Residential Sorting and the Incidence of Local Public Goods: Theory and Evidence from Air Pollution

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Abstract

While the costs of environmental policies are generally thought to be regressive, the distribution of benefits is less understood. This paper explores the incidence of an unexpected decrease in air pollution in metropolitan Los Angeles by estimating the resulting change in housing costs and neighborhood demographics. The decrease in air pollution was caused jointly by the California Electricity Crisis of 2000 and the RECLAIM cap-and-trade program for NO_x emissions and impacted neighborhoods differentially based on their location relative to major polluters and local wind patterns. I measure local exposure to this pollution shock using a dispersion model developed by atmospheric scientists which calculates the effect of individual firms' emissions on the air quality of nearby locations. The estimates show that (a) housing rents increase significantly and as much as house prices; (b) 9% of low-income households leave the sample area due to improved air quality; and (c) low-income households are rarely home owners who would benefit from increased housing wealth. I show that a standard residential sorting model predicts that when low-income residents respond to improved amenities by leaving, the distribution of benefits from the improvement is likely regressive. Together, these results suggest that the distribution of benefits from improved air quality likely favors higher-income households.

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1 Introduction

Past research suggests that the costs of many environmental policies fall disproportionately on low-income households, while much less is known about the distribution of benefits (Parry et al. 2006; Bento 2013). This is especially true in the case of local air pollution. More polluted neighborhoods tend to be poorer, raising the possibility that air quality policies could especially benefit these residents. But like any place-based policy, improvements to air quality are likely to impact housing markets, potentially raising home values and rents. This could give a larger share of the benefits to higher-income households (who are more likely to be homeowners) and induce lower-income households to simply move in the face of rent increases.

Past empirical findings about the effects of air quality changes on neighborhoods' rents and demographic composition are mixed. Early work implies a more regressive distribution of benefits, though these studies did not focus specifically on incidence. Davis (2011) finds that the construction of a new power plant in a neighborhood causes rents and house prices to fall similarly, and the average household becomes poorer and less educated. Similarly, Banzhaf and Walsh (2008) find that population flows into cleaner neighborhoods, with some evidence that average income responds negatively to pollution exposure. In contrast, more recent work comes to the opposite conclusion. Currie et al. (2015) and Bento, Freedman, and Lang (2015) find no change in neighborhood demographics in response to changes in pollution exposure. Bento, Freedman, and Lang (2015) and Grainger (2012) also find that effect of air pollution on rents is about half the effect on house prices.

One possible explanation for these conflicting results is the systemic mismeasurement of pollution exposure, highlighted by Sullivan (2017), which arises due to the complex atmospheric forces that determine the geographic distribution of air pollution. When pollution leaves a firm's smoke stack, most of it travels downwind and significant concentrations can reach areas far beyond the firm's own neighborhood. Use of concentric circles to define treatment areas—one of the predominant methods of defining treatment groups in the wider pollution literature and the method used by most of the studies cited above—does not account for this fact. This leads to misspecification of who is exposed to pollution and who is not. In a quasi-experimental framework, assignment to "treatment" and "control" areas is often incorrect. This in turn leads to severe bias in the estimated impact of a pollution change—even with an ideal natural experiment—as demonstrated empirically in the case of house prices by Sullivan (2017). That study finds that using a rigorous, wind-based measure pollution exposure yields estimates that are an order of magnitude larger than estimates from conventional methods and estimates from prior research.

The goal of this paper is to use both a natural experiment and a rigorous, atmospheric science–based measure of pollution exposure to measure the effects pollution has on neighborhood-level outcomes. I use an atmospheric dispersion model developed by the American Meteorological Soceity and the U.S. Environmental Protection Agency (EPA) to determine which areas are actually affected by an exogenous shock to firm-level pollution emissions. Using this model and administrative data from firms' in-stack emission monitors, I calculate every firm's pollution contribution to every point in a 100-meter grid covering most of the Los Angeles/Long Beach area. This allows me to precisely measure how much each neighborhood, defined by Census block groups, benefited from the exogenous air quality improvement. The exogenous drop in pollution which I exploit was caused by the California Electricity Crisis of 2000, which precipitated the near collapse of RECLAIM, a then nascent cap-and-trade market for NO_x in southern California, which in turn caused firms in the area to quickly adopt abatement technology. This led to a sudden and permanent decrease in pollution levels which differed across neighborhoods. Using AERMOD, the Crisis, and block group data from the 2000 Census and 2005–2009 ACS, I am able to estimate the effects of a sudden pollution change on neighborhood characteristics.

To motivate the neighborhood-level analysis and the interpretation of the results, I present a model of residential sorting based on Epple, Filimon, and Romer (1984) and subsequent literature, especially Banzhaf and Walsh (2008). The canonical version of this model predicts that when a city or neighborhood's amenities improve, people flow into the area until rising prices stem the flow of immigrants and a new equilibrium is achieved. However, the comparative statics derived in past versions of this model do not allow for the possibility that low-income incumbent residents may respond to an amenity improvement and subsequent increase in housing costs by leaving the area. I expand the scope of these derivations to show that the canonical model does allow for low-income residents to "flee" an amenity improvement, and that this occurs if and only if their willingness to pay (WTP) for the local amenity is significantly lower than their higher-income neighbors' WTP. Thus, a significant out-migration of lower-income households following an improvement would suggest that these households value the improvement much less than higher-income households.

The empirical results suggest that the benefits of the Crisis and RECLAIM flowed more to high-income households than low-income households. First, housing rents increased significantly in improved neighborhoods and the increase was very similar to the one found for house sales by Sullivan (2017). Thus, lower-income renters were not shielded from the price increase that accompanied the amenity improvement. Second, improved neighborhoods became richer and better educated but less populous, with fewer people, households, and housing units. These effects are driven by the emigration of low-income households (income below $30,000) from improved areas. Higher-income households also moved into these newly cleaned areas, though not enough to offset the lower-income emigrants. As far as these households were renters and not home owners, the residential sorting model suggests that they valued the air quality improvement less than the income high-income households. Third, I find that home-ownership rates in ex ante low-income neighborhoods were low and that large gains in property values from the relatively larger pollution improvements in these neighborhoods did not offset low home-ownership rates. That is, even though poorer households saw larger improvements because their neighborhoods were initially more polluted, so few of these households owned their homes that, as a group, they enjoyed a much smaller positive wealth shock due to home value appreciation than higher-income residents did. Each of these findings points in the direction of a relatively regressive distribution of benefits.

