College of Business
and Public Policy
UNIVERSITY of ALASKA ANCHORAGE

Department of Economics Working Paper
WP 2020-01
March 2020

The Coal-to-Gas Fuel Switching and its Effects on Housing Prices

Nathaly M. Rivera
University of Alaska Anchorage

Scott Loveridge
Michigan State University

UAA DEPARTMENT OF ECONOMICS
3211 Providence Drive
Rasmuson Hall 302
Anchorage, AK 99508

http://econpapers.uaa.alaska.edu/

The Coal-to-Gas Fuel Switching and its Effects on Housing Prices*

Nathaly M. Rivera† Scott Loveridge

This version: March 2020

Abstract

We derive causal property value impacts of the coal-to-gas fuel switching conversion implemented by several power plants in the United States. We use an extensive dataset of property transactions around the country and adopt several spatial difference-in-difference approaches that use records of residential property transactions of homes with wind exposure and proximity to the switching plants before and after the switch. A triple-differences control function estimator using coal-fired plants that did not innovate strengthens these estimations. Our results indicate that the shutdown of coal-fired generators increases property values of downwind homes by 15% in the immediate vicinity of fuel-switching plants ($\leq$ 1.2mi), which brings to light the strong disamenity effect of coal-fired power plants. Our back-of-the-envelope calculations suggest that the fuel switching led to a $1.78 billion-increase in property values around the country.

Keywords: Fossil Fuels, Fuel Switching, Environmental Quality, Housing Market, Environmental Valuation, Hedonic Models

JEL Classification: D62, L94, Q51, Q53

*Rivera is in the Department of Economics at University of Alaska Anchorage. Loveridge is in the Department of Agricultural, Food, and Resource Economics at Michigan State University. We thank to the Zillow Group for granting us access to the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the authors and do not reflect the position of Zillow Group. We thank to Joseph Herriges, Satish Joshi, and Frank Lupi for their comments to an earlier version of this draft. We also thank to the members of Department of Economics at the University of Alaska Anchorage, to André Albuquerque, Alexander James, Shanjun Li, Brett Watson, Ralph Winkler, and to participants of the 24th European Association of Environmental and Resource Economist and the 7th Economics of Low-Carbon Markets. All errors are ours.

†Corresponding author. ✉: nmrivera@alaska.edu

1. Introduction

The recent increase in the natural gas supply due to the advance in hydraulic fracking led power companies in the United States to increase their share of natural gas-fired power generation in lieu of coal-fired generation. As natural gas burns cleaner than coal, this coal-to-gas conversion led to an improvement of environmental quality at both a global and a local scale, through reduction in greenhouse gas emissions and lower discharge of local airborne pollutants, respectively (Linn et al., 2014; Holland et al., 2018; Linn and Muehlenbachs, 2018; Johnsen et al., 2019).[1] To the extent that households benefit from cleaner air through the possibility of better health, clearer views, and more enjoyment from outdoor activities (Grainger, 2012), the use of a cleaner fuel is expected to be capitalized into the price of residential properties that benefit from the air quality improvement increasing thus households' welfare.

In this paper, we shed light on the previous idea by studying the causal impact that the coal-to-gas fuel switching process carried out by the U.S. power sector had on property values of residential homes located in the immediate vicinity of the switching facilities.[2] To carry out our goal, we use a hedonic price model to estimate households' willingness to pay for a local air quality improvement. We identify several power stations that, between 2009 and 2018, switched their primary fuel from coal to natural gas by incorporating new generation units into their plants. Later, we match them to an extensive dataset of residential property transactions using the stations' geographical location. Our final dataset includes 10 coal-to-gas power plants and more than 300,000 properties throughout the country, which gives us enough variation to control for potential spatial macroeconomic effects affecting housing prices (Muehlenbachs et al., 2015).

For identification, we exploit the temporal and regional variation in the timing of the fuel switching. In our baseline specification, we estimate a hedonic price model in differences that compares sale prices between properties that are located near or downwind from the switching plants, and properties that are located farther away or upwind from these facilities, before and after the switching. To account for the broad set of negative externalities from the coal-fired generation (Davis, 2011) and separate out the effect of air pollution from

[1] Emissions leakages from transmission and distribution pipelines could undermine some of the benefits (in terms of reduced emissions) that burning natural gas has on the environment. The drilling and extraction of natural gas from wells, and its transportation in pipelines results in leakage of methane, a greenhouse gas that is roughly 30 times stronger than CO_2 at trapping heat in the atmosphere. Evidence shows that this leakage can reach up to 9% of this fuel total life-cycle emission (Tollefson, 2013). Notwithstanding, life-cycle greenhouse gas emissions of natural gas have been shown to be lower relative to the diesel and coal combustion (Jaramillo et al., 2007; Burnham et al., 2011).

[2] We use the terms "coal-to-gas", "fuel switching" and "treated" power plants interchangeably throughout the paper.

other disamenity effects, we estimate additional specifications using homes in the vicinity of coal-fired power plants that did not switch as an additional control set. We enhance these estimations with two triple-differences designs that combine the two previous sources of variation. Since there could be omitted variables common to neighborhoods that host coal-to-gas-fired plants, we estimate our main equations with an instrumental variable approach that uses a control function estimator. Through all the specifications, we distinguish between the time of shutdown of the first coal-fired generators and the startup of new gas-fired units.

Our empirical exercise provides strong indications of a positive welfare impact of the coal-to-gas power plant conversion process in the immediate vicinity of these switching stations. Findings from our main and preferred double-differences specification using wind exposure suggest that shutting down coal-fired generators increases the value of downwind properties by roughly 15 percent in the immediate vicinity of these plants ($\leq$ 1.2mi or 2km). This effect increases in magnitude when properties in the neighborhood of coal-fired-non-switching facilities are used as controls. Results from our main triple-differences estimator that combines these two differentials indicate a 37 percent price increase, on average, for residential homes within 1.2 miles of the switching plants after the shutdown of coal-fired generators and relative to homes around coal-fired-non-switching plants. These effects increase in magnitude after startup of gas-fired generators, which is in line with many of these fuel-switching plants shutting down additional generators and expanding their capacity over time, which adds an extra boost to the local economy. Our back-of-the-envelope calculations using our preferred and conservative estimation suggest that the coal-to-gas fuel switching led to a $1.78-billion property value gain in the immediate vicinity of the fuel-switching plants.

Our work makes several contributions to the existing literature. First, it adds to the rich body of studies on the property value impacts of proximity to disamenities in general (Kohlhase, 1991; Mendelsohn et al., 1992; Greenstone and Gallagher, 2008; Gamper-Rabindran and Timmins, 2013; Kiel and McClain, 1995a,b), and power plants in particular (Blomquist, 1974; Gamble and Downing, 1982; Davis, 2011; Hodge, 2011a; Deng et al., 2014; Currie et al., 2015; Farah et al., 2019). Our contribution is to particularly study the case of the coal-to-gas fuel conversion, filling in the gap on the spillover effects of technology innovations in the electric sector on the residential housing market. In this conceptual sense, our study is close to the work by Farah et al. (2019)) on the impact of the coal-switching on residential properties in the Appalachian region. Yet, we expand Farah et al. (2019)'s analysis to the entire country, providing a more comprehensive overview of the fuel switching phenomenon in the United States. Additionally, our results are informative of the fuel switching impact at the extensive margin, as we center the analysis around plants running with coal at first and switching later to (new) gas-fired generators, instead of looking at the relative share in the use of these fuels. In doing so, we document property price capitalizations due to the fuel-switching that come from a long-term innovation with lasting consequences on the environment as opposed to a temporary effect. Finally, our work also expands on the recent literature regarding the benefits that the increase in the natural gas supply has on air quality (e.g. Linn et al. (2014); Linn and Muehlenbachs (2018); Johnsen et al. (2019)), electricity prices (Linn et al., 2014; Linn and Muehlenbachs, 2018), as well as wage rates and housing prices (Jacobsen, 2019). Our findings represent additional evidence on some of the indirect non-market benefits of the energy boom in the U.S.

The remainder of this work proceeds as follows. Section 2 briefly discusses the analytical framework, while Section 3 documents the data. Section 4 presents the empirical strategy and Section 5 the main results. Section 6 concludes.

2. Analytical Framework

In this paper, we use the hedonic price model to elicit average marginal willingness-to-pay measures for a nonmarginal improvement in local air quality due to the fuel switching. Studies that apply hedonic price modeling to associate housing prices and quantities of environmental quality date back to Ridker (1967) and Ridker and Henning (1967), under the reasoning that the value of a house can be considered a function of its characteristics, such as structural, neighborhood, and environmental characteristics (Freeman, 1979).[3] This section briefly describes the hedonic price method and its implications when evaluating a local improvement in an environmental amenity. The model anticipates that housing prices increase in response to an increase in environmental quality.

The hedonic price theory considers that an item h can be valued by a vector z of characteristics $(z_1, z_2, ..., z_j)$, including local environmental quality. The price of house h can be considered as the sum of each of its homogeneous attributes in a price function, P_h, described as follows:

$$P_h(z) = P(z_1, z_2, ..., z_j). \tag{1}$$

This function $P_h(z)$ is referred to as the hedonic price function and indicates the amount that an individual must pay for a bundle with characteristics z. The partial derivative of $P_h(\cdot)$ with respect to z_j, $\partial P_h(\cdot)/\partial z_j$, gives the marginal implicit price of characteristic z_j. Utility-maximizing individuals derive at the same time utility from housing item h. In the housing market equilibrium arising from the interactions of buyers and sellers, individuals'

[3]For a more comprehensive review of hedonic price applications, see Mendelsohn and Olmstead (2009) and Freeman III et al. (2014).

marginal willingness to pay (WTP) for characteristic z_j equals the marginal implicit price of that characteristic.

Rosen (1974) distinguishes the price hedonic function $P_h(z)$ from the bid function $\theta_i = \theta(M, z_j, z_{-j}, u^*)$, which represents what an individual i is willing to pay for different values of characteristic z_j, holding income M, other characteristics z_{-j}, and utility constant at a level u^*. Heterogeneous individuals' preferences and income lead to different bid functions, and so to different chosen quantities of characteristic z_j. The relationship between the hedonic price function $P_h(z)$, and the bid functions θ_1 and θ_2 for individuals 1 and 2, respectively, for characteristic z_j is depicted in Figure 1.

[INSERT FIGURE 1 ABOUT HERE]

Suppose z_j is a measure of local environmental quality. Figure 1 shows that both bid functions exhibit diminishing marginal willingness to pay for z_j, and that given the hedonic price function, individuals 1 and 2 choose levels of environmental quality where their marginal WTP for z_j equals the marginal implicit price determined by the hedonic price function at $z_j^{'}$ and $z_j^{''}$, respectively. Given the market equilibrium, individuals' utilities would be lower at sites with higher or lower levels of environmental quality.

Now, consider that the coal-to-gas conversion process improves air quality in a neighborhood from $z_j^{'}$ to $z_j^{''}$.[4] From Figure 1, this non-marginal change is expected to increase the price of house h. For individual 1, originally consuming $z_j^{'}$, the new price for environmental quality exceeds her/his WTP for the air quality amenity. This individual can decide to relocate to a place with lower air quality and restore the equilibrium, or to stay, in which case she/he would be better off due to an increase in wealth. If the individual relocates, the welfare effect of the nonmarginal change in z_j comes from the gain to the new individual that locates in the neighborhood experiencing the amenity enhancement, represented by her WTP for an air quality improvement. If the individual stays, the welfare effect is the change in wealth experienced by the homeowner individual. The implied change in total welfare from an air quality improvement, therefore, can be obtained by multiplying the observed equilibrium price differential due to the coal-to-gas conversion by the number of local residential housing units affected by this conversion.

[4] To establish welfare effects of this non-marginal change in air quality from $z_j^{''}$ to $z_j^{'}$, we assume that the change is a localized change (Palmquist, 1992), and therefore, the hedonic price function does not shift in response to this change. This is a valid assumption as the number of counties that we study only represents a small portion of the entire U.S. housing market (see Section 3). Hence, any air quality improvement in these counties is not enough to force a significant relocation of individuals that could lead to a new hedonic price equation.

3. Data

3.1 Power Plants

Data on electricity generation units (EGUs) come from the Annual Electric Generator Reports (Form EIA-860), compiled by the Energy Information Administration (EIA). This survey data contains annual information on existing and planned generator units that belong to medium and large-scale power plants with generation capacity equal or higher than 1 MW.[5] From this survey, we consider EGUs capacity, age, primary technology, and primary fuel type, among other features. A key feature in establishing accurate market effects of the fuel switching is the geographical location of the switching stations. The EIA-860 form reports the geo-location of each power plant in the U.S. since 2009, which is the primary reason to study the period between 2009 and 2018.[6]

Power plants generally operate with more than one EGU and, depending on their combustion technology, can have several boilers (Ummel, 2012). This complexity challenges the plant classification as EGUs can run with more than one fuel source. Thus, to identify the stations that switched from coal to natural gas in at least one of their generators, we classify the EGUs by their primary technology and their primary fuel source. We identify those proposed gas-fired EGUs from the set of "proposed EGUs" during 2009 and 2018 that were expected to run with natural gas (or blast furnace gas or other gas) as their primary fuel. This leads us with 1,141 proposed gas-fired EGUs located in 368 different power stations across the country. The spatial location of the power stations with at least one proposed new gas-fired EGU is displayed in the top panel of Figure 2.

[INSERT FIGURE 2 ABOUT HERE]

Though the proposed gas-fired EGUs were expected to start power generation during the study period, it is not certain that they were in fact operating, or that they are actually planned to replace old coal-fired EGUs. To solve this, we first identify the set of proposed gas-fired EGUs that were effectively generating electricity during 2009-2018 by matching them to gas-fired units in operation. In this process, we dismiss all generators running with primary fuels other than natural gas (or blast furnace gas or other gas), and then discard all the plants that during the study period report to have generators with a status other than "in operation" as a manner of avoiding that factors other than fuel switching could confound

[5] Further information on the Form EIA-860 and the public data available at Form EIA-860's website: https://www.eia.gov/electricity/data/eia860/.

[6] Another reason for selecting 2009 as the starting period is to minimize the effects of the subprime mortgage crisis and subsequent recession.

the analysis.[7] The resulting dataset corresponds to the set of power plants continuously in operation with at least one new gas-fired EGU generating power in 2009 or afterwards.

