Polluting and Commuting: Evidence from Louisiana Housing Prices

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Abstract

This paper examines the impact of industrial air pollution on the Louisiana real estate market–particularly the sale price of homes and the number of homes sold. Changes in weather patterns at industrial facilities impact the transport and dispersion of pollution from those facilities from one year to another. These changes in weather provide an exogenous source of variation in pollution concentrations observed at homes over time, which is exploited through the NOAA's HYSPLIT model. Examining the near universe of home sales in Louisiana from 1998-2018, results show that real estate sales decrease with increases in pollution concentration, and that those decreases in sales are concentrated among lower-valued homes, while higher-valued homes sell more.

1 Introduction

In Louisiana, manufacturing has accounted for 13 to 28 percent of all state gross domestic product over the last 20 years, making it perhaps the most important industry sector in the state from 1997 to 2023.[1] That output represents many benefits for Louisiana residents, including industrial jobs and the wages that come with them. However, that output also represents costs like air pollution, which produces industrial odors, smog, aesthetically undesirable landscape, safety risks associated with industrial leaks and explosions, and many potential health effects. From 1997 to 2021, Louisiana's manufacturing sector emitted 430,000 tons of pollution into the air every year on average.[2]

This paper asks how Louisiana residents value air pollution, controlling for industrial jobs within commuting distance. I use real estate sale price as the primary outcome variable under the assumption that the sale price of a home capitalizes the full amenity benefits and costs

[1]According to the Bureau of Economic Analysis Regional Economic Accounts. (See Figure A1).
[2]According to the Louisiana Department of Environmental Quality's emissions inventory (see Figure A2).

of living in a particular geographic location–including the costs and benefits of proximity to industrial facilities and the jobs and air pollution they produce. The transport and dispersion of air pollution emitted from industrial facilities is modeled based on historical weather data, generating identifying variation in pollution spread across the state.

There is anecdotal evidence that at least some Louisiana residents care about the environmental effects of having industrial polluters in their backyard. A group of St. James Parish[3] residents gained national media attention when they founded RISE St. James in 2018 as a vehicle to advocate against the opening of a petrochemical complex that Formosa Plastics wanted to build in the area. In 2022, a district court threw out Formosa's permits, halting their plans, but as of 2024, Formosa's permits had been reinstated and St. James locals had appealed to the Louisiana Supreme Court (Dryfoos, 2024). National media articles have highlighted the 85-mile stretch of the Mississippi river between Baton Rouge and New Orleans, where many of the state's industrial facilities are located, referring to the areas as "Cancer Alley" (Groner, 2021). President Joe Biden even used the term in a speech in 2021, leading Louisiana Senator Bill Cassidy–a medical doctor–to fire back, claiming that higher cancer rates in that area are caused by lifestyle choices–not industrial pollution (Baurick, 2021). If Louisiana residents are aware of the headlines, their awareness may be reflected in their valuation of the pollution to which they are exposed at their homes. Louisiana incentivizes growth in its manufacturing and energy sectors by providing large property tax exemptions to companies in these sectors when they invest in new physical capital.[4] If Louisianians are concerned about industrial pollution, then the benefits of industrial development may be attenuated by costs to the real estate market.

Identifying the impact of pollution on real estate price is challenging for several reasons. First, *omitted variable bias*. Many factors impact the value of real estate, from the quality of local school districts and infrastructure, to the convenience of local amenities, to the availability of local employment opportunities, to individual home characteristics, and these factors may be correlated with air pollution. Omitting important controls could lead to results that overstate or understate the impact of pollution on home price. Second, *reverse causality*. The locations of homes and air-pollution-emitting facilities are not randomly assigned. Their locations are chosen by builders. Builders may select to build higher quality homes in areas further from pollution sources with cleaner air and lower quality homes in areas with more polluted air. In turn, industrial facilities are limited on where they can build, and it is possible that, for example, wealthier neighborhoods successfully lobby against plants being built nearby and poorer neighborhoods do not. Louisianians are also not randomly assigned to live in certain homes or

[3] Parishes are Louisiana's county equivalent.

[4] Property tax exemptions are handled through the Louisiana Economic Development (LED) Industrial Tax Exemption Program (ITEP), which is described further in section 3.

purchase certain real estate parcels, and the mass of pollution emitted from industrial facilities in each year is not random, and may be anticipated by Louisianians. If taste for clean air is not homogenous, individuals who do not value clean air may sort into areas with more polluted air, and from then on, see little to no change in housing prices with changes in air quality.

This study therefore takes advantage of the distribution and changes in weather patterns to generate exogenous variation in pollution exposure. When pollution is emitted into the air, it does not spread out "evenly". Weather pushes the pollution into different areas more than others. As a result, at any given time, a home may be exposed to different levels of pollution depending on whether the home is upwind or downwind from a pollution source. In other words, while the amount of pollution emitted from an industrial facility annually is not random, and neither is that facility's location, the weather that impacts where its pollution emissions go *is* random. I model how the weather spreads pollution from every pollution-emitting facility in the data over time using the National Oceanic and Atmospheric Administration (NOAA) HYSPLIT program (Draxler, 1999; Draxler & Hess, 1997, 1998; Stein et al., 2015). Using historical weather data, HYSPLIT calculates both pollution *transport* (what direction prevailing winds and other factors pushed the pollution emitted from a facility) and pollution *dispersion* (how much the pollution "spread out" over time, diluted by the surrounding air) and maps the results. Given that over 2000 facilities have produced air pollution in Louisiana from one time period to another, modeling pollution spread from every facility produces incredibly fine geographic variation in industrial pollution exposure over time. Since pollution can be transported great distances in a fairly short period, another advantage of this strategy is that the dispersion of air pollution from a facility say, in the southern state region to a home many miles away in the northern region is captured within the HYSPLIT model, yet it is difficult to argue that individuals select their homes or builders choose to build homes based on pollution that may or may not come from industrial facilities hundreds of miles to the south. They can only observe whether the average ambient air quality is better or worse on one day or another. If the average daily air quality to which a person is exposed at their home is not favorable to them on enough days over the course of a year, it may impact home value in the following year, or whether an individual chooses to move altogether.

In addition to differences in weather over time that impact airborne pollutant transport and dispersion from industrial facilities, I am also interested in "unauthorized" releases of pollution from industrial facilities. These unauthorized releases represent explosions, chemical leaks, and other unanticipated emissions released by industrial facilities. The use of the data divided in this manner is twofold: First, it answers another potential question, as to whether home buyers respond differently to leaks and explosions than they do to the ambient daily pollution they face. Second, it represents another quasi-random source of variation in emissions faced at a home in a given year. While individuals may choose to live near industrial facilities, they may or may not also expect chemical leaks, flaring, and explosions.

To control for most unobservables, I make use of census block and parish-by-year fixed effects under the assumption that at the parish-year and block level, almost all neighborhood characteristics that impact home price are captured, limiting omitted variable bias. If neighborhoods are homogenous in terms of individual home quality, then much of the individual differences between homes sold are controlled.

The results of the analysis suggest that Louisiana residents do not discount the sale prices of their homes as a result of higher air pollution. Most results in the main model are positive and statistically insignificant. These results are robust to specifications with time fixed effects, to an instrumental variables approach, and to different lagged models, with a few coefficients of perverse sign. I argue that as unobservables are more finely controlled, coefficients showing the impact of pollution on home price shrink toward zero. In other words, home prices in Louisiana do not reflect the effect of air pollution. However, a tract-level analysis suggests that fewer homes sell in response to more air pollution: the number of homes sold declines between 0.2 and 0.226 percent per one percent increase in the concentration of particulate matter pollution, and by 0.225 percent per one percent increase in concentration of nitrogen oxides faced by the census tract. The decrease in sales is concentrated among lower-valued homes, while higher-valued homes sell more. If pollution changes the composition of homes sold over time, shifting sales towards high-value homes and away from low-value homes, then this composition effect would bias the price effect of pollution upwards, potentially disguising a "true" downward effect on property values.

This paper contributes to the literature on pollution and home values in the following ways: (1) Most papers on the relationship between pollution and home values in the United States look at very geographically limited areas even within-state due to research design. They often focus only on homes that are very close to industrial air pollution sources (within 5 miles). The research design of this paper allows comparisons among the near universe of home sales in Louisiana from 1998-2018 to be exploited, whether the home is close to a pollution source "as the crow flies" or not. (2) Much of the existing literature relies on decennial observations of home values from U.S. censuses, limiting analyses to county-level or tract-level estimates, and leaving more room for important unobservables in intervening years. In this paper, individual home sales are observed annually at their exact coordinate location. (3) Because this paper does not depend on linear distance from industrial facilities to establish a causal relationship between pollution and home values, it is easier to separate the effects of industrial pollution from positive labor market effects or curb appeal. (4) Most of the existing literature focuses on plant openings and/or closings in some capacity, and assumes that homes the same linear distance from the plant opening or closing face the same treatment effect. This paper incorporates variation in pollution exposure between homes that are the same linear distance from a facility based on whether the home is "upwind" or "downwind" of the air-polluting facility on average in a given year. (5) Most of the existing literature finds a negative relationship between industrial pollution exposure and home values, but this paper does not, except when emissions are unauthorized. This finding suggests that the external validity of research on pollution and home values should be approached with caution, and that heterogeneity in taste for clean air is an important factor. Researchers should be attentive to the individual and group characteristics that may drive heterogeneity in taste for clean air in future literature.

The paper continues as follows: Section 2 reviews the existing literature. Section 3 describes the data used in the analysis. Section 4 covers methodology. Section 5 covers the main results. Section 6 describes additional analyses and robustness exercises. Section 7 concludes.

2 Literature Review

The study of the relationship between pollution and the housing market starts with Ridker and Henning (1967), who found that a drop in sulfation level exposure was associated with an increase in median home value across midwestern census tracts. This approach was widely replicated, and pooling from a range of replicatable reports and published and unpublished papers from 1967 to 1988, Smith and Huang (1995) estimated marginal willingness to pay (in the form of housing values) for reductions in total suspended particulate (TSP) pollution. With the caveat that marginal willingness to pay varied substantially across cities covered in the pool of literature (suggesting large differences in how much residents care about pollution between cities), as well as a few cities with coefficients showing a perverse sign, they found that residents were willing to pay between \$0 and \$98.52 for a 1 μu/m^3 decrease in TSP with a median price of \$22.40 per 1 μu/m^3. The 1970 Clean Air Act presented Chay and Greenstone (2005) with an opportunity to exploit "non-attainment" status as an instrument for decreases in TSP. Their results indicated that a 1 μu/m^3 reduction in TSP resulted in a 0.2 to 0.4 percent increase in mean home price. Unlike the results of earlier studies, their results were robust–both to changes in the sample of counties, the year(s) used to indicate non-attainment status, and the presence of regional fixed effects. Greenstone and Gallagher (2008) took a similar approach, examining similar counties that either did or did not qualify for a "Superfund" cleanup of hazardous waste sites in a regression discontinuity model. They looked at tract-level estimates, estimates at adjacent tracts, and at outcomes in "rings" in 2 and 3 mile radiuses around sites. They found only small and statistically insignificant changes in the prices of residential property. Under the assumption that pollution transported from sources at least 80km away should be correlated with pollution exposure but uncorrelated with local economic development, Bayer, Keohane, and Timmins (2009) modeled the spread of this distant pollution in a county to county source-receptor matrix model developed by the EPA and looked at the change in housing prices from the 1990 census to the 2000 census. They found that a median household's marginal willingness to pay for better air quality was about \$149-\$185 per unit decrease in PM10 concentration. Currie, Davis, Greenstone, and Walker (2015) focused on homes in 5 different states[5] that are within 2 miles of a plant in the TRI data "as the crow flies" and used homes 1-2 miles from a plant as a comparison group ("untreated") for homes within 0.5-1 mile from the same plant ("treated"). In their main model specification, homes within 0.5 miles of a newly opened plant decreased in value by about 11 percent compared to comparison homes 1-2 miles out.[6] They also found that the negative impacts on housing values are concentrated in communities with below median income, college education share, and share of white residents. Bartik, Currie, Greenstone, and Knittel (2019) exploited the geography and geology of shale plays as well as the timing of fracking initiation and found increases in income, employment, wages, rental rates, and housing prices as a result of fracking, but increased crime rates. However, this paper did not directly address air emissions from fracking. Xue, Li, Yang, and Wei (2022) examined the impact of PM 2.5 on housing prices in 16 districts of Beijing from 2009 to 2018. Concentration of PM 2.5 in each district was estimated using a model that receives weather data like precipitation, wind direction and speed, humidity, and surface pressure as inputs. They found that a percentage point increase in PM 2.5 decreased housing prices by 0.541 percent.

The relationship between pollution and health has also been of interest to economists and has a strong connection with the literature on pollution and home price. Many economists have found that infant health was adversely impacted by pollution (Alexander & Schwandt, 2022; Chay & Greenstone, 2003; Currie, Greenstone, & Meckel, 2017; Currie, Greenstone, & Moretti, 2011). Pollution decreased life expectancy (Deryugina, Heutel, Miller, Molitor, & Reif, 2019; Deschenes, Greenstone, & Shapiro, 2017; Ebenstein, Fan, Greenstone, He, & Zhou, 2017) and increased healthcare utilization (Deryugina et al., 2019; Deschenes et al., 2017). Outside of the field of economics, several studies have found positive correlations between pollution and cancer (Hamra et al., 2014; Turner et al., 2011; White et al., 2023; Wong et al., 2016).

Synthesizing the literature, most studies on home values and air pollution suggest that residents do care about air quality, and much of the literature on health impacts from pollution–particularly among more vulnerable populations like children and the elderly–suggest that they *should* care. However, there are still areas of the literature on home values and pollution that deserve to be investigated further. For one, much of the literature concerns small areas or a

[5] Florida, New Jersey, Pennsylvania, Texas, and Michigan

[6] But the same results did not occur with plant closings.

handful of states, limiting external validity. If–as Chay and Greenstone (2005) contend–taste for clean air is heterogenous, then it may be possible that residents of some states care more about clean air than others. Additionally, while most U.S. papers find air pollution negatively impacts home prices (Bayer et al., 2009; Chay & Greenstone, 2005; Currie et al., 2015), Greenstone and Gallagher (2008) find null effects. This could be a result of heterogeneity in taste for clean air, but it is worth noting that Currie et al. (2015) is the only U.S. paper among the group that is able to utilize annual sales data on home prices instead of decennial census home value data, and that within that paper, while plant openings decrease home values, home values do not increase with plant closings. Given the research design, where homes 1-2 miles away from polluting facilities are treated as counterfactuals for homes within 0.5 miles of a facility, and the authors do not measure the pollution emitted from each facility and just use plant openings and closings as a treatment effect, is it worth considering whether the changes in home values from plant openings occur due to reductions in "curb appeal". Put another way: perhaps the values of homes within 0.5 miles of a plant fall not because residents care about air quality, but because the facility is an eyesore, and after the plant closes, the facility remains an eyesore. To probe this possibility, in a supplementary exercise, I control for homes with an industrial air polluter "in their backyard".

Using a similar research design to my own, Deryugina et al. (2019) use wind direction and speed observed at pollution monitors as an instrument for the spread of particulate matter to other areas over the following days, but with geriatric health as an outcome. There are also similarities with Bayer et al. (2009) who use a source-receptor matrix model developed by the EPA to instrument for pollution concentrations faced at homes as a result of industrial pollution emitted 80 or more kilometers away.

3 Data

The unit of observation in the main analysis is an individual Louisiana real estate parcel h sold in year t. While data availability varies by year across combined data sets, the main analysis concerns annual data from 1998 to 2018. Summary statistics are presented in Table 1. The following subsections describe the data.

3.1 Real Estate Sales Data

Real estate sales data for the state of Louisiana is provided by individual parish tax assessors at the parcel-date level. While sales data is available for all parishes, the parcel maps required to geolocate real estate parcels are available for 55 out of 64 parishes. The 9 parishes with no parcel maps are not used since the exact locations of their sold parcels are not known. The first year of data available varies by parish. Table A1 indicates the first year that records are available from each parish, the nine missing parishes, and–as an indicator of size–the population and number of housing units in 2010 in each parish according to the 2010 U.S. Census. Most of the missing parishes are small, with the exception of two parishes that comprise the New Orleans area–Orleans parish and Jefferson parish.[7] Due to the availability of other data, the sales record data is cut down such that the first year of interest is 1998. This cuts the number of observations down to 518,071 real estate transactions.

The sales data includes both commercial and residential real estate, identified via parish and parcel number. It includes the date that each parcel was transferred to a new owner, the parcel's location by latitude and longitude, the acreage of the parcel, and the purchase price of the property in nominal terms. Additional 2018 records on parcel characteristics from assessors offices allow residential parcels to be identified and separated from commercial properties. 293,485 parcel sales in the 1996-2018 data are residential properties. I conduct analyses on the sample of all sold parcels from 1998-2018 as well as the residential parcels only.

From the data, two outcome variables are constructed. (1) Real price per acre (which is the real purchase price of the real estate parcel divided by its acreage) and (2) Total annual sales by census tract. Nominal prices are deflated to real prices using South shelter CPI with 1982-1984 as the base year (BLS, 2024). Figures 1 and 2 show the change in the median price of real estate over time. Figure **??** displays the average change in the number of parcels sold per census tract over time. Figures 3-5 display the geographic distribution of the outcome variables over the whole range of the data.

One of the limitations of this data is that few individual home-level characteristics are known–for example, the number of bedrooms or bathrooms in the home, how well-kept it is, and it's age are not known. As a result, I must operate under the assumption that homes in the same Louisiana census block are similar in terms of these characteristics. I.e., "neighborhoods" are composed of similar homes.

3.2 Pollution Emissions Data

The Louisiana Department of Environmental Quality (LDEQ) provided the annual pollution emissions data from their Emissions Release Inventory Center (ERIC) database after a public records request. Under state law, each facility in the state that emits one or more pollutants defined in Louisiana Administrative Code (LAC) 33:III must report their emissions to the LDEQ

[7]While it is preferred to have the universe of sales for every parish, the New Orleans area suffered catastrophic damage within the data range in 2005 as a result of Hurricane Katrina. The impact of the event on home prices could cause interference with the analysis. Other south Louisiana parishes are turned off in a robustness exercise probing the impacts of hurricanes on the results.

each year in mass units (U.S. tons or pounds).[8] The ERIC data is provided at the individual facility-release-point-air-pollutant level, and includes the amount of each air pollutant of interest released at each individual facility, from the specific stack or vent or other release point which emitted it. However, I sum to the annual facility-pollutant level.[9]

Among the LDEQ's list of tracked pollutants are 16 known and probable carcinogens and 55 suspected human carcinogens and known or suspected human reproductive toxins. ERIC also tracks output of criteria pollutants including particulate matter, sulfur dioxide (SO_2), nitrogen oxides (NO_x), and carbon monoxide (CO). I use ERIC data annually from 1996 to 2017[10] and sum at the facility level.[11] From 2006 onward, ERIC separates all emissions into "routine" and "unauthorized" categories. "Routine" emissions are those emissions a facility expected to emit, while "unauthorized" emissions result from equipment failure or flaring that allows the unintended release of air toxics or criteria pollutants.

