeric variable*): The quarterly unemployment rate at the county level. Here, g denotes the mapping of months to quarters.
- $HC_{c,t}$ (*numeric variable*): A set of controls for the characteristics of the average home in a county

[1] In particular, "Light" corresponds to $0-11\frac{\mu g}{m^3}$, "Medium" to $12-22\frac{\mu g}{m^3}$, and "Heavy" to $23^+\frac{\mu g}{m^3}$. Weights of 6, 17, and 25, respectively, were used.

- Density_c: The 2020 county density – we assume that the density of counties are roughly constant over this period.

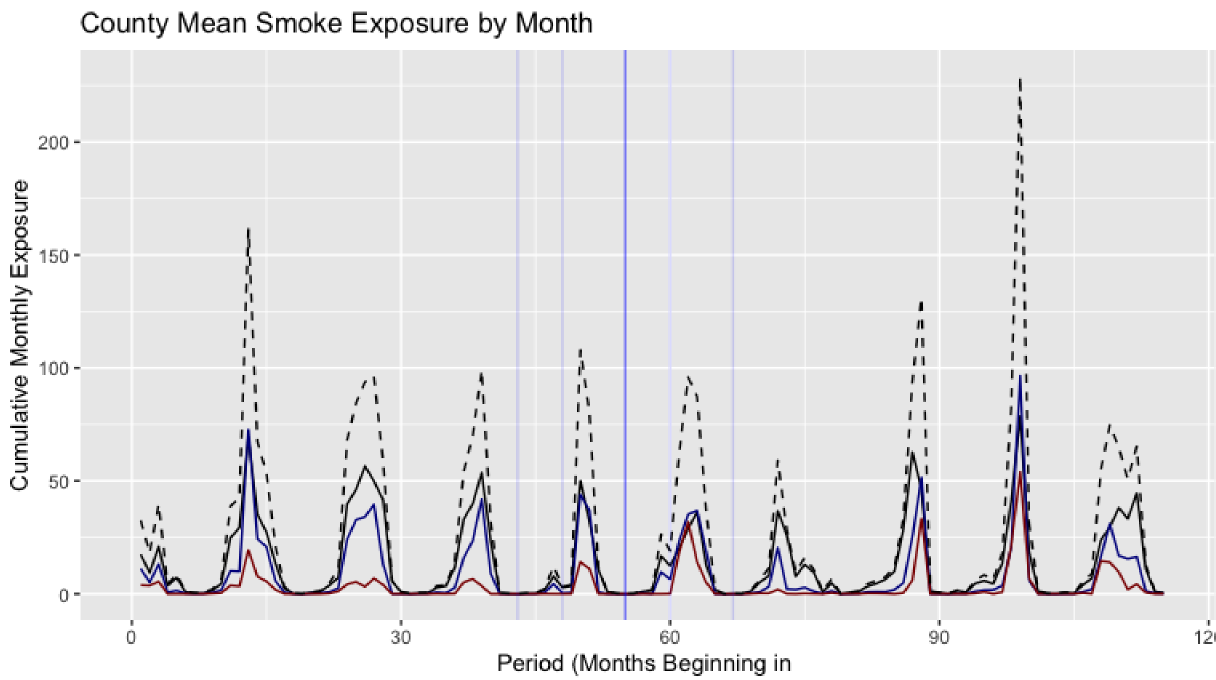
3.7 Models

3.7.1 Modeling Assumptions

We argue that the wildfire smoke distribution is plausibly exogenous because it is governed by large scale flows in the atmosphere as well as local weather variations. Because smoke plumes travel thousands of miles from East to West across the U.S., smoke exposure outside of the geographic West is generally unrelated to the factors which cause wildfires. This produces a natural experiment setup in which some counties are treated with smoke while others are not, with variation in treatment status that is as good as random.

In order to determine treatment status, we divide the period from 2010 to 2019 at a threshold month and compare the average in the before period to the average in the after period. Because there is no hard threshold for when we can think of treatment turning on, we compare the coefficients estimated across five potential cutoff dates: December 2013, May 2014, December 2014, May 2015, and December 2015. Although the graph does not show a drastic increase in wildfire smoke in the second part of the decade, there is a very change in the distribution of wildfire smoke across this period, with large swaths of the Eastern and Northern U.S. receiving large percentage increases in wildfire smoke.