We use a similar procedure to identify the set of retired coal-fired generators. From the set of "retired EGUs", we identify the units for which coal, or any of its derivatives, is listed as their primary fuel source.[8] This leads us to 518 retired coal-fired EGUs in 232 plants across the country, whose location is displayed in the bottom panel of Figure 2. We match these EGUs to the set of coal-fired operable units to identify the exact time of retirement. Here, we dismiss all the generators that during 2009 and 2018 report primary fuels other than coal (or its derivatives), and then we rule out plants that over time report their generators with a status other than "in operation". The final dataset contains all the power stations that, between 2009 and 2018, retired at least one coal-fired EGU in continuous operation prior to the retirement. As a final step, we put together the set of plants with new gas-fired generators and the set of plants with retired coal-fired generators. The results is a set of 10 plants in the states of Colorado, Georgia, Indiana, Minnesota, North Carolina, Pennsylvania, and South Carolina, as shown in Figure 3. Table 1 displays the list of these fuel-switching plants (or "treated" plants), including the stations' names, their location, and the number of new EGUs introduced. This Table displays the timing of the switching as well, which we define as follows: (1) the year in which the coal-to-gas plants shutdown the first coal-fired generator, and (2) the year in which they put the first gas-fired unit into operation.

[INSERT FIGURE 3 ABOUT HERE]

[INSERT TABLE 1 ABOUT HERE]

3.2 Emission Data

Information on emissions from power plants come from the Form EIA-923 from the EIA as well. This survey is an operation report that contains plant-level detailed information such as plants' generation, fuel consumption, fossil fuel stocks, and emissions. We specifically use the annual schedules 8A-F on nitrogen dioxides (NO_X) emission rates at the plant-level.[9]

[7] Other status are "temporary out of service" or "stand by".

[8] Coal derivatives refer to anthracite coal, bituminous coal, lignite coal, coal-derived synthesis gas, sub-bituminous coal, refined coal, anthracite culm, bituminous gob, fine coal, lignite waste, and waste coal.

[9] Nitrogen dioxides (NO_X) are a group of reactive gases that include nitrogen dioxide, nitrous acid, and nitric acid. Although mobile sources are responsible for the highest domestic anthropogenic release of NO_X into the atmosphere, stationary fossil fuel combustion represents 29% of the annual domestic NO_X emissions (U.S. Environmental Protection Agency, 2018). Evidence about outdoor exposure to NO_X suggests an increase in asthma and bronchitis diagnoses in children (Pershagen et al. (1995); Orehek et al. (1976); Chauhan et al. (2003); Gauderman et al. (2005)). Also, NO_X can react to the presence of heat and sunlight in the atmosphere to create ground-level ozone (smog), a pollutant associated with lung diseases, and premature deaths (Bell et al., 2004, 2005).

Though data on PM, SO_2, or Mercury was also available, we dismiss these variables due to the significant number of missing entries.

Figure 4 shows average NO_X emissions for the coal-to-gas plants (left-hand panel), and for coal-fired plants that are located in the same states than fuel-switching plants but did not innovate (middle panel). In Figure 4, we also include plants that belong to the treated states but that, at the beginning of our study, period were running with natural gas as their primer fuel (right-hand panel). The first thing to notice from Figure 4 is that, as expected, average NO_X emissions from coal-fired power stations (middle panel) are substantially higher than those from gas-fired units (right-hand panel). Fuel-switching plants (left-hand panel), however, start the period with emission levels significantly higher than similar coal-fired plants that did not innovate (middle panel), suggesting that fuel-switching plants are relatively more dirty than other (similar) coal-fired stations. By the end of the study period, however, coal-to-gas-fired plants reach an emission level similar to the one exhibited by gas-fired plants. The visual exercise in Figure 4 constitutes evidence that local air quality is expected to improve around coal-fired power plants switching to natural gas.

[INSERT FIGURE 4 ABOUT HERE]

3.3 Property Transactions and Weather

Data on property transactions come from Zillow, a national web-based real estate data provider, with information on buying, selling, renting, and remodeling of more than 110 million homes in the U.S. The Zillow data contain information on structural characteristics of properties, such as the number of rooms, number of bathrooms, their address and geographical location, the square footage, the year the structure was built, and the number of stories.

From the full dataset, we select transaction records of residential properties sold in the state where treated plants are located. We restrict the data to only arm's-length transactions on single-family residential homes that involve a single parcel. To minimize data entry error, we trim the top and bottom 1% of the data using square feet, number of full bathrooms, total bedrooms and total rooms. We also dismiss all transactions reporting a construction year after the sale year. Finally, we discard all transactions with a sales price less than $10,000, and at a distance equal or smaller than 10 miles ($\approx$16 km) from the treated plants. The final dataset contains more than 300,000 property transaction records that took place near treated plants and between 2009 and 2018. The descriptive statistics for these main variables are in Panel A of Table 2.

[INSERT TABLE 2 ABOUT HERE]

Data on weather come from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climate Network Daily catalog, from which we gather station-level data on temperature and wind speed. We match station-level information to homes using shortest distance between a monitoring station and the house. Descriptive statistics for these variables are in Panel B of Table 2.

4. Empirical Strategy

4.1 Baseline Specification

Our goal in this study is to capture housing market effects of local air quality improvements in the neighborhood of coal-fired plants switching to natural gas. To this end, we compare the sales prices of properties located at certain distances from the fuel-switching plants, before and after the switching. While this first difference gives us an idea of how prices of nearby properties change over time after controlling for year-level unobservable factors, time-invariant unobservables that vary with distance to the plants may still affect property values. For instance, houses might not necessarily perceive the air quality improvements from the fuel switching if they are located outside the trajectory that emissions from these plants normally follow, which could be the case of houses that are located upwind or farther away from the switching plants. To account for this spatial heterogeneity, we combine the previous time difference with a second one that is consistent to the presence of spatial-level unobservables. We specifically estimate the following difference-in-difference (DD) baseline equation:

$$\ln(y)_{ijt} = \beta_0 + \beta_1 1[S]_{ijt}^{d\leq\theta} + \beta_2 1[t \geq t^*]_{ijt} + \beta_3 1[S]_{ijt}^{d\leq\theta} \times 1[t \geq t^*]_{ijt} + \mathbf{X}_{it}\eta + \kappa + \epsilon_{ijt}, \quad (2)$$

where $\ln(y)_{ijt}$ is the log of the price y of house i in the neighborhood of plant j sold at time t; $1[t \geq t^*]_{ijt}$ is an indicator variable taking 1 if house i was sold in year $t \geq t^*$ where t_j^* is plant j's switching year (=0 otherwise); $\mathbf{X}_{it}$ is a vector of house i characteristics and weather during year t; κ is a spatial fixed-effect (i.e. county, and state $\times$ year); and ϵ_{ijt} is an idiosyncratic error. An important variable in our baseline equation (2) is the indicator $1[S]_{ijt}^{d\leq\theta}$ that takes the value of 1 if house i, sold in year t, is located at a distance $d \leq \theta$ from plant j (=0 otherwise). We refer to this specification as the "near/far", which gives us a broad approximation of the fuel switching effect on property prices.

Though proximity to a dirty facility might be an important indicator of exposure to pollution, other factors such as wind direction can drastically affect the trajectory of emissions and thus marginal willingness-to-pay estimates for air quality improvements. For this reason, we reinforce the DD specification in equation (2) using wind exposure to pollution obtained from the HySplit Trajectory Model, from the NOAA Air Resources Laboratory, on the 24-hour trajectory of emissions from each of the treated plants (Stein et al., 2015).[10] With this information, we split the sample between properties that are located downwind and upwind the switched plants using a 90-degree angle range (and its opposite) around the trajectory revealed for each treated plant. In this "downwind/upwind" DD design, the indicator $1[S]$ is replaced with wind exposure taking 1 if house i is located downwind and at a distance $d \leq \theta$ from plant j, and 0 otherwise. In this second specification, the coefficient β_3 in equation (2) measures the property price impact of the fuel switching on downwind properties. This is our preferred specification. Figures A1 and A2 in the Appendix describe both the "near/far" DD and the "downwind/upwind" DD designs.

In the estimation of equation (2), it is important to take into account the timing of the switch, or in other words, the time of the treatment implementation. We follow two different approaches to identify this period. In the first approach, we consider the year in which treated plants stop using the first coal-fired generator (see Table 1, column 6), which allows us to identify the property house impact of the halting high emission generators. We call this "treatment 1" and constitutes our main treatment. Yet, as shown in Table 1, the majority of the coal-fired power stations switching from natural gas were not only switching fuels, but also expanded their capacity. To the extent that this increased capacity comes together with more direct or indirect jobs, then potential housing price capitalizations will not only capture local air quality improvements but also any boost to the local economy. To differentiate these effects, we use an additional treatment period, "treatment 2", defined as the time when the first gas-fired units start the generation in each plant (Table 1, column 7). We anticipate that if any, treatment 2 will derive higher treatment effects.[11]

Empirical evidence shows that in most cases, pollution is detectable only at a small radius of distance from the polluting facility, which generally does not exceed 2 miles (Davis (2011); Hodge (2011b); Currie et al. (2015); Muehlenbachs et al. (2015)). Based on this, we consider several small radii of distances for θ, starting at 0.6mi and with 0.3-mi increments

[10] We run the HySplit model considering the 24-hour trajectory of emissions during the year of dismissal of the first coal-fired generator in each plant. For more information on the trajectory model, see NOAA Air Resources Laboratory's website: `https://www.ready.noaa.gov/HYSPLIT_traj.php`.

[11] In a fashion similar to Figure 4, Figure A3 (Appendix) plots NO_X emissions by state and type of plant. Solid red lines indicate the year of shutdown of the first coal-fired generator (or treatment 1) and dashed blue lines indicate the year of startup of the first gas-fired generators (or treatment 2). For cases with only solid lines, these two years coincide. As observed in this Figure, treatment 1 seems to be the most accurate time with regards to a substantial emission downsize. See for instance Colorado (panel a), Indiana (panel c), Minnesota (panel d), North Carolina (panel e), and South Carolina (panel g). For Georgia (panel b), average NO_X emissions fall drastically during the year of retirement of the first coal-fired EGU, while for Pennsylvania (panel f) this happens after startup of the first gas-fired EGU, as shown by the dashed line.

up to $\bar{\theta}$.[12] To avoid the transition of houses between the treatment and the control groups when varying the radii size, the variable $1[S]_{ijt}^{d\leq\theta}$ takes the value of 0 whenever house i is located at distance $d > \bar{\theta}$ from plant j. We decide on the value of $\bar{\theta}$ using a strategy similar to Muehlenbachs et al. (2015). Figure A4 (Appendix) displays the residuals from the regression of (log) prices on our covariates $\mathbf{X}_{it}$ and fixed effects κ, before (dashed line) and after (solid line) the two treatments and at different distances from the plants. In panel (a), we observe a notable increase in property prices after treatment 1 and up to 5 miles from the facility, distance after which this difference becomes less sharp. A similar conclusion is observed in panel (b) for treatment 2. The price differential before and after the fuel switching is evident in Figure A4 regardless of the type of treatment, and significant only up to miles 4-5. For this reason, we set $\bar{\theta}$ equal to 5 miles.[13] Distances to power plants are calculated using the *geodist* command in Stata®. All estimations allow for standard errors to be clustered at the county-year level.

4.2 Homes Near Coal-Fired Plants that Do Not Innovate

While the previous approach allows us to identify housing market capitalizations of proximity to fuel-switching facilities, our goal is to identify the property price impact of a localized improvement in air quality from reduced coal combustion. To properly disentangle the effect of changes in local air quality from the general (dis)amenity effect of proximity to fossil-fueled power plants, we consider an additional approach that takes into account potential unobservable factors that could be common to neighborhoods hosting the siting of these plants. To that end, we replace the previous spatial source of variation with the price differential that emerges from the comparison of homes that are located in the vicinity of treated plants and homes that are located in the vicinity of coal-fired plants that did not switch. In other words, we use houses near coal-fired-non-switching power plants as controls in lieu of houses that are located either upwind or farther away from a treated plant, through which we enhance the homogeneity of homes across the treatment and control groups. In this case, we modify equation (2) as follows:

$$\ln(y)_{ijt} = \gamma_0 + \gamma_1 1[Treated]_{ijt}^{d\leq\theta} + \gamma_2 1[t \geq t^*]_{ijt} + \gamma_3 1[Treated]_{ijt}^{d\leq\theta} \times 1[t \geq t^*]_{ijt} + \mathbf{X}_{it}\zeta + \kappa + \nu_{ijt}, \tag{3}$$

where $\ln(y)_{ijt}$ is the log of the price y of house i, sold in year t, and located in the vicinity of plant l, with $l \in L$, and $L = \{T \cup C\}$ corresponds to the joint set of treated plants (T)

[12] We start at 0.6 miles because is roughly equivalent to 1 kilometer.

[13] This means that $1[S]_{ijt}^{d\leq\theta}$ takes 0 whenever house i is located at distance $d \in [5, 10]$ from plant j.

and coal-fired-non-switching power plants (C).[14] The variable $1[t \geq t^*]_{ijt}$ takes 1 if home i, in the vicinity of plant $l \in T$, is sold in year $t \geq t^*$ where t^* is plant j's switching year (or if home i is in the vicinity of coal-fired power plant $l \in C$ near a switching plant $l \in T$), and 0 otherwise; and the indicator $1[Treated]_{ijt}^{d \leq \theta}$ takes 1 if house i is at distance $d \leq \theta$ from a treated plant $l \in T$, and 0 if house i is at distance $d \leq \theta$ from a control plant $l \in C$, where θ is set equal to 5 miles. The graphical intuition behind this design is in Figure A5 (Appendix). In this alternative specification, γ_3 reflects the property price impact of proximity to a fuel-switching plant after controlling for time-invariant and time-variant unobservable factors that are common to neighborhoods hosting the siting of polluting plants.

4.3 Triple-Differences Estimators

We add robustness to the previous designs by combining them in two different triple-differences (DDD) estimations. First, we use homes with downwind and upwind exposure in combination with homes that are located near and farther away from a switching plant, before and after the switching. We call this the "downwind/upwind near/far" DDD estimation, from which we derive an estimator that is robust to time-variant and time-invariant unobservables that vary with wind exposure and distance to the fuel-switching plants. Second, we use homes with downwind and upwind exposure that are relatively close to both treated and control plants, that is, coal-fired plants that did not innovate. We call this the "downwind/upwind near treated/near coal" DDD approach, which delivers an estimator that is robust to time-variant and time-invariant unobservables that vary with wind exposure, while controlling for factors that are common to neighborhoods hosting coal-fired power plants (Davis, 2011). Ultimately, our goal is deriving treatment effects solely due to air quality improvements while taking into account unobservables common to neighborhoods around these facilities, thus, this last DDD specification is our preferred DDD design. Figures A6 and A7 (Appendix) depict these two DDD designs.

4.4 Control Function Approach

One identification concern is the existence of omitted variables common to neighborhoods around coal-to-gas plants that could affect both the probability of switching fuels and property prices. For instance, favorable educational trends in certain neighborhoods might push home values up and simultaneously exert political pressures on the emission levels of polluting facilities accelerating the fuel switching process. If relevant factors common to fuel-switching neighborhoods are omitted from the analysis, then our estimates that use homes

[14] We only select those coal-fired power plants that are located in the same states as treated plants.

around other plants that did not switch would be upward biased. To shed light on this concern, Figure A8 (Appendix) exhibits the trends in rental prices for homes in the neighborhood of treated plants (solid line) and coal-fired-non-switching power plants (dashed line) for 2009, the pre-treatment year in our sample. As anticipated, rental prices differ between treated and control areas, an indication that the coal-to-gas switching could be endogenous to omitted variables.