I focus on a few selected emissions types: SO_2, NO_x, particulate matter 2.5 microns or less ($PM_{2.5}$), and particulate matter 10 microns or less (PM_{10}) or PM_{Large}.[12]. I select these pollutants because first, all are among the six criteria pollutants identified in the Clean Air Act, which denotes them as among the most common sources of air pollution in the country. Second, SO_2 and NO_x produce unpleasant odors which are identifiable to humans in large enough concentrations. SO_2 can harm vegetation and damage surfaces. Breathing in SO_2 and NO_x can cause respiratory issues, especially to those with asthma and among more vulnerable age groups (children and the elderly). Further, NO_x and SO_2 are contributors to particulate matter pollution, which produces visible haze. Particulate matter is tracked in varying sizes in order to measure its capacity to enter the lungs and cause respiratory damage. Particulate matter has been linked to lung and heart problems and can disrupt the ecosystem through its impact on waterways and soil. All of these pollutants can also contribute to acid rain (EPA, 2024a,

[8]This data is collected within the ERIC system and is passed by the LDEQ to the U.S. Environmental Protection Agency (EPA) for their triennial inventories such as the more widely familiar Toxic Release Inventory (TRI) program and National Emissions Inventory (NEI). The advantage of the LDEQ ERIC data over the EPA's emissions inventories is that the ERIC data is available annually instead of triennially.

[9]The LDEQ's Electronic Document Management System (EDMS) provides individual records by facility ID that allow any missing coordinate locations of facilities in the ERIC data to be filled.

[10]The data was provided by the LDEQ from 1984 to 2021. The years after 2017 are not used because there is no outcome data with which to match. Missing data for key pollutants in earlier years and general uncertainty among ERIC staff regarding the certification of the inventory data prior to 1991 leads to the 1996 cutoff.

[11]The coordinate location of the facility is calculated as the mean coordinates of all the release points associated with the facility when the coordinates of each release point are identified.

[12]In 1998, facilities began reporting PM_{10} emissions to the LDEQ. Prior to this period, facilities reported TSP–total suspended particulates between 0.1 and 30 microns. Using TSP in the early period and PM_{10} when it becomes available results in the PM_{Large} variable.

2024b, 2024c). Figure 6 displays annual emissions aggregated at the state level. Figure 7 displays unauthorized emissions.

3.3 Industrial Jobs Data

Data on the number of jobs at each site comes from the Louisiana Economic Development (LED) Industrial Tax Exemption Program (ITEP) (LED, 2024). Through this incentive program, businesses in the manufacturing sector in Louisiana can apply for exemptions on property taxes when they make investments in physical capital. These investments can be anything from a capital addition on an existing site to the construction of an entirely new manufacturing facility. As part of the application process, businesses must submit the number of existing jobs currently associated with the site and new permanent jobs they estimate their project will bring to the site. When the business applies for an ITEP renewal, they report the number of jobs onsite again. These are actual counts of the number of permanent jobs onsite. They are not subject to the employer's beliefs about the number of jobs that will be added. While jobs are reported only every five years at the time of an ITEP application or renewal, many large facilities (and therefore large industrial polluters) put in multiple applications for different projects at the same sites and ultimately report the number of jobs onsite annually. For sites with gaps in annual job counts, I impute the number jobs between periods where they are unavailable. One of the advantages of the ITEP job counts over more aggregated data sources is that I am able to determine the exact coordinate location of every site, and then calculate the driving distance between every ITEP job site and every home in the parish assessors data. I use the ArcGIS Pro drive time trade areas tool to estimates the number of facilities in the ITEP data that are within commuting distance of each real estate parcel based on the estimated drive time between the home and facility. The number of ITEP jobs within 10, 20, 30, 40, 50, and 60 minutes of a home are added up and used in the main analysis. Figure 8 summarizes the ITEP job counts at the state level annually and compares the results to state level U.S. Census Bureau Quarterly Workforce Indicators (QWI) employment counts in the manufacturing and utilities sectors (U.S. Census Bureau, 2024). QWI data is very comprehensive, covering 95 percent of jobs in the private sector in the United States (U.S. Census Bureau, 2019). However, the data is not accessible at the facility level like the ITEP data. I therefore use the QWI estimates as a helpful check of the job counts reported by facilities in the ITEP data instead of using the QWI data directly.[13]

[13]ITEP data is reported by project ID, and names of companies applying and addresses reported in the data may change over time, or a site may be associated with two or more owners. Careful cleaning of the data by hand allows projects to be assigned to the same sites to prevent double counting.

4 Methodology

To understand the methodology, first consider a simple scenario with only one pollution-emitting facility and two homes. The facility in question is a chemical plant operating on the west bank of the Mississippi river just north of Plaquemine, Louisiana in 1998. Based on the coordinate location of the chemical plant, the surrounding terrain, and the weather observed every six hours in 1998[14], the HYSPLIT program maps the average daily transport and dispersion of pollution from the chemical plant.[15] The map output shows whether a home sold in Sunshine across the river would be most likely to receive the bulk of the chemical plant's air pollution in that year due to prevailing winds in 1998, or whether pollution would be primarily pushed southward over a home that sold in Plaquemine, or in some other direction. Suppose the home sold in Plaquemine and the home sold in Sunshine are the same distance from the chemical plant "as the crow flies". Even so, the home in Plaquemine and the home in Sunshine are exposed to different levels of pollution based on the weather that year. If the wind is less favorable to one homeowner than another in a given year, this may be reflected in their valuation of their home.

In reality, the home in Plaquemine and the home in Sunshine do not face air pollution from just one chemical plant, but from many facilities, since there are hundreds of industrial facilities outputting air pollution in Louisiana in 1998 various distances away. Weather may place a home upwind of one facility but downwind of others in a given year, producing further variation in pollution exposure. Overlaying all of the HYSPLIT-generated pollution maps from every facility operating in Louisiana that year produces a very geographically detailed map of industrial pollution transport and dispersion. Through this map, the average daily concentration of pollution faced at any location in the state in 1998 (say–a home in Sunshine, Louisiana) can be estimated. I repeat this same process for every data year, generating geographic variation within-year between homes, and over time.

The homeowner in Plaquemine and the homeowner in Sunshine don't just face different pollution levels–they also face different commute times. Suppose residents of both homes are considering a job at the chemical plant. The homeowner in Plaquemine can reach the chemical plant job within 5-10 minutes by car. The homeowner in Sunshine is separated from the chemical

[14]The selected meteorological data comes from The NCEP/NCAR Reanalysis Project, which contains 2.5 degree resolution latitude-longitude data, outputting surface-level and upper-level wind, temperature, and precipitation data every 6 hours from 1948 to present (NCEP & NCAR, 2024)

[15]HYSPLIT is a globally-recognized tool produced by the NOAA, used extensively in the atmospheric sciences to track the transport and dispersion of air pollution in historic and real-time forecast settings. Its primary users are the NOAA's National Weather Service (NWS), who depend on the program to forecast air pollution coming from wildfires and industrial accidents and toxic releases and make emergency response decisions. Thousands of other users make use of program each year to model air pollution transport and dispersion.

plant by the Mississippi river, and must drive to a bridge or take a ferry to cross the river, resulting in a 40-45 minute commute time. In summary, the two homeowners the same linear distance from the same chemical plant are therefore likely to face a different mix of jobs within suitable commute times, and a different air quality randomized by weather patterns. Including additional parish-by-year and block fixed effects which control for changes over time and local neighborhood characteristics controls for most unobservable differences between the homes.

Turning from theory to math, the unit of observation in the main analysis is an individual real estate parcel (or home) h sold in year t. At the time of sale, the real sale price per acre (y_{ht}) is observed. The average daily concentration of industrial pollution to which that home was exposed in the previous year $t-1$ is denoted $C_{h,p,t-1}$, where p indicates industrial air pollutant type (SO_2, $PM_{2.5}$, PM_{10}, or NO_x). However, $C_{h,p,t-1}$ is not observed, as each individual home sold does not have an air quality monitor measuring the exact amount of air pollution at that location the year before it was sold. While $C_{h,p,t-1}$ is not observed, it can be estimated as $\widehat{C}_{h,p,t-1}$ using the HYSPLIT program.

From HYSPLIT, each facility in the ERIC data acquires an average daily transportation and dispersion output map for that year. The map contains multiple dispersion factors $D_{a,f,t}$ which take on one of five possible dispersion values in geographic grid cell a: $D_{a,f,t} = [0, 1.0 \times 10^{-14}, 1.0 \times 10^{-13}, 1.0 \times 10^{-12}, 1.0 \times 10^{-11}]$. In other words, $D_{a,f,t} > 0$ denotes a grid cell through which air pollution from facility f traveled, and its exact value denotes its level of dispersion.

Given that home h is located in grid cell a, the average daily concentration of industrial air pollutant p at home h is then calculated as follows:

$$\widehat{C}_{h,p,t} = \sum_{f=1}^{F} D_{h,f,t} * E_{p,f,t} \tag{1}$$

Where $\widehat{C}_{h,p,t}$ is the average daily concentration of Louisiana industrial pollutant p at home h in year t (in $\mu u/m^3$), $f = [1, .., F]$ indexes facilities emitting pollutant p in year t, and $E_{p,f,t}$ is the average daily mass of emissions in microns (μu) of pollutant p emitted from facility f in year t.

Summing up the concentration of pollutant p coming from every facility f at every grid cell a produces a very fine map of Louisiana industrial emissions, where homes h are very unlikely to share the exact same pollution concentration value.

4.1 Validating HYSPLIT Concentrations

Since $C_{h,p,t}$ cannot be observed, it is not possible to fully verify that the concentration of industrial pollutant p modeled at home h is correct. That said, reasonable upper bounds on the concentration estimates validity can be set by comparing the HYSPLIT model concentrations of SO_2, $PM_{2.5}$, PM_{10}, and NO_2 estimated at the locations of pollution monitors in Louisiana with the average hourly readings of those monitors.[16] Pollution monitors are likely to measure a higher, and noisy, measure of pollution deriving from industrial sources for a few reasons: (1) Air pollution comes from many sources, including automobiles, boats, planes, and trains, windblown dust, wildfires, and many other sources. (2) when generating an average hourly concentration at the location of each monitor using HYSPLIT, an assumption is made that industrial facilities output their annual emissions evenly every hour over the course of an entire year. (3) Since the HYSPLIT output observes the wind speed and direction at facility f, at the location of monitor h, it is possible that wind coming from a direction where no facility is located disperses the local pollution observed at the monitor further. For all these reasons, air quality monitor readings are best understood as reasonable upper bounds on the concentrations of each pollutant coming from industrial sources. i.e., if the hourly $PM_{2.5}$ concentration is consistently measured at a monitor at 15 $\mu u/m^3$, it is unreasonable for the HYSPLIT concentration model to predict that the area where the monitor is located consistently faces hourly concentrations of $PM_{2.5}$ equal to 200 $\mu u/m^3$ coming only from industrial sources.[17] Figures A5-A12 compare the average hourly pollution concentration readings observed at pollution monitors throughout the year to hourly versions of the HYSPLIT estimated concentrations at those locations. These results bring some confidence that the HYSPLIT estimates are generally modest. The correlation between monitor readings and HYSPLIT concentrations are 0.622, 0.249, 0.276, and 0.553 for nitrogen dioxide, sulfur dioxide, PM 2.5, and PM 10 respectively.[18]

4.2 Main Model

Following from equation (1), the main equation of interest is:

$$ln(y_{h,t}) = \alpha + \beta_1 ln(\widehat{C}_{h,p,t-l}) + \beta_2 ln(J_{m,h,t-l}) + \gamma_{block} + \gamma_{parish \times t} + \epsilon \tag{2}$$

Where $y_{h,t}$ is real price per acre of home h sold in year t, $J_{m,h,t-l}$ denotes the number of industrial jobs within driving minutes $m = [10, 20, 30, 40, 50, 60]$ of home h in year $t-l$, γ_{block} is a block fixed effect, $\gamma_{parish \times t}$ is a parish×year fixed effect, and ϵ is the error term.[19]

[16] Since NO_x is a group of pollutants, one of its major components that is measured at a reasonable number of monitors, NO_2, is used as a comparison pollutant.

[17] Louisiana pollution monitors are not randomly spaced. They are almost all located in the southeast state region where more industrial activity occurs.

[18] The full geographic variation in the data is too fine to visually display. However, Figure 9 aggregates concentrations at the tract level over time to give an idea of how concentrations of geographically distributed.

[19] Using the 2010 Census boundaries, Louisiana has 64 parishes, 1,148 census tracts, and 204,447 census blocks.

In addition to main model (2), another model is estimated separating ”unauthorized” from ”routine” emissions during the 2006-2018 period where this status is known. The equation is as follows:

$$ln(y_{h,t}) = \alpha + \beta_1 ln(\widehat{C}^U_{h,p,t-l}) + \beta_2 ln(\widehat{C}^R_{h,p,t-l}) + \beta_3 ln(J_{m,h,t-l}) + \gamma_{block} + \gamma_{parish\times t} + \epsilon \quad (3)$$

Where $\widehat{C}^U_{h,p,t-l}$ is the estimated average daily concentration of unauthorized industrial pollutant emissions faced by home h in year $t-l$ and $\widehat{C}^R_{h,p,t-l}$ is that industrial pollution that was expected to be released.

4.3 Tract-Level Model

In addition to the main analysis concerning home sale prices, another question of interest is whether the volume of total sales changes with industrial pollution exposure. Answering this question requires that the unit of observation transition to the total number of home sales in census tract c in year t. The concentration of industrial pollution faced by that census tract in year $t-l$ is the average concentration over the tract's area, $\widehat{C}_{c,p,t-l}$. The model produced is as follows:

$$ln(y_{c,t}) = \alpha + \beta_1 ln(\widehat{C}_{c,p,t-l}) + ln(J_{cz,t-l}) + \alpha_{parish\times t} + \epsilon \quad (4)$$

Where $y_{c,t}$ is the total number of homes sold in census tract c in year t, or alternatively the number of homes sold for a *low* price or a *high* price. $J_{cz,t-l}$ is the number of jobs in commuting zone (cz) in year $t-l$, and $\alpha_{area\times t}$ represents $parish \times year$ fixed effects.[20]

5 Results

The following subsections present the results from the models specified in section 4.

5.1 Main Model Results

Results from running equation (2) on the whole real estate sample are presented in Table 2. As anticipated, the number of industrial jobs within commuting distance is positively associated with real price per acre. For example, a 1 percentage point increase in the number of industrial job within a 10-minute commute is associated with a 0.014 to 0.015 percent increase in real price per acre. On the other hand, with the exception of NO_x, the relationship between pollution

[20] While not every area of the state of Louisiana is assigned a commuting zone, every ITEP job in the data happens to fall within an assigned commuting zone.

concentration and real price per acre is positive in sign. Only the coefficient for SO_2 is statistically significant, indicating that a one percentage point increase in sulfur dioxide concentration leads to a 0.021 percentage point increase in real price per acre the following year. Table A2 cuts the real estate sample to only parcels that were assessed as homesteads in 2018. The negative sign on the concentration of NO_x disappears, and it still faces standard errors too large to establish statistical significance. The coefficients on concentrations of $PM_{2.5}$, PM_{Large}, and SO_2 are positive and significant at at least the 10 percent level.

Tables A3-A6 probe the results with a variety of alternative fixed effects specifications. For each of these tables, columns (1)-(4) contain no time fixed effects, but slowly introduce smaller area fixed effects. As the area fixed effects shrink down to the census tract and census block, a negative relationship between pollution and home price emerges. However, when year or parish by year fixed effects are added in columns (5)-(8) , the sign of the coefficient on the pollutant concentration of interest is consistently positive except for NO_x, which only switches in sign in the presence of parish by year and block fixed effects[21]. The coefficients of interest in columns (5)-(8) also shrink in magnitude as area fixed effects become "finer", bringing the impact of each pollutant on real price per acre closer to zero. Tables A3-A6 also report "Oster delta". As noted by Oster (2019), stable coefficients shown in conventional control sensitivity tests do not necessarily imply lower bias, but that the observed controls may be lower variance and explain less of the change in the outcome than unobservables. Oster suggests that authors calculate a statistic that will be referred to here as "Oster delta". Given assumptions about the maximum possible R-squared the analysis could ever observe (R_{max}), the absolute value of Oster delta indicates how large unobservables would need to be to make the treatment effect of an observable equal zero. In general, the larger the Oster delta, the more robust the treatment effect.[22] The observed Oster deltas in Tables A3-A6 are quite small. For example, in Table A5 column (7), the Oster delta of 0.0202 suggests that unobservables need only be 0.0202 times as important as the concentration of industrial SO_2 to bring the impact of SO_2 on real price per acre to zero.[23] In columns (5)-(8) of every fixed effects sensitivity test table, Oster delta shrinks as more and more unobservables are controlled for through finer area fixed effects. This suggests it may reasonable to conclude that the "true" impact of industrial air pollution on real estate price per acre in Louisiana is null.

Results from the calculations that consider unauthorized versus routine emissions (equation 3) are displayed in Table 3. In the case of all four pollutants, unauthorized discharge emissions have

[21]A question of interest may be how many singletons are lost to the fixed effects specifications. 14,000 or fewer singletons are automatically dropped from the results from Table 2. Less than 12,000 singelton observations are automatically dropped from the homestead sample in Table A2.

[22]Oster (2019) suggests an Oster delta of 1 might be a sufficient delta for most analyses.

[23]Where observed in all tables, calculations of the Oster delta assume $R_{max} = 0.9$.

a negative impact on real estate price per acre. However, standard errors are fairly large, such that only the coefficient on the concentration of SO_2 is statistically significant–and only at the 10 percent level. The coefficient implies that a 1 percentage point increase in the concentration of unauthorized SO_2 pollution observed at home h in year $t-1$ decreases real price per acre by 0.003 percent. In contrast to the coefficients on unauthorized releases, the coefficients on routine releases are positive, and only the coefficients on NO_x and SO_2 obtain standard errors small enough to be statistically significant at the 10 percent level. These results are for the whole sample of real estate sales. The results for the residential subsample are shown in Table A7. Coefficients on unauthorized discharge of particulate matter lose their negative sign. The negative signs on unauthorized NO_x and SO_2 remain, but are not statistically significant, and the coefficient on NO_x is particularly small.

5.2 Effect on Home Sales

Finally, turning to the tract-level estimates, Table 4 reports the tract-level summary statistics, and Tables 5-7 report results from equation (4). Table 5 shows that the number of home sales per census tract declines with increases in the concentration of air pollution faced by the census tract over time, though the standard errors in column (2) for tract-level concentration of SO_2 are large. In column (1), a 1 percent increase in the concentration of NO_x faced by a census tract results in a 0.225 percent decrease in the number of homes sold in a census tract the following year. In column (3), a 1 percent increase in the concentration of large particulate matter results in a 0.226 percent decrease in homes sold the following year. In column (4), a 1 percent increase in $PM_{2.5}$ decreases the number of homes sold in the census tract in the following year by 0.2 percent. In Tables 6 and 7, these results are decomposed into the number of parcels in each tract that sell for less than \$30,000 or more than \$200,000, respectively.[24] Results show that the sign on the low-priced parcels remain negative, but the relationship between "high-priced" parcel sales and air pollution concentration is positive.

These results are consistent with several possible mechanisms. It could be that overall, Louisianians see improvements in local amenities from increased industrial output that these results fail to capture. This leads some homeowners who might have placed their home on the market in some other circumstance to remain in the area. However, it is the lower priced homes that sell less, while high priced homes sell more. It could be that uncaptured improvements in local amenities drive up home values to the point that more owners are induced to sell their homes at the new price, or that out-of-tract buyers with larger incomes are attracted by the amenities and move in, increasing turnover of higher-valued homes. However, it could also be that Louisianians who can afford to move out of tract put their homes up for sale, while owners

[24] In 1982-1984 U.S. dollars.

of lower-valued homes stay.