2 Theory

The model presented here follows the framework of Epple, Filimon, and Romer (1984) and subsequently Epple, Filimon, and Romer (1993), Epple and Sieg (1999), Banzhaf and Walsh (2008), and others. Households, defined by their income, choose to live in one of J communities based on each community's exogenous level of amenities and endogenous housing price. By imposing the assumption that household preferences exhibit single-crossing in income and the amenity, the existence of a unique equilibrium is guaranteed and communities will be stratified by prices, amenities, and household income.

The contribution of this paper is in the derivation of comparative statics and other results using a three-city version of this model rather than a two-city version. With two communities stratified by income and amenities, changes to either amenity bundle result in population flowing into the newly improved area as predicted by Tiebout (1956) (see, e.g., Banzhaf and Walsh 2008). This transition is depicted in Figure 1. If the higher-income community improves its amenities, the previously marginal households with income $\tilde{y}$ will move into the newly improved community. However, both of these communities have one exogenous boundary, which precludes the possibility that people might "flee" an amenity improvement because other participants in the market have bid up prices. A three-city model (see Figure 2) allows for this possibility in the middle city which has no exogenous boundaries.

2.1 Model Setup

Definition 1 (Community)**.** A community $j \in \{1, \ldots, J\}$ is characterized by (p_j, g_j), its endogenous unit price of housing and its exogenous amenity level. Housing in community j is supplied according to $S^j(p)$ which has the following properties: $S^j_p > 0$; $S^j(p^l_j) = 0$ for some lower bounding price $p^l_j > 0$; and $0 < S^j(p) < \infty$ for $p > p^l_j$.

Definition 2 (Household)**.** A household is characterized by its income, y, which follows a distribution $f(y)$ with continuous support $[y_l, y_h]$. A household's preferences are characterized by indirect utility $V(y, p, g)$ which is assumed to have the following basic properties: $V_y > 0$; $V_p < 0$; $V_g > 0$. Households also have housing demand $h(p, y)$ which is assumed to be independent of g and to have the following properties: $h_p < 0$, $h_y > 0$, $0 < h < \infty$.[1] Households choose the community (p_j, g_j) that maximizes their utility.

An equilibrium is as an allocation of households to communities such that (a) no household wants to move to another community (spatial equilibrium); and (b) the housing market in each community clears (internal equilibrium). The extensive literature on this and similar spatial models has found that characterizing this equilibrium and guaranteeing its existence requires some additional structure.[2] The approach used in the papers previously cited, which I follow here, is to assume V satisfies single-crossing in p and g.

Assumption 1 (Single-crossing preferences)**.** Assume $V(y, p, g)$ satisfies the *single-crossing property* in p and g:

$$M(y, p, g) = -\frac{V_g(y, p, g)}{V_p(y, p, g)} = \left.\frac{\mathrm{d}p}{\mathrm{d}g}\right|_{V=\bar{V}(y)} \tag{1}$$

1. See Epple and Sieg (1999) or Sieg et al. (2004) for an example and discussion of an indirect utility function that satisfies these properties.

2. See Epple and Sieg (1999) and Kuminoff, Smith, and Timmins (2013) for a discussion.

is monotonically increasing in y for all (y, p, g).

Note that $M(y, p, g)$ is the slope of an indifference curve in (p, g) space for a fixed y. Assumption 1 requires that the slope of this curve be increasing with y.

Epple, Filimon, and Romer (1984) show that under Assumption 1 an equilibrium like the one described above will take the following form:[3]

Definition 3 (Equilibrium; Epple, Filimon, and Romer 1984)**.** Without loss of generality, suppose that communities are indexed such that $g_j < g_{j+1}$. Under Assumption 1, an equilibrium can be characterized by a set of boundary incomes $\{\tilde{y}_1, \ldots, \tilde{y}_{J-1}\}$ and prices $\{p_1, \ldots, p_J\}$ such that $\tilde{y}_j < \tilde{y}_{j+1}$ and $p_j < p_{j+1}$, where the following conditions hold:

$$V\left(\tilde{y}_j, p_j, g_j\right) = V\left(\tilde{y}_j, p_{j+1}, g_{j+1}\right) \quad \forall j < J \tag{2}$$

$$\int_{\tilde{y}_{j-1}}^{\tilde{y}_j} h(p_j, y) f(y)\, \mathrm{d}y = S^j(p_j) \quad \forall j \tag{3}$$

where $\tilde{y}_0 = y_l$ and $\tilde{y}_J = y_h$.

The first set of conditions are boundary indifference (or spatial equilibrium) conditions which require the household which borders j and $j+1$ on the income continuum to be indifferent between the two. The second set of conditions are internal equilibrium conditions for each community, which require housing demanded to equal housing supplied. Epple, Filimon, and Romer (1993) show that such an equilibrium exists and is unique.

2.2 Implications of the Model

In this section, I derive conditions under which some households may respond to an improvement in their community by leaving it. The key assumption of the model, single-crossing preferences, effectively requires that higher-income households have a higher MWTP for g than lower-income households.[4] Thus, for community j, the lowest-income household $\tilde{y}_{j-1}$ has a lower MWTP for the amenity than the highest-income household

3. Epple and Sieg (1999) extend this model to include heterogeneity in preferences as well as income and characterize the equilibrium similarly. In that case, where α is the preference parameter, community boundaries are lines $\tilde{y}_j(\alpha)$ in income-preference space.

4. Recall that single-crossing requires $\mathrm{d}p/\mathrm{d}g = M(y, p, g)$ to be increasing in y. Let $\bar{V} = V(y, g, p(g))$ be a fixed utility level where $p(g)$ is a function such that $p \leq p(g) \Rightarrow V(y, g, p(g)) \geq \bar{V}$. That is, $p(g)$ is the highest price the household can pay for g without its utility falling below $\bar{V}$. Differentiating $\bar{V} = V(y, g, p(g))$ with respect to g yields Equation (1).

$\tilde{y}_j$, meaning that the higher-income household will bid more for an increase in g. If the difference in MWTP is large enough, the price of housing in community j may increase enough that the lower-income household is better off moving to community $j-1$.

However, such "fleeing" of an amenity improvement can only occur in a community where both upper and lower income boundaries are endogenous, otherwise low-income households are mechanically blocked from fleeing or high-income households are mechanically blocked from flowing into the area and bidding up prices. As such, I consider the case where $J=3$, since the case of $J=2$ considered in past literature does not include any communities with two endogenous boundaries. Proofs of all propositions are given in Appendix A.