We offer a solution to this potential endogeneity with an instrumental variable approach that uses a control function (CF) estimation method in our double- and triple-differences equations.[15] In particular, we estimate the following first-stage binary response model on the probability of switching fuels:

$$P(s_{it} = 1) = \delta_1 + \mathbf{Z}_{\mathbf{it}}^{'}\boldsymbol{\delta_2} + \kappa + e_{it}, \tag{4}$$

where s_{it} is an indicator variable taking 1 if plant i switched fuels in year t (=0 otherwise), $\mathbf{Z_{it}}$ is a vector of plant-year characteristicis, κ are state-level fixed effects, and e_{it} is an error term that follows a standard normal distribution. The vector $\mathbf{Z_{it}}$ includes state-fixed effects in addition to exogeneous variables such as summer and winter generation capacity, and age of the oldest generator.[16] After estimating equation (4), we compute the generalized probit residuals, $\hat{gr}_{it}$, which we include we include as an additional regressor in the estimation of equations (2) and (3) and in our triple-differences estimations. We adjust the standard errors in the second step using the Delta Method.

5. The Property Value Impact of the Coal-to-Gas Fuel Switching

5.1 Differences-in-Differences

The first set of DD estimations on the property value impact of fuel switching is displayed in Table 3.[17] Panel A exhibits the estimation results for the DD parameter β_3 in equation (2) for the "near/far" DD specification, while Panel B exhibits similar results but for the

[15] The control function approach has been proven to be more efficient in estimating average treatment effects when the potential endogenous variable is a binary variable (Wooldridge, 2010), which in our case is equal to 1 whenever a coal-fired plant switches to natural gas, and 0 otherwise.

[16] Ideally, we would include other plant-level characteristics such as NO_X emissions. Unfortunately, we were not able to do so due to some missing data for treated plants in NC and PA.

[17] Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at `http://www.zillow.com/ztrax`. The results and opinions are those of the authors and do not reflect the position of Zillow Group.

"downwind/upwind" design, both using a control function estimation approach.[18] The information is displayed by treatment, and the different columns represent several buffers of distance around the treated stations. Further results follow a similar format.

[INSERT TABLE 3 ABOUT HERE]

Starting with the "near/far" approach in Panel A, we observe no property value impacts of adjacency to a power station that shuts down one of its coal-fired generators (i.e. treatment 1). Yet, when we allow the treatment to be defined as the startup of new gas-fired EGUs, we observe positive and significant property price impacts that vary with distance to the plants. In particular, the results for treatment 2 in Panel A reveal that power generation by new gas-fired EGUs increases property values by 12% within .9 miles of distance from these plants relative to homes that are located at more than 5 miles away. This impact remains positive and significant when larger radii of distances are considered. Indeed, the average marginal price effect on residential homes within 5 miles from stations with new gas-fired EGUs is estimated at roughly 24% relative to homes farther away.

While treatment 2 suggests positive and significant effects when using the "near/far" DD approach, it is hard to attribute this effect to a potential reduction in air pollution from reduced coal combustion. If the coal-to-gas-switching led to an improvement in air quality, retiring coal-fired generation units should impact prices of homes that are truly affected by emissions from these plants. To shed light on this, Panel B displays the results of the estimation of equation (2) but using wind exposure as the source of spatial variation, our preferred DD specification.[19,20] In this case, the two different treatments both yield positive and significant results. When the shutting of a coal-fired generator is considered, the result in Panel B of Table 3 indicates a positive and significant exp(.136)-1 = 15% price increase for downwind homes that are within 1.2 miles of distance from these plants relative to homes outside the trajectory of these plants' emissions. This effect remains positive and significant up to 1.5 miles. In this last case, we see that the shutdown of the first coal-fired generators in fuel switching stations led to a 10% increase in property prices of downwind residential homes within 1.5 miles of distance from these stations. We take these results as suggestive evidence of the property price impact of coal-to-gas fuel switching.

[18] OLS results are similar as these estimations only use information around treated plants.

[19] Estimation results for the DD parameter are not computable for the .6-mile radius due to the small number of observations with downwind exposure within this buffer.

[20] Figure A9 (Appendix) displays the parallel trends assumption (left-hand side panels) using downwind (treatment) and upwind (control) exposure, before and after treatment 1 (panel a) and treatment 2 (panel b). As shown, the common trends assumption clearly holds for treatment 1, while for treatment 2 there is a switch in trends two years before the treatment. This switch in trends is likely due to the past occurrence of treatment 1.

When we define the treatment as the startup of new gas-fired generators, we also observe a positive and significant estimated effect, although higher in magnitude relative to treatment 1. This could be reflecting reduced emissions from either the subsequent shutdown of additional coal-fired units following treatment 1, and captured by treatment 2, or the later removal of ashes and other residuals associated with the coal burning and generally accumulated on site. In any case, the average impact on downwind houses within 1.2 miles gets roughly equivalent to a 35% price increase. The effect is significant at several miles from the switching plants. A complete picture of the "downwind/upwind" DD estimation results for the entire set of distances considered is depicted in Figure 5 for treatment 1 (panel a), and for treatment 2 (panel b).

[INSERT FIGURE 5 ABOUT HERE]

To corroborate whether the previous positive price impact shown in Table 3 are in fact due to a reduction of the negative externalities from coal combustion, Table 4 shows the results after the estimation of equation (3), that is, the DD results using homes around coal-fired power plants that did not switch as controls.[21] We present the results by treatment and estimation method, that is, OLS or the instrumental variable approach using a Control Function (CF) estimation. Starting with treatment 1 and averaged across all columns, the results for the OLS estimator suggest that the shutting down of coal-fired generators increase property values of homes in the vicinity of these plants by 12% relative to homes around a coal-fired-non-switching plant located in the same state. This effect is statistically different from zero for all homes within 2 miles from treated plants. Similar results are found for treatment 2, although a bit higher in magnitude. On average, the OLS estimates indicate that the coal-to-gas switch led to a property price increase of a 13% for homes in the vicinity of coal-to-gas plants relative to homes near a coal-fired plant after the starting of new gas-fired generators.

[INSERT TABLE 4 ABOUT HERE]

To address the endogeneity concern in the previous results, we present the second-stage CF estimates that use the generalized residuals, from the first-stage regression on the probability of switching fuels, as an additional regressor in estimating equation (3) (see Table A1 for first-stage results). The CF results indicate no evidence of property value impacts of the fuel switching on homes near a coal-to-gas plant relative to similar homes near a coal-fired station, suggesting an upward bias in the previous OLS results. Thus, once the probability

[21] The parallel trends assumption for this specification is displayed in the right-hand side panel of Figure A9.

of switching fuels is taken into account, we find no effects of the fuel-switching on nearby homes relative to similar homes near plants that did not switch fuels. Next, we strengthen this specification with wind exposure to pollution.

5.2 Triple-Differences Estimation

To verify the strength of the previous results, Table 5 exhibits the triple-differences estimation that combines the two preceding approaches. First, we use homes' wind exposure to pollution from treated plants in combination with proximity to these stations, before and after the treatments. This "downwind/upwind near/far" DDD is presented in Panel A of Table 5. The second approach combines downwind exposure with proximity to both treated and control plants. This is the "downwind/upwind near treated/near control" DDD approach shown in Panel B. We present the two set of DDD results for treatments 1 and 2, and for the OLS and CF estimators.

[INSERT TABLE 5 ABOUT HERE]

When spatial variation comes from both wind exposure and proximity to fuel-switching plants (Panel A), the OLS results indicate that, relative to far and upwind homes, a reduction in coal combustion increases property values in more than a 100% for downwind homes located within a 0.6-mile distance from these facilities. This effect, however, disappears at farther distances from the plants. The results for the CF estimator corroborate this conclusion, although the estimated effect is found to be roughly 10% smaller in magnitude, which once again suggests the existence of an upward bias in the OLS estimation. When we consider treatment 2, the OLS estimator indicates an increase in property prices of a similar magnitude and within .6 miles from the treated facility as well. Notwithstanding, this effect turns into a negative impact when larger radii are considered. A negative price impact on downwind homes that are located in the vicinity of switching stations after these plants put gas-fired units into operation will certainly be affected by any lagged effect from the shutdown of the coal-fired units in the first place. For instance, if the closure of coal-fired units is coupled with short-term market expectations about future improvements in local environmental quality and economic conditions, by the time in which the new gas-fired units are introduced is then possible that these previous expectations are no longer in place, in which case a negative effect would be merely reflecting a price adjustment relative to the post-treatment-1 situation. These expectations can vary by wind exposure and proximity to the facilities, adding an extra complexity to the analysis. Later in the text, we shed light on this possibility by analyzing heterogeneous treatment effects over time.

The results for the triple-difference estimators using wind exposure and proximity to both treated and control plants (Panel B) suggest a positive and statistically significant property price impact. When power plants retire a coal-fired generator, our OLS estimator indicates a 37% price difference between downwind and upwind homes within 1.2 miles from these plants relative to a similar difference between homes around coal-fired plants that do not retire their generators. This effect is similar in magnitude when we use our instrumental variable estimation. When larger radii for near properties are considered, we still find a positive and significant effect. For instance, when selecting homes located within 1.8 miles from treated plants, our CF estimate suggest that a reduction in coal combustion in the power industry leads to a 20% price differential between downwind and upwind homes around a coal-to-gas price relative to the similar homes around coal-fired-non-switching plants. Neighborhoods around coal-fired plants are expected to have common demographic characteristics (Davis, 2011). Thus, we use this result as suggestive evidence that the coal-to-gas switching increases property values by reducing some of the negative externalities associated exclusively with coal-fired generation. At the same time, the significant price differential between homes with downwind and upwind exposure to pollution from these plants implies that this effect is largely due to an air quality improvement around plants curbing their coal combustion.

Findings in the bottom panel of Table 5 suggest a larger price impact when these plants start their gas combustion, which is consistent with a boost to the local economy due to a potential expansion in plants' capacity (see Table 1). Another plausible explanation comes from the presence of factors common to coal-fired power plants with the potential of affecting downwind homes only, such as coal ash and on-site coal residual accumulation, which can be fully removed from these places once the gas combustion starts generating posterior improvements in environmental quality for downwind homes. In any case and when taken together, the results in Table 5 are a strong evidence of the positive welfare effects of the coal-to-gas conversion process on property values of homes affected by the coal-fired generation. Figure 6 displays the causal effect of the coal-to-gas fuel switching for all the distance buffers using wind exposure and proximity to both treated and control plants (Panel B of Table 5).

[INSERT FIGURE 6 ABOUT HERE]

5.3 Robustness Checks

Our results are robust to several other exercises summarized in Table 6. First, Panel A of Table 6 presents the results of our double-differences CF estimator using homes around gas-fired power plants as controls. We observe that, on average, and relative to homes that are located in the vicinity of gas-fired stations, homes within 0.6 miles from coal-fired plants that are switching to natural gas experience a 30% price increase after this conversion. In Panel B we present the results of a double-differences exercise that splits the area of upwind exposure to pollution from treated plants in two equal parts, A and B (see Figure A10 for a graphical explanation). Using one of them as a placebo set of homes (part A), we find no effects of the fuel switching after the closure of a coal-fired generator or after startup of the new gas-fired generators, and for none of the distance buffers considered. Finally, Panel C exhibits the triple-differences CF estimator splitting the upwind area and using proximity to treated and coal-fired power plants. The results reveal no property price effects of the coal-to-gas switching process.

[INSERT TABLE 6 ABOUT HERE]

5.4 Announcement Effects

Though the previous results represent robust evidence that the fuel switching led to a positive price impact, none of the previous specifications can rule out the possibility that these effects are indeed responding to households' expectations regarding a future decline in airborne contamination instead of capturing actual reductions. To test this idea, we replace the year of the treatment implementation by the year in which the natural gas power generation was first announced in the local newspapers of areas hosting fuel-switching plants. For all the cases, this year precedes the closure of the first coal-fired generator. Table 7 presents these results for all the different estimations, using the announcement year as the treatment year.

[INSERT TABLE 7 ABOUT HERE]

Overall, we cannot reject the existence of announcement effects in the immediate vicinity of coal-to-gas-fired power plants. For instance, when using our double-difference estimator with wind exposure (Panel B), we see that roughly 80% of the property price impact found previously for downwind homes within 0.9 miles (Table 3, Panel B) can be attributed to households' anticipation to the eventual positive effects of the fuel switching. Yet, these effects are found to be sensitive to the comparison group. For example, the results in Panel C reveal that neighborhoods near a plant announcing the fuel switching experience a decrease in property prices relative to similar neighborhoods around coal-fired plants that are not planning to switch. Yet, when we enrich this approach with variation in wind exposure, the results in Panel E once again suggest that around 80% of the previous effect estimated in Table 5 (Panel B) is due to anticipation effects. Whether the previous findings are driven by buyers' and sellers' expectations instead of by improvements in environmental amenities, can be answered through the exploration of time-heterogeneous impacts of the fuel switching.

[INSERT FIGURE 7 ABOUT HERE]

Figure 7 plots the CF treatment effects of the coal-to-gas switching using our preferred estimation design ("Downwind/Upwind" DD) for the three different treatment specifications: the announcement in local newspapers, the closure of the first coal-fired EGUs (treatment 1) and the startup of the first gas-fired EGUs (treatment 2). Dashed lines represent 95% confidence intervals. We observe that homes with downwind pollution exposure located in the immediate vicinity of treated plants (within 1.2 miles) exhibit a positive although weakly significant announcement (anticipation) effect. This effect turns out to be strongly significant and close to the 16% price increase for the period between the fuel-switching announcement and the shutting down of the first coal-fired generators (treatment 1), which we take as evidence of an effective minimization of the negative externalities associated to the coal burning. The estimated impact turns into a roughly 54% price increase between the closure of these coal-fired units and the startup of the new generators (treatment 2). This gradual increase in prices over time as we modify the treatment suggest that households are correctly responding to the minimization of negative externalities from the coal combustion. In particular, the estimated impact in Figure 7 suggest that even when households seem to have anticipated to the coal-to-gas fuel switching, the positive treatment effects remains in place (within 1.2 miles from these plants) after these stations effectively close their coal-fired generators. Furthermore, this effect becomes even more significant by the time in which these plants start the operation of the new gas-fired generators. Indeed, these last effects seem to persist inclusive for downwind homes located beyond 2 miles from these plants.

6. Conclusions

Fossil-fuel power generation is accountable for pronounced impacts on local air quality. Yet, the recent coal displacement by natural gas as the primary fuel source in the U.S. power generation promises several environmental improvements at both the global and the local scale. In this work, we delve into the property value impacts of the coal-to-gas fuel-switching process carried out by several power stations throughout the country. We use an extensive dataset of property transactions that took place in the vicinity of switching power plants from 2009 to 2018. To approach causality, we use difference-in-difference estimation equations combined with triple differences designs that use an instrumental variable estimator to control for endogeneity.