Similar to equation (3), results are also reported for unauthorized discharge versus routine discharge at the tract level in Tables 8-10. The sign of the results remain the same when looking at all parcel sales regardless of sale price (Table 8). However, lower-priced parcel sales decrease with increases in routine emissions, while increasing with unauthorized emissions (Table 9), and the reverse is true for higher-priced parcels (Table 10).

5.3 An Instrumental Variables Approach

One potential concern with HYSPLIT concentration estimates is that much of the variation in the concentration of pollution faced in each home in each year could be attributable to endogenous increases and decreases in pollution emissions from each facility rather than exogenous changes in the dispersion and transportation of their air emissions. To relieve this concern, the HYSPLIT concentration maps are regenerated, holding the emissions from each facility ($E_{p,f,t}$) in equation (1) constant over time, and equal to the average emissions produced by the facility over the data range (i.e., $E_{p,f,t}$ becomes $\bar{E}_{p,f}$). In this case, the only temporal variation in $\widehat{C}_{h,p,t}$ comes from the variation in the transport and dispersion of pollutants from each facility over time, and $E_{p,f}$ now merely "weights" each facility's time-invariant output. Let the resulting concentration be denoted $\bar{C}_{h,p,t}$. In a reduced form approach, $\bar{C}_{h,p,t}$ is substituted in for $\widehat{C}_{h,p,t}$ in equation (2). Within an instrumental variables approach, the impact of $\bar{C}_{h,p,t}$ on $y_{h,t}$ is identified if average daily changes in weather patterns at pollution-emitting facilities that lead to changes in the transport and dispersion of air pollution over Louisiana impact $y_{h,t}$ only through their impact on air pollution concentration observed at home h in year $t-l$. First stage results in Table 11 show that the weighted instruments are highly correlated with the HYSPLIT concentration estimates used in the main analysis, with f-statistics between 7,949 and 16,740.

Reduced form results of the instrumental variables approach are shown in Table 12. Comparing with the results in Table 2, the coefficient on nitrogen oxides has turned positive and significant at the 10 percent level. Other than that, the signs of the coefficients on the pollution concentrations remain the same (positive) with large standard errors, though their magnitudes are larger.

6 Supplementary Analyses

The following subsections contain additional exercises that further investigate the results and test robustness.

6.1 Lag Tests

Tables A12 through A15 test whether industrial pollution exposure more than one year prior to a home sale has different impacts. No new conclusions can be drawn from the results. Coefficients routinely reverse in sign among NO_x add $PM_{2.5}$ results and maintain large standard errors. The positive, statistically significant impact of sulfur dioxide on real price per acre disappears after time t-2. Coefficients are consistently positive for large particulate matter, but only one coefficient (for pollution at time t-1) is significant at the 10 percent level.

Tables A16 through A19 display lag test results for the number of parcels sold by census tract. The main results in Table 5 are robust across different lagged specifications. Even the coefficients do not change much. For example, in Table A16, a 1 percentage point increase in PM 2.5 pollution decreases home sales in a census tract between 0.200 and 0.206 percentage points across different lag specifications.

6.2 Hurricane Effects

Over the range of years considered in the analysis, Louisiana faced damage from many hurricanes– most infamously, hurricane Katrina smashed into the southeast Louisiana region in 2005, devastating the New Orleans area when levees broke. In the same year, hurricane Rita crashed into the southwestern state area, where Lake Charles–another industrial hub–is located. Figure A3 displays a map of the parishes by hurricane damage from 1994-2018. Figure A4 plots the estimated damage caused by each hurricane over time and its name. It is clear to see that Rita and Katrina were the most damaging hurricanes faced by the state of Louisiana from 1994-2018, causing over $10 billion in combined damage (in 1982-1984 dollars) according to the NOAA NWS Storm Events Database (NOAA NCEI, 2024). In fact, the damage caused by Rita alone was more than twice the damage caused by all other hurricanes over the data period besides Katrina, and Katrina caused more than twice the damage of all other hurricanes combined, *including* Rita. Katrina damaged or destroyed hundreds of thousands of homes and displaced hundreds of thousands of people. This presents a considerable shock to local housing markets.

While the presence of parish-year fixed effects aid in controlling for hurricane damage and its subsequent impact on home values, to further test the main results against hurricane interference, the data sample is divided into pre-2005 and post-2007 periods.[25] Tables A20 and A21 display the results of splitting the main parcel-level sample between a 1998-2004 (pre-Katrina) period and a 2007-2018 (post-Katrina) period.[26] The results show that the positive relationship between

[25]Since the unauthorized vs. routine discharge data is not available until 2006, this analysis is only conducted on the sample of total emissions.

[26]Lagged variables like industrial jobs within commuting distance and annual emissions (which impacts the emissions concentration) start in 2006 by omitting real estate sales in 2006 as well.

pollution emissions and real estate values is concentrated in the post-Katrina period. From 1998-2004, the relationship between home values and pollution concentration is negative except for $PM_{2.5}$. Results are also reported for the tract-level analysis looking at the number of home sales in Tables A23 and A24. The negative relationship observed between total home sales and pollution concentration does not change from the results in Table 5. Low priced parcels also continue to sell less and high priced parcels continue to sell more (Tables A25-A28).

Another test of the data is conducted by leaving out all parishes that comprise the New Orleans area in Table A22. However, while some of the magnitudes change, the sign of results do not change from those in Table 2. The effect of a 1 percent increase in sulfur dioxide is almost exactly the same, leading to a 0.022 percent increase in home values.

6.3 Curb Appeal

One comment about literature on home values and pollution is that some of the literature is unable to separate the effects of pollution from the effects of reductions in curb appeal due to proximity to industrial pollution sources. Industrial facilities are typically somewhat unsightly, coming with large smoke stacks, large parking lots, and otherwise aesthetically undesirable appearances. To test the impact of "curb appeal", the number of facilities within 0.5 miles of every home sale in the data is calculated and used as a time-invariant control. The result of adding this variable to the main analysis is presented in Table A29. The previous results remain essentially the same, and having one or more facilities within 0.5 miles of a home is negatively associated with home price, though standard errors are large.

7 Conclusion

This analysis has investigated the relationship between air pollution in the state of Louisiana and home values and number of homes sold, using real estate sales data from 1998-2018. I utilized the impact of weather patterns on the transport and dispersion of air pollution from industrial facilities over the state as a source of random variation in the average daily concentration of industrial air pollution experienced at a home or census tract a year before homes sell.

Contrary to much of the previous literature which finds a negative relationship between industrial air pollution (or a proxy for that air pollution) and real estate values, I find a largely statistically insignificant relationship between home values and concentration of particulate matter pollution and sulfur dioxide, and a negative relationship between home values and concentrations of nitrogen oxides. Only the coefficient on sulfur dioxide is statistically significant. However, sensitivity tests suggest that the "true" effect of industrial air pollution on home prices approaches zero as unobservables are accounted for, and that all the results (including those for sulfur dioxide) could be overcome by omitted variables not captured by parish by year and block fixed effects. Lagging pollution exposure does not significantly change the results, nor does a reduced form instrumental variables model.

Decomposing the results between unauthorized and routine emissions in the 2006-2018 period does show negative impacts on real estate price from air pollution, concentrated in experiences with unauthorized discharge of air pollution. However, standard errors are typically large, and sensitivity tests again suggest that these results could go to zero with relatively small effort from unobserved variables. I contend that the results suggest that Louisianians, on average, do not negatively value clean air–at least not when the pollution they face is due to routine emissions from industrial sources.

Splitting the data into pre and post hurricane Katrina periods shows that the positive signs on the effects of industrial pollution on real estate values are concentrated in the post-Katrina period. This matter deserves further investigation. For example, it is possible that hurricanes in 2005 present a substantial shock in which more risk-averse Louisiana residents permanently moved away, and those who stayed are not as concerned about pollution as Louisianians who left. However, the tract-level results on the number of homes sold per census tract do not decompose differently between a pre and post Katrina period.

Results using the number of real estate parcels sold per census tract as an outcome variable suggest that the number of homes sold declines between 0.2 and 0.226 percent per one percent increase in the concentration of particulate matter pollution, and by 0.225 percent per one percent increase in concentration of nitrogen oxides faced by the census tract. Results also show that those declines in home sales are concentrated among lower-valued homes, while higher-valued homes sell more, especially in the presence of higher concentrations of nitrogen oxides and sulfur dioxide, both of which are capable of producing unpleasant odors. However, when the sources of pollution are further separated into unauthorized versus routine pollution, sales of lower-value homes increase with unauthorized pollution releases, while sales of higher-value homes do not. There are two possible explanations for the way that the number of sales decomposes between high-sale-price homes and low-sale-price homes. First, the demand for low-valued homes is decreasing and the demand for high-valued homes for sale is increasing due to local amenity benefits unable to be captured in a tract-level analysis, which drives buyers into the census tract. This effect could also "bid up" the sale price of real estate in general in the area. Second, the supply of high value homes available for sale increases with more pollution. This could happen if individuals in higher-valued homes "take flight" in response to higher pollution levels the previous year, choosing to move to areas with cleaner air, while residents in lower valued homes stay. Whether the effects of industrial pollution on home sales are due to a decrease in demand for homes in the area or a decrease in the supply of homes available for sale or both is still a source of investigation. However, these results suggest that further decomposition of the impacts of pollution on home prices may be instructive, to formally see if Louisianians respond differently to pollution based on income. These results also suggest that a “true” downward impact of air pollution on housing prices could be obscured by a change in the composition of homes sold over time. Identifying a sub-sample of homes sold more than once in the assessor’s data and comparing the values of those specific homes over time may aid in determining if composition changes play a role in the results. However, real estate parcel identifiers change in the data over time, as do the property lines of some parcels, leading to challenges in defining a repeated-sales sample.

If it is true that Louisianians do not negatively value air pollution–at least not at levels observed throughout the state–a question still left to be explored in further papers is whether they *should*. Perhaps organizations like RISE St. James have not gained considerable traction locally despite the national media attention placed on Cancer Alley in recent years, or perhaps Louisianians do not believe their claims. Perhaps Louisianians are prone to believe voices like Senator Bill Cassidy, who contended in 2021 that higher cancer rates are fully explained by lifestyle choices and have nothing to do with industrial pollution exposure. It is also possible that pollution typically fails to reach thresholds where Louisianans observe the difference in air quality, whether their health is impacted or not. A natural next step is to examine the impact of Louisiana industrial pollution on cancer rates and other health outcomes.

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8 Figures

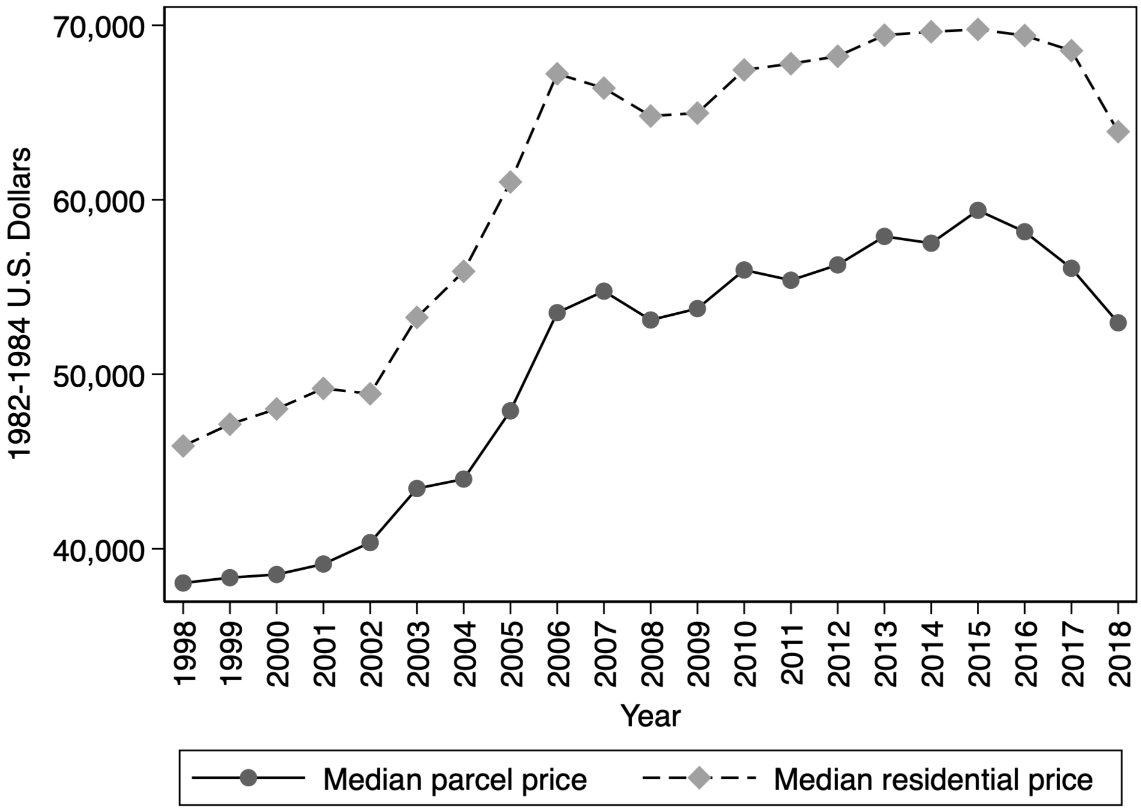


Figure 1: Median Real Estate Purchase Price, 1998-2018

Note: Median real estate sale prices in the state of Louisiana from 1998 to 2018, deflated by 1982-1984 South shelter CPI. Median parcel price considers all sold real estate parcels in the assessors sales data. Median residential price is the median price only among parcels that are homesteads. Data comes from 55 parish assessors offices.

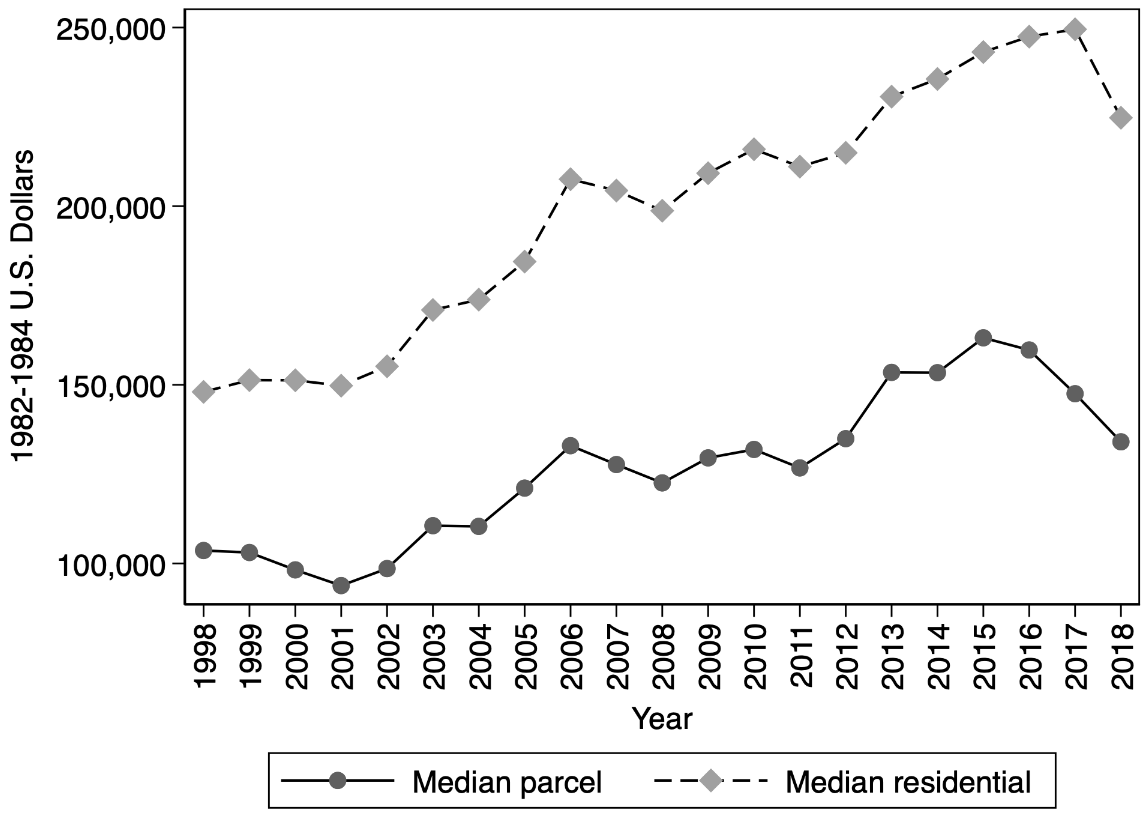


Figure 2: Median Real Estate Purchase Price Per Acre, 1998-2018

Note: Median real estate sale prices in the state of Louisiana per acre from 1998 to 2018, deflated by 1982-1984 South shelter CPI. Median parcel price considers all sold real estate parcels in the assessors sales data. Median residential price is the median price only among parcels that are homesteads. Data comes from 55 parish assessors offices.

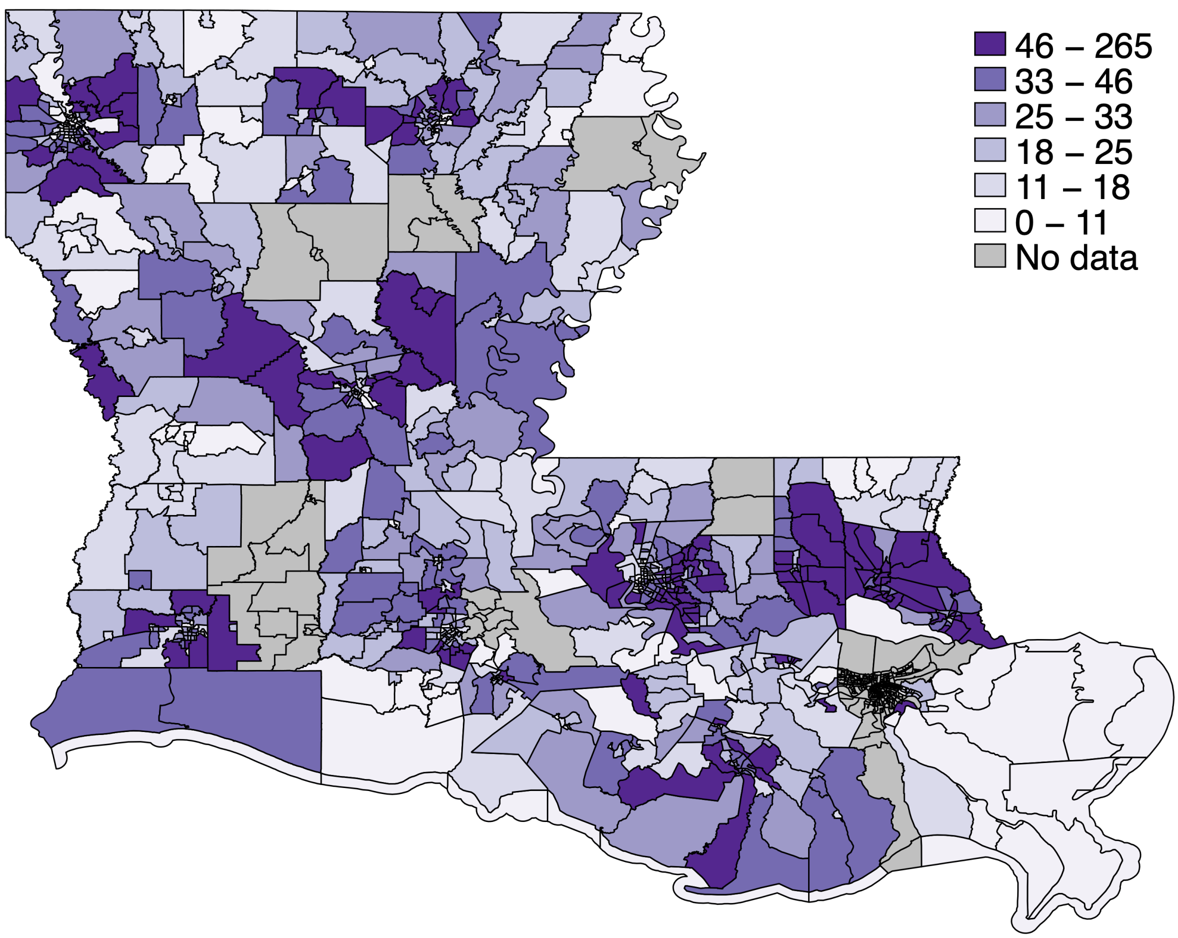


Figure 3: Average annual number of homes sold by census tract, 1998-2017

Note: Tract-Level home sales averaged by year from 1998 to 2017. 2018 home sales are omitted because available assessors data ends halfway through the year. Data ranges in legend are determined by quartiles. Data comes from parish assessors offices.