Below, we refer to the percentage change in mean smoke exposure between the interval of June 2010 to the treatment threshold and the interval from the treatment threshold to June 2019 as a **"medium run percentage change"** in wildfire smoke exposure for linguistic ease. All use of this terminology in the paper refers to this specific definition.



3.8 Model Specifications

We model the effect of wildfire smoke on housing prices in a number of forms, allowing us to use different features of the variability in smoke exposure to estimate the causal effect of wildfire smoke under different modeling assumptions.

We first estimate an OLS model with a number of controls given by

$$\text{ZHVI}_{c,t} = \beta_{\text{OLS}} \cdot \text{smoke}_{c,t} + \gamma \cdot \text{unemp}_{c,t} + \text{density}_c + T_t + \epsilon_{c,t},$$

running it both for $ZHVI_{c,t}$ and $\log(ZHVI)_{c,t}$ to look at level and percentage effects. In this context, we interpret β_{OLS} as the effect of a 1 $\frac{\mu g}{m^3}$ increase in wildfire smoke exposure on housing prices. This regression does not exploit the random variability in the distribution of wildfire smoke, so it is not to be interpreted as a causal estimate, just as a correlation.

We next estimate a similar model, but instead of using the monthly smoke exposure, we estimate the equation with the medium run percentage change in smoke percentage change.

$$\text{ZHVI}_{c,t} = \beta_{\text{OLS}} \cdot \Delta\text{smoke}_{c,t}^{(t^*=60)} + \gamma \cdot \text{unemp}_{c,t} + \delta \cdot \text{density}_c + T_t + \epsilon_{c,t}.$$

Estimating this equation also does not yield causal estimates, but it gives the corresponding correlational estimate for the effect of a change in the multiyear average.

Next, we run our main regression of interest, the treatment/control group regression given by

$$\text{ZHVI}_{c,t} = \beta \cdot \text{smoke\_treatment}_{c,t}^{(t^*=60)} + \gamma \cdot \text{unemp}_{c,t} + \delta \cdot \text{density}_c + F_c + T_t + \epsilon_{c,t}.$$

The dummy $\text{smoke\_treatment}_{c,t}^{(t^*=60)}$ turns on if $t > 60$, corresponding to the months following January 2015 and later, and if county c is in the treatment group. To characterize treatment status, we choose threshold values for the percentage change in smoke score across the pre- and post-treatment periods. The threshold values we select are arbitrary, therefore all results must be carefully analyzed for sensitivity and robustness (see below). For the main regression, we characterize a county as "treated positive" if the increase in the mean smoke score from the pre- to post-treatment period is greater than 50%, as "control" if the magnitude of the change in means is less than 5%, as "treated negative" if the decrease is greater than 50% in magnitude, and as "boundary" otherwise.

The final set of models which we estimate are those which have "buckets" for smoke exposure corresponding to a percentage change of omitting the"boundary" counties:

$$\text{ZHVI}_{c,t} = \left(\sum_b \beta_b \cdot B_b^{(t^*=60)} \right) + \gamma \cdot \text{unemp}_{c,t} + \delta \cdot \text{density}_c + F_c + T_t + \epsilon_{c,t}.$$

Here, we allow more flexibility by letting the difference-in-differences coefficient depend on the treatment level. Moreover, this specification allows us to look at potential threshold values: we expect the coefficient to be approximately zero near zero, and we can measure thresholding behavior by examining how wide the band is wherein the coefficients remain near zero.

3.9 Main Results

3.10 OLS Model

The base OLS regression results are in line with what we would expect from our priors. We detect a somewhat sizable negative relationship, with increase of one microgram per meter squared of exposure per month associated with a \$138.91 decline in housing values as measured by ZVHI, or alternatively, a 0.1% decline in housing prices.