Suppose $J=3$, so the vector of endogenous variables is $(\tilde{y}_1, \tilde{y}_2, p_1, p_2, p_3)$ and the exogenous variables of interest are (g_1, g_2, g_3). (Figure 2 depicts the income continuum and the boundaries of each of the three communities.)

Proposition 1. *The following conditions hold:*

$$\frac{\partial \tilde{y}_2}{\partial g_2} > 0; \quad \frac{\partial p_2}{\partial g_2} > 0; \quad \frac{\partial p_3}{\partial g_2} < 0 \tag{4}$$

$$\frac{\partial \tilde{y}_1}{\partial g_2} \propto \frac{\partial p_1}{\partial g_2} \tag{5}$$

and the sign of $\partial \tilde{y}_1 / \partial g_2$ *is ambiguous.*

These comparative statics are not surprising.[5] In response to the improvement to Community 2, the price of housing there increases and some residents of Community 3 move in. The proportionality in Equation (5) also follows economic intuition, with p_1 decreasing if some Community 1 residents move up to Community 2 and p_1 increasing if some residents of Community 2 flee into Community 1. The fact that these last two effects cannot be signed without additional conditions is consistent with the previously discussed intuition where the behavior of the poorer incumbents depends on the difference in MWTP of the boundary households.

Proposition 2.

$$\frac{\partial \tilde{y}_1}{\partial g_2} > 0$$

5. Proposition 3, given in Appendix A, shows that the effects of a change in g_1 or g_3 are likewise consistent with past results.

if and only if

$$\frac{M(\tilde{y}_2, p_2, g_2)}{M(\tilde{y}_1, p_2, g_2)} > R^* \tag{6}$$

where R^* *depends on* $(\tilde{y}_2, g_2, g_3, p_2, p_3)$.

The right side of the inequality, R^*, is a term that captures the trade-offs the $\tilde{y}_2$ households face when choosing between Community 2 and Community 3. (See Appendix A for a precise definition and brief discussion of R^*.) This term serves as a bound on how different the MWTP for g can be within a community before an improvement in g leads to emigration by the poorest households.

This result gives a provides a bridge between observable behavior and preferences: households observed fleeing the improvement value it significantly less than those who stay or those who move in. If these households are predominantly lower-income, as the model predicts, this would imply that the amenity-improving policy has a more regressive distribution of benefits. Testing for such a disparity by income is a primary empirical goal of this paper.

3 Research Design

3.1 Measuring Air Quality with AERMOD

A key problem in the study of air pollution is knowing who is exposed to pollution and how much they are exposed to. Unlike wages and other economic variables, there are no large-sample data on individual-level pollution exposure. One approach to measuring the effect of a policy intervention is to use an individual's (or a neighborhood's) proximity to an affected firm as a measure of their exposure to the policy's effects.[6] A drawback to this approach is that air pollution is blown away from its source in the direction of the wind, meaning two neighborhoods equidistant from a pollution source can see pollution exposure that is different by several orders of magnitude. Pooling such neighborhoods together and treating them as equally exposed causes estimates of pollution's effects to be

6. This is the approach taken by Davis (2011), Banzhaf and Walsh (2008), Currie et al. (2015), and others. Grainger (2012) and Bento, Freedman, and Lang (2015) take a similar approach. Instead of using proximity to firms, they use proximity to individual monitors because local regulators have an incentive to target firms near monitors for special enforcement of air quality regulations because the monitors are the metric for local compliance with regulations. However, this does not solve the issue of whether individuals or neighborhoods are located upwind or downwind of the firms affecting the monitor.

biased toward zero. Another widely used approach to this problem is to proxy for local exposure with data from nearby pollution monitors, usually via interpolation. However, pollution monitors in the United States are sparse relative to pollution sources and so they miss most of the local variation created by each of this sources, again biasing estimates toward zero. These problems are discussed in more detail by Sullivan (2017), which also presents empirical evidence of these biases in the context of pollution's effect on housing prices.

A solution to these problems is to use an atmospheric dispersion model to explicity account for meteorology and for the local spikes in pollution exposure around each individual pollution source. A dispersion model uses data on a polluting firm and the meteorology around the source to predict the impact of the firm's pollution on air quality of nearby locations. In this paper, I use AERMOD, the EPA's legally preferred model for short-range applications. This preference is based on the model's high accuracy as established by peer-reviewed field tests (Perry et al. 2005).[7] To account for meteorological conditions, AERMOD uses hourly data on temperature, wind speed, and wind direction at multiple elevations; the standard deviation of vertical wind speed; the convectively and mechanically driven mixing heights; and other parameters.[8] To account for firm characteristics, AERMOD also uses smoke stack's height and diameter, the temperature and velocity of the gas exiting the stack, and the rate at which the pollutant in question is emitted from the stack (mass per unit time). Given this data, the model outputs the concentration of emissions at location i in micrograms per cubic meter of air, abbreviated $\mu g/m^3$. Figure 6a depicts exposure in greater Los Angeles to industrial NO_x emissions in 2000.[9]

AEMROD's predictions at individual locations can be used to construct neighborhood-level measures of average exposure.[10] First, AERMOD is used to create aermod_{it}, exposure at location i and time t, where i is a point in a 100 meter raster covering the sample area. This 100-meter measure is then used to find the average exposure to each Census block via numerical quadrature, assuming a uniform distribution of population within each block.

7. Validation experiments such as Perry et al. (2005) are conducted by placing a dense network of several dozen monitors around a firm, releasing a rare, non-reactive tracer chemical, then comparing model predictions to monitor readings. Regulatory preference for AERMOD is stated in 40 CFR pt. 51, app. W (2004). See Cimorelli et al. (2005) for a rigorous development of the model itself.

8. A full list of the variables used is found in the AERMOD user manual or Cimorelli et al. (2005).

9. Discussion of the sample area is given in Section 3.3.

10. The construction of the exposure measure is discussed in more detail in Section 4.5.

The block-level averages can then be used to create a block group–level average, aermod_{nt}, weighting by block population.