Our findings indicate positive and significant impacts of this fuel-switching process within 1.2 miles from the coal-to-gas power plants. These impacts are found after the shutdown of coal-fired generation units persisting after the first gas-fired units are put into operation. In particular, the findings from our preferred "downwind/upwind" double-differences estimation reveal that downwind homes within 1.2 miles from fuel-switching plans experience a 15% increase in property prices after the closure of coal-fired generators relative to upwind homes. Our estimation exercise also reveals that some households anticipate to the fuel switching as reflected by a price increase in affected homes before the reduction in coal combustion. Yet, a deeper analysis on yearly heterogeneous effect indicates that even though households anticipate, they do so correctly, and so the positive price effects of the fuel switching remain in place even after plants shutdown their coal-fired units or start up their gas-fired generation.

We can use the previous estimated impact to provide some back-of-the-envelope welfare estimates of the fuel switching. The average home price within 1.2 miles from the coal-to-gas plants in our sample is equal to \$261,273. A 15% price increase is equivalent to \$39,191 dollars on average for a single house in the immediate vicinity of these plants. For each coal-to-gas plant in our sample, we have an average of 196 houses that are in close proximity (within 1.2 miles $\approx$ 2km), and from Figure 2, we have that an average of 232 coal-fired power plants projected to switch to natural gas. This gives us a total welfare impact of \$1.78 billion dollars in the immediate vicinity of the stations switching from coal to natural gas. Considering that many of these plants are simultaneously increasing their capacity which might boost the local economy, we conclude this is a conservative estimate of the whole fuel-switching impact on property prices in the United States.

Our findings need to be considered in light of recent debates regarding the future of coal-fired power generators in the country. The so called "war on coal" has centered the public's attention on the negative economic effects of moving the grid towards a cleaner generation, while ignoring the potential benefits that this fuel switching may bring to local economies. Access to a cleaner air (Linn and Muehlenbachs, 2018; Johnsen et al., 2019), or lower electricity prices (Linn and Muehlenbachs, 2018) are some of the channels through which the coal displacement by a natural gas can improve local welfare. Here, we provide evidence of a complementary channel: property prices. Other co-benefits of a cleaner grid that complement this equation are the potential health improvements and health cost savings from a reduced poor air quality. To the extent that this innovation is coupled with increments in capacity and plant expansions might add an extra boost to local economies increasing some of the indirect benefits of this fuel conversion.

References

Bell, M. L., Dominici, F., and Samet, J. M. (2005). A Meta-Analysis of Time-Series Studies of Ozone and Mortality With Comparison to the National Morbidity, Mortality, and Air Pollution Study. *Epidemiology*, 16(4):436–445.

Bell, M. L., McDermott, A., Zeger, S. L., Samet, J. M., and Dominici, F. (2004). Ozone and Short-term Mortality in 95 US Urban Communities, 1987-2000. *JAMA*, 292(19):2372–2378.

Blomquist, G. (1974). The effect of electric utility power plant location on area property value. *Land Economics*, 50(1):97–100.

Burnham, A., Han, J., Clark, C. E., Wang, M., Dunn, J. B., and Palou-Rivera, I. (2011). Life-Cycle Greenhouse Gas Emissions of Shale Gas, Natural Gas, Coal, and Petroleum. *Environmental Science & Technology*, 46(2):619–627.

Chauhan, A. J., Inskip, H. M., Linaker, C. H., Smith, S., Schreiber, J., Johnston, S. L., and Holgate, S. T. (2003). Personal exposure to nitrogen dioxide (NO2) and the severity of virus-induced asthma in children. *The Lancet*, 361(9373):1939–1944.

Currie, J., Davis, L., Greenstone, M., and Walker, R. (2015). Environmental Health Risks and Housing Values: Evidence from 1,600 Toxic Plant Openings and Closings. *The American Economic Review*, 105(2):678–709.

Davis, L. W. (2011). The Effect of Power Plants on Local Housing Values and Rents . *Review of Economics and Statistics*, 93(4):1391–1402.

Deng, G., Hernandez, M. A., and Xu, S. (2014). When Power Plants Leave Town: Environmental Quality and the Housing Market in China. Available at SSRN 2502442.

Farah, N., Boslett, A., and Hill, E. (2019). The king is dead, long live the king? the effects of power plants on housing prices in the age of coal-switching. *Unpublished Manuscript*.

Freeman, A. M. (1979). The Hedonic Price Approach to Measuring Demand for Neighborhood Characteristics. In Segal, D., editor, *The Economics of Neighborhood*, chapter 9, pages 191–217. Elsevier.

Freeman III, A. M., Herriges, J. A., and Kling, C. L. (2014). *The Measurement of Environmental and Resource Values: Theory and Methods*. Routledge.

Gamble, H. B. and Downing, R. H. (1982). Effects of nuclear power plants on residential property values. *Journal of Regional Science*, 22(4):457–478.

Gamper-Rabindran, S. and Timmins, C. (2013). Does cleanup of hazardous waste sites raise housing values? Evidence of spatially localized benefits. *Journal of Environmental Economics and Management*, 65(3):345–360.

Gauderman, W. J., Avol, E., Lurmann, F., Kuenzli, N., Gilliland, F., Peters, J., and McConnell, R. (2005). Childhood Asthma and Exposure to Traffic and Nitrogen Dioxide. *Epidemiology*, 16(6):737–743.

Grainger, C. A. (2012). The Distributional Effects of Pollution Regulations: Do Renters Fully Pay for Cleaner Air? *Journal of Public Economics*, 96(9-10):840–852.

Greenstone, M. and Gallagher, J. (2008). Does Hazardous Waste Matter? Evidence from the Housing Market and the Superfund Program. *The Quarterly Journal of Economics*, 123(3):951–1003.

Hodge, T. R. (2011a). The effect of ethanol plants on residential property values: Evidence from michigan. *Journal of Regional Analysis and Policy*, 41(1100-2016-89865):148–167.

Hodge, T. R. (2011b). The Effect of Ethanol Plants on Residential Property Values: Evidence from Michigan. *The Journal of Regional Analysis Policy*, 41(2):148–167.

Holland, S. P., Mansur, E. T., Muller, N., and Yates, A. J. (2018). Decompositions and policy consequences of an extraordinary decline in air pollution from electricity generation. Technical report, National Bureau of Economic Research.

Jacobsen, G. D. (2019). Who wins in an energy boom? evidence from wage rates and housing. *Economic Inquiry*, 57(1):9–32.

Jaramillo, P., Griffin, W. M., and Matthews, H. S. (2007). Comparative Life-cycle Air Emissions of Coal, Domestic Natural Gas, LNG, and SNG for Electricity Generation. *Environmental Science & Technology*, 41(17):6290–6296.

Johnsen, R., LaRiviere, J., and Wolff, H. (2019). Fracking, coal, and air quality. *Journal of the Association of Environmental and Resource Economists*, 6(5):1001–1037.

Kiel, K. A. and McClain, K. T. (1995a). House Prices during Siting Decision Stages: The Case of an Incinerator from Rumor through Operation. *Journal of Environmental Economics and Management*, 28(2):241–255.

Kiel, K. A. and McClain, K. T. (1995b). The effect of an incinerator siting on housing appreciation rates. *Journal of Urban Economics*, 37(3):311–323.

Kohlhase, J. E. (1991). The impact of toxic waste sites on housing values. *Journal of Urban Economics*, 30(1):1–26.

Linn, J. and Muehlenbachs, L. (2018). The heterogeneous impacts of low natural gas prices on consumers and the environment. *Journal of Environmental Economics and Management*, 89:1–28.

Linn, J., Muehlenbachs, L., and Wang, Y. (2014). How do natural gas prices affect electricity consumers and the environment? *Resources for the Future Discussion paper*, (14-19).

Mendelsohn, R., Hellerstein, D., Huguenin, M., Unsworth, R., and Brazee, R. (1992). Measuring hazardous waste damages with panel models. *Journal of Environmental Economics and Management*, 22(3):259–271.

Mendelsohn, R. and Olmstead, S. (2009). The Economic Valuation of Environmental Amenities and Disamenities: Methods and Applications. *Annual Review of Environment and Resources*, 34:325–347.

Muehlenbachs, L., Spiller, E., and Timmins, C. (2015). The Housing Market Impacts of Shale Gas Development. *The American Economic Review*, 105(12):3633–59.

Orehek, J., Massari, J. P., Gayrard, P., Grimaud, C., and Charpin, J. (1976). Effect of Short-Term, Low-Level Nitrogen Dioxide Exposure on Bronchial Sensitivity of Asthmatic Patients. *Journal of Clinical Investigation*, 57(2):301–307.

Palmquist, R. B. (1992). Valuing Localized Externalities. *Journal of Urban Economics*, 31(1):59–68.

Pershagen, G., Rylander, E., Norberg, S., Eriksson, M., and Nordvall, S. L. (1995). Air Pollution Involving Nitrogen Dioxide Exposure and Wheezing Bronchitis in Children. *International Journal of Epidemiology*, 24(6):1147–1153.

Ridker, R. G. (1967). *Economic Costs of Air Pollution, Studies in Measurement*. Frederick A. Praeger, Publishers, New York.

Ridker, R. G. and Henning, J. A. (1967). The Determinants of Residential Property Values with Special Reference to Air Pollution . *The Review of Economics and Statistics*, 49(2):246.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *The Journal of Political Economy*, 82(1):34–55.

Stein, A., Draxler, R. R., Rolph, G. D., Stunder, B. J., Cohen, M., and Ngan, F. (2015). Noaa's hysplit atmospheric transport and dispersion modeling system. *Bulletin of the American Meteorological Society*, 96(12):2059–2077.

Tollefson, J. (2013). Methane Leaks Erode Green Credentials of Natural Gas. *Nature*, 493(7430):12.

Ummel, K. (2012). Carma Revisited: an Updated Database of Carbon Dioxide Emissions from Power Plants Worldwide. Available at SSRN: https://ssrn.com/abstract=2226505.

U.S. Environmental Protection Agency (2018). Inventory of US Greenhouse Gas Emissions and Sinks: 1990-2016. *Environmental Protection Agency 2018*.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT press.

Figures and Tables

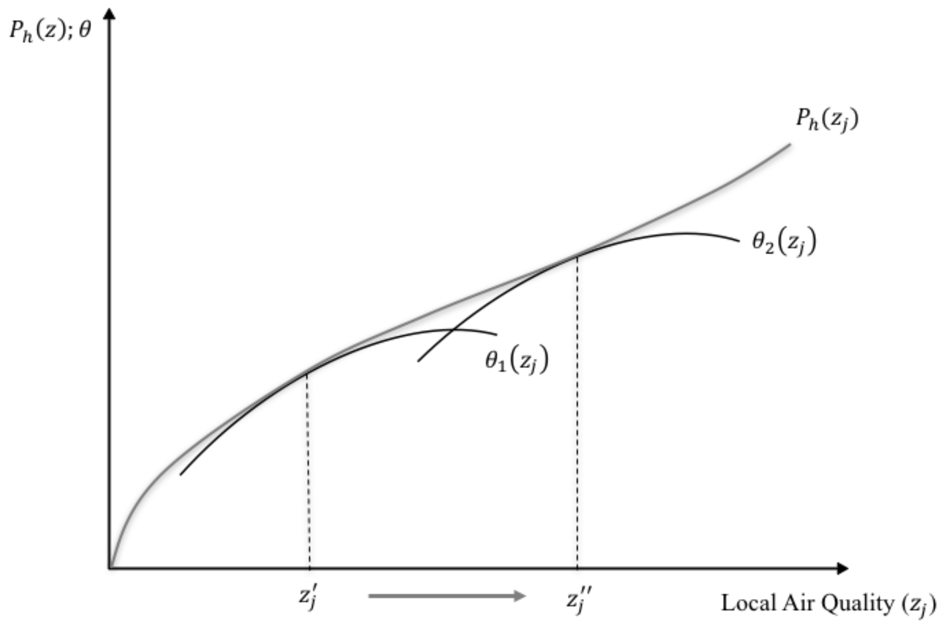
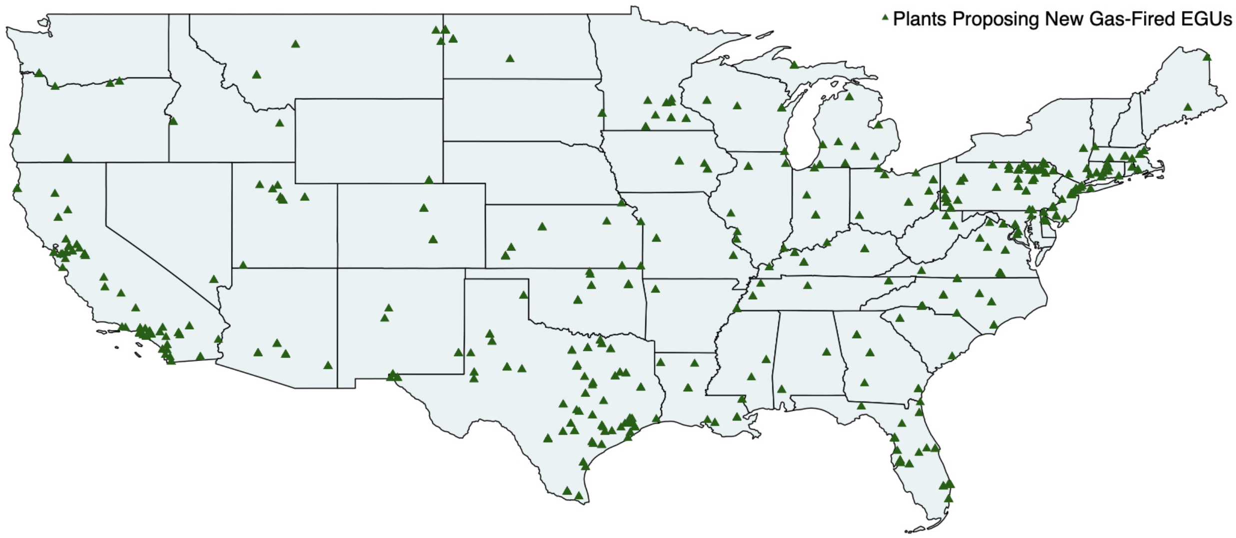
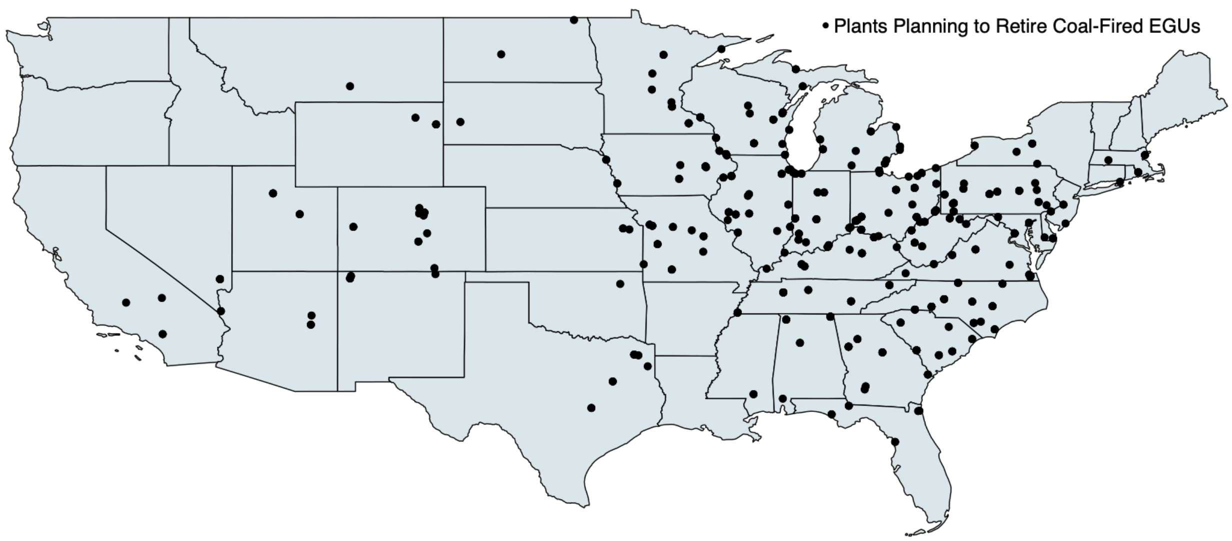


Figure 1: Bid Curves and the Hedonic Price Function in a Hedonic Market for Local Air Quality



(a) Power Plants Proposing Gas-Fired Generators



(b) Power Plants Planning to Retire Coal-Fired Generators

Figure 2: Power Plants Proposing Gas-Fired and Retiring Coal-Fired Generators

Notes: Using data from EIA-860 forms.