The second set of OLS models has a coefficient which can be interpreted as a 1% increase in medium run percentage change in smoke exposure is associated with a \$310.85 *increase* in housing prices. This has a perverse sign to what we would expect when thinking about air quality as a good people are willing to pay for. Exploring the figures used in the analysis of the buckets models shows that the areas which received the largest increases in smoke exposure, mainly the geographic northeast, also happen to be more expensive, so this effect is certainly not causal and can be easily explained by spurious correlation.

3.11 Treatment/Control Model

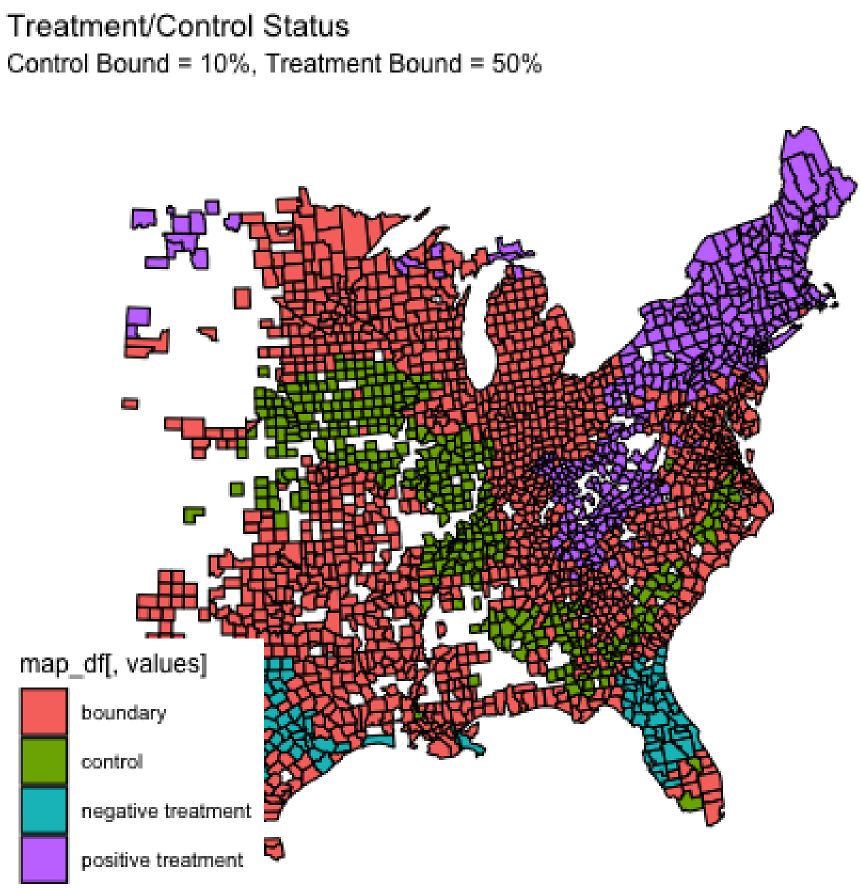
The treatment control model attempts to overcome the endogeneity by selecting a set of control counties (selected under the assumed good-as-random assignment of having an medium run smoke exposure percentage change less than some threshold) and a set of treatment counties (selected as higher than some threshold). Although the model was run with county fixed effects, it appears that spatial autocorrelation within the treatment and control groups is responsible for the positive observed coefficient. Examination of the map of treatment and control groups supports this hypothesis. From the map below, we can see how despite the randomized boundaries of the regions, they are largely connected and hence suffer from autocorrelation.

Table 11: OLS Results

	Dependent variable:			
	zhvi.score	logZHVI	zhvi.score	logZHVI
	(1)	(2)	(3)	(4)
n.score	−138.910***	−0.001***		
	(3.567)	(0.00002)		
m.s.pch60			31,084.830***	0.209***
			(351.238)	(0.002)
unemp	−12,133.240***	−0.094***	−12,155.620***	−0.095***
	(76.539)	(0.0005)	(75.170)	(0.0005)
density	37.048***	0.0001***	36.065***	0.0001***
	(0.166)	(0.00000)	(0.165)	(0.00000)
Constant	236,814.200***	12.497***	228,138.400***	12.443***
	(1,637.335)	(0.010)	(1,604.653)	(0.010)
Observations	247,825	247,825	247,825	247,825
R^2	0.258	0.237	0.276	0.261
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 12: Treatment/Control Results