While AERMOD has been thoroughly vetted by atmospheric scientists, I also validate its predictions in the sample area against contemporaneous monitor readings in Figure 3. Sub-figure (a) plots the AERMOD-predicted exposure to NO_x at the northern monitor in the sample area (see Figure 6a) over time as well as the actual monitor readings from that monitor, and sub-figure (b) plots the same for the southern monitor. Plotted values are averages from the fourth quarter of each year because the AERMOD and monitor readings are most comparible at this time. This is because relatively fewer chemical reactions occur in the atmosphere during this time of year; these reactions are discussed in more detail below.[11]

Figure 3 shows a stark similarity in AERMOD and monitor patterns over time, suggesting that AERMOD is measuring pollution exposure with accuracy. The most notable feature of these time series is the drop in NO_x following the California Electricity Crisis in the latter part of 2000 which mirrors the drop in firms' NO_x emissions shown in Figure 5. (Both the Crisis and Figure 5 are discussed in detail in Section 3.) There are some discrepancies between the AERMOD and the monitors, which most likely due to other sources of NO_x like cars, atmospheric chemistry, or the limitations of the meteorological data discussed in Section 4.5. Nevertheless, the AERMOD predictions appear to track changes in pollution exposure over time with accuracy.

A final caveat—and potential advantage—about measuring dispersion model predictions is that they do not necessarily take into account chemical reactions that occur in the atmosphere. Many pollutants react with other chemicals in the atmosphere once they are emitted. In particular, NO_x can combine with free oxygen through several intermediary reactions to form ozone, which itself is not emitted directly by polluters and is only present at ground level as a product of NO_x-based reactions. Though AERMOD and other dispersion models are capable of modeling this chemical process, it requires high-quality data on

11. It should also be noted that each variable is measured in different units, mass per volume $\mu g/m^3$ for AERMOD and parts-per-million (ppm) for the monitors. Both the RECLAIM firm-level monitoring system and AERMOD measure firm emissions by mass of NO and NO_2 emitted (i.e. grams of NO_x) and AERMOD outputs local concentrations in mass per volume of air ($\mu g/m^3$). In contrast, monitors measure the number of NO and NO_2 molecules relative to other molecules in the air. It generally possible to convert between these two units using the ideal gas law. However, RECLAIM's monitoring systems do not differentiate between NO and NO_2 and the relative ratio of these chemicals is crucial to converting between $\mu g/m^3$ and ppm. Given this limitation of the data, and the near certainty that the NO/NO_2 mix varies both across firms and across time within firms, it is best to compare the AERMOD predictions and monitor readings as is.

pre-existing levels of many other pollutants.[12] The lack of such data is the very problem for which AERMOD is the proposed solution, and because of this lack of data I do not model this conversion. This changes the interpretation of the AERMOD prediction from "exposure to NO_x" to "exposure to NO_x and ozone", which is a more comprehensive and policy-relevant metric.

While AERMOD solves the problem of measuring pollution exposure, it does not eliminiate the need for a natural experiment to identify the effect of pollution exposure on economic outcomes of interest..

3.2 Electricity Crisis as Natural Experiment

To identify the causal effect of pollution exposure on house prices, I use the natural experiment created by the California Electricity Crisis of 2000, which unexpectedly and permanently lowered NO_x emissions through its effect on the RECLAIM cap-and-trade program.

In 1994, the South Coast Air Quality Management District (SCAQMD), which regulates air pollution in Los Angeles, Orange, San Bernardino, and Riverside Counties, instituted a cap-and-trade program for NO_x emissions called RECLAIM (see Fowlie, Holland, and Mansur 2012). At the beginning of the program, firms were given an initial allocation of RECLAIM Trading Credits (RTCs) for each of the upcoming years. Under the program, firms must surrender one current-year RTC at the end of the year for every pound of NO_x emitted. Excess RTCs can be sold to other firms but not banked for future years. To ease firms' transition into the program, the total number of RTCs was set to be higher than total emissions initially and decrease over time The aggregate RTC cap was anticipated to become binding (when total emissions would equal or exceed total RTCs available to the market) around 1999.

However, firms did not adequately plan for the day when the trading cap would be binding. In order for total emissions to stay under the RTC cap, some firms would need lower NO_x emissions by either installing abatement equipment to remove NO_x from their emitted smoke or by decreasing production. But RTC prices were so low there was little short-run incentive to install abatement equipment. SCAQMD publicly reported in mid-

12. Besides UV light, the NO_x–ozone reactions also depend on a class of several dozen chemicals called volatile organic compounds, or VOC's. The rate of NO_x–ozone conversion can also depend on the relative ratios of NO, NO_2, and ozone.

1998 that then current abatement installations were lagging behind what was necessary to avoid the coming "cross-over point" when emissions would equal or exceed permits. Some firms had even canceled orders for abatement equipment they had made prior to the start of the cap-and-trade program. Firm managers later reported that they believed other "companies were reducing their emissions or were going to begin installing [abatement equipment], and as a result believed that they would be able to buy credits... [and] that long-term RTC prices would continue to stay low or would at least gradually rise to the cross-over point" (EPA 2002, p. 24).

This failure to anticipate increased RTC prices caused the cap-and-trade market to nearly collapse at the onset of the California Electricity Crisis in mid-2000. The facet of the Crisis most critical to RECLAIM was that electricity demand theatened to exceed potential supply.[13] To prevent rolling black-outs, many electricity producers significantly increased generation and, as a result, their NO_x emissions. This caused the aggregate RTC cap to finally bind which in turn caused a dramatic spike in RTC prices, from $2,800 per ton in 1999 to $62,000 by the end of 2000. Figure 4 plots aggregate NO_x emissions, total RTCs, and average RTC prices over time and depicts this sudden change in the market.

Firms not generating electricity responded by finally installing abatement equipment, ultimately leading to a permanent decrease in the average firm's emissions by almost 40%. This sudden drop is shown by the solid lines in Figure 5 which plots the quarterly and annual average of firm emissions scaled by the firm's own sample maximum. The dashed lines show emissions for electricity generators, which also decreased their emissions once the Crisis had subsided by more than 50% relative to pre-Crisis levels.

The permanence of these pollution reductions, despite the temporary nature of the Crisis, is due to the permanence of the RECLAIM cap-and-trade market. RECLAIM's aggregate emissions cap was the true driving force behind the pollution reductions. The cap, which firms had failed to anticipate, became permanently binding during the Crisis. Had firms adapted to the future binding of the cap—as each firm believed all other firms were doing—there may not have been any permanent change in pollution due to the Crisis. Instead, the Crisis synchronized and hastened the long-term adaptation to the Crisis that should have already happened.