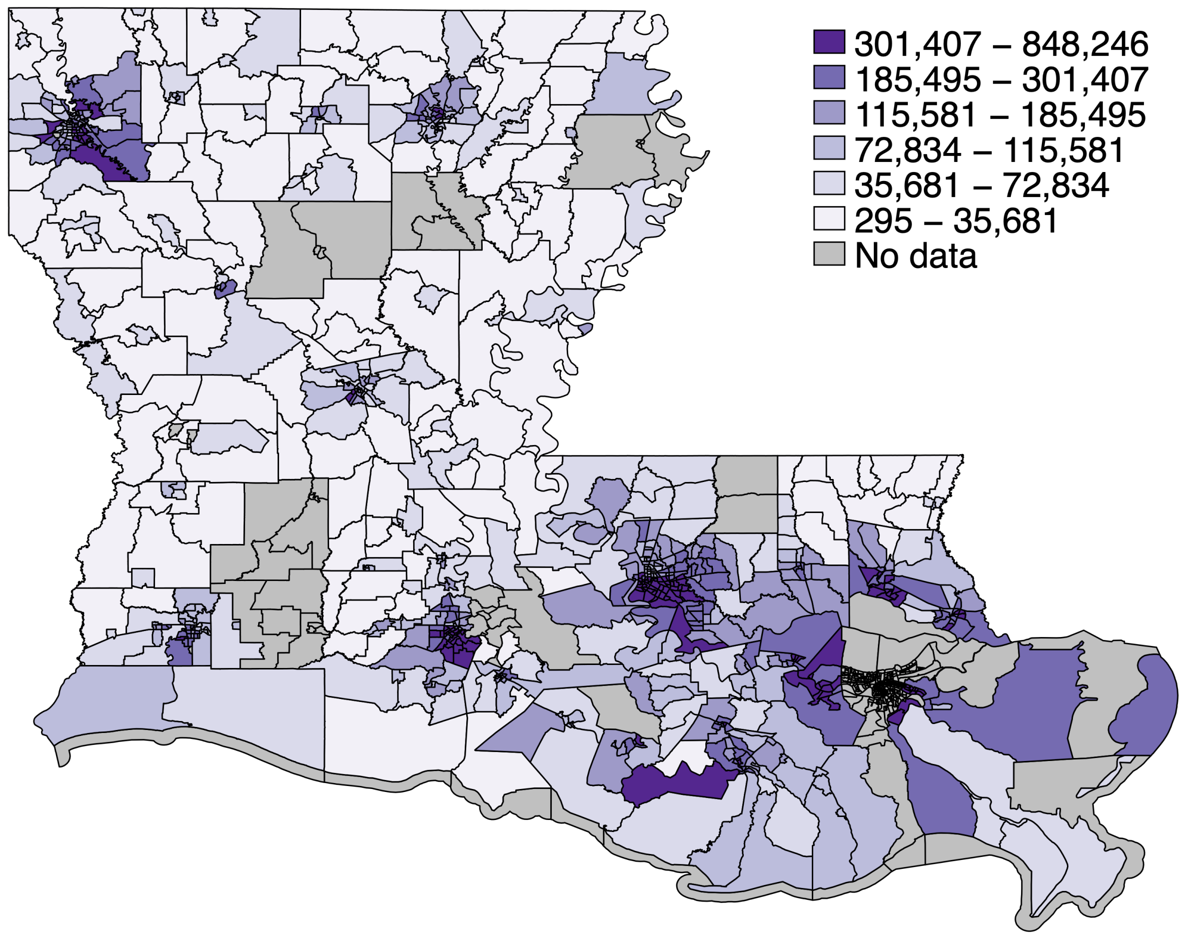


Figure 4: Average real price per acre of homes sold by census tract, 1998-2018

Note: Tract-Level average real price per acre averaged by year from 1998 to 2018. Data ranges in legend are determined by quartiles. Prices are deflated by 1982-1984 South shelter CPI. Data comes from parish assessors offices.

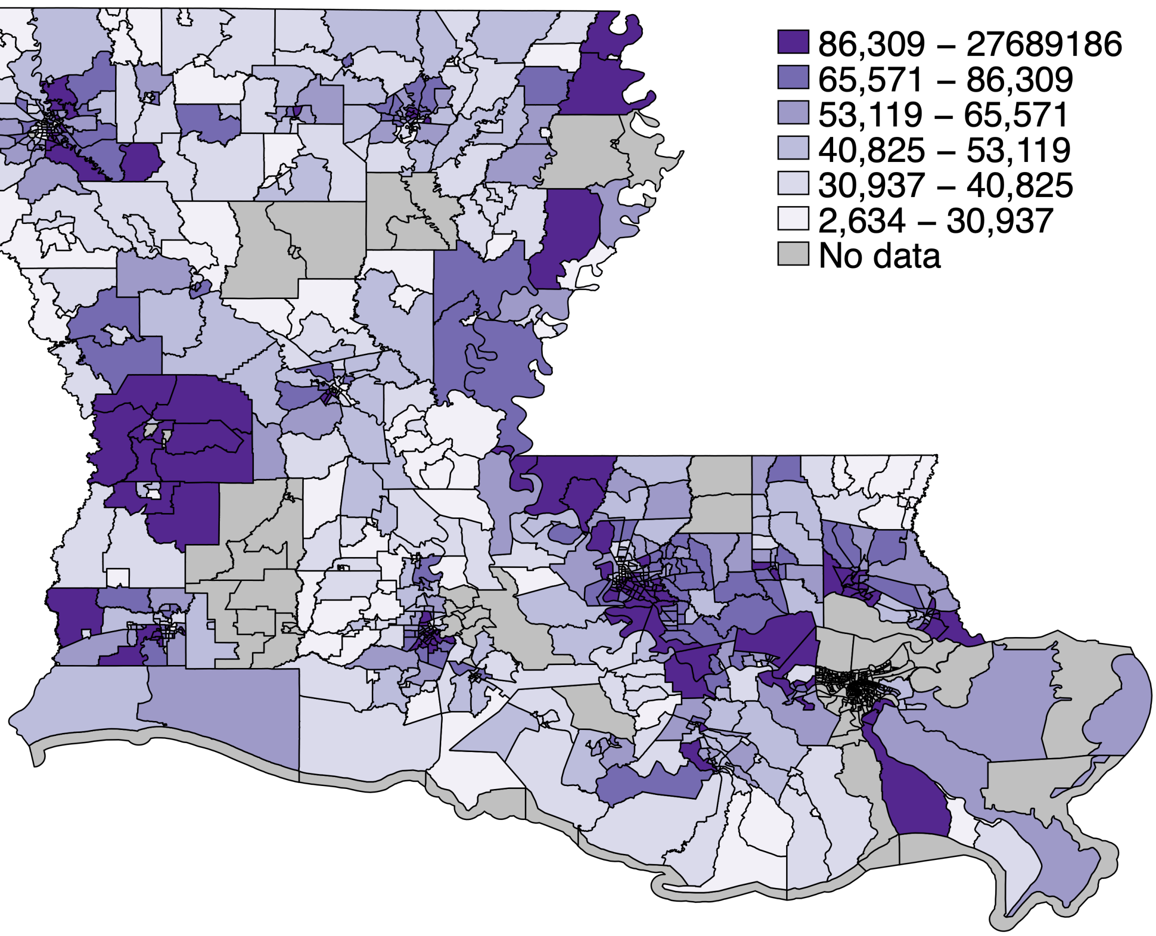


Figure 5: Average real purchase price of homes sold by census tract, 1998-2018

Note: Tract-Level average real estate purchase price averaged by year from 1998 to 2018. Data ranges in legend are determined by quartiles. Prices are deflated by 1982-1984 South shelter CPI. Data comes from parish assessors offices.

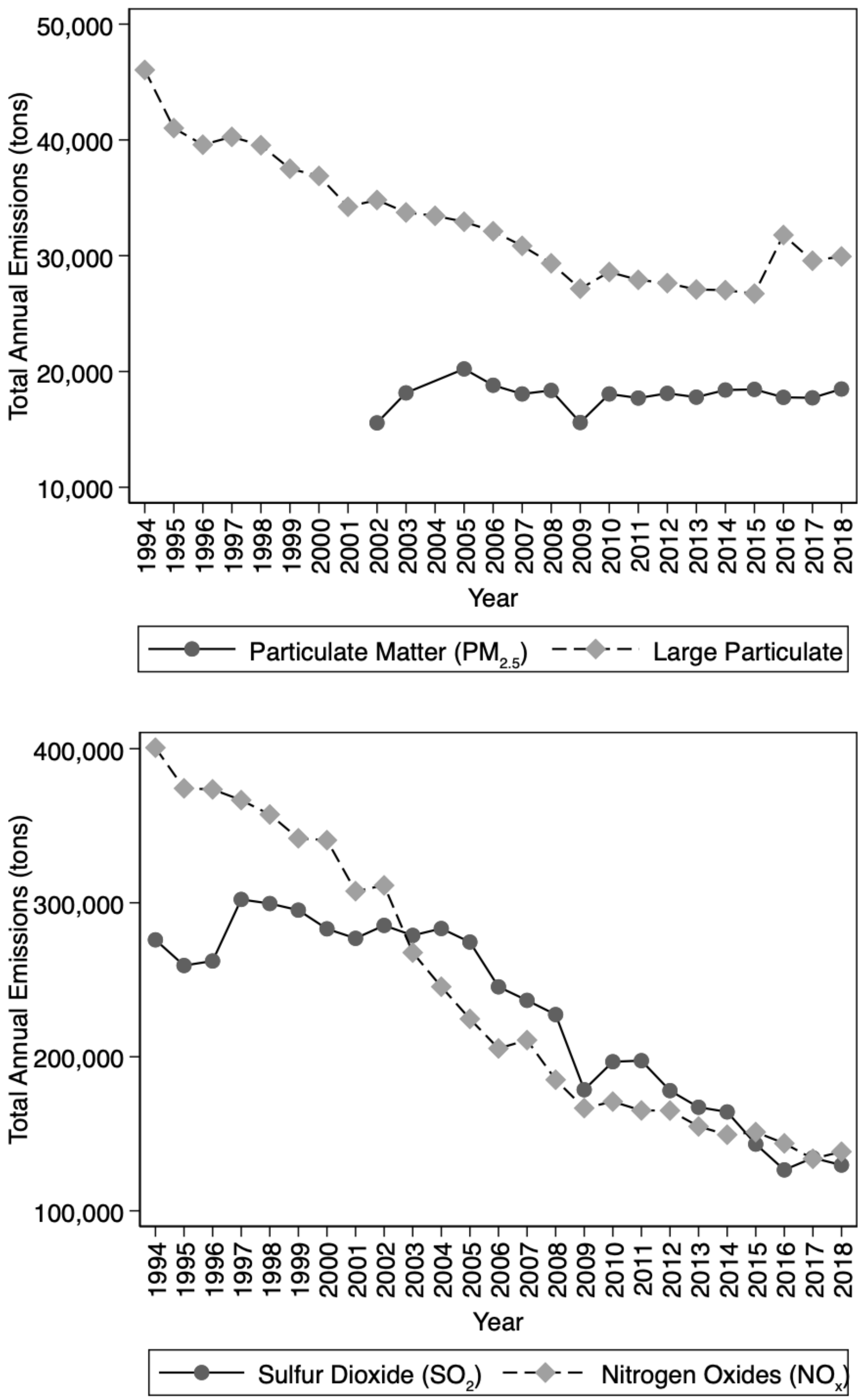


Figure 6: Total Annual Tons of Emissions Released, 1994-2018

Note: The sum of all emissions output (in tons) reported by all facilities in LDEQ ERIC from 1994 to 2018.

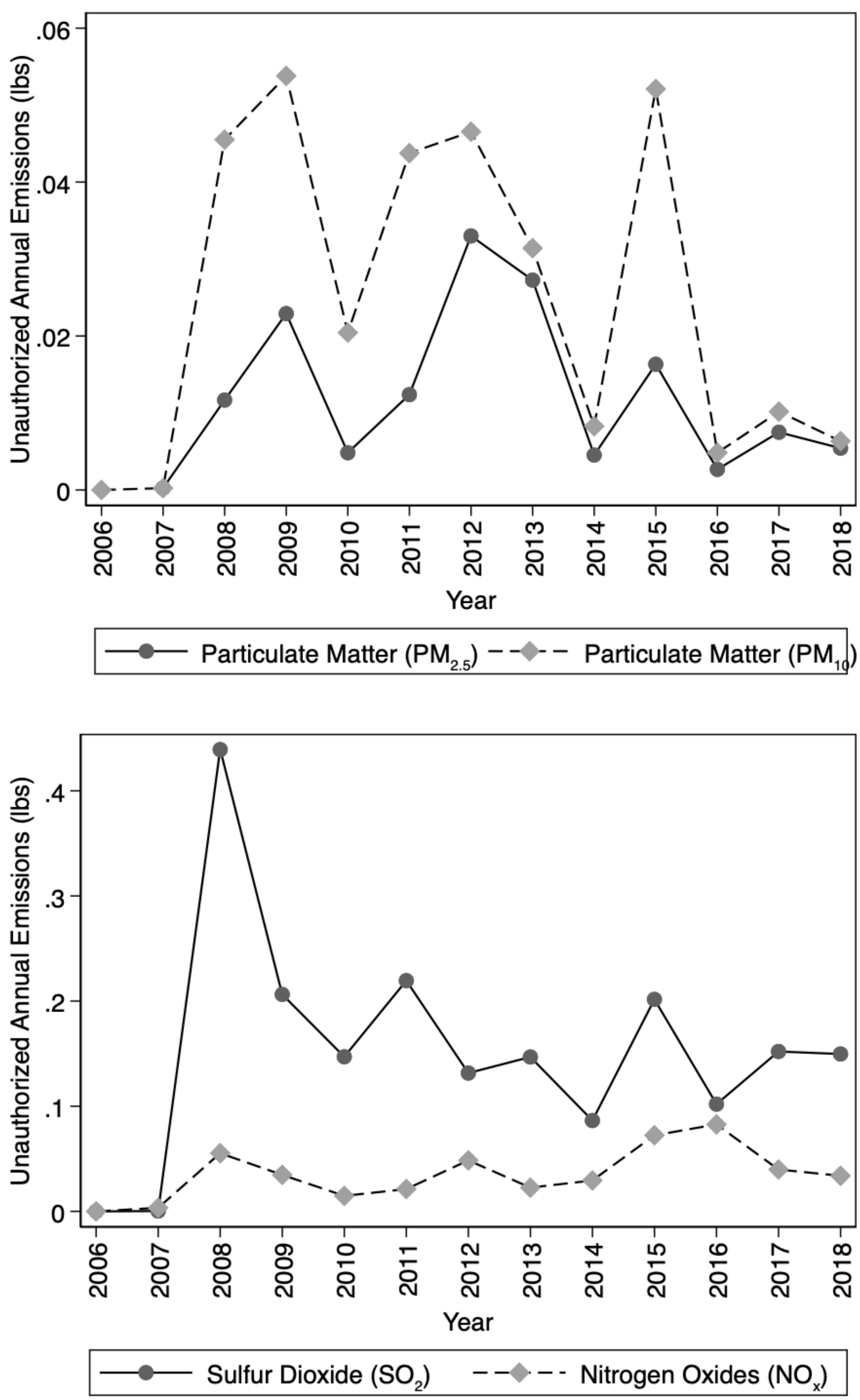


Figure 7: Total Annual Tons of Unauthorized Emissions Released, 2006-2018

Note: The sum of all unauthorized emissions output (in tons) reported by all facilities in LDEQ ERIC from 2006 (when data split by unauthorized versus routine emissions first becomes available) to 2018.