Coefficient	Value	Standard Error
(Intercept)	84997.9926	(1192.2196)
treat.k5.t25	7048.6579	(174.0785)
unemp	1507.4164	(40.8662)
(Intercept)	89832.5871	(1418.2894)
treat.k5.t50	4981.8987	(206.1134)
unemp	1042.3432	(58.7912)
(Intercept)	166978.0474	(1110.3854)
treat.k10.t25	6646.7527	(127.0532)
unemp	1410.9679	(35.5550)
(Intercept)	170480.2136	(1171.2642)
treat.k10.t50	4587.3365	(152.5765)
unemp	989.8005	(45.8351)



3.12 Buckets Model

We estimate the difference in differences bucket model described in the model section above. We choose two specifications which divide up the counties into buckets with 10% changes (here referred to as the Twenty One Buckets model) and the 20% changes (here referred to as the Twelve Buckets Model). For example, Bucket-3 in the Twenty One Buckets model includes all counties in the eastern United States which experienced a medium run percentage decrease in wildfire smoke of -30% to -40%. This gives us multiple treatment groups each with a different treatment level. One observation is that certain buckets contain very few counties, especially at the extremes, hence, inference from these groups is harder to justify.

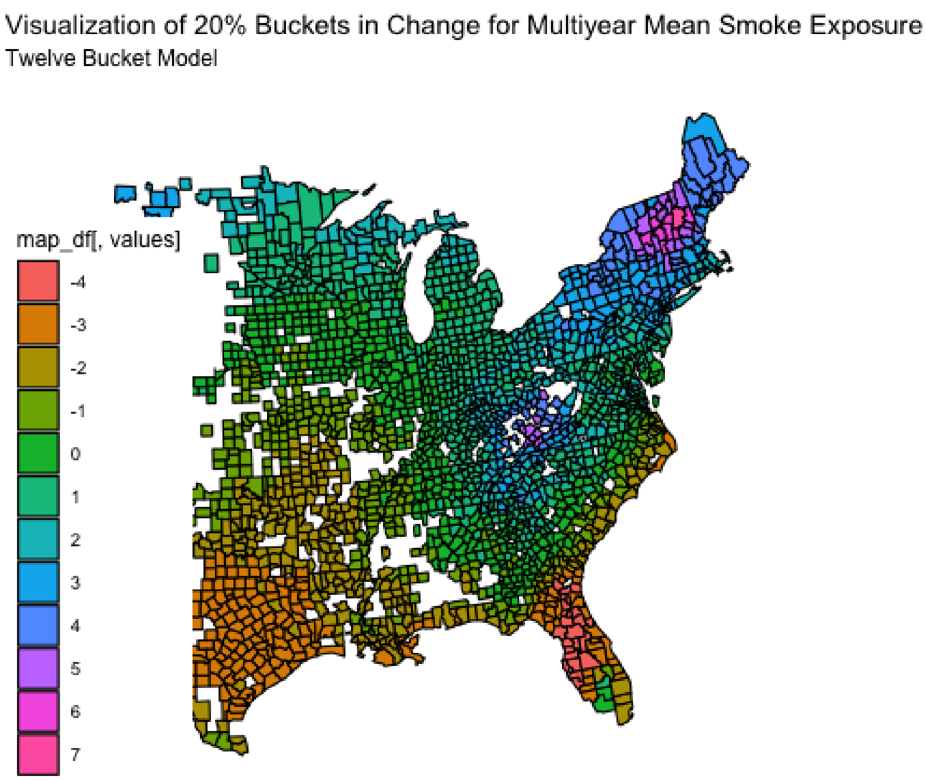
The results of the regressions are recorded in the tables below. We can see that the unemployment and density controls have the correct sign and similar magnitude to that in the OLS version. The coefficients on the buckets are more difficult to parse. In the model we wrote down, these should represent the effect of a medium run smoke change in the range associated with each bucket on housing prices. If the model were correctly capturing the causal effect, we would expect to see the effect be strongly positive for large decreases in the smoke exposure, strongly negative for the large increases in smoke exposure, and closer to zero as we approach zero from either end. This pattern is most definitely not observed, and leads us to question the validity of the model.