The sudden, permanent drop in emissions that followed the Crisis can be used to

13. The exact causes of the Crisis, such as the derelguation of wholesale electricity markets and market manipulation by certain actors, remain a source of debate. See Borenstein (2002) and Weare (2003), especially Section 3.

construct a set of instruments for local residents' exposure to firms' pollution. When faced with high RTC prices, firms with more emissions had a larger incentive to cut emissions, so the Crisis should have had a larger effect on houses downwind of these firms. A house's pre-Crisis exposure to industrial emissions can be used to gauge its exposure to the "treatment" of the Crisis relative to other houses. Houses with higher pre-Crisis exposure will on average experience larger decreases in pollution exposure.

Using aermod_{nt}, the AERMOD-predicted exposure to neighborhood/block group n in time t, I define pre-Crisis exposure aermod_pre_n as the average exposure across all 8 quarters in 1995 and 1996, the first two years for which firm-level emissions data is available. With aermod_pre_n, the most natural instrument is $\text{aermod\_pre}_n \times \text{post}_t$ where $\text{post}_t = \mathbf{1}\{t \geq 2001\}$ is an indicator variable for post-Crisis years. This is essentially a variable-intensity difference-in-difference instrument.

The identification assumption behind this instrument is that there are no coincidental changes in house prices or non-industrial pollution exposure that are correlated with the instruments, conditional on the other covariates. For example, the housing bubble might have induced more appreciation in poorer neighborhoods which may be relatively more polluted before the Crisis due to residential sorting. Fortunately, we can explicitly control for time trends in such risk variables, and the build up of the bubble was not a discrete event like the Crisis was, so this assumption can be assessed using the event study. Another potential problem is that the instruments might be correlated with changes in NO_x from cars. This would bias second-stage estimates upward if industrial exposure were correlated with automobile exposure *and* the Crisis also caused a sudden and permanent drop in car usage in the area. The former condition is unlikely given the large area that firms affect, while highways rarely have a significant impact beyond 500 meters (Karner, Eisinger, and Niemeier 2010; Anderson 2015). Furthermore, traffic data show that no significant change in driving patterns coincided with the Crisis.[14]

14. Unreported regressions show traffic patterns had no significant break from trend through the period of the Crisis. I use data from the California Department of Transportation's Freeway Performance Management System (PeMS) for the Bay Area (region 11), 1999–2005. The Bay Area is used because data for Los Angeles only go back to 2001.

3.3 Estimation Strategy

The following empirical equation relates block group SES outcomes to pollution exposure:

$$y_{nt} = \text{aermod}_{nt}\beta + \text{post}_t\alpha + \delta_n + \left(\boldsymbol{W}_n \times \text{post}_t\right)\boldsymbol{\Gamma} + \varepsilon_{nt} \tag{7}$$

where y_{nt} is some characteristic of block group n (e.g., population) in period t; aermod_{nt} is exposure to industrial NO_x-based pollution; δ_n are block group fixed effects; $\boldsymbol{W}_n$ is a vector of time-invariant block group characteristics detailed below; and ε_{nt} is the usual residual term. Period t indexes data from either the 2000 Census, before the Crisis, or the ACS 5-year average for 2005–2009, the earliest available block group data after the Crisis. These controls account for a number of factors that may confound estimates of β. The block group fixed effects, δ_n, capture of all time-invariant characteristics about the neighborhood.

The vector $\boldsymbol{W}_n$ controls for differential effects by block group characteristics over time by including two kinds variables. The first kind is dummy variables for the block group's location within the metropolitan area, defined by a 10 km grid.[15] This allows different parts of the metropolitan area to have different secular trends. The second kind of variables in $\boldsymbol{W}_n$ control for the block group's socio-economic characteristics in the year 2000. For example, if labor market shocks over this period differentially affect low- and high-education workers, this could be captured in part by β if pollution exposure is correlated with educational attainment. To solve this problem, I include the following year 2000 block group characteristics in $\boldsymbol{W}_n$: population; number of households; log median household income; fraction of households with low income (less than \$30,000); fraction with middle income (\$30–60,000); fraction with high income (at least \$60,000); population over age 25; fraction of adults over age 25 with no high school diploma; fraction with high school diploma but no time at college; fraction white (non-Hispanic); fraction Hispanic; fraction black. These variables are discussed further in Section 4.2. The low, middle, and high income bins are chosen because they break the population roughly into terciles.

15. Given the large size of the sample region, the ideal geographic unit for these trends would be individual cities, which have economically meaningful boundaries (unlike zip codes) and are generally small but not so small as to be computationally burdensome (unlike tracts and zip codes). Unfortunately, many cities are not geographically convex, and the cities of Los Angeles and Long Beach cover a large portion of the sample region while also having a great deal of within-city heterogeneity. To overcome these issues, I use a 10-km gridwhich is aligned to preserve as many city boundaries as possible. This grid results in 17 different areas that each get their own time effects.

Using the instrument described in Section 3.2, the reduced-form estimate of the Crisis' effect is simply

$$y_{nt} = \left(\text{aermod\_pre}_n \times \text{post}_t\right)\pi + \text{post}_t\alpha + \delta_n + \left(\boldsymbol{W}_n \times \text{post}_t\right)\boldsymbol{\Gamma} + \varepsilon_{nt} \tag{8}$$

I restrict the region of analysis to the southwest region of SCAQMD territory, roughly between Santa Monica and Huntington Beach (see Figure 6a), to minimize measurement error due to geography. All of the major polluters are located in this region and locations farther away from the pollution sources are likely to have less actual exposure from the firms and more noise in the modeling prediction, decreasing the signal-to-noise ratio of the pollution measure. Predicting the pollution distribution is also more complicated farther inland because of the San Gabriel and Santa Ana Mountains, which can act like a dam, collecting pollution blown from the coasts. To avoid these problems, I restrict my sample to houses within 10 kilometers of a major electric firm in Los Angeles or Orange County.[16]

4 Data

4.1 Houses

Data on home sales and housing characteristics come from county registrar and assessors' offices and were collected by DataQuick, Inc. The data include any property that has been assessed and most sales, refinances, and foreclosures in California after 1990. Data for each property includes square footage, lot size, number of bedrooms and bathrooms, and the year the property was built. Each sale or refinance includes the value of the mortgage and any additional loans taken against the property, as well as interest rates as estimated by DataQuick using proprietary methods. Latitude and longitude are also included for each property.

I drop sales that fall outside normal market transactions and which may not accurately reflect the market's valuation of the house. Specifically, all transactions must be arms-length, non-distressed sales (i.e., no foreclosure sales or short sales) with a price of at least \$10,000. I also drop a sale if the property transacted within the previous 90 days, as many of these transactions are duplicates. The sample is also restricted to homes built before

16. I also include in this group the southwestern most firm in the area in order to include the Palos Verdes Peninsula in the regression sample.