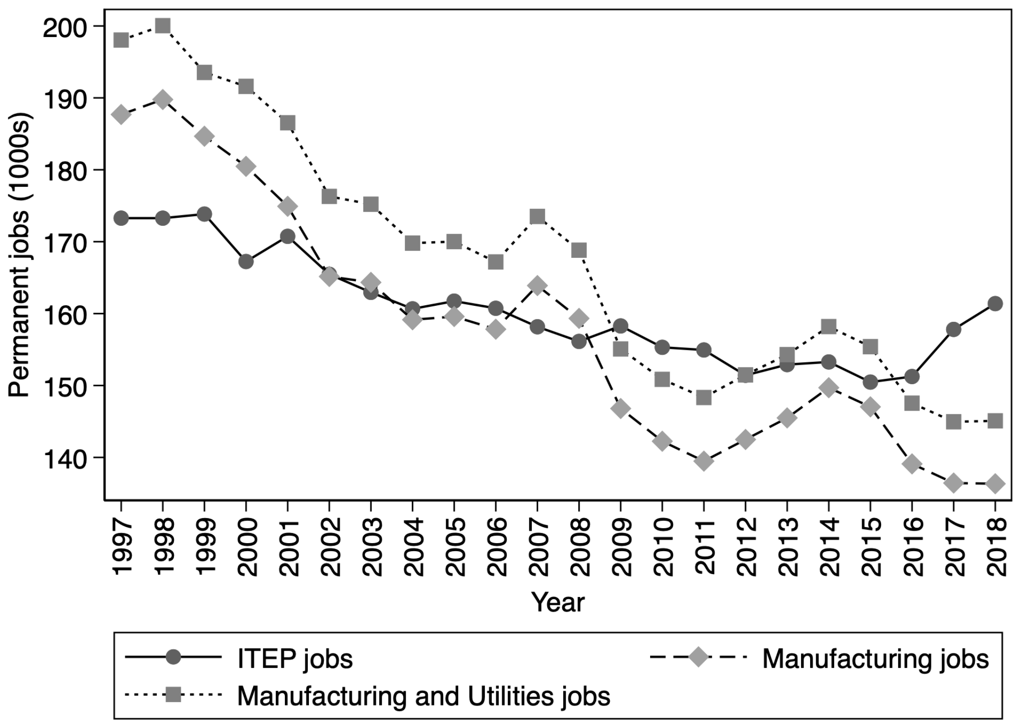
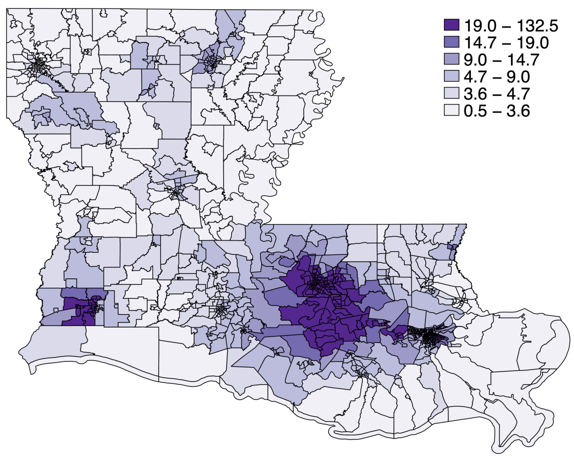
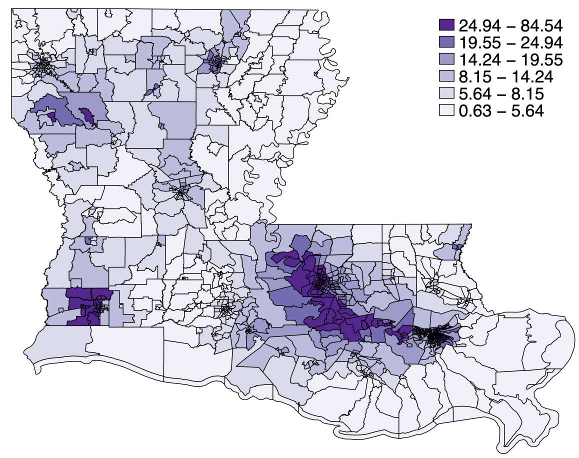


Figure 8: Annual total Louisiana ITEP jobs vs. QWI estimates

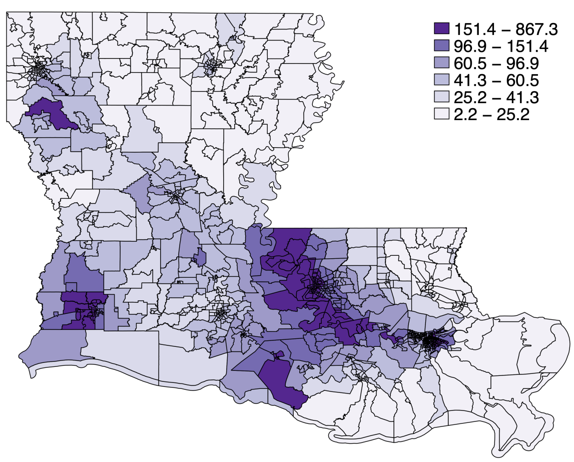
Note: Counts of all jobs in the LED ITEP data in each year, compared to state-level Quarterly Workforce Indicators (QWI) data for manufacturing and manufacturing + utilities jobs to see how well ITEP jobs fit state-level estimates. Most facilities in the ITEP data are in the manufacturing sector.



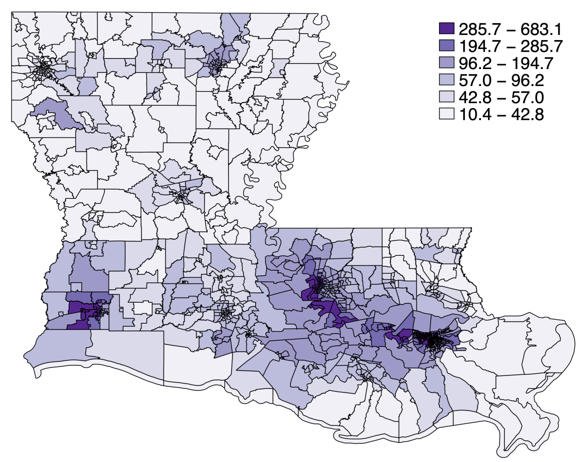
(a) $PM_{2.5}$ ($\mu u/m^3$)



(b) PM_{large} ($\mu u/m^3$)



(c) NO_x ($\mu u/m^3$)



(d) SO_2 ($\mu u/m^3$)

Figure 9: Average daily emissions concentration by census tract, 1994-2018

Note: HYSPLIT concentration output aggregated up to the census tract level. As described in section 4.

9 Tables

Table 1: Summary Statistics

	Count	Mean	Standard Dev.	Minimum	Maximum
Real Estate					
Real Price Per Acre	518,071	205619.53	257685.96	0.06	5.94e+06
Real purchase price	518,071	69,860.99	236340.23	40.27	5.12e+07
Total Emissions					
Particulate Matter 2.5	465,386	10.41	18.87	0.20	1,841.59
Large particulate	518,071	13.74	14.17	0.23	215.92
Nitrogen oxides	518,071	81.17	98.40	0.00	1,080.69
Sulfur dioxide	518,071	73.27	105.88	0.17	1,439.68
Routine Emissions					
Particulate Matter 2.5	384,960	9.02	10.38	0.20	67.87
Large particulate	384,960	13.01	13.46	0.23	215.92
Nitrogen oxides	384,960	73.05	81.36	2.81	793.30
Sulfur dioxide	384,960	61.69	88.41	0.17	1,087.50
Unauthorized Emissions					
Particulate Matter 2.5	384,960	0.00	0.00	0.00	0.00
Large particulate	384,960	0.00	0.00	0.00	0.00
Nitrogen oxides	384,960	0.00	0.00	0.00	0.00
Sulfur dioxide	384,960	0.00	0.00	0.00	0.00
Industrial Jobs					
Jobs 10 minutes	518,071	814.15	1,498.01	0.00	16,883.23
Jobs 20 minutes	518,071	3,639.83	3,884.47	0.00	30,627.27
Jobs 30 minutes	518,071	7,624.14	7,102.14	0.00	44,317.11
Jobs 40 minutes	518,071	12,333.08	10,488.26	0.00	51,889.18
Jobs 50 minutes	518,071	17,566.98	13,283.29	0.00	69,236.51
Jobs 60 minutes	518,071	24,181.26	16,263.44	0.00	82,922.43
Observations	518071				

Note: Real estate variables are summarized from 1998 to 2018. All other variables are summarized from 1997 to 2017.

Table 2: Main Model Results, Full Sample, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate matter 2.5, t-1)				0.011
				(0.008)
ln(Large particulate, t-1)			0.015	
			(0.010)	
ln(Sulfur dioxide, t-1)		0.021***		
		(0.007)		
ln(Nitrogen oxides, t-1)	-0.002			
	(0.010)			
ln(Jobs 10 minutes)	0.015***	0.015***	0.015***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.024***	0.024***	0.024***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.019***	0.019***	0.019***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 40 minutes)	0.023***	0.023***	0.023***	0.023**
	(0.009)	(0.009)	(0.009)	(0.009)
ln(Jobs 50 minutes)	0.007	0.007	0.007	0.013
	(0.022)	(0.022)	(0.022)	(0.024)
ln(Jobs 60 minutes)	0.016	0.016	0.016	0.014
	(0.021)	(0.021)	(0.021)	(0.024)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.738	0.738	0.738	0.741
N	504,541	504,541	504,541	451,386

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Routine and Unauthorized Emissions Model, Full Sample, 2006-2018

	(1)	(2)	(3)	(4)
Unauthorized emissions				
ln(PM 2.5, t-1)				-0.002
				(0.002)
ln(PM 10, t-1)			-0.002	
			(0.002)	
ln(SO2, t-1)		-0.003*		
		(0.002)		
ln(NOx, t-1)	-0.001			
	(0.001)			
Routine emissions				
ln(PM 2.5, t-1)				0.015
				(0.010)
ln(PM 10, t-1)			0.017	
			(0.011)	
ln(SO2, t-1)		0.013*		
		(0.008)		
ln(NOx, t-1)	0.020*			
	(0.012)			
Industrial Jobs				
ln(Jobs 10 minutes)	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.023***	0.023***	0.023***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.020***	0.020***	0.020***	0.020***
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Jobs 40 minutes)	0.032***	0.032***	0.032***	0.032***
	(0.011)	(0.011)	(0.011)	(0.011)
ln(Jobs 50 minutes)	0.005	0.005	0.005	0.005
	(0.027)	(0.027)	(0.027)	(0.027)
ln(Jobs 60 minutes)	0.018	0.018	0.018	0.018
	(0.025)	(0.025)	(0.025)	(0.025)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.743	0.743	0.743	0.743
N	370,134	370,134	370,134	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Census Tract Summary Statistics, 1998 - 2018

	Count	Mean	Standard Dev.	Minimum	Maximum
Real Estate and Jobs					
Real price per acre	15,086	165699.34	156574.90	18.39	2.01e+06
Median real price per acre	15,086	659041.16	2.60e+06	0.37	2.22e+08
Number of homes sold	16,693	31.04	36.95	0.00	824.00
Number of Jobs 2	9,492	23,441.31	14,771.07	4.00	53,343.45
Total Emissions					
Particulate Matter 2.5	18,368	12.41	26.86	0.23	1,738.45
Sulfur Dioxide	24,108	90.30	102.63	0.16	1,275.46
Nitrogen Oxides	22,960	141.88	145.68	3.62	1,057.21
Particulate Matter (large)	24,108	16.34	13.50	0.25	173.30
Routine Emissions					
Particulate Matter 2.5	13,776	10.51	9.81	0.23	64.87
Sulfur Dioxide	13,776	71.09	81.57	0.16	988.94
Nitrogen Oxides	13,776	103.42	99.27	3.62	793.54
Particulate Matter (large)	13,776	15.05	12.75	0.25	173.30
Unauthorized Emissions					
Particulate Matter 2.5	13,776	0.00	0.00	0.00	0.00
Sulfur Dioxide	13,776	0.00	0.00	0.00	0.00
Nitrogen Oxides	13,776	0.00	0.00	0.00	0.00
Particulate Matter (large)	13,776	0.00	0.00	0.00	0.00
Observations	24108				

Note: Real estate variables are summarized at the tract level from 1998 to 2018. All other variables are summarized from 1997 to 2017.

Table 5: Parcels Sold By Census Tract, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.200***
				(0.063)
ln(Large Particulate, t-1)			-0.226***	
			(0.066)	
ln(Sulfur Dioxide, t-1)		-0.055		
		(0.057)		
ln(Nitrogen Oxides, t-1)	-0.225***			
	(0.066)			
ln(Industrial jobs)	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.495	0.486	0.486	0.414
N	14,853	15,537	15,067	11,328

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Parcels Sold For Less Than $30,000 By Census Tract, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.215***
				(0.051)
ln(Large Particulate, t-1)			-0.257***	
			(0.053)	
ln(Sulfur Dioxide, t-1)		-0.169***		
		(0.046)		
ln(Nitrogen Oxides, t-1)	-0.279***			
	(0.058)			
ln(Industrial jobs)	0.011***	0.012***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.438	0.431	0.438	0.429
N	13,514	14,140	13,740	10,520

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Parcels Sold For $200,000 Or More By Census Tract, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				0.075
				(0.052)
ln(Large Particulate, t-1)			0.084	
			(0.053)	
ln(Sulfur Dioxide, t-1)		0.161^{**}		
		(0.071)		
ln(Nitrogen Oxides, t-1)	0.153^{***}			
	(0.059)			
ln(Industrial jobs)	0.004	0.003	0.004	0.004
	(0.003)	(0.003)	(0.003)	(0.003)
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.233	0.241	0.234	0.226
N	5,069	5,330	5,290	4,599

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Parcels Sold By Census Tract, Unauthorized or Routine, 2006-2018

	(1)	(2)	(3)	(4)
Unauthorized emissions				
ln(PM 2.5, t-1)				-0.057**
				(0.028)
ln(PM 10, t-1)			-0.032	
			(0.027)	
ln(SO2, t-1)		-0.189***		
		(0.041)		
ln(NOx, t-1)	-0.034			
	(0.030)			
Routine emissions				
ln(PM 2.5, t-1)				-0.181**
				(0.071)
ln(PM 10, t-1)			-0.194***	
			(0.074)	
ln(SO2, t-1)		0.108		
		(0.067)		
ln(NOx, t-1)	-0.187**			
	(0.073)			
ln(Industrial jobs)	0.001	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.364	0.369	0.366	0.368
N	7,925	7,931	7,931	7,931

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Parcels Sold For Less Than \$30,000 By Census Tract, Unauthorized or Routine, 2006-2018

	(1)	(2)	(3)	(4)
Unauthorized emissions				
ln(PM 2.5, t-1)				0.096***
				(0.027)
ln(PM 10, t-1)			0.084***	
			(0.024)	
ln(SO2, t-1)		0.007		
		(0.032)		
ln(NOx, t-1)	0.143***			
	(0.027)			
Routine emissions				
ln(PM 2.5, t-1)				-0.263***
				(0.053)
ln(PM 10, t-1)			-0.291***	
			(0.054)	
ln(SO2, t-1)		-0.168***		
		(0.045)		
ln(NOx, t-1)	-0.335***			
	(0.058)			
ln(Industrial jobs)	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.425	0.414	0.423	0.420
N	7,431	7,437	7,437	7,437

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Parcels Sold For $200,000 Or More By Census Tract, Unauthorized or Routine, 2006-2018

	(1)	(2)	(3)	(4)
Unauthorized emissions				
ln(PM 2.5, t-1)				-0.056*
				(0.033)
ln(PM 10, t-1)			-0.026	
			(0.029)	
ln(SO2, t-1)		-0.077		
		(0.060)		
ln(NOx, t-1)	-0.031			
	(0.034)			
Routine emissions				
ln(PM 2.5, t-1)				0.074
				(0.059)
ln(PM 10, t-1)			0.085	
			(0.059)	
ln(SO2, t-1)		0.195**		
		(0.093)		
ln(NOx, t-1)	0.166***			
	(0.060)			
ln(Industrial jobs)	0.004	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.213	0.217	0.209	0.209
N	3,511	3,513	3,513	3,513

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: First Stage, Instrumental Variables Model

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)	1.258***			
	(0.011)			
ln(Large particulate, t-1)		1.135***		
		(0.009)		
ln(sulfur dioxide, t-1)			1.096***	
			(0.012)	
ln(Nitrogen oxides, t-1)				1.036***
				(0.009)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
Drive time controls	Yes	Yes	Yes	Yes
F-Statistic	12664.96	16740.66	7949.04	14312.58
R-squared	451,386	504,541	504,541	504,541

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Instrumental Variables Model, Full Sample, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				0.092
				(0.061)
ln(Large particulate, t-1)			0.096	
			(0.060)	
ln(sulfur dioxide, t-1)		0.076		
		(0.060)		
ln(Nitrogen oxides, t-1)	0.103^{*}			
	(0.060)			
ln(Jobs 10 minutes)	0.015^{***}	0.015^{***}	0.015^{***}	0.015^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.024^{***}	0.024^{***}	0.024^{***}	0.024^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.019^{***}	0.019^{***}	0.019^{***}	0.019^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 40 minutes)	0.023^{***}	0.023^{***}	0.023^{***}	0.023^{***}
	(0.009)	(0.009)	(0.009)	(0.009)
ln(Jobs 50 minutes)	0.007	0.007	0.007	0.007
	(0.022)	(0.022)	(0.022)	(0.022)
ln(Jobs 60 minutes)	0.016	0.016	0.016	0.016
	(0.021)	(0.021)	(0.021)	(0.021)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.738	0.738	0.738	0.738
N	504,541	504,541	504,541	504,541

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

Table A1: Home Sales Per Parish

Parish	Minimum Year	Housing Units 2010	Population in 2010	Number of Sales
Acadia	1987	61773	25387	7728
Allen	Missing	25764	9733	-
Ascension	1979	107215	40784	14731
Assumption	1977	23421	10351	3958
Avoyelles	1983	42073	18042	4868
Beauregard	1977	35654	15040	2553
Bienville	1977	14353	7718	1280
Bossier	1987	116979	49351	17421
Caddo	1975	254969	112028	41523
Calcasieu	1977	192768	82058	31073
Caldwell	Missing	10132	4994	-
Cameron	1990	6839	3593	1394
Catahoula	1985	10407	4877	1951
Claiborne	2000	17195	7761	1388
Concordia	1992	20822	9383	2934
De Soto	1977	26656	12290	2846
East Baton Rouge	1977	440171	187353	77142
East Carroll	1994	7759	2904	50
East Feliciana	1990	20267	8014	1602
Evangeline	1993	33984	14662	1798
Franklin	1981	20767	9034	1992
Grant	1983	22309	8886	2735
Iberia	1977	73240	29698	10803
Iberville	1983	33387	12707	2716
Jackson	2001	16274	7680	2031
Jefferson	Missing	432552	189135	-
Jefferson Davis	Missing	31594	13306	-
LaSalle	1975	14890	6560	3557
Lafayette	1975	221578	93656	31322
Lafourche	1978	96318	38582	13970
Lincoln	1975	46735	19479	9923
Livingston	1977	128026	50170	18294
Madison	Missing	12093	4804	-
Morehouse	1978	27979	12423	4798
Natchitoches	1978	39566	18587	6106
Orleans	Missing	343829	189896	-
Ouachita	1978	153720	64481	31837
Plaquemines	1978	23042	9596	2766

Pointe Coupee	1981	22802	11130	3569
Rapides	1976	131613	55684	27302
Red River	2003	9091	4128	829
Richland	1980	20725	8621	1838
Sabine	1976	24233	14130	5909
St Bernard	1982	35897	16794	5976
St Charles	1985	52780	19896	5714
St Helena	Missing	11203	5150	-
St James	1981	22102	8455	2325
St John	1977	45924	17510	8460
St Landry	1985	83384	35692	10548
St Martin	Missing	52160	21941	-
St Mary	1977	54650	23028	8080
St Tammany	1977	233740	95412	59220
Tangipahoa	1976	121097	50073	29462
Tensas	1992	5252	3357	1147
Terrebonne	1977	111860	43887	22375
Union	2000	22721	11346	1968
Vermilion	1977	57999	25235	4340
Vernon	1987	52334	21433	2065
Washington	2002	47168	21039	2836
Webster	1981	41207	19336	5560
West Baton Rouge	1976	23788	9324	4337
West Carroll	2002	11604	5046	1290
West Feliciana	1977	15625	5097	2124
Winn	Missing	15313	7234	-

Note: List of parishes for which sales data is available from assessors. Nine parish assessors did not provide sales data. These include Allen, Caldwell, Jefferson, Jefferson Davis, Madison, Orleans, St. Helena, St. Martin, and Winn.