Figure 3: Location of Treated Power Plants

Notes: Using data from EIA-860 forms.

Table 1: Treated Power Plants

ID	Plant Name	State	# Retired EGUs	# New EGUs	Year 1^{st} Coal-F EGU is Retired	Year 1^{st} Gas-F EGU Starts	Average Capacity (MW) Coal Units	Average Capacity (MW) Gas Units
1	Cherokee	CO	3	3	2011	2015	365	600
2	Jack McDonough	GA	2	7	2011	2011	502	2,201
3	Eagle Valley	IN	4	3	2016	2018	257	644
4	Black Dog	MN	2	1	2015	2018	219	228
5	Buck	NC	4	1	2011	2011	369	170
6	Dan River	NC	3	3	2012	2012	276	470
7	Hunlock Power St.	PA	1	2	2010	2011	43	99.3
8	W S Lee	SC	2	3	2014	2018	200	792
9	SABIC Innovativer	IN	1	1	2017	2017	3	98.5
10	W Campus Penn St	PA	2	2	2015	2017	1.1	5

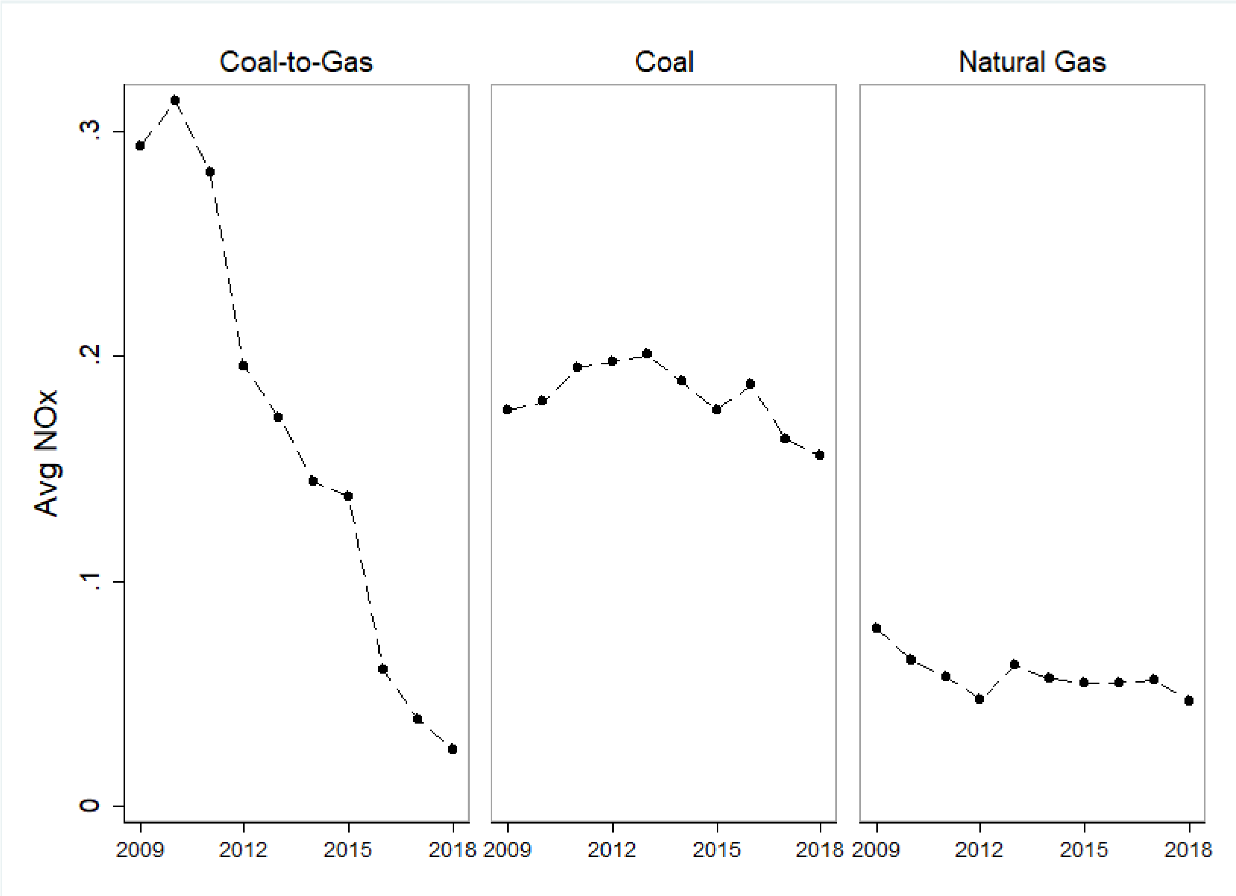


Figure 4: Power Plants and NO_X Emissions

Notes: 2009-2018 data from the EIA-923 forms. Emissions from Coal-to-Gas plants correspond to the emissions from 8 out of 10 treated plants identified in our sample. Coal and Natural Gas represent emissions from coal-fired power plants and natural-gas-fired power plants in our control group, respectively.

Table 2: Descriptive Statistics of Houses at Distance $\leq$ 10mi from Treated Plants

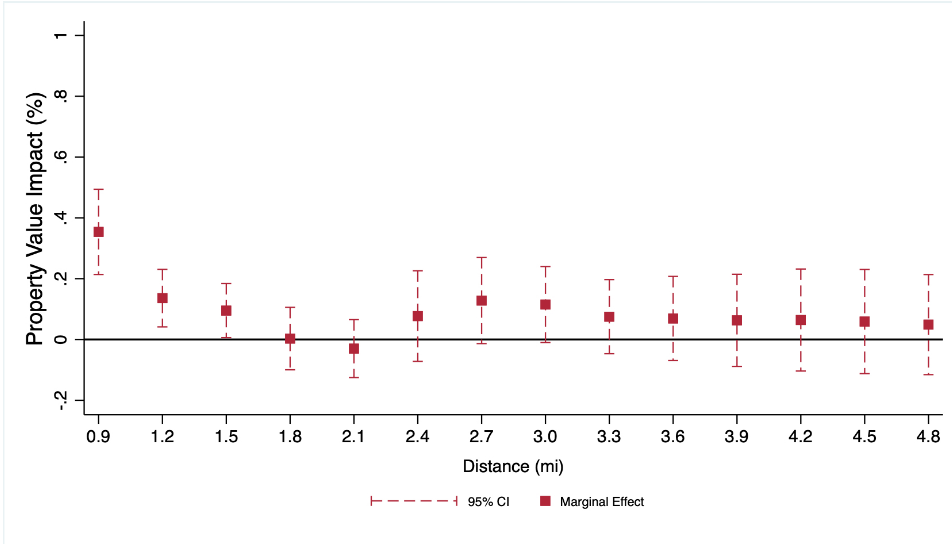
Variables	Mean	S.D.	Min	Max	N
Panel A. House Characteristics:					
Sales Price ($)	300,814.90	354,977.09	10,000	117,500,000	306,862
# of Full Bathrooms	1.88	0.87	0	4	306,862
# of Half Bathrooms	0.35	0.56	0	9	306,805
# of Rooms	4.19	3.34	0	11	306,862
# of Bedrooms	3.03	0.92	0	5	306,862
Home age	53.82	30.80	0	214	306,862
Square feet	1,672.60	753.7	712	5,696	306,862
Exterior Walls (material):					
Brick (%)	14.50				198,895
Stucco (%)	8.18				112,120
Siding (%)	19.95				273,565
Wood (%)	15.13				207,485
Other (%)	42.24				579,153
Panel B. Weather:					
Daily Maximum Temperature (F)	69.91	18.59	-14.8	104	301,540
Daily Temperature Range (F)	23.53	7.83	0.9	59.1	301,526
Daily Average Wind Speed	6.15	3.18	0	31.2	301,540
Daily Maximum Wind Speed	13.71	5.69	2.9	55	301,431

Notes: Weather variables obtained from the Global Surface Summary of the Day Data (NOAA). Wind speed is in knots to tenths.

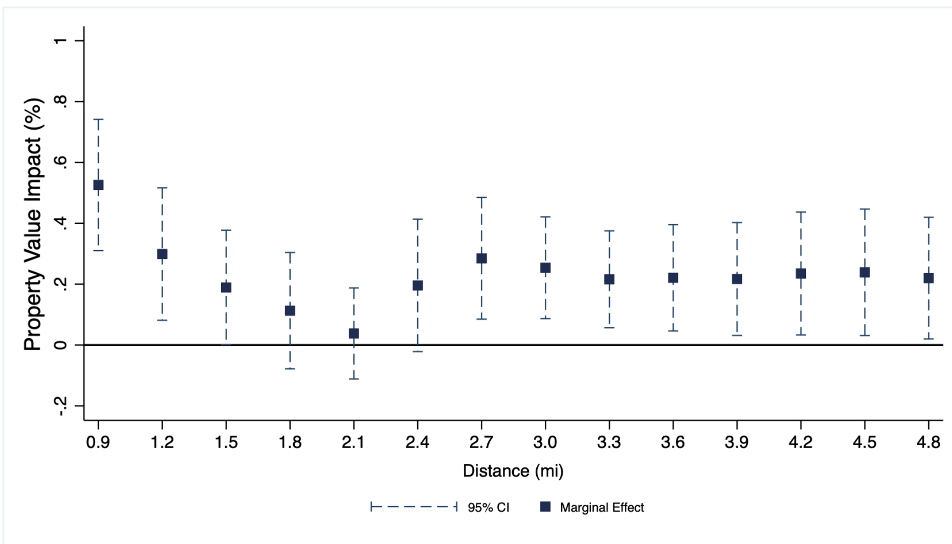
Table 3: Coal-to-Gas Impact on Property Prices - Double Differences (DD)

	Distance from Treated Plants					
	$\leq$ 0.6mi	$\leq$ 0.9mi	$\leq$ 1.2mi	$\leq$ 1.5mi	$\leq$ 1.8mi	$\leq$ 2.1mi
Panel A: Near/Far DD:						
Treatment 1 (β_3)	0.024	0.010	0.038	0.042	0.064	0.053
	(0.052)	(0.052)	(0.068)	(0.076)	(0.081)	(0.076)
Treatment 2 (β_3)	0.070	0.124**	0.183**	0.218**	0.236***	0.226***
	(0.051)	(0.054)	(0.061)	(0.068)	(0.069)	(0.065)
Panel B: Downwind/Upwind DD:						
Treatment 1 (β_3)	-	0.354***	0.136**	0.095**	0.003	-0.034
	-	(0.072)	(0.048)	(0.045)	(0.052)	(0.049)
Treatment 2 (β_3)	-	0.526***	0.299**	0.189*	0.113	0.039
	-	(0.110)	(0.111)	(0.096)	(0.098)	(0.076)
Obs. Panel A	225,089	226,390	228,170	229,928	232,648	235,720
Obs. Panel B	140	556	1,313	2,036	3,370	4,833

Notes: Control function estimates that include # of bathrooms, # of half bathrooms, # of bedrooms, # of rooms, type of exterior walls, house age, square feet, weather, and county, and state $\times$ year fixed effects as regressors. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. Clustered standard errors at the county $\times$ year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.