1995 to preclude direct sales from developers to consumers. The top 0.1% of sales are winsorized.

Table 1 shows average sale price, house hedonics, and quarter of sale broken down by the number of times a house transacted during the sample period. House prices are deflated to real 2014 dollars using the all-items CPI. Houses are are not used in summary statistics or regressions if they fall outside the sample region described in Section 3.3.

4.2 Census Block Groups

Data on Census block group demographics are taken from the 2000 Census and 2005–2009 5-year American Community Survey (ACS) sample. For each block group, these data include total population; white (non-Hispanic) population; Hispanic population; black population; the number of households; median of household income; median rent; and educational attainment for individuals age 25 and older. The data also include the block groups' total land area, which I use to calculate population density (population per square mile). I group educational attainment into three categories: people who did not graduate high school; people who graduated high school but do not have a bachelor's degree; and people who hold at least a bachelor's degree. To reduce noise, I drop block groups that have less than 400 people in 2000, which is roughly the 4th percentile of all block groups and constitutes less than 0.5% of all people in the sample. In specifications using median rent, I drop observations with top coded values ($2001) in either year. Table 2 presents summary statistics for both 2000 and 2005–2009.

4.3 Firms

There are several components to the firm-level data, which cover firm emissions over time, the firm's name and location, and physical characteristics of the firm's polluting equipment. The firm data also include information about RECLAIM Trading Credit (RTC) allocations and subsequent trades.

Most of the data come from SCAQMD via public records requests (SCAQMD 2015a). These data include each firm's name, address, SCAQMD-assigned ID number, the mass of NO_x the firm emitted every quarter from 1994 to 2014, and all relevant RTC data, including initial allocation of RTCs, the quantity, price, and vintage of exchanged RTCs, and the ID numbers of participating firms. Firms' operating addresses were geocoded to get latitude and longitude to represent the location of the firm's smoke stacks, which are required by AERMOD and other location-based calculations (see Appendix B.1 for more details).

AERMOD requires data on the physical characteristics of firms' polluting equipment (smoke stack height and diameter, and temperature and velocity of gas exiting the smoke stack), which I take from the National Emissions Inventory (NEI). Regulators often collect these data specifically to run atmospheric dispersion models like AERMOD, but the data collected by SCAQMD could not be made available (SCAQMD 2015b). However, the National Emissions Inventory (NEI) has these data for many firms along with each firm's name, address, SIC, and the type of combustion process behind each stack. I matched most firms to the NEI by reconstructing the NEI-specific ID number from the SCAQMD ID number and other administrative variables, and I validated these matches using fuzzy string matching on firm names and addresses. Any remaining firms were matched via fuzzy string matching and manually checked. For firms with missing stack data, I impute values using the firm's SIC and the stack's equipment-type code (SCC). Details of the imputation process and the construction of the firm-level data in general are outlined in Appendix B.

Table 3 gives summary statistics by industry (4-digit SIC) on emissions, smoke stack parameters, electric-generator status, average distance to the nearest meteorological station, and the number of firms in each industry group.

4.4 Meteorology Data

Data on local meteorological conditions come from SCAQMD. Before building new polluting equipment, firms must submit an impact report to SCAQMD using AERMOD to show how the new equipment will impact ambient pollution levels. To facilitate the making of these reports, SCAQMD makes AERMOD-ready meteorological data available on its website.[17]

These data were gathered by 27 meteorological stations throughout SCAQMD. The data consist of hourly data on temperature, wind speed, and wind direction at multiple elevations; the standard deviation of vertical wind speed; the convectively and mechanically driven mixing heights; and other parameters.[18] Each station provides at least three years

17. The data are most easily accessible via the SCAQMD website: http://www.aqmd.gov/home/library/air-quality-data-studies/meteorological-data/data-for-aermod

18. A full list of the variables used is found in the AERMOD user manual or Cimorelli et al. (2005).

of data between 2006 and 2012. While these stations were not in operation at the time of the Crisis, wind patterns at the given locations are very stable over time.

4.5 AERMOD-based Measure of Exposure

I use AERMOD, which maps firm-level output to local exposure, to construct a measure of a block group's exposure from all industrial sources. Software for using AERMOD is available on the EPA's website and includes documentation, Fortran source code, and pre-compiled executables for Windows.[19]

Location ℓ's exposure to NO_x emissions from firm f at time t can be written $\text{NOx}_{ft} \cdot h(d_{f\ell}, \theta_{f\ell}; \boldsymbol{S}_f)$, where $\boldsymbol{S}_f$ contains information on the firm's smoke stacks, as well as local meteorological conditions. The data I use for NOx_{ft} and $\boldsymbol{S}_f$ are described in Sections 4.3 and 4.4. A firm's meteorological data is taken from the nearest meteorology monitor. The values for $(d_{f\ell}, \theta_{f\ell})$ are calculated by AERMOD from firms and houses' latitude and longitude. AERMOD then outputs $\text{aermod}_{\ell ft}$, the location's exposure to the firm's emissions. The location's total exposure to industrial NO_x emissions is simply $\text{aermod}_{\ell t} = \sum_f \text{aermod}_{\ell ft}$.

For block group–level exposure, I first calculate exposure at the block level, then calculate the population-weighted average for each block group. At the block level, I use the process described above where ℓ is the Census-provided internal point for each block.[20] This is a more attractive approach than using the block group's internal point because it accounts for heterogeneity in population and exposure across the block group and is a closer approximation to the average exposure to the block group's residents. For house-level exposure, I use

Because AERMOD loops over all firms, locations, and meteorological data, it is very computationally intensive for such a large sample, so I impose several restrictions on the data to make calculation more feasible.[21] First, I only calculate a firm's exposure to houses that are within 20 kilometers of the firm and set exposure outside this radius to zero.

19. See http://www.epa.gov/scram001/dispersion_prefrec.htm. I use AERMOD version 13350, compiled using Intel Fortran Compiler 15.0 for Linux and run on the Odyssey cluster supported by the FAS Division of Science, Research Computing Group at Harvard University.

20. Analyses using Census geographies like block groups or ZCTA's often use the "centroid" of the geography as its the representative point in space. However, the Census Bureau is very particular to note that because these geographies are not convex, the true centroid may lie outside the geography of interest. As a solution, the Census Bureau calculates "internal points," which are constrained to be inside the geography.