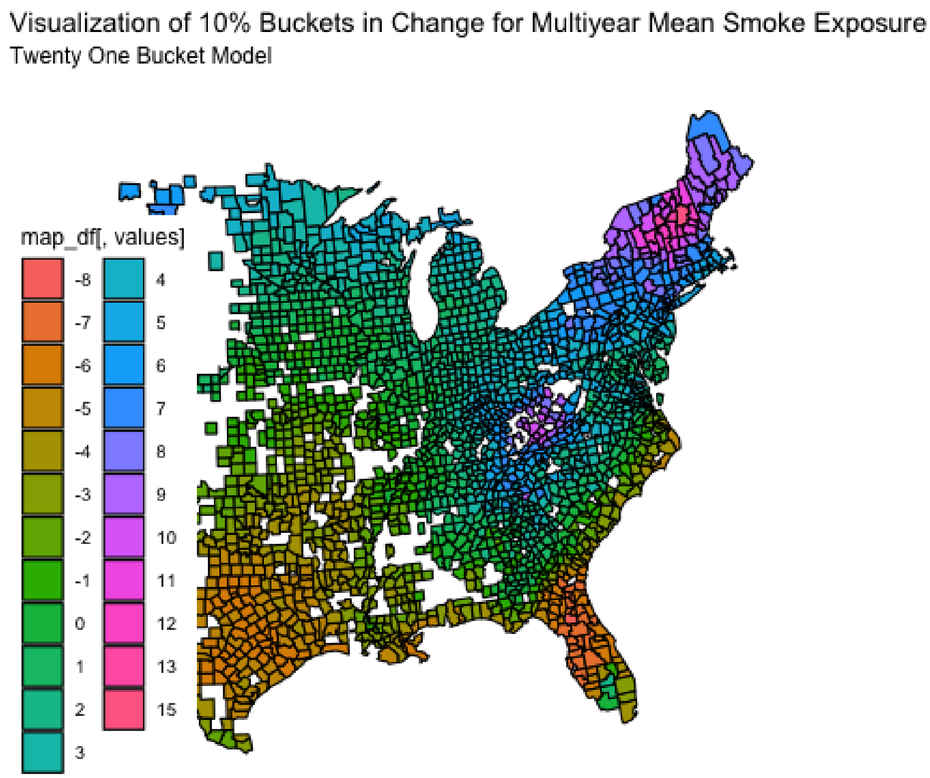
Table 13: Twenty One Bucket Results

Coefficient	Value	Standard Error
(Intercept)	229167.1007	(1593.4667)
bucket-7	7579.4415***	(2120.9187)
bucket-6	12452.7418***	(1322.5544)
bucket-5	-12753.8180***	(1197.0110)
bucket-4	-40523.6278***	(1145.9454)
bucket-3	-31501.3615***	(1119.2566)
bucket-2	-45392.7693***	(1152.7616)
bucket-1	-46298.2183***	(1116.4600)
bucket0	-49104.0762***	(1016.8342)
bucket1	-21775.0823***	(1050.0574)
bucket2	-998.0032	(991.8717)
bucket3	-4714.8775***	(1017.3990)
bucket4	-3.2480	(1087.7196)
bucket5	18657.1179***	(2951.1417)
bucket6	6160.8812***	(1303.4413)
bucket7	17543.1939***	(1382.0056)
bucket8	-7915.7779***	(1742.4632)
bucket9	-13751.0039***	(1784.5302)
bucket10	-26182.7457***	(3613.4257)
bucket11	NA	NA
bucket12	41973.9373***	(3751.1691)
bucket13	43425.8995***	(6390.6147)
bucket14	NA	NA
bucket15	27061.5994***	(8999.2158)
unemp	-11785.0877***	(74.9822)
density	36.1491***	(0.1647)