Table A2: Main Model Results, Homestead Sample, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate matter 2.5, t-1)				0.015*
				(0.008)
ln(Large particulate, t-1)			0.020*	
			(0.011)	
ln(Sulfur dioxide, t-1)		0.018**		
		(0.007)		
ln(Nitrogen oxides, t-1)	0.008			
	(0.010)			
ln(Jobs 10 minutes)	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.024***	0.024***	0.024***	0.023***
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 30 minutes)	0.005	0.005	0.005	0.007
	(0.009)	(0.009)	(0.009)	(0.009)
ln(Jobs 40 minutes)	0.046***	0.046***	0.046***	0.033**
	(0.017)	(0.017)	(0.017)	(0.016)
ln(Jobs 50 minutes)	-0.006	-0.006	-0.006	0.027
	(0.037)	(0.037)	(0.037)	(0.036)
ln(Jobs 60 minutes)	0.050	0.050	0.050	0.032
	(0.041)	(0.041)	(0.041)	(0.042)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.767	0.767	0.767	0.771
N	269,848	269,848	269,848	238,490

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Main Model Fixed Effects Sensitivity Test ($PM_{2.5}$) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(PM 2.5, t-1)	0.118***	0.136***	-0.008	-0.021***	0.144***	0.291***	0.079***	0.011
	(0.013)	(0.010)	(0.007)	(0.004)	(0.014)	(0.015)	(0.014)	(0.008)
ln(Jobs 10 minutes)	0.045***	0.040***	0.030***	0.014***	0.045***	0.038***	0.030***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.080***	0.051***	0.025***	0.021***	0.080***	0.048***	0.026***	0.023***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.045***	0.036***	0.014**	0.016***	0.044***	0.036***	0.015**	0.020***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.005)
ln(Jobs 40 minutes)	-0.032	-0.018	0.040***	0.026***	-0.034	-0.020	0.037***	0.023**
	(0.033)	(0.019)	(0.014)	(0.010)	(0.033)	(0.019)	(0.013)	(0.009)
ln(Jobs 50 minutes)	0.119**	0.081**	-0.000	0.011	0.105**	0.072**	-0.004	0.013
	(0.051)	(0.034)	(0.024)	(0.025)	(0.050)	(0.032)	(0.024)	(0.024)
ln(Jobs 60 minutes)	0.209***	0.060*	0.063***	0.016	0.222***	0.070**	0.068***	0.014
	(0.037)	(0.031)	(0.023)	(0.024)	(0.036)	(0.030)	(0.023)	(0.024)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.0734	-.0053	-.0363	.0885	.0989	.0206	.0057
R-squared	0.215	0.373	0.542	0.738	0.220	0.386	0.549	0.741
N	465,386	465,386	465,383	451,399	465,386	465,376	465,374	451,386

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Main Model Fixed Effects Sensitivity Test (PM_{Large}) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Large PM, t-1)	0.094***	0.141***	-0.080***	-0.089***	0.140***	0.341***	0.107***	0.015
	(0.016)	(0.012)	(0.009)	(0.006)	(0.016)	(0.017)	(0.017)	(0.010)
ln(Jobs 10 minutes)	0.046***	0.041***	0.032***	0.014***	0.045***	0.039***	0.030***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.082***	0.055***	0.028***	0.022***	0.082***	0.051***	0.028***	0.024***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.042***	0.036***	0.015**	0.016***	0.042***	0.035***	0.016**	0.019***
	(0.010)	(0.009)	(0.007)	(0.005)	(0.010)	(0.008)	(0.006)	(0.005)
ln(Jobs 40 minutes)	-0.033	-0.021	0.041***	0.028***	-0.038	-0.026	0.038***	0.023***
	(0.031)	(0.019)	(0.013)	(0.009)	(0.031)	(0.018)	(0.013)	(0.009)
ln(Jobs 50 minutes)	0.136***	0.087***	-0.000	0.014	0.113**	0.073**	-0.009	0.007
	(0.049)	(0.033)	(0.024)	(0.023)	(0.048)	(0.031)	(0.023)	(0.022)
ln(Jobs 60 minutes)	0.196***	0.052*	0.056**	0.007	0.216***	0.067**	0.067***	0.016
	(0.036)	(0.031)	(0.023)	(0.022)	(0.035)	(0.029)	(0.022)	(0.021)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.0618	-.0382	-.0978	.0761	.12	.0249	.0063
R-squared	0.209	0.363	0.538	0.732	0.219	0.385	0.550	0.738
N	518,071	518,071	518,069	504,583	518,071	518,034	518,033	504,541

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: Main Model Fixed Effects Sensitivity Test (SO_2) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(SO2, t-1)	0.033***	-0.002	-0.090***	-0.056***	0.092***	0.218***	0.060***	0.021***
	(0.011)	(0.009)	(0.005)	(0.004)	(0.012)	(0.015)	(0.011)	(0.007)
ln(Jobs 10 minutes)	0.047***	0.043***	0.031***	0.014***	0.046***	0.041***	0.031***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.084***	0.057***	0.028***	0.022***	0.085***	0.055***	0.028***	0.024***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.043***	0.037***	0.014**	0.016***	0.044***	0.037***	0.016**	0.019***
	(0.010)	(0.009)	(0.007)	(0.005)	(0.010)	(0.008)	(0.006)	(0.005)
ln(Jobs 40 minutes)	-0.029	-0.023	0.041***	0.028***	-0.036	-0.028	0.038***	0.023***
	(0.031)	(0.019)	(0.013)	(0.009)	(0.031)	(0.017)	(0.013)	(0.009)
ln(Jobs 50 minutes)	0.155***	0.093***	-0.001	0.013	0.125***	0.075**	-0.009	0.007
	(0.051)	(0.034)	(0.024)	(0.023)	(0.048)	(0.031)	(0.023)	(0.022)
ln(Jobs 60 minutes)	0.180***	0.047	0.058**	0.009	0.207***	0.066**	0.066***	0.016
	(0.037)	(0.032)	(0.023)	(0.022)	(0.035)	(0.030)	(0.022)	(0.021)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		-.0016	-.1066	-.174	.0953	.1126	.026	.0202
R-squared	0.208	0.362	0.538	0.732	0.218	0.382	0.550	0.738
N	518,071	518,071	518,069	504,583	518,071	518,034	518,033	504,541

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A6: Main Model Fixed Effects Sensitivity Test (NO_x) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(NOx, t-1)	0.001**	0.000	-0.001***	-0.002***	0.237***	0.390***	0.103***	-0.002
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.018)	(0.016)	(0.010)
ln(Jobs 10 minutes)	0.047***	0.043***	0.031***	0.014***	0.044***	0.039***	0.031***	0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.085***	0.057***	0.027***	0.021***	0.080***	0.051***	0.028***	0.024***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.044***	0.037***	0.014**	0.016***	0.041***	0.035***	0.016**	0.019***
	(0.010)	(0.009)	(0.007)	(0.005)	(0.010)	(0.008)	(0.006)	(0.005)
ln(Jobs 40 minutes)	-0.026	-0.023	0.042***	0.028***	-0.041	-0.025	0.038***	0.023***
	(0.032)	(0.019)	(0.013)	(0.009)	(0.031)	(0.018)	(0.013)	(0.009)
ln(Jobs 50 minutes)	0.166***	0.093***	0.001	0.017	0.096**	0.071**	-0.009	0.007
	(0.051)	(0.034)	(0.024)	(0.024)	(0.047)	(0.031)	(0.023)	(0.022)
ln(Jobs 60 minutes)	0.171***	0.048	0.055**	0.004	0.225***	0.072**	0.067***	0.016
	(0.039)	(0.032)	(0.023)	(0.023)	(0.034)	(0.029)	(0.022)	(0.021)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.061	-.2929	-1.117	.1086	.097	.0188	-.0009
R-squared	0.208	0.362	0.537	0.731	0.224	0.386	0.550	0.738
N	518,071	518,071	518,069	504,583	518,071	518,034	518,033	504,541

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Routine and Unauthorized Emissions Model, Homestead Sample, 2006-2018

	(1)	(2)	(3)	(4)
Unauthorized emissions				
ln(PM 2.5, t-1)				0.001
				(0.002)
ln(PM 10, t-1)			0.001	
			(0.002)	
ln(SO2, t-1)		-0.001		
		(0.002)		
ln(NOx, t-1)	-0.000			
	(0.001)			
Routine emissions				
ln(PM 2.5, t-1)				0.016
				(0.011)
ln(PM 10, t-1)			0.024^{**}	
			(0.012)	
ln(SO2, t-1)		0.013		
		(0.008)		
ln(NOx, t-1)	0.024^{*}			
	(0.013)			
Industrial Jobs				
ln(Jobs 10 minutes)	0.006^{***}	0.006^{***}	0.006^{***}	0.006^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.025^{***}	0.025^{***}	0.025^{***}	0.025^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 30 minutes)	0.004	0.004	0.004	0.004
	(0.010)	(0.010)	(0.010)	(0.010)
ln(Jobs 40 minutes)	0.042^{**}	0.041^{**}	0.042^{**}	0.042^{**}
	(0.019)	(0.019)	(0.019)	(0.019)
ln(Jobs 50 minutes)	0.031	0.031	0.031	0.031
	(0.040)	(0.040)	(0.040)	(0.040)
ln(Jobs 60 minutes)	0.032	0.033	0.032	0.033
	(0.051)	(0.051)	(0.051)	(0.051)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.775	0.775	0.775	0.775
N	192,351	192,351	192,351	192,351

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A8: Routine and Unauthorized Emissions Model Fixed Effects Sensitivity Test ($PM_{2.5}$) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Unauthorized PM 2.5, t-1)	0.007***	0.004***	-0.000	-0.002***	0.017***	-0.011***	0.003	-0.002
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)	(0.002)
ln(Routine PM 2.5, t-1)	0.145***	0.213***	0.025**	-0.027***	0.139***	0.301***	0.107***	0.015
	(0.015)	(0.013)	(0.011)	(0.007)	(0.014)	(0.017)	(0.017)	(0.010)
ln(Jobs 10 minutes)	0.045***	0.039***	0.030***	0.014***	0.045***	0.038***	0.030***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.077***	0.045***	0.024***	0.021***	0.077***	0.044***	0.024***	0.023***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.055***	0.038***	0.017**	0.018***	0.055***	0.038***	0.018***	0.020***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)
ln(Jobs 40 minutes)	-0.027	-0.009	0.043***	0.033***	-0.027	-0.011	0.041***	0.032***
	(0.034)	(0.020)	(0.014)	(0.011)	(0.035)	(0.019)	(0.013)	(0.011)
ln(Jobs 50 minutes)	0.102*	0.066*	-0.012	0.002	0.104*	0.061*	-0.013	0.005
	(0.054)	(0.034)	(0.023)	(0.026)	(0.054)	(0.033)	(0.023)	(0.027)
ln(Jobs 60 minutes)	0.197***	0.061**	0.068***	0.023	0.190***	0.064**	0.069***	0.018
	(0.038)	(0.031)	(0.022)	(0.025)	(0.038)	(0.030)	(0.021)	(0.025)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.1507	-.0003	-.4178	.035	-.0139	.0074	-.0132
R-squared	0.217	0.373	0.539	0.741	0.219	0.380	0.543	0.743
N	384,960	384,960	384,958	370,140	384,960	384,956	384,955	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A9: Routine and Unauthorized Emissions Model Fixed Effects Sensitivity Test (PM_{Large}) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Unauthorized Large PM, t-1)	0.009***	0.005***	0.000	-0.002***	0.028***	-0.009***	0.003	-0.002
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.003)	(0.002)	(0.002)
ln(Routine Large PM, t-1)	0.144***	0.237***	0.029***	-0.008	0.136***	0.345***	0.106***	0.017
	(0.016)	(0.014)	(0.011)	(0.007)	(0.016)	(0.017)	(0.019)	(0.011)
ln(Jobs 10 minutes)	0.045***	0.038***	0.030***	0.014***	0.045***	0.037***	0.030***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.077***	0.045***	0.024***	0.021***	0.077***	0.044***	0.024***	0.023***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.054***	0.037***	0.017**	0.018***	0.056***	0.037***	0.018**	0.020***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)
ln(Jobs 40 minutes)	-0.028	-0.008	0.043***	0.033***	-0.027	-0.010	0.042***	0.032***
	(0.034)	(0.020)	(0.014)	(0.011)	(0.035)	(0.019)	(0.013)	(0.011)
ln(Jobs 50 minutes)	0.099*	0.064*	-0.012	0.001	0.102*	0.058*	-0.013	0.005
	(0.054)	(0.033)	(0.023)	(0.026)	(0.054)	(0.032)	(0.023)	(0.027)
ln(Jobs 60 minutes)	0.200***	0.061**	0.068***	0.024	0.189***	0.066**	0.069***	0.018
	(0.038)	(0.030)	(0.022)	(0.025)	(0.038)	(0.030)	(0.022)	(0.025)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.2207	.0096	-.3993	.0631	-.0116	.008	-.0128
R-squared	0.216	0.373	0.539	0.741	0.220	0.381	0.543	0.743
N	384,960	384,960	384,958	370,140	384,960	384,956	384,955	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Routine and Unauthorized Emissions Model Fixed Effects Sensitivity Test (SO_2) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Unauthorized SO2, t-1)	0.016***	0.007***	0.000	-0.002***	0.101***	0.016***	0.002	-0.003*
	(0.001)	(0.001)	(0.000)	(0.000)	(0.004)	(0.003)	(0.002)	(0.002)
ln(Routine SO2, t-1)	0.073***	0.123***	0.009	0.010**	-0.007	0.205***	0.052***	0.013*
	(0.011)	(0.010)	(0.007)	(0.005)	(0.011)	(0.015)	(0.011)	(0.008)
ln(Jobs 10 minutes)	0.047***	0.041***	0.030***	0.014***	0.047***	0.040***	0.030***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.080***	0.048***	0.024***	0.021***	0.077***	0.047***	0.024***	0.023***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.056***	0.039***	0.017**	0.018***	0.060***	0.040***	0.018***	0.020***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)
ln(Jobs 40 minutes)	-0.023	-0.009	0.043***	0.033***	-0.011	-0.011	0.042***	0.032***
	(0.035)	(0.020)	(0.014)	(0.011)	(0.036)	(0.019)	(0.014)	(0.011)
ln(Jobs 50 minutes)	0.117**	0.067**	-0.012	0.002	0.149***	0.060*	-0.013	0.005
	(0.055)	(0.034)	(0.023)	(0.026)	(0.057)	(0.033)	(0.023)	(0.027)
ln(Jobs 60 minutes)	0.184***	0.058*	0.068***	0.023	0.103**	0.063**	0.068***	0.018
	(0.039)	(0.031)	(0.022)	(0.025)	(0.040)	(0.030)	(0.022)	(0.025)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.1837	.0009	-.2206	.1659	.0135	.003	-.0126
R-squared	0.217	0.371	0.539	0.741	0.230	0.378	0.543	0.743
N	384,960	384,960	384,958	370,140	384,960	384,956	384,955	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Routine and Unauthorized Emissions Model Fixed Effects Sensitivity Test (NO_x) 1998-2018

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ln(Unauthorized NOx, t-1)	0.011***	0.007***	0.000	-0.002***	0.026***	-0.001	0.001	-0.001
	(0.001)	(0.001)	(0.000)	(0.000)	(0.003)	(0.002)	(0.002)	(0.001)
ln(Routine NOx, t-1)	0.206***	0.259***	0.031***	-0.007	0.195***	0.388***	0.129***	0.020*
	(0.015)	(0.014)	(0.011)	(0.007)	(0.015)	(0.019)	(0.019)	(0.012)
ln(Jobs 10 minutes)	0.044***	0.039***	0.030***	0.014***	0.044***	0.038***	0.030***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.075***	0.045***	0.024***	0.021***	0.075***	0.043***	0.024***	0.023***
	(0.005)	(0.004)	(0.003)	(0.004)	(0.005)	(0.004)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.054***	0.037***	0.017**	0.018***	0.055***	0.037***	0.018***	0.020***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.010)	(0.008)	(0.007)	(0.006)
ln(Jobs 40 minutes)	-0.030	-0.008	0.043***	0.033***	-0.028	-0.009	0.042***	0.032***
	(0.034)	(0.020)	(0.014)	(0.011)	(0.035)	(0.019)	(0.013)	(0.011)
ln(Jobs 50 minutes)	0.093*	0.064*	-0.012	0.002	0.100*	0.057*	-0.013	0.005
	(0.053)	(0.034)	(0.023)	(0.026)	(0.053)	(0.032)	(0.023)	(0.027)
ln(Jobs 60 minutes)	0.202***	0.064**	0.068***	0.024	0.185***	0.070**	0.069***	0.018
	(0.037)	(0.030)	(0.022)	(0.025)	(0.037)	(0.030)	(0.021)	(0.025)
Area Fixed Effects	None	Parish	Tract	Block	None		Tract	Block
Time Fixed Effects	None	None	None	None	Year	Parish x Year	Parish x Year	Parish x Year
Oster delta		.2365	.0177	-.31	.0648	-.0009	.0014	-.0112
R-squared	0.221	0.374	0.539	0.741	0.224	0.381	0.543	0.743
N	384,960	384,960	384,958	370,140	384,960	384,956	384,955	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A12: Main Model, NO_x Lag Test

	(1)	(2)	(3)	(4)	(5)
ln(Total nitrogen oxides, t-1)	-0.000	0.003	0.003	0.004	0.004
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ln(Total nitrogen oxides, t-2)		-0.005	-0.001	0.000	-0.004
		(0.010)	(0.010)	(0.010)	(0.011)
ln(Total nitrogen oxides, t-3)			0.001	0.007	0.009
			(0.010)	(0.010)	(0.011)
ln(Total nitrogen oxides, t-4)				0.001	0.005
				(0.010)	(0.010)
ln(Total nitrogen oxides, t-5)					-0.014
					(0.010)
ln(Jobs within 30 minute drive, t-1)	0.068***	0.068***	0.068***	0.068***	0.068***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Block Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.737	0.738	0.738	0.739	0.739
N	504,541	495,922	486,362	476,695	465,335

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A13: Main Model, SO_2 Lag Test

	(1)	(2)	(3)	(4)	(5)
ln(Total sulfur dioxide, t-1)	0.021***	0.021***	0.021***	0.018***	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
ln(Total sulfur dioxide, t-2)		0.011	0.012*	0.014**	0.011
		(0.007)	(0.007)	(0.007)	(0.007)
ln(Total sulfur dioxide, t-3)			0.004	0.007	0.006
			(0.007)	(0.007)	(0.007)
ln(Total sulfur dioxide, t-4)				0.010	0.010
				(0.007)	(0.007)
ln(Total sulfur dioxide, t-5)					0.004
					(0.007)
ln(Jobs within 30 minute drive, t-1)	0.068***	0.068***	0.068***	0.068***	0.068***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Block Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.737	0.738	0.738	0.739	0.739
N	504,541	495,922	486,362	476,695	465,335

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Main Model, $PM_{2.5}$ Lag Test

	(1)	(2)	(3)	(4)	(5)
ln(Total PM 2.5, t-1)	0.013*	0.009	0.006	0.019*	0.020*
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)
ln(Total PM 2.5, t-2)		0.011	0.003	-0.001	0.016
		(0.008)	(0.008)	(0.008)	(0.010)
ln(Total PM 2.5, t-3)			-0.001	-0.009	-0.009
			(0.008)	(0.008)	(0.008)
ln(Total PM 2.5, t-4)				0.012	0.010
				(0.008)	(0.008)
ln(Total PM 2.5, t-5)					0.004
					(0.008)
ln(Jobs within 30 minute drive, t-1)	0.068***	0.069***	0.069***	0.070***	0.071***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Block Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.741	0.741	0.742	0.742	0.742
N	451,386	435,475	417,337	396,115	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A15: Main Model, Large Particulate Matter Lag Test