(a) Treatment 1: Shutdown of First Coal-Fired EGUs



(b) Treatment 2: Starting up of First Gas-Fired EGUs

Figure 5: Downwind/Upwind Double-Differences Estimation Results

Notes: Double-differences control function estimates that include # of bathrooms, # of half bathrooms, # of bedrooms, # of rooms, type of exterior walls, house age, square feet, weather, and county, and state × year fixed effects as regressors. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. Clustered standard errors at the county × year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 4: Coal-to-Gas Impact on Property Prices - Double Differences (DD) Using Homes Near Coal-Fired Plants as Controls

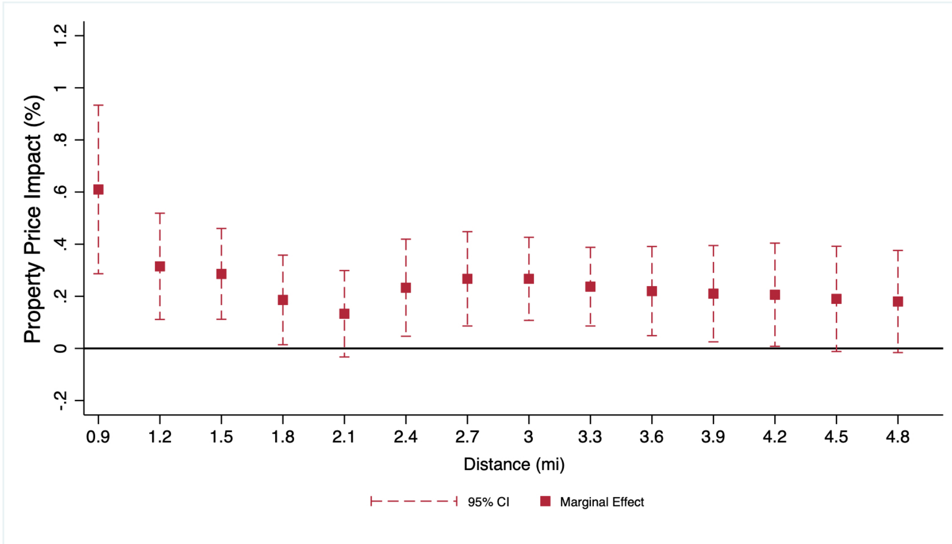
	Estimation Method	Distance from Treated Plants $\leq$ 0.6mi	$\leq$ 0.9mi	$\leq$ 1.2mi	$\leq$ 1.5mi	$\leq$ 1.8mi	$\leq$ 2.1mi
Treatment 1 (γ_3)	OLS	0.140	0.084**	0.119***	0.116***	0.130***	0.129***
		(0.085)	(0.040)	(0.033)	(0.031)	(0.027)	(0.023)
	CF	0.317	0.379	0.291	-0.167	-0.197	0.020
		(0.544)	(0.512)	(0.331)	(0.249)	(0.243)	(0.188)
Treatment 2 (γ_3)	OLS	0.108	0.092	0.114**	0.093**	0.116***	0.167***
		(0.071)	(0.056)	(0.046)	(0.037)	(0.035)	(0.030)
	CF	0.501	0.380	0.430*	0.216	0.159	0.144
		(0.371)	(0.292)	(0.222)	(0.174)	(0.171)	(0.152)
Obs.		1,461	3,818	6,964	10,438	15,368	21,154

Notes: All estimations include number of bathrooms, number of half bathrooms, number of bedrooms, number of rooms, type of exterior walls, house age, square feet, weather, and county, and state $\times$ year fixed effects as regressors. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. OLS = Ordinary Least Square Estimates. CF = Control Function Estimates. Clustered standard errors at the county $\times$ year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

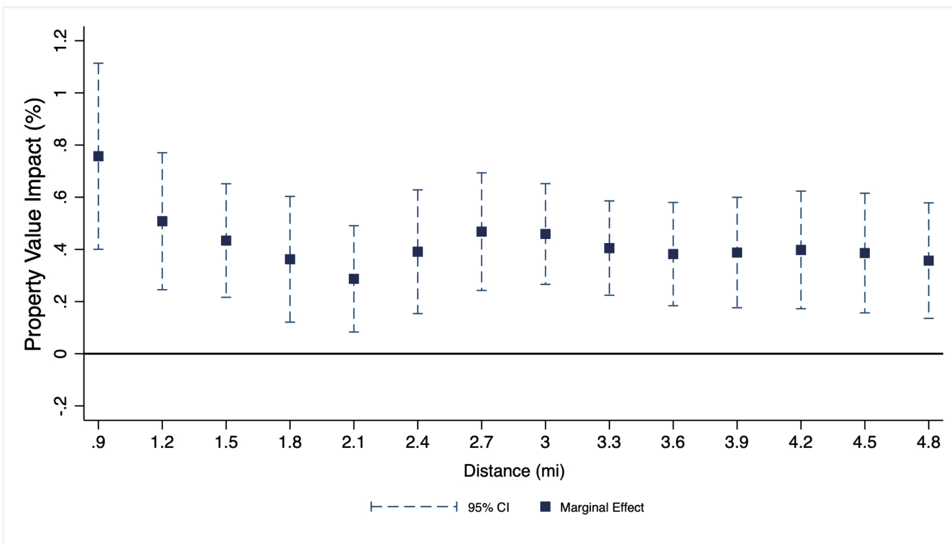
Table 5: Coal-to-Gas Impact on Property Prices - Triple Differences (DDD)

	Estimation	Distance from Treated Plants					
	Method	$\leq$ 0.6mi	$\leq$ 0.9mi	$\leq$ 1.2mi	$\leq$ 1.5mi	$\leq$ 1.8mi	$\leq$ 2.1mi
Panel A: Downwind/Upwind NearTreated/FarTreated DDD:							
Treatment 1	OLS	0.962***	-0.133	-0.364	-0.205	-0.152	-0.190
		(0.175)	(0.213)	(0.239)	(0.220)	(0.146)	(0.134)
	CF	0.955***	-0.136	-0.368	-0.212	-0.152	-0.191
		(0.176)	(0.214)	(0.240)	(0.220)	(0.146)	(0.135)
Treatment 2	OLS	0.971***	-0.332*	-0.771***	-0.703**	-0.405**	-0.435**
		(0.162)	(0.191)	(0.138)	(0.234)	(0.198)	(0.168)
	CF	0.971***	-0.333*	-0.772***	-0.707**	-0.408**	-0.441**
		(0.162)	(0.191)	(0.138)	(0.234)	(0.199)	(0.169)
Panel B: Downwind/Upwind NearTreated/NearControl DDD:							
Treatment 1	OLS	0.437***	0.601***	0.313**	0.285**	0.186**	0.133
		(0.111)	(0.166)	(0.103)	(0.088)	(0.087)	(0.085)
	CF	0.410	0.610***	0.315**	0.286**	0.186**	0.133
		(0.856)	(0.165)	(0.104)	(0.089)	(0.088)	(0.085)
Treatment 2	OLS	0.203*	0.777***	0.519***	0.442***	0.372**	0.289**
		(0.114)	(0.177)	(0.133)	(0.113)	(0.124)	(0.105)
	CF	1.273	0.757***	0.508***	0.434***	0.362**	0.287**
		(0.801)	(0.182)	(0.134)	(0.111)	(0.123)	(0.104)
Obs. Panel A		80,821	81,237	81,994	82,717	84,051	85.514
Obs. Panel B		629	1,478	2,897	4,487	6,898	9,502

Notes: All estimations include number of bathrooms, number of half bathrooms, number of bedrooms, number of rooms, type of exterior walls, house age, square feet, weather, and county, and state × year fixed effects as regressors. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. OLS = Ordinary Least Square Estimates. CF = Control Function Estimates. Clustered standard errors at the county × year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.



(a) Treatment 1: Shutdown of First Coal-Fired EGUs



(b) Treatment 2: Starting up of First Gas-Fired EGUs

Figure 6: Downwind/Upwind NearTreated/NearCoal Triple-Differences Estimation Results

Notes: Triple-differences control function estimates that include number of bathrooms, number of half bathrooms, number of bedrooms, number of rooms, type of exterior walls, house age, square feet, weather, and county, and state $\times$ year fixed effects as regressors. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. Clustered standard errors at the county $\times$ year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 6: Robustness Checks

	Distance from Treated Plants					
	$\leq$ 0.6mi	$\leq$ 0.9mi	$\leq$ 1.2mi	$\leq$ 1.5mi	$\leq$ 1.8mi	$\leq$ 2.1mi
Panel A: NearTreated/NearGas DD:						
Treatment 1	0.215*	0.008	-0.011	-0.045	-0.050	-0.063
	(0.116)	(0.075)	(0.065)	(0.066)	(0.061)	(0.056)
Treatment 2	0.305**	0.114	0.078	0.031	0.026	0.015
	(0.127)	(0.070)	(0.068)	(0.068)	(0.058)	(0.053)
Panel B: UpwindA/UpwindB NearControl DD:						
Treatment 1	0.386	0.022	0.006	-0.028	-0.097	-0.067
	(0.236)	(0.138)	(0.143)	(0.115)	(0.086)	(0.077)
Treatment 2	0.172	0.020	0.028	0.015	-0.056	-0.070
	(0.193)	(0.120)	(0.122)	(0.109)	(0.081)	(0.071)
Panel C: UpwindA/UpwindB FarTreated/FarControl DDD:						
Treatment 1	-0.002	-0.017	-0.022	-0.035	-0.039	-0.035
	(0.086)	(0.077)	(0.070)	(0.068)	(0.068)	(0.070)
Treatment 2	-0.047	-0.060	-0.070	-0.078	-0.078	-0.079
	(0.079)	(0.069)	(0.062)	(0.062)	(0.061)	(0.062)
Obs. Panel A	2,444	8,075	16,022	25,928	39,940	56,846
Obs. Panel B	133	303	532	697	1,019	1,418
Obs. Panel C	26,821	24,919	23,084	21,823	20,608	19,124

Notes: Control function estimations that include number of bathrooms, number of half bathrooms, number of bedrooms, number of rooms, type of exterior walls, house age, square feet, weather, and county, and state $\times$ year fixed effects as regressors. Upwind A and B refers to the split of the upwind area into two equal-area triangles (see Figure A10 (Appendix) for a graphical description). Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. OLS = Ordinary Least Square Estimates. CF = Control Function Estimates. Clustered standard errors at the county $\times$ year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Table 7: Announcement Effects

	Distance from Treated Plants					
	$\leq$ 0.6mi	$\leq$ 0.9mi	$\leq$ 1.2mi	$\leq$ 1.5mi	$\leq$ 1.8mi	$\leq$ 2.1mi
Panel A: Near/Far DD:						
Treatment: Announcement	0.014	-0.004	0.040	0.101	0.103	0.087
	(0.089)	(0.063)	(0.077)	(0.099)	(0.115)	(0.103)
Panel B: Downwind/Upwind DD:						
Treatment: Announcement	-	0.289***	0.205**	0.071	0.029	-0.035
	-	(0.082)	(0.091)	(0.077)	(0.075)	(0.053)
Panel C: NearTreated/NearControl DD:						
Treatment: Announcement	-0.271**	-0.164**	-0.069	0.003	-0.033	-0.002
	(0.110)	(0.075)	(0.064)	(0.053)	(0.044)	(0.038)
Panel D: Downwind/Upwind Near/Far DDD:						
Treatment: Announcement	-1.075***	-0.282	-0.284	-0.328	-0.197	-0.257**
	(0.177)	(0.293)	(0.221)	(0.210)	(0.141)	(0.117)
Panel E: Downwind/Upwind NearTreated/NearControl DDD:						
Treatment: Announcement	0.045	0.529**	0.393**	0.108	0.068	0.055
	(0.204)	(0.237)	(0.177)	(0.131)	(0.132)	(0.101)
Obs. Panel A	225,089	226,390	228,170	229,928	232,648	235,720
Obs. Panel B	140	556	1,313	2,036	3,370	4,833
Obs. Panel C	1,461	3,818	6,964	10,438	15,368	21,154
Obs. Panel D	80,821	81,237	81,994	82,717	84,051	85,514
Obs. Panel E	629	1,478	2,897	4,487	6,898	9,502

Notes: Control function estimations that include number of bathrooms, number of half bathrooms, number of bedrooms, number of rooms, type of exterior walls, house age, square feet, weather, and county, and state $\times$ year fixed effects as regressors. Announcement refers to the year in which the switch to natural gas was first announced in the local news. Clustered standard errors at the county $\times$ year level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

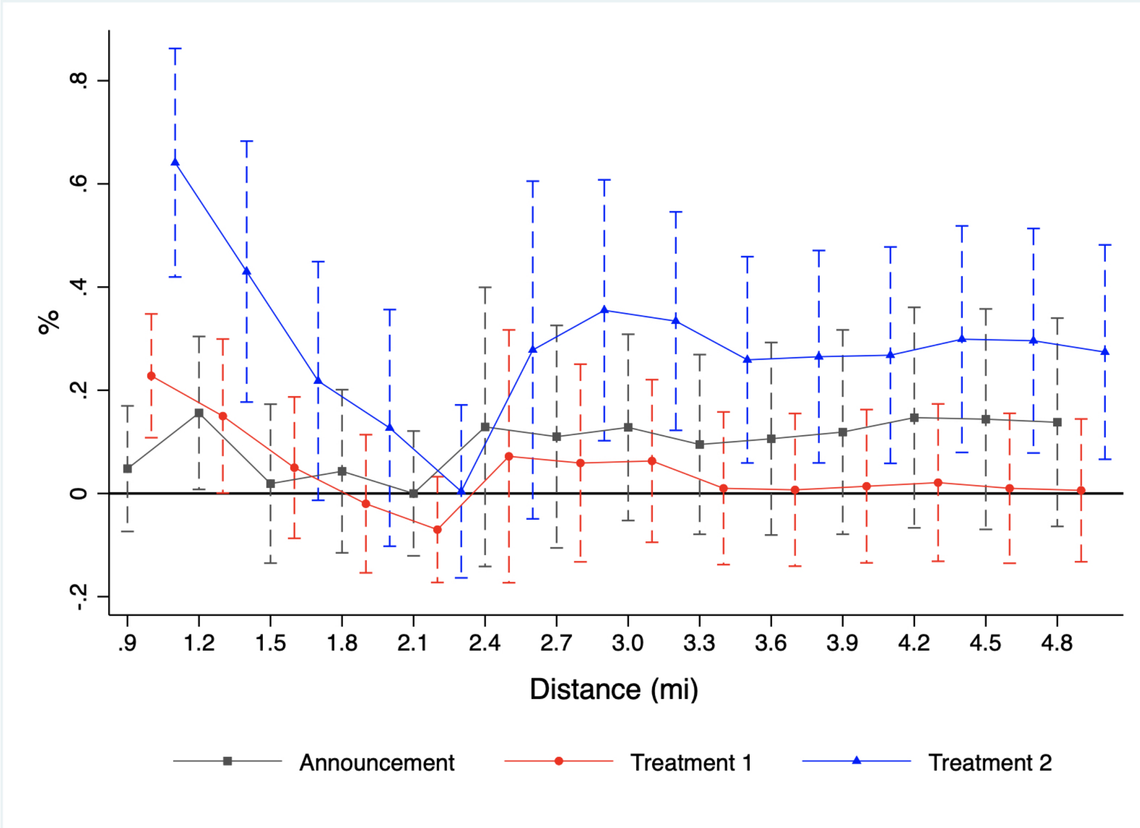


Figure 7: Yearly Heterogeneous Effects of the Coal-to-Gas Switching

Notes: Control function estimates using a Downwind/Upwind DD specification. Announcement refers to the year in which the fuel switching was announced in local newspapers. Treatment 1 refers to the shutdown of the first coal-fired generators. Treatment 2 refers to the startup of the first natural gas-fired generators. Dashed lines represent 95% confidence intervals.