21. Even with these restrictions, the model takes approximately 210 CPU days to process all the data.

Second, I use one year of meteorological data, 2009, which is also the only year during which all of the meteorological stations described in Section 4.4 were operating. Third, for houses, I round each house's latitude and longitude coordinates to the nearest 100 meters and assign houses within the same 100-meter grid square the same exposure.

5 Empirical Results

5.1 Income Stratification

The residential sorting model presented in Section 2 predicts that sorting will result in stratified neighborhoods—neighborhoods with the best amenities will also have residents with the highest incomes who pay the highest rents. Figure 7 compares these variables across neighborhoods for the year 2000, before the Crisis. Each sub-figure is a binned scatterplot, which divides the x-axis variable into quantiles with equal numbers of observations and then plots the average x and y values within those quantile bins. This reduces the noise in a full scatterplot while allowing the data to be represented in a fairly nonparametric manner.

The plots in Figure 7 are consistent with neighborhood stratification as predicted by the model. Sub-figures (a) and (b) compare exposure to industrial NO_x emissions to median household income and rent, respectively. Low rents and incomes are strongly associated with high pollution exposure, consistent with stratification. Similarly, sub-figure (c) plots household income against rent and shows a strong positive relationship, again consistent with stratification.

5.2 Rent

The model in Section 2 predicts that housing costs will increase after an amenity improvement. Using a similar research design as this paper, Sullivan (2017) estimates the effect of the Crisis on house prices using repeat housing sales. That paper finds that the reduced form effect of the instrument on prices is 0.0032, meaning that each unit of treatment intensity increased home prices by roughly 0.3 percent. The second-stage semi-elasticity of exposure to prices is -0.0073, implying a MWTP to reduce pollution of $3,272.

Table 4 shows that rents respond to air pollution in very similar manner. Columns 1 and 2 show the reduced-form estimates, based on Equation (8), with the natural log of the block group's median rent as the dependent variable. The preferred specification is estimated in column 2 which weights each block group by its number of renter households in 2000 so that outliers from block groups with few renters do not skew the results. However, as column 1 (raw population weights) shows, the weights used do not dramatically change the point estimates. The estimates show that log rents increased by 0.0031 for every unit of treatment intensity, very similar to the effect on log house prices (0.0032) from Sullivan (2017). The second-stage estimates in columns 3 and 4 are likewise large and, in the case of the preferred specification in column 4, statistically significant.

This stands in contrast with some of the more recent work on capitalization of rents versus house prices which found rents to be less responsive to changes in air quality (Grainger 2012; Bento, Freedman, and Lang 2015). It also suggests that low-income households, who are predominantly renters, are not shielded from the price effects of air quality improvement.

5.3 Demographics

Table 5 explores how the composition of neighborhoods changes in response to the Crisis-induced pollution reduction. Panel A shows the correlation of pollution exposure, measured by AERMOD, on the log of median block group income, log population, log number of households, log number of housing units; and the fraction of households in "low" (less than \$30,000), "middle" (\$30–60,000), and "high" (more than \$60,000) income groups. Each regression includes the controls listed in Section 3.3. While Figure 7 shows strong relationships between pollution exposure and income, columns 1 show's no statistically significant relationship between the two after conditioning on neighborhood fixed effects and trend effects for year 2000 demographics. Columns 5–7, which measure the effect of a neighborhoods income distribution, as opposed to just its median, also show no effect at conventional levels, nor is there any significant effect for the three measures of population in columns 2–4. The contrast between these results and Figure 7 supports the concern that pollution exposure is correlated with other spatial amenities and neighborhood characteristics, and credibly measuring the effects of pollution exposure will require an sudden exogenous shock to pollution.

Panel B shows the effects of such a shock by estimating the reduced-form effect of the Crisis-induced pollution reduction. Column 1 shows no significant effect on log median income. This is not inconsistent with the model, which has several ambiguous predictions about median or average income. For example, if a neighborhood improves its air quality and the condition for low-income leaving given in Proposition 2 does not hold, the neighborhood will have an increase in both lower- and higher-income households, make the effect on median income ambiguous. Similarly, if a neighborhood is at the top of the income distribution (Community 3 in Section 2 or Figure 2), an amenity improvement will *decrease* median income. The two-stage least squares (2SLS) results in Panel C, where aermod_pre $\times$ post is the excluded instrument for aermod, mirror those of Panel B

Columns 2–7 are highly suggestive evidence that low-income households fled neighborhoods with improved air quality. Columns 2–4 measure the effect of the pollution cleanup on three metrics of neighborhood size: population, number of households, and number of housing units. In all three cases, neighborhood size decreases, with the first two estimates being only marginally significant and the effect on housing units being significant at 5%. This suggests that, on average, neighborhoods that improved actually lost rather than gained residents as past theory on Tiebout sorting would predict. Such a result is only consistent with "fleeing" of an amenity improvement. Columns 5–7, which look at how the within-neighborhood income distribution changed, is also consistent with a story of low-income residents fleeing. Column 5 shows that the fraction of low-income households decreased significantly, while Column 7 shows an increase in the proportion of high-income residents of similar magnitude. However, the decrease in the proportion of low-income households does not necessarily indicate any fleeing, as these numbers could be explained by a large influx of high-income households and no outflow of low-income.

Table 6 confirms that low-income households fled the improvements, on average, by estimating separate effects for each income group. Each column re-estimates the effect of the Crisis on the number of households in a block group, but restricts the outcome variable to low-, middle-, or high-income households, respectively. The effect on low-income households (column 1) is statistically significant and negative. Given the average treatment intensity in the sample, this coefficient implies that sample area had roughly 9% fewer low-income households than it would have had the Crisis not lowered pollution levels.

Table 7 further confirms that low-income households were most affected by the Crisis by re-estimating the demographic effects of Table 5 while allowing the effect of the Crisis to differ with the initial income distribution of each neighborhood. Column 1 shows that neighborhoods with a higher proportion of low-income households ex ante did in fact see a significant increase in median neighborhood income. Columns 2–4 show that low-income neighborhoods experienced significant decreases in population, number of total households, and number of housing units, with middle-income neighborhoods seeing an increase in households. Finally, columns 5–7 show that low-income neighborhoods, more than others, saw a decrease in the fraction of low-income households, as well as a marginally significant increase in high-income households.

5.4 Home-ownership and Incidence

This evidence of low-income households leaving improved areas suggests that these households valued the amenity improvement significantly less than their higher-income neighbors. However, this interpretation depends on the model's assumption that all households are renters to absentee landlords, which is obviously not the case here. Since the pollution reduction increased housing values, incumbent home owners reaped a wealth windfall. It is entirely possible that low-income households, who are more likely to be liquidity constrained, might sell their homes to realize this unexpected capital gain, then re-optimize given their new budget constraint.