Table 14: Twelve Bucket Model

Coefficient	Value	Standard Error
(Intercept)	230009.7616***	(1597.6566)
bbucket-4	-6109.1748**	(2816.4182)
bbucket-3	-15963.0936***	(2170.0217)
bbucket-2	-49418.9504***	(2132.6985)
bbucket-1	-59533.4319***	(2137.8051)
bbucket0	-50296.4293***	(2113.8585)
bbucket1	-16378.6261***	(2107.8347)
bbucket2	-13641.8188***	(2128.6999)
bbucket3	-2330.2844	(2192.0692)
bbucket4	-24349.1420***	(2335.0775)
bbucket5	-11080.8776***	(2710.7456)
bbucket6	28559.8834***	(3801.7263)
bbucket7	13223.2686	(9228.9809)
unemp	-11874.6629***	(75.0590)
density	36.0975	(0.1644)



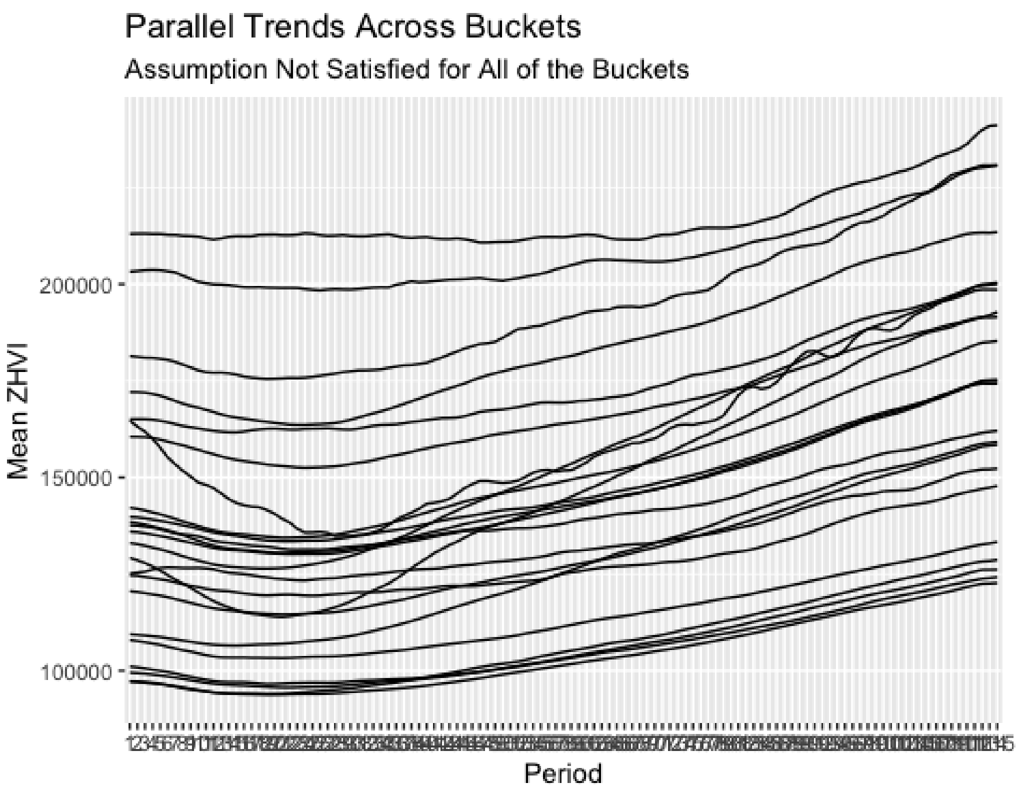


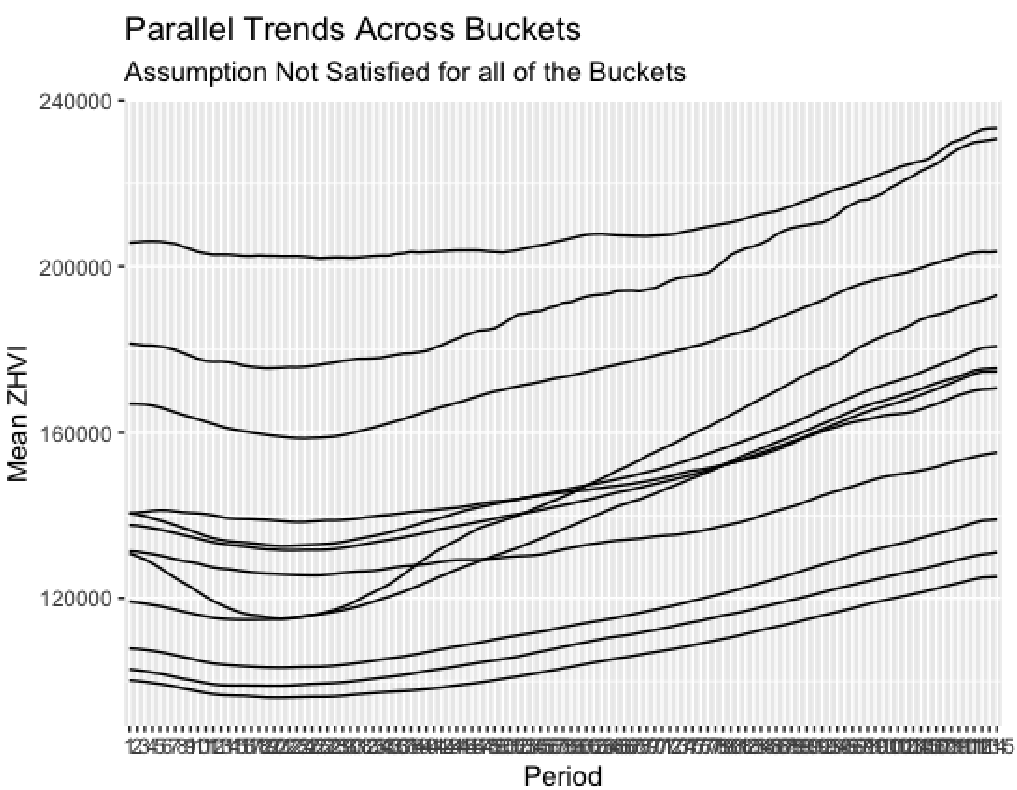
3.13 Robustness Checks

3.14 Parallel Trends