A. Supplemental Material

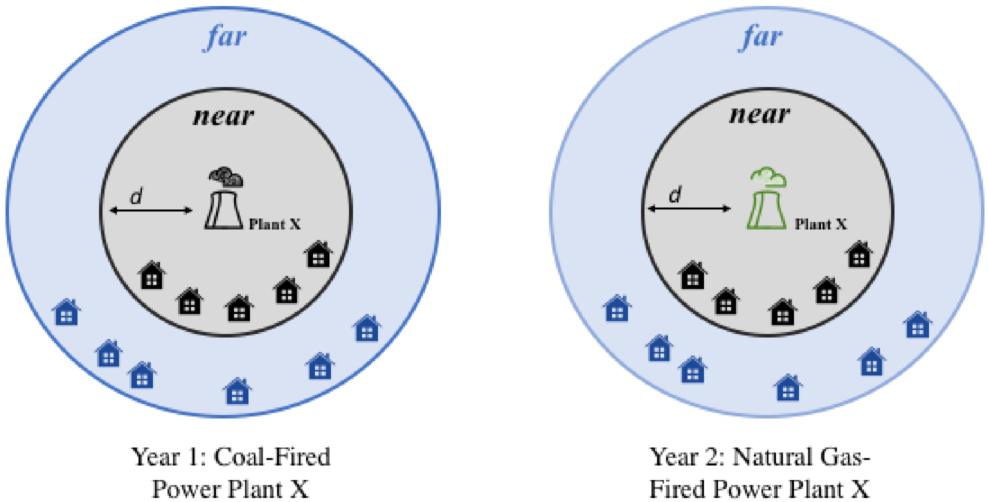


Figure A1: Near/Far Differences-in-Differences Design

Notes: The figure depicts the spatial assortment of houses around a coal-to-gas-fired power plant X before (left-hand side) and after (right-hand side) the switching. In both cases, a radius of distance d from power plant X is used to define the set of houses that are located "near" the switching facility (gray area). In this double differences design, the first price difference comes from the comparison of housing units inside the gray area (near X), and housing units inside the blue area (far X). The second price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching.

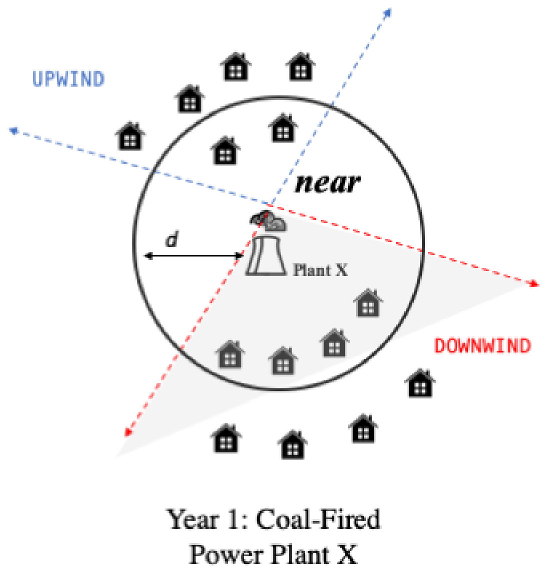
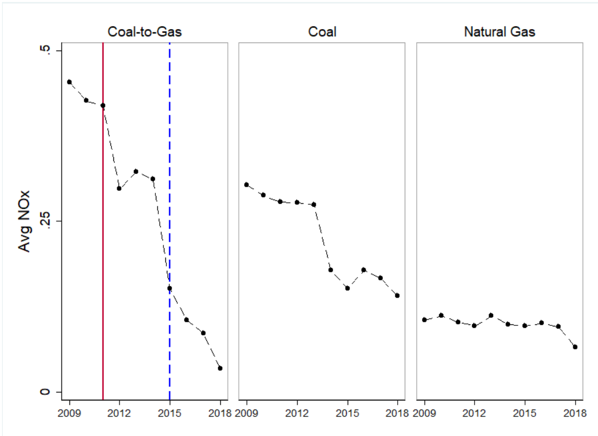
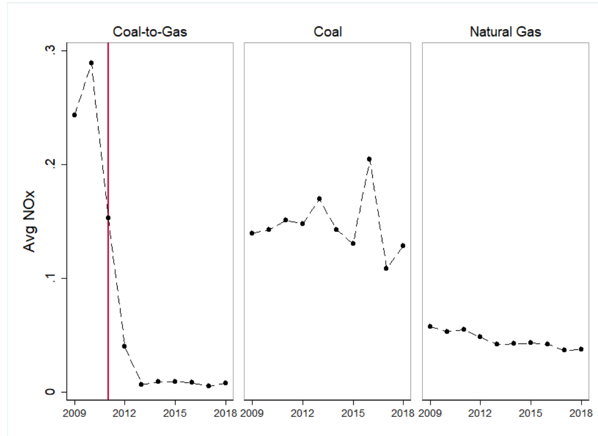


Figure A2: Downwind/Upwind Differences-in-Differences Design

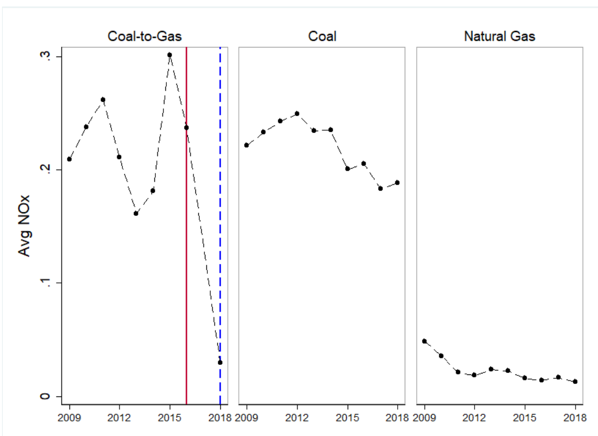
Notes: The figure depicts the spatial assortment of houses around a coal-to-gas-fired power plant X before (left-hand side) and after (right-hand side) the switching. Based on the downwind exposure, obtained from the HySplit Trajectory Model, we select homes that are located upwind and downwind the facility using a 90°-range around the plant. In this double differences design, the first price difference comes from the comparison of housing units inside the gray area (downwind X), and housing units at the opposite (upwind X). The second price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching.



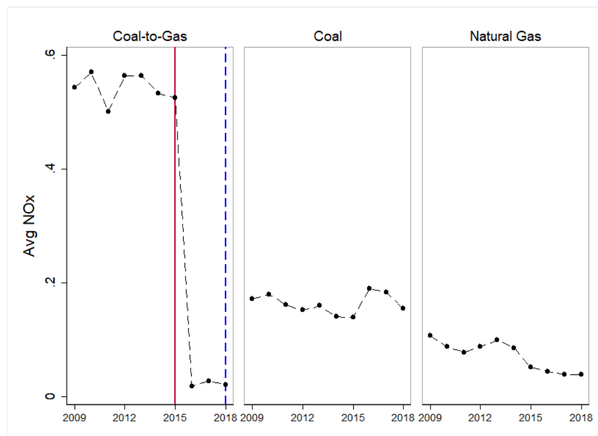
(a) Colorado



(b) Georgia



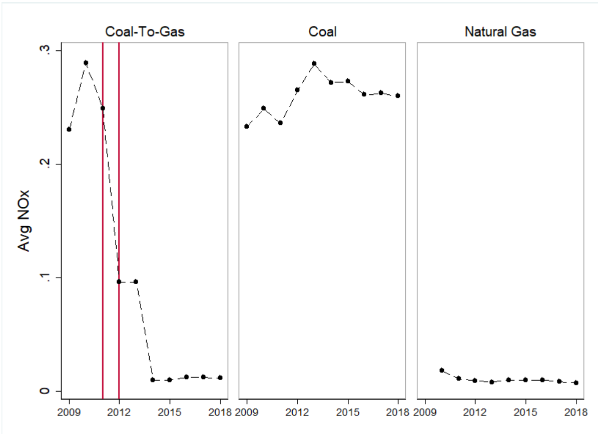
(c) Indiana



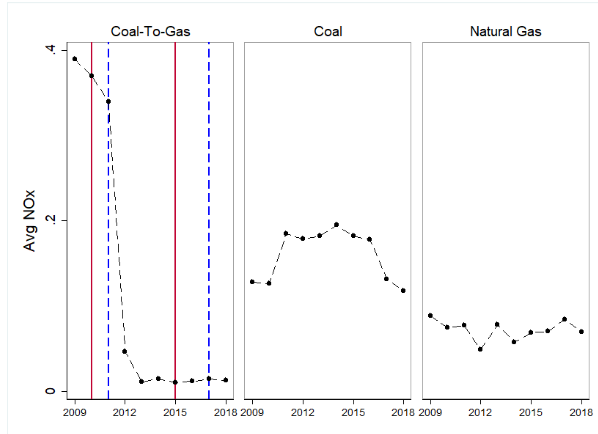
(d) Minnesota

Figure A3: Power Plants and NO_X Emissions by Selected State

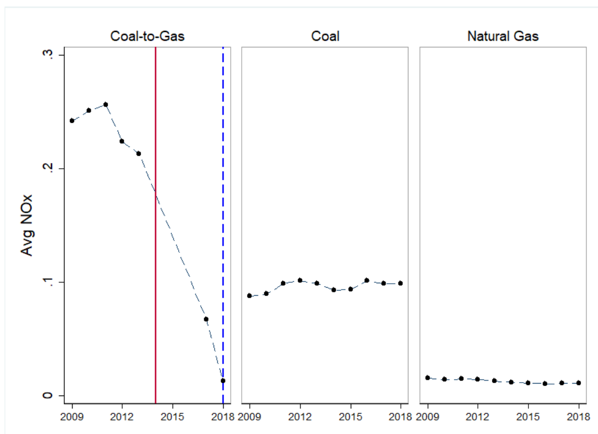
Notes: The red line indicates the shutdown of the first coal-fired EGU (treatment 1), while the blue line represents the startup of the first gas-fired EGU (treatment 2). No blue line means that treatment 1 and treatment 2 coincide.



(e) North Carolina



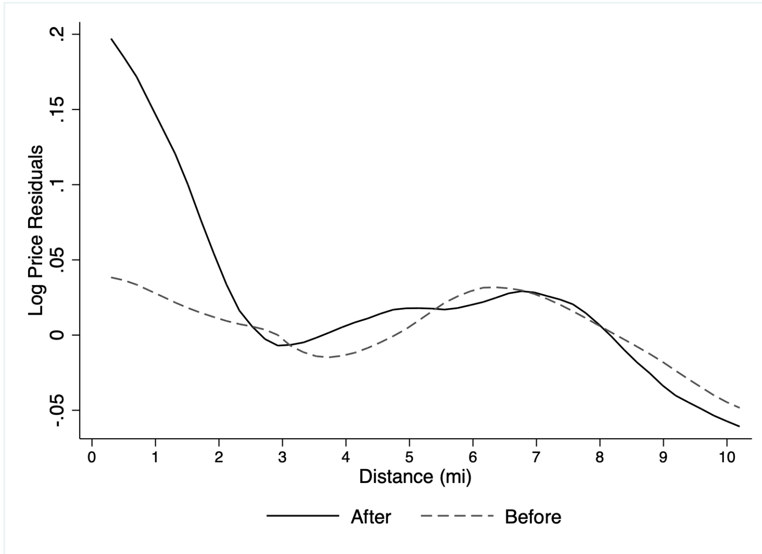
(f) Pennsylvania



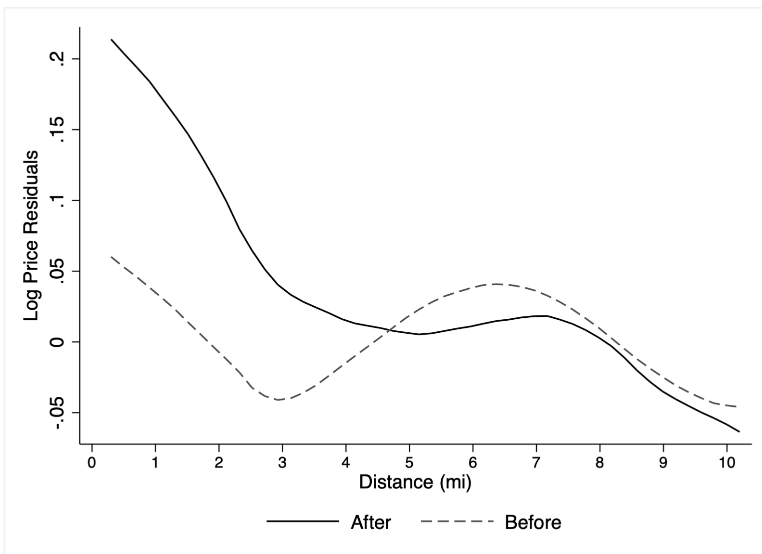
(g) South Carolina

Figure A3: Power Plants and NO_X Emissions by State (Continued)

Notes: The red line indicates the shutdown of the first coal-fired EGU (treatment 1), while the blue line represents the startup of the first gas-fired EGU (treatment 2). No blue line means that treatment 1 and treatment 2 coincide.



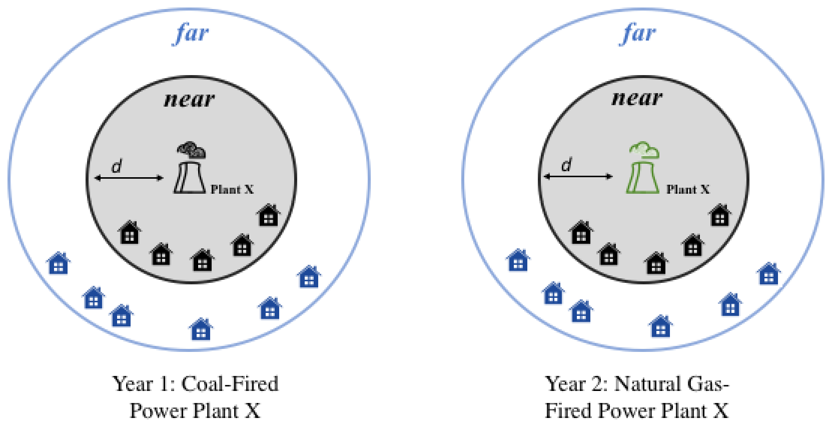
(a) Treatment 1: Shutdown of First Coal-Fired EGU



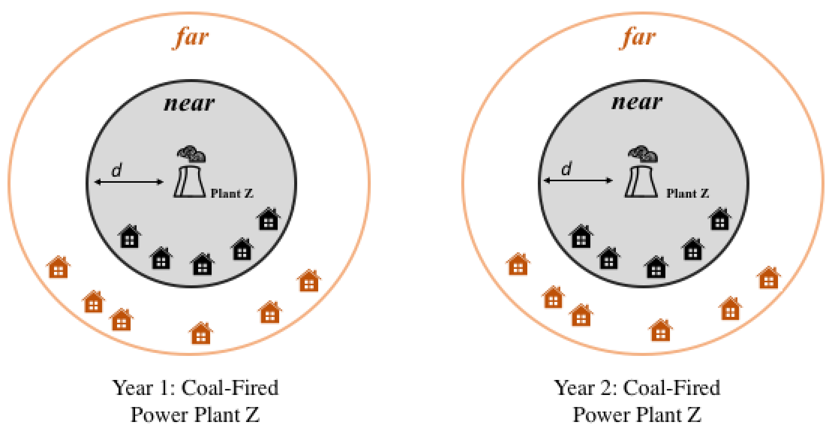
(b) Treatment 2: Startup of First Gas-Fired EGU

Figure A4: Property Value Prices and Distance from Coal-to-Gas Plants

Notes: Based on Muehlenbachs et al. (2015). Outcomes are log price residuals from the regression of prices (in logs) on the number of full baths, number of half baths, number total bedrooms, type of exterior walls, house age, squared feet, weather, and county, plant, and state $\times$ year fixed effects.