	(1)	(2)	(3)	(4)	(5)
ln(Total large particulate, t-1)	0.017*	0.015	0.015	0.013	0.011
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
ln(Total large particulate, t-2)		0.015	0.016	0.015	0.013
		(0.010)	(0.010)	(0.010)	(0.010)
ln(Total large particulate, t-3)			0.005	0.006	0.006
			(0.010)	(0.010)	(0.010)
ln(Total large particulate, t-4)				0.012	0.010
				(0.009)	(0.010)
ln(Total large particulate, t-5)					0.005
					(0.010)
ln(Jobs within 30 minute drive, t-1)	0.068***	0.068***	0.068***	0.068***	0.068***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Block Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.737	0.738	0.738	0.739	0.739
N	504,541	495,922	486,362	476,695	465,335

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A16: ln(Number of Parcels Sold) Lag Test (PM 2.5)

	(1)	(2)	(3)	(4)	(5)
	t-1	t-2	t-3	t-4	t-5
ln(PM 2.5)	-0.200***	-0.205***	-0.206***	-0.204***	-0.201***
	(0.063)	(0.064)	(0.064)	(0.064)	(0.064)
ln(Industrial Jobs)	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.414	0.396	0.383	0.373	0.368
N	11,328	10,689	10,033	9,357	8,673

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A17: ln(Number of Parcels Sold) Lag Test (Large Particulate Matter)

	(1)	(2)	(3)	(4)	(5)
	t-1	t-2	t-3	t-4	t-5
ln(Large particulate)	-0.222***	-0.220***	-0.228***	-0.230***	-0.231***
	(0.068)	(0.067)	(0.068)	(0.069)	(0.069)
ln(Industrial Jobs)	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.466	0.466	0.467	0.461	0.454
N	14,061	14,061	14,061	13,569	13,075

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A18: ln(Number of Parcels Sold) Lag Test (Nitrogen Oxides)

	(1)	(2)	(3)	(4)	(5)
	t-1	t-2	t-3	t-4	t-5
ln(Nitrogen Oxides)	-0.224***	-0.210***	-0.211***	-0.220***	-0.238***
	(0.067)	(0.067)	(0.068)	(0.068)	(0.070)
ln(Industrial Jobs)	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.467	0.468	0.467	0.471	0.466
N	13377.000	13366.000	13358.000	13339.000	12846.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A19: ln(Number of Parcels Sold) Lag Test (Sulfur Dioxide)

	(1)	(2)	(3)	(4)	(5)
	t-1	t-2	t-3	t-4	t-5
ln(Sulfur Dioxide)	-0.045	-0.039	-0.047	-0.063	-0.073
	(0.059)	(0.058)	(0.059)	(0.059)	(0.060)
ln(Industrial Jobs)	0.002	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.458	0.458	0.458	0.458	0.453
N	14061.000	14061.000	14061.000	14061.000	13569.000

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A20: Main Model Test: Pre Katrina, 1998-2004

	(1)	(2)	(3)	(4)
ln(Particulate matter 2.5, t-1)				0.009
				(0.056)
ln(Large particulate, t-1)			-0.021	
			(0.028)	
ln(Sulfur dioxide, t-1)		-0.015		
		(0.018)		
ln(Nitrogen oxides, t-1)	-0.035			
	(0.029)			
ln(Jobs 10 minutes)	0.017***	0.017***	0.017***	0.009**
	(0.003)	(0.003)	(0.003)	(0.004)
ln(Jobs 20 minutes)	0.034***	0.034***	0.034***	0.037***
	(0.010)	(0.010)	(0.010)	(0.012)
ln(Jobs 30 minutes)	0.030***	0.030***	0.030***	0.055**
	(0.010)	(0.010)	(0.010)	(0.022)
ln(Jobs 40 minutes)	0.000	0.000	0.000	-0.030
	(0.020)	(0.020)	(0.020)	(0.026)
ln(Jobs 50 minutes)	-0.031	-0.031	-0.031	-0.002
	(0.031)	(0.031)	(0.031)	(0.038)
ln(Jobs 60 minutes)	0.044*	0.043*	0.043*	0.033
	(0.026)	(0.026)	(0.026)	(0.040)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.782	0.782	0.782	0.814
N	73,415	73,415	73,415	22,866

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A21: Main Model Test: Post Katrina, 2007-2018

	(1)	(2)	(3)	(4)
ln(Particulate matter 2.5, t-1)				0.015
				(0.010)
ln(Large particulate, t-1)			0.017	
			(0.011)	
ln(Sulfur dioxide, t-1)		0.013^{*}		
		(0.008)		
ln(Nitrogen oxides, t-1)	0.020^{*}			
	(0.012)			
ln(Jobs 10 minutes)	0.014^{***}	0.014^{***}	0.014^{***}	0.014^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.023^{***}	0.023^{***}	0.023^{***}	0.023^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.020^{***}	0.020^{***}	0.020^{***}	0.020^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
ln(Jobs 40 minutes)	0.032^{***}	0.032^{***}	0.032^{***}	0.032^{***}
	(0.011)	(0.011)	(0.011)	(0.011)
ln(Jobs 50 minutes)	0.005	0.005	0.005	0.005
	(0.027)	(0.027)	(0.027)	(0.027)
ln(Jobs 60 minutes)	0.018	0.018	0.018	0.018
	(0.025)	(0.025)	(0.025)	(0.025)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.743	0.743	0.743	0.743
N	370,134	370,134	370,134	370,134

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A22: Main Model Test: Drop New Orleans Area, 1998-2018

	(1)	(2)	(3)	(4)
ln(Particulate matter 2.5, t-1)				0.002
				(0.009)
ln(Large particulate, t-1)			0.011	
			(0.011)	
ln(Sulfur dioxide, t-1)		0.022***		
		(0.007)		
ln(Nitrogen oxides, t-1)	-0.018			
	(0.011)			
ln(Jobs 10 minutes)	0.018***	0.018***	0.018***	0.018***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.025***	0.025***	0.025***	0.024***
	(0.004)	(0.004)	(0.004)	(0.003)
ln(Jobs 30 minutes)	0.018***	0.018***	0.018***	0.018***
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 40 minutes)	0.025**	0.025***	0.025***	0.026**
	(0.010)	(0.010)	(0.010)	(0.010)
ln(Jobs 50 minutes)	-0.011	-0.011	-0.011	-0.010
	(0.023)	(0.023)	(0.023)	(0.024)
ln(Jobs 60 minutes)	0.038*	0.038*	0.038*	0.040*
	(0.020)	(0.020)	(0.020)	(0.022)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.741	0.741	0.741	0.743
N	397,349	397,349	397,349	355,947

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A23: Parcels Sold By Census Tract, Pre-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.268***
				(0.069)
ln(Large Particulate, t-1)			-0.246***	
			(0.067)	
ln(Sulfur Dioxide, t-1)		-0.088		
		(0.058)		
ln(Nitrogen Oxides, t-1)	-0.236***			
	(0.068)			
ln(Industrial Jobs)	0.004	0.004	0.004	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.444	0.439	0.447	0.489
N	4,028	4,028	4,028	1,295

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A24: Parcels Sold By Census Tract, Post-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.214***
				(0.068)
ln(Large Particulate, t-1)			-0.212***	
			(0.071)	
ln(Sulfur Dioxide, t-1)		-0.022		
		(0.062)		
ln(Nitrogen Oxides, t-1)	-0.216***			
	(0.071)			
ln(Industrial Jobs)	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.368	0.359	0.369	0.370
N	8,673	8,673	8,673	8,673

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A25: Parcels Sold For Less Than $30,000 By Census Tract, Pre-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.229***
				(0.066)
ln(Large Particulate, t-1)			-0.264***	
			(0.058)	
ln(Sulfur Dioxide, t-1)		-0.170***		
		(0.051)		
ln(Nitrogen Oxides, t-1)	-0.275***			
	(0.068)			
ln(Industrial Jobs)	0.011***	0.012***	0.011***	0.010***
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.412	0.407	0.414	0.446
N	3,521	3,521	3,521	1,168

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A26: Parcels Sold For Less Than $30,000 By Census Tract, Post-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				-0.211***
				(0.052)
ln(Large Particulate, t-1)			-0.244***	
			(0.054)	
ln(Sulfur Dioxide, t-1)		-0.167***		
		(0.047)		
ln(Nitrogen Oxides, t-1)	-0.260***			
	(0.059)			
ln(Industrial Jobs)	0.011***	0.011***	0.011***	0.011***
	(0.002)	(0.002)	(0.002)	(0.002)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.422	0.417	0.423	0.420
N	8,121	8,121	8,121	8,121

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A27: Parcels Sold for $200,000 Or More By Census Tract, Pre-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				0.074
				(0.084)
ln(Large Particulate, t-1)			0.054	
			(0.062)	
ln(Sulfur Dioxide, t-1)		0.116		
		(0.077)		
ln(Nitrogen Oxides, t-1)	0.102			
	(0.071)			
ln(Industrial Jobs)	0.006	0.005	0.006	0.009*
	(0.004)	(0.005)	(0.004)	(0.005)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.212	0.214	0.209	0.255
N	905	905	905	343

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A28: Parcels Sold For \$200,000 Or More By Census Tract, Post-Katrina

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				0.048
				(0.057)
ln(Large Particulate, t-1)			0.075	
			(0.059)	
ln(Sulfur Dioxide, t-1)		0.160^{**}		
		(0.072)		
ln(Nitrogen Oxides, t-1)	0.154^{**}			
	(0.062)			
ln(Industrial Jobs)	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
Tract Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	No	No	No	No
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
R-squared	0.215	0.217	0.212	0.211
N	3,799	3,799	3,799	3,799

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A29: Main Model Test: Curb Appeal

	(1)	(2)	(3)	(4)
ln(Particulate Matter 2.5, t-1)				0.011
				(0.008)
ln(Large particulate, t-1)			0.015	
			(0.010)	
ln(sulfur dioxide, t-1)		0.021***		
		(0.007)		
ln(Nitrogen oxides, t-1)	-0.002			
	(0.010)			
ln(Jobs 10 minutes)	0.015***	0.015***	0.015***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)
ln(Jobs 20 minutes)	0.024***	0.024***	0.024***	0.023***
	(0.003)	(0.003)	(0.003)	(0.003)
ln(Jobs 30 minutes)	0.019***	0.019***	0.019***	0.020***
	(0.005)	(0.005)	(0.005)	(0.005)
ln(Jobs 40 minutes)	0.023***	0.023***	0.023***	0.023**
	(0.009)	(0.009)	(0.009)	(0.009)
ln(Jobs 50 minutes)	0.007	0.007	0.007	0.012
	(0.022)	(0.022)	(0.022)	(0.024)
ln(Jobs 60 minutes)	0.016	0.016	0.016	0.014
	(0.021)	(0.021)	(0.021)	(0.024)
Facility within 0.5 miles	-0.038	-0.038	-0.038	-0.040
	(0.029)	(0.029)	(0.029)	(0.031)
Block Fixed Effects	Yes	Yes	Yes	Yes
Year X Parish Fixed Effects	Yes	Yes	Yes	Yes
Oster delta	-.0007	.0155	.0048	.0043
R-squared	0.738	0.738	0.738	0.741
N	504,541	504,541	504,541	451,386

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

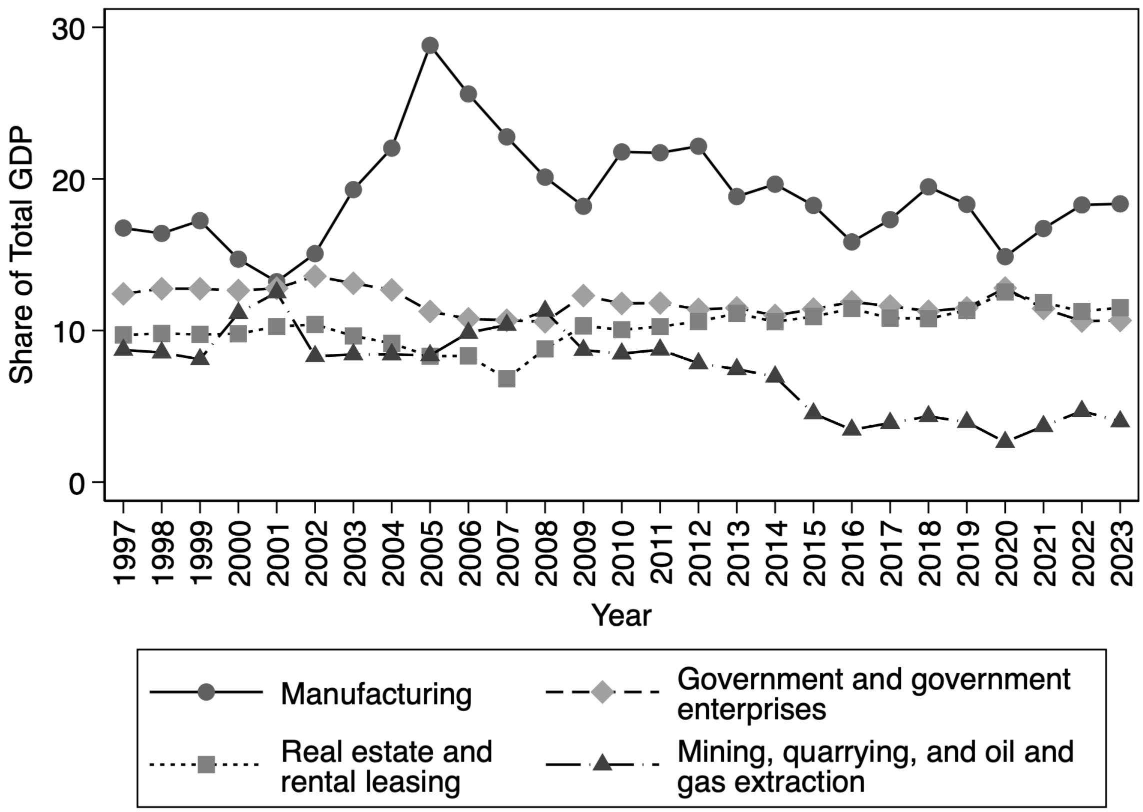


Figure A1: Louisiana GDP By Top 2-Digit NAICS Sectors

Note: Figure shows Louisiana's top sources of GDP by 2-digit NAICS sector as a percentage of total Louisiana GDP that year, using GDP data from the Bureau of Economic Analysis (BEA) Regional Economic Accounts.

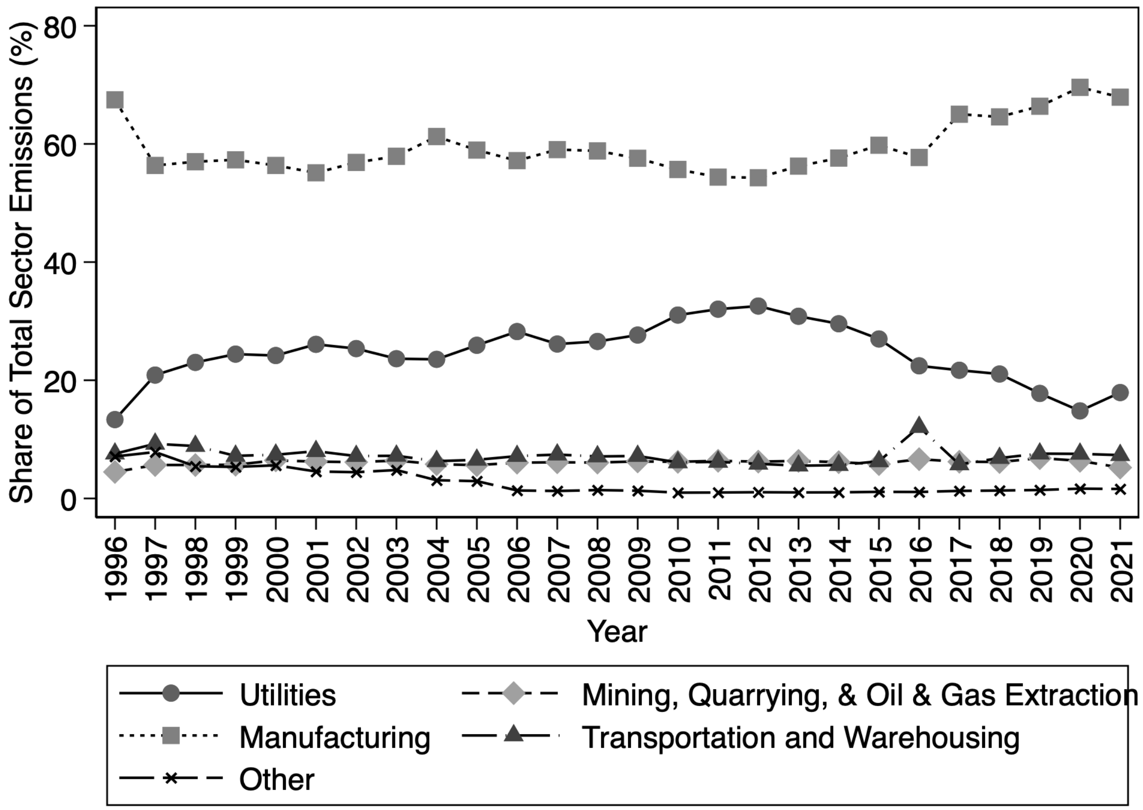


Figure A2: Total Louisiana Emissions By Top 2-Digit NAICS Sectors

Note: Figure shows which industry sectors are responsible for most of Louisiana's industrial pollution over time. The figure is constructed by summing up the total mass of emissions (of all pollutants) tracked in the LDEQ ERIC database each year by the 3-digit NAICS code of each facility in the data and divides by the sum total of emissions from all industries in each year.

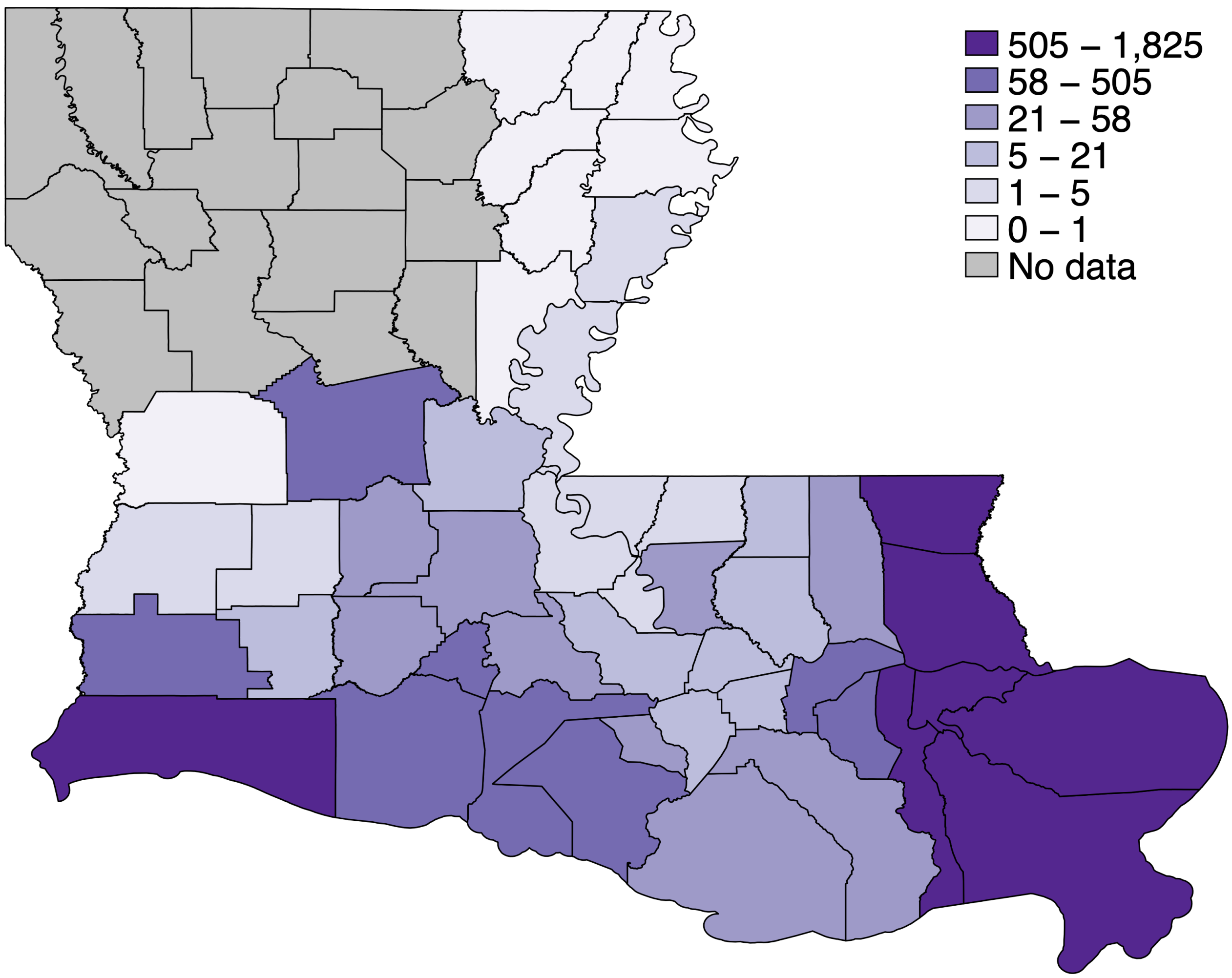


Figure A3: Total Hurricane Property Damage ($ Millions) by Parish, 1994-2018

Note: Total hurricane property damage from 1994 to 2018 by National Weather Service (NWS) forecast zone (summed to Parish level). Estimates of real property damage, deflated by South shelter CPI with a 1982-1984 base year.