We plot the mean ZHVI across the Treatment/Control groups in each period and examine the evolution in time. From the graph, it is visually clear that the trends in the means are close to parallel, and it seems that there is a small dip in the ZHVI for the treatment group after treatment.

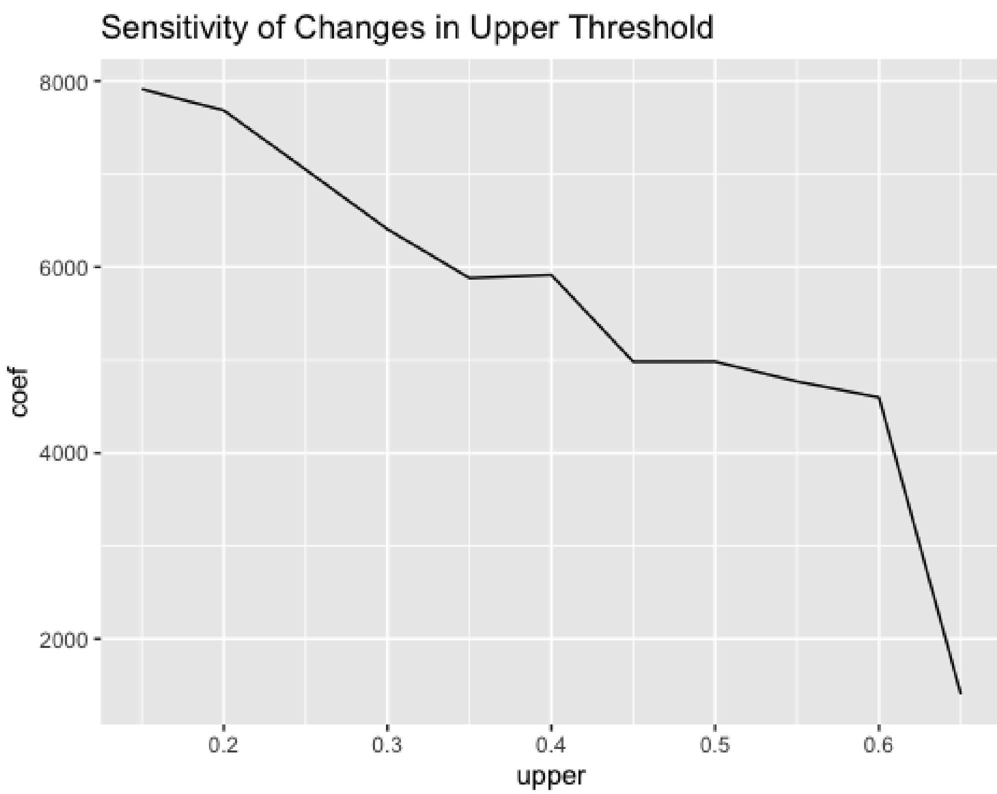
For the buckets case, we plot the mean evolution in time within each bucket. As we can see, the trends are not parallel in aggregate, although the majority of lines seems to follow a parallel trends pattern. The outlier lines tend to be those with small sample sizes. Because the parallel trends assumption fails in these circumstance, we can not make causal inference on the basis of this model. The nonparallel trends may account to some extent for the significant coefficients which seem to show no clear pattern in the buckets model.