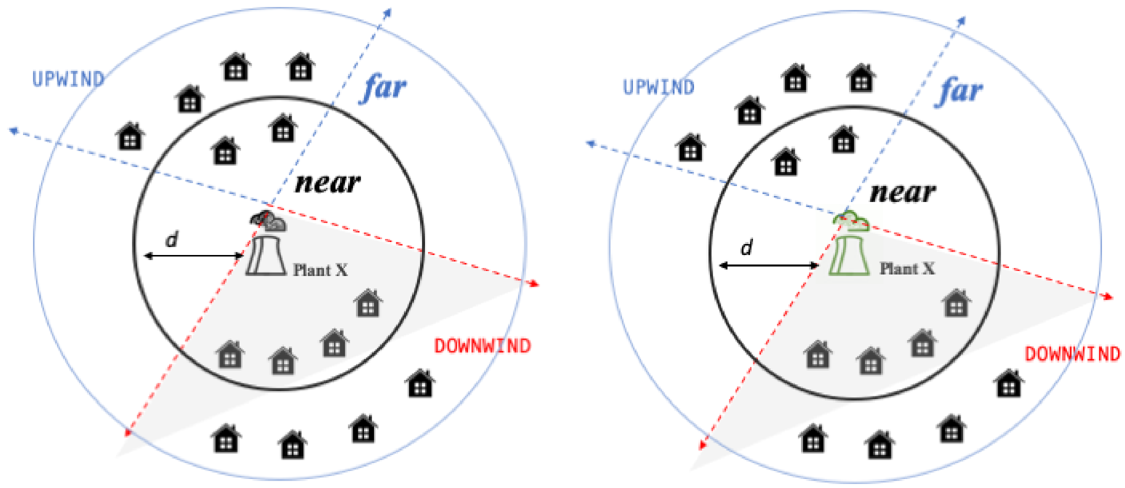
(a) Coal-to-Gas-Fired Plant X



(b) Coal-Fired Plant Z

Figure A5: Near Coal-to-Gas/Near Coal Differences-in-Differences Design

Notes: The top figure (panel a) depicts the spatial assortment of houses around a coal-to-gas-fired power plant X, before (left-hand side) and after (right-hand side) the switching. A radius of distance d from power plant X is used to define the set of houses that are located "near" the switching facility (gray area). The bottom figure (panel b) depicts the spatial assortment of houses around a coal-fired power plant Z, that did not switch, before (left-hand side) and after (right-hand side) power plant X switched to gas. A radius of distance d from power plant Z is used to define the set of houses that are located "near" the control facility (gray area). In this double differences design, the first price difference comes from the comparison of housing units inside the gray area that surrounds power plant X, and housing units inside the gray area that surrounds power plant Z. The second price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching.

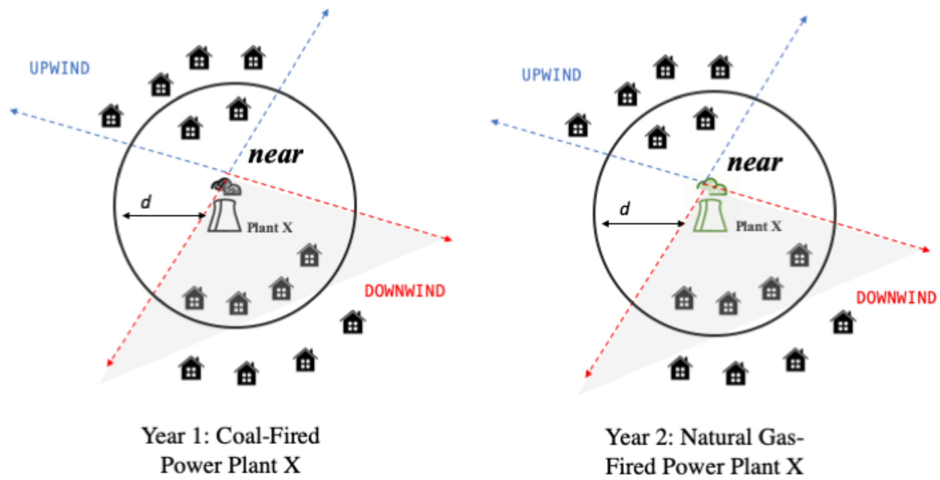


Year 1: Coal-Fired Power Plant X

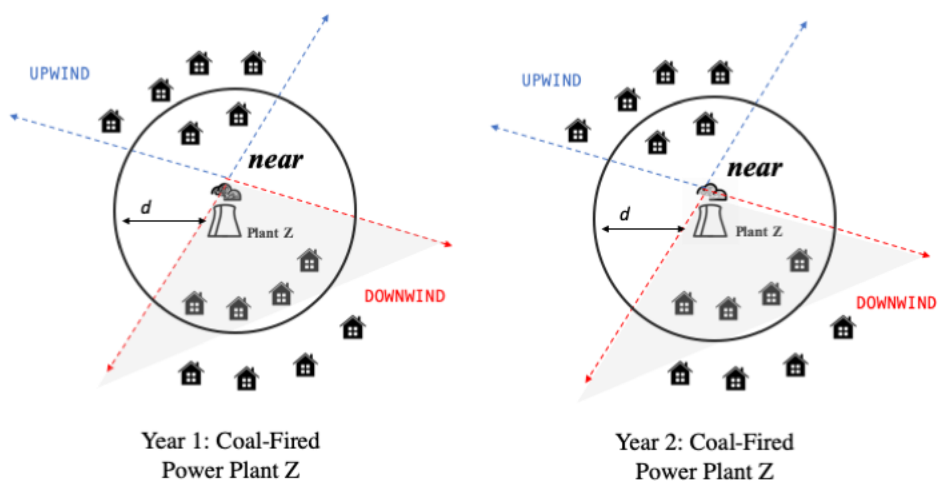
Year 2: Natural Gas-Fired Power Plant X

Figure A6: Downwind/Upwind Near/Far Triple Differences Design

Notes: The figure depicts the spatial assortment of houses around a coal-to-gas-fired power plant X before (left-hand side) and after (right-hand side) the switching. Based on the downwind exposure, obtained from the HySplit Trajectory Model, we select homes that are located upwind and downwind the facility using a 90°-range around the plant. In this double differences design, the first price difference comes from the comparison of housing units inside the gray area (downwind X), and housing units at the opposite (upwind X). The second price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching. In this triple differences design, the first price difference comes from the comparison of housing units inside the gray area (downwind X), and housing units at the opposite (upwind X). The second price difference comes from the comparison of housing units inside the black area (near X), and housing units outside in the blue area (far X). The third price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching.



(a) Coal-to-Gas-Fired Plant X



(b) Coal-Fired Plant Z

Figure A7: Downwind/Upwind Near Coal-to-Gas/Near Coal Triple Differences Design

Notes: The top figure (panel a) depicts the spatial assortment of houses around a coal-to-gas-fired power plant X, before (left-hand side) and after (right-hand side) the switching. The bottom figure (panel b) depicts the spatial assortment of houses around a coal-fired power plant Z, that did not switch, before (left-hand side) and after (right-hand side) power plant X switched to gas. In this triple differences design, the first price difference comes from the comparison of housing units inside the gray area (downwind X), and housing units at the opposite (upwind X). The second price difference comes from the comparison of houses that are located near power plant X, and houses that are located near power plant Z. The third price difference comes from the comparison of housing units before (year 1) and after (year 2) the switching.

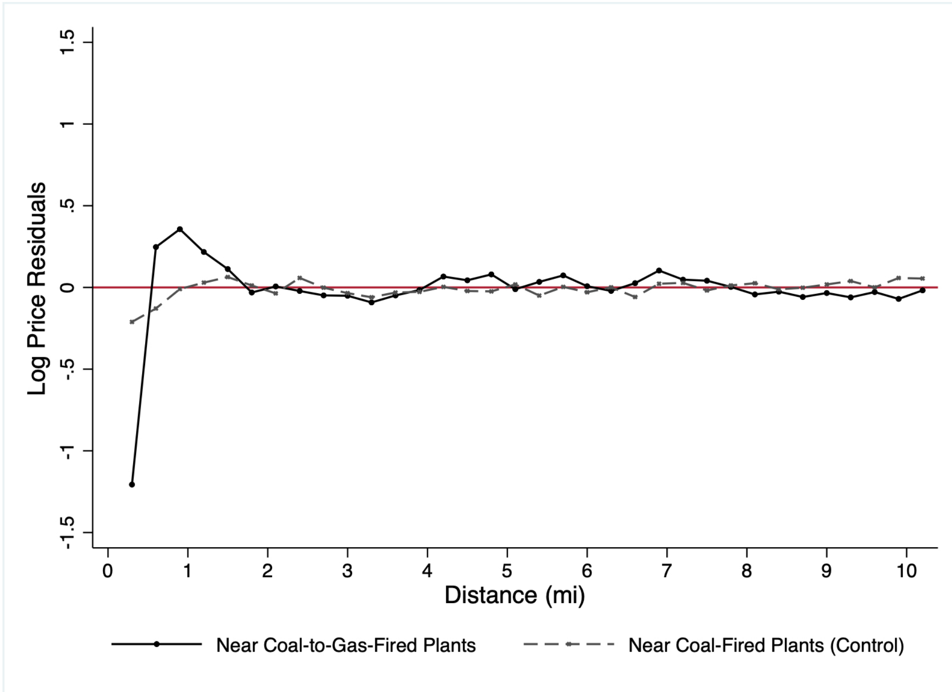
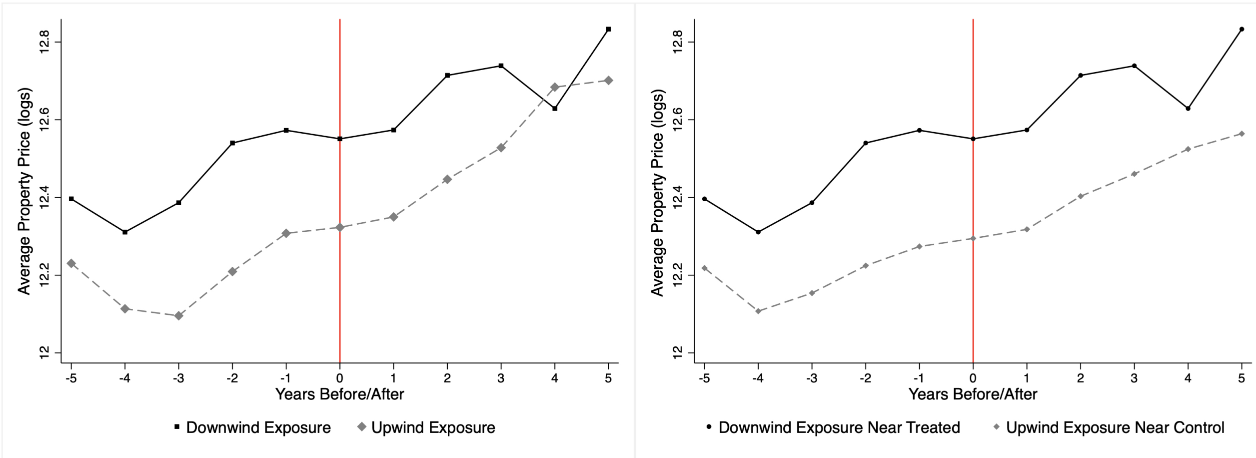
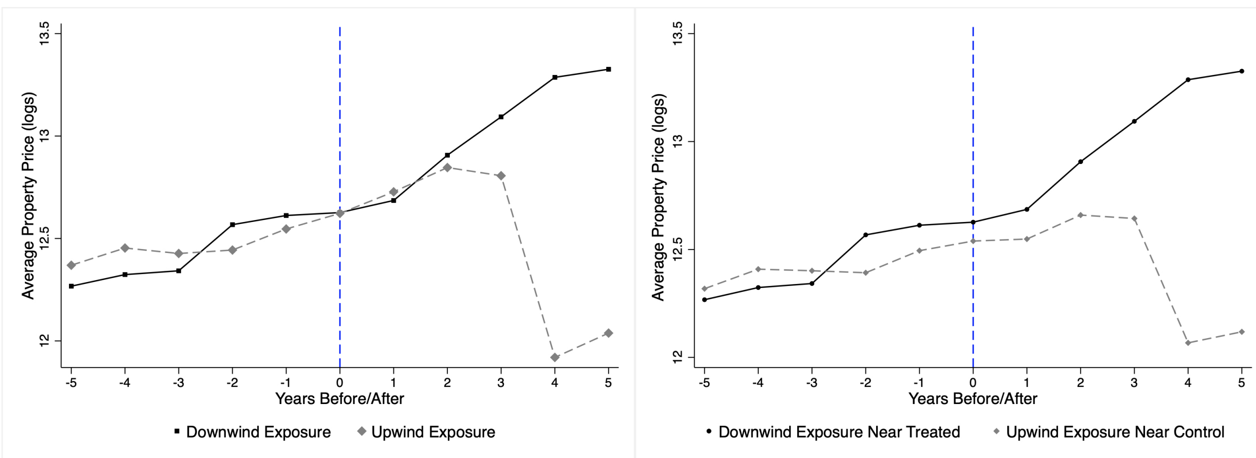


Figure A8: Property Prices of Homes Near Treated and Control Plants During 2009

Notes: Log price residuals from the regression of prices (in logs) on the number of full baths, number of half baths, number total bedrooms, number total rooms, type of exterior walls, house age, squared feet, weather, and county, and state $\times$ year fixed effects.



(a) Treatment 1: Shutdown of First Coal-Fired EGU



(b) Treatment 2: Startup of First Gas-Fired EGU

Figure A9: Overview of Common Trends Assumption

Notes: Left-hand side panels use downwind and upwind homes that are located at a distance < 5mi from a treated plant, while right-hand side panels use downwind and upwind homes that are located at a distance < 5mi from either a treated (coal-to-gas-fired) or a control (coal-fired) plant.

Table A1: Probit Estimation Results

	Treatment 1		Treatment 2	
	γ_2	Marginal Effects	γ_2	Marginal Effects
Summer Capacity (MW)	-0.082**	-0.0065***	-0.077**	-0.0048**
	(0.033)	(0.002)	(0.034)	(0.002)
Winter Capacity (MW)	0.081**	0.006***	0.076**	0.005**
	(0.032)	(0.002)	(0.033)	(0.002)
Plant's age	0.063**	0.005***	0.045***	0.003***
	(0.020)	(0.001)	(0.011)	(0.001)
Obs.	720		720	
Pseudo-R^2	0.476		0.473	
% Correct Predictions	94%		94%	

Notes: Probit estimation on the probability of switching fuels using coal-to-gas-fired plants (treated) and coal-fired plants (controls). All estimations include state fixed effects. Treatment 1 refers to shut down of the first coal-fired generators. Treatment 2 refers to start up of the first natural gas-fired generators. Clustered standard errors at the state level in parentheses. Significance levels: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.001$.

Figure A10: Robustness Check: Split of Upwind Homes Into Areas A and B