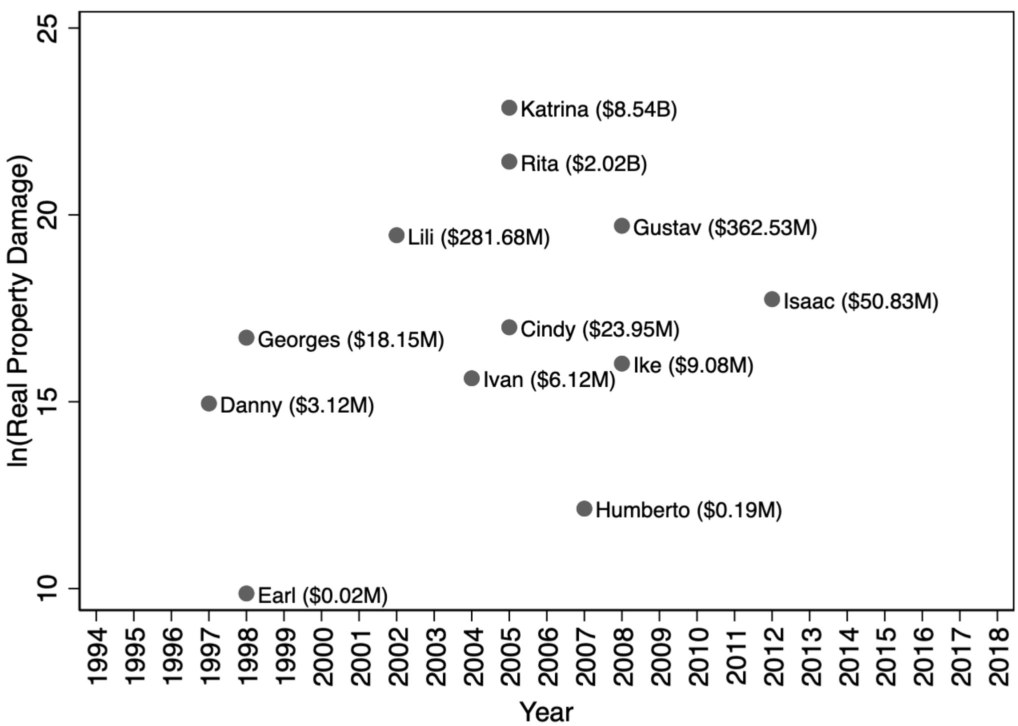


Figure A4: Total Hurricane Property Damage ($ Millions) by Storm, 1994-2018

Note: Total hurricane property damage from 1994 to 2018 by storm (summed to State level). Estimates of real property damage, deflated by South shelter CPI with a 1982-1984 base year.

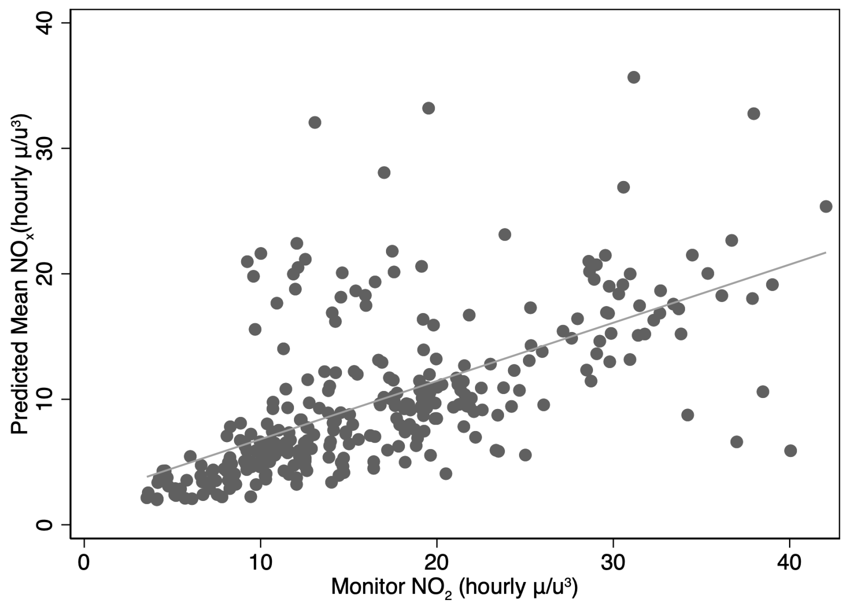


Figure A5: Predicted Nitrogen Oxides (NOx) vs Nitrogen Dioxide Monitors, 1994-2018

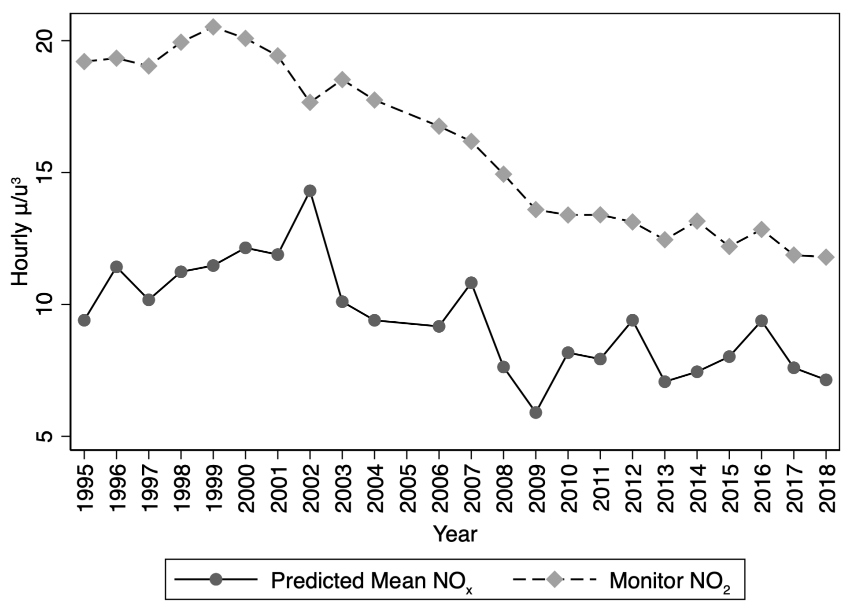


Figure A6: Predicted State Mean Nitrogen Oxides (NOx) vs Nitrogen Dioxide (NO2) Monitors, 1994-2018

Note: HYSPLIT predicted concentration of industrial nitrogen oxides at the coordinate location of a pollution monitor versus nitrogen dioxide monitor readings.

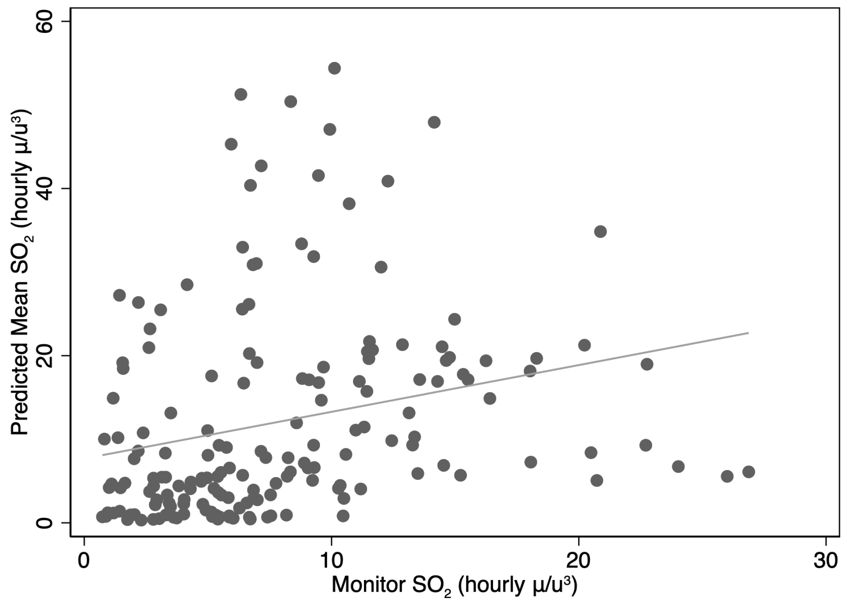


Figure A7: Predicted Sulfur Dioxide (SO2) vs SO2 Monitors, 1994-2018

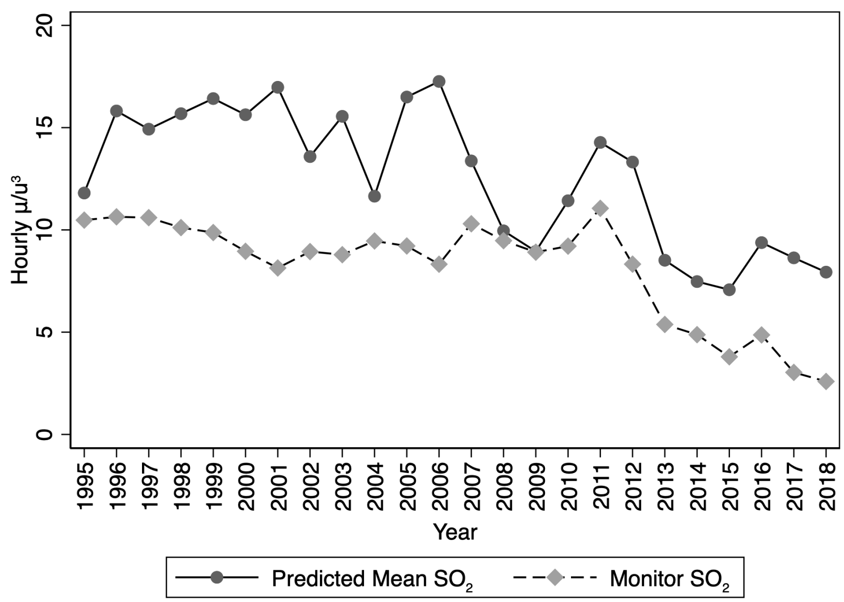


Figure A8: Predicted State Mean Sulfur Dioxide (SO2) vs SO2 Monitors, 1994-2018

Note: HYSPLIT predicted concentration of industrial sulfur dioxide at the coordinate location of a pollution monitor versus sulfur dioxide monitor readings.

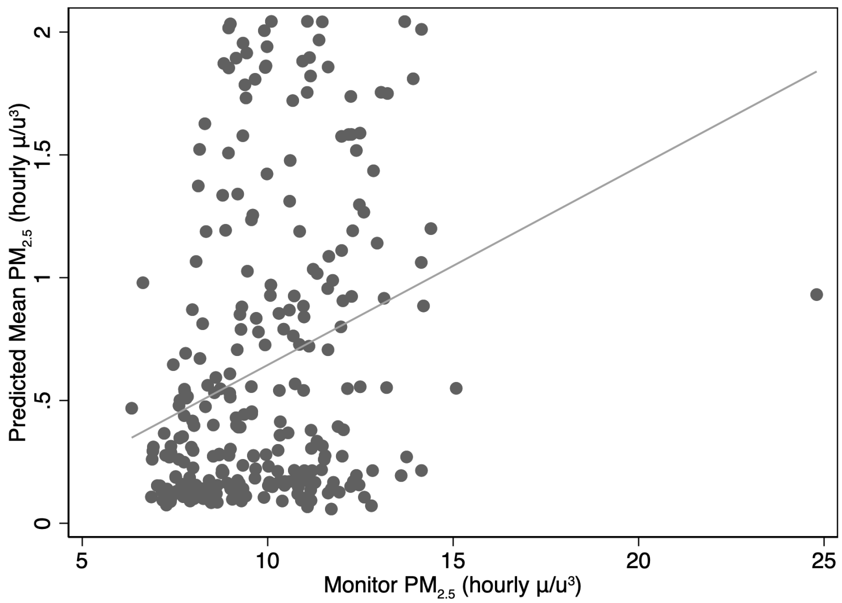


Figure A9: Predicted PM 2.5 vs PM 2.5 Monitors, 2002-2018

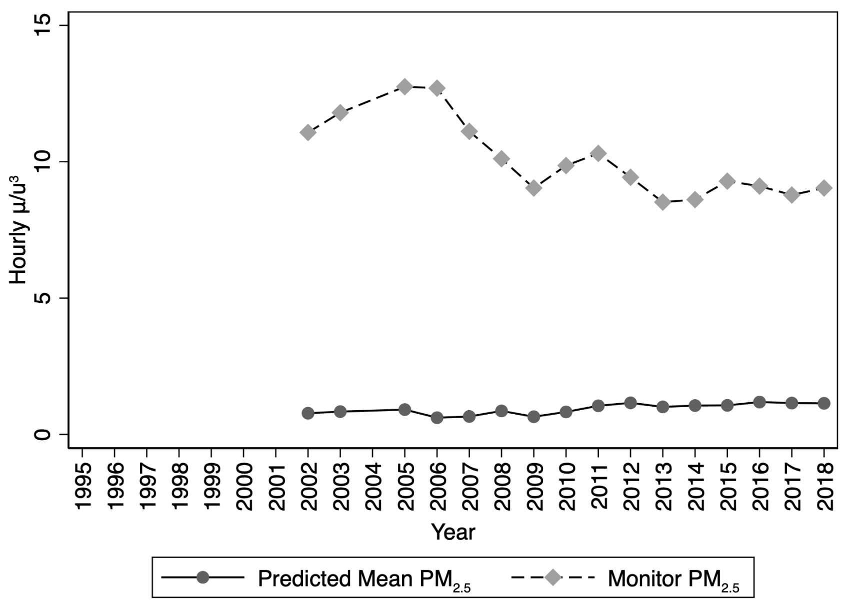


Figure A10: Predicted State Mean PM 2.5 vs PM 2.5 Monitors, 2002-2018

Note: HYSPLIT predicted concentration of industrial PM 2.5 at the coordinate location of a pollution monitor versus PM 2.5 monitor readings.

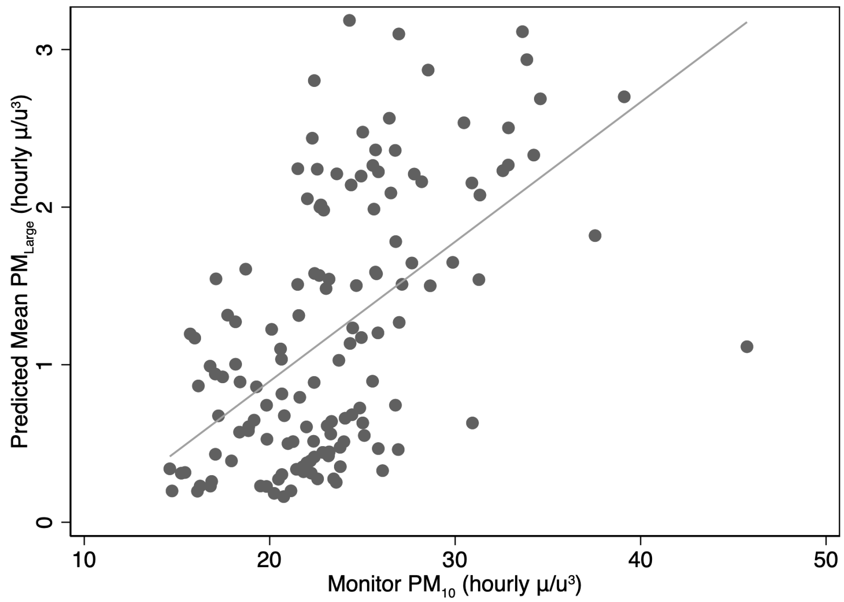


Figure A11: Predicted PM 10 vs PM 10 Monitors, 1994-2018

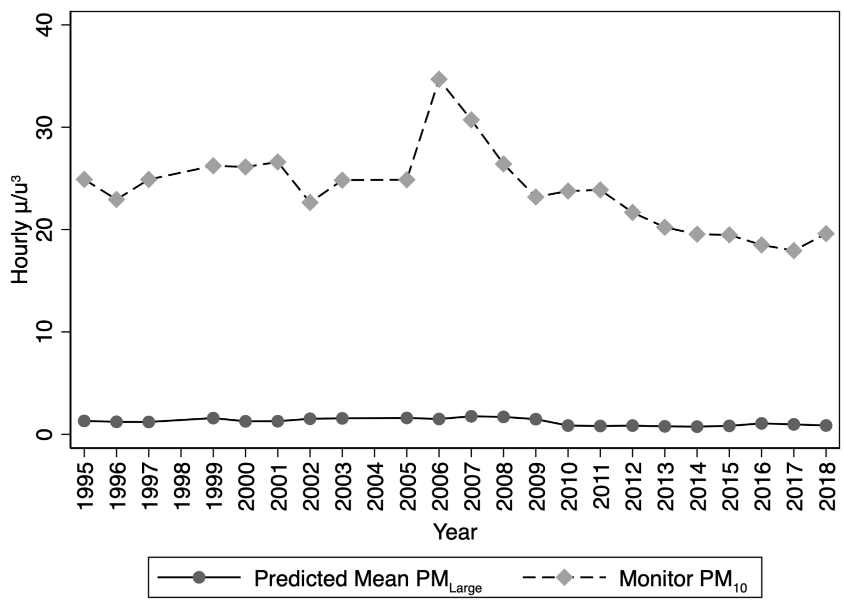


Figure A12: Predicted State Mean PM 10 vs PM 10 Monitors, 1994-2018

Note: HYSPLIT predicted concentration of industrial large particulate matter at the coordinate location of a pollution monitor versus PM 10 readings (almost all large particulate matter is PM 10).