Parallel Trends Across Buckets
Assumption Not Satisfied for All of the Buckets
Mean ZHVI
200000
150000
100000
Period


Parallel Trends Across Buckets
Assumption Not Satisfied for all of the Buckets
Mean ZHVI
240000
200000
160000
120000
Period

3.15 Percent Change Threshold for Treatment/Control Model:

Because we are selecting which counties are in the treatment group by setting the the threshold, it is crucial to analyze how sensitive the results are to our choice of threshold. In the figure we graph the coefficient output for $t^* = 60$ as a function of the selection threshold for inclusion in the treatment group. We can see that as we contract the treatment group by making the percentage change required more restrictive, the coefficient drops down. This makes some sense intuitively, for including only the counties which have the most extreme change in smoke should increase the negative effect. It is worth noting that even with a very restrictive threshold, we still cannot overcome the spatial autocorrelation to get the negative estimate we expect.



3.16 Treatment Start Time:

We run the OLS and Treatment-Control models at the five different treatment periods mentioned above and compare the results in the table below. We can see that the results are indeed sensitive to the choice of time period, which casts further doubt on the validity of the model for causal inference.

Table 15: Treatment Start Time Sensitivities

Coefficient	Value	Standard Error
(Intercept)	98895.6742***	(923.2356)
treat.k10.t50	-3507.9245***	(147.0831)
unemp	2191.4596***	(45.5383)
(Intercept)	92085.7062***	(1427.3480)
treat.k10.t50	1546.4467***	(176.6525)
unemp	805.2211***	(56.6808)
(Intercept)	102848.6906***	(956.3864)
treat.k10.t50	-3673.3737***	(156.4296)
unemp	1592.4215***	(38.3191)
(Intercept)	170480.2136***	(1171.2642)
treat.k10.t50	4587.3365***	(152.5765)
unemp	989.8005***	(45.8351)
(Intercept)	160269.1325***	(1270.8943)
treat.k10.t50	-5971.5360***	(318.7610)
unemp	1860.2984***	(52.6187)

3.17 Conclusion

The geographic clustering of the treatment variable represents the most significant problem with the validity of the model. Because smoke density is a roughly continuous variable, the treatment status of a county strongly predicts the status of its neighbors. This spatial autocorrelation is very challenging to deal with in this context and is likely responsible for the failure to produce causal estimates in these models. Overall, I overestimated the extent to which random variation in the smoke data would overcome the spatial correlation of housing prices. The design may have worked better if the distribution of wildfire smoke were more erratic and spotty, so that neighboring counties could be compared more directly.

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