Figure 8a plots the results of a local linear regression of a block group's home-ownership rate in 2000 on its median household income in 2000, weighted by the block group's population in 2000. Ownership rate is strongly correlated with income, increasing from around 10% for the poorest neighborhoods to about 95% for the richest. This suggests that low-income emigrants did not leave in order to realize capital gains, suggesting a regressive distribution of benefits from the pollution reduction.

One final factor that might make the distribution of benefits more progressive is the fact that poorer areas were more polluted to begin with and thus enjoyed a more significant improvement. It is possible that the few low-income home owners enjoyed such a large price windfall that average benefits to low-income households was still large. However, Figure 8b shows this was not the case.

The dashed line in Figure 8b plots house-price windfall per capita by income using a local linear regression and the housing sale–based MWTP estimate from Sullivan (2017). This dashed line represents the per capita gain through home values if all households were incumbent homeowners. As the figure shows, poorer areas did indeed see much larger gains on average: the lowest-income areas see a gain of \$3,500–4,000 per person, while the highest-income areas receive roughly \$2,000.

But this differential is not enough to offset the much wider gap in home-ownership rates. The solid line in Figure 8b plots the windfall per capita for local owner-residents only. In the extreme case where all households are marginal and house prices capture all the welfare gains of the pollution clean up, the plot shows that the clean up is indeed regressive. In the more realistic case with many inframarginal households, it is more difficult to say.

6 Conclusion

This paper examines how neighborhood composition and rents change in response to changes in air quality. I extends Epple, Filimon, and Romer's (1984) widely used model of spatial equilibrium to show that evidence of lower-income households "fleeing" amenity improvements suggests that a policy to improve amenities may have a relatively regressive distribution of benefits. I then use block group data from the Census to estimate how households responded to the exogenous change in pollution levels caused by the California Electricity Crisis of 2000.

Together, the results suggest that low-income households did not benefit as much from the improvement in air quality as high-income households did. First, housing rents increase just as much as housing prices and low-income renters still have to pay for improved air quality. Second, neighborhoods with improved air quality see a significant decrease in low-income residents, with suggestive evidence that they are displaced by higher-income newcomers. Third, home-ownership rates among low-income households are low, suggesting they did not directly benefit from the air quality improvement through a wealth windfall and did not leave in response to an increase in wealth.

Thus, while Sullivan (2017) finds that the air quality improvement significantly increased aggregate welfare, this paper finds that lower-income residents did not benefit as much as higher-income residents. Given past evidence that the costs of air quality improvements are generally borne more by low-income households, it appears that a policy to improve air quality, even if specifically targeted at low-income neighborhoods, is likely to be a regressive policy due to resident sorting and the housing market.

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A Proofs

Definition 4 (Notation)**.** For simplicity of notation, let

$$
\begin{aligned}
X^j &= \int_{\tilde{y}_{j-1}}^{\tilde{y}_j} h_p(p_j, y) f(y)\,\mathrm{d}y - S_p^j(p_j) \\
H^{ij} &= h(p_i, \tilde{y}_j) f(\tilde{y}_j) \\
V^{ij} &= V(\tilde{y}_i, p_j, g_j)
\end{aligned}
$$

Lemma 1. *The following hold:*

$$
\begin{aligned}
H^{ij} &> 0 \quad \forall i, j \\
X_j &< 0 \quad \forall j \\
V_y^{j,j} - V_y^{j,j+1} &< 0 \quad \forall j < J
\end{aligned}
$$

Proof. $H^{ij} > 0$ follows from non-negative demand and non-negative probability distribution f. $X^j < 0$ follows from downward-slopping demand and upward-slopping supply: $h_p < 0$ and $S_p^j > 0$. For the last inequality, recall that that, by definition of $\tilde{y}_1$, we have $V(\tilde{y}_1, p_1, g_1) = V(\tilde{y}_1, p_2, g_2)$ and for $y \in (\tilde{y}_1, \tilde{y}_2]$, $j = 2$ is preferred to $j = 1$. Thus, for $0 < \varepsilon < \tilde{y}_2 - \tilde{y}_1$, we have $V(\tilde{y}_1 + \varepsilon, p_1, g_1) < V(\tilde{y}_1 + \varepsilon, p_2, g_2)$, so $V_y^{j,j} - V_y^{j,j+1} < 0$. $\square$

Lemma 2. *If V satisfies single-crossing, then, for arbitrary p, g, and $y_2 > y_1 > 0$,*

$$
\frac{V_p(y_1, p, g)}{V_p(y_2, p, g)} > \frac{V_g(y_1, p, g)}{V_g(y_2, p, g)}
$$

Proof. Single-crossing requires $M = -V_g/V_p$ to be monotonically increasing in y.

$$
\begin{aligned}
& M(y_2, p, g) > M(y_1, p, g) \\
\Leftrightarrow & -\frac{V_g(y_2, p, g)}{V_p(y_2, p, g)} > -\frac{V_g(y_1, p, g)}{V_p(y_1, p, g)} \\
\Leftrightarrow & \frac{V_p(y_1, p, g)}{V_p(y_2, p, g)} > \frac{V_g(y_1, p, g)}{V_g(y_2, p, g)}
\end{aligned}
$$

$\square$

Proposition 1. *The following conditions hold:*

$$\frac{\partial \tilde{y}_2}{\partial g_2} > 0; \quad \frac{\partial p_2}{\partial g_2} > 0; \quad \frac{\partial p_3}{\partial g_2} < 0 \tag{4}$$

$$\frac{\partial \tilde{y}_1}{\partial g_2} \propto \frac{\partial p_1}{\partial g_2} \tag{5}$$

and the sign of $\partial \tilde{y}_1/\partial g_2$ is ambiguous.

Proof. For $J = 3$, the equilibrium conditions given by Definition 3 can be written $\boldsymbol{F}(\boldsymbol{\theta},\boldsymbol{g}) = \mathbf{0}$ where $\boldsymbol{\theta} = (\tilde{y}_1, \tilde{y}_2, p_1, p_2, p_3)$, $\boldsymbol{g} = (g_1, g_2, g_3)$, and

$$\boldsymbol{F}(\boldsymbol{\theta},\boldsymbol{g}) = \begin{pmatrix} V(\tilde{y}_1, p_1, g_1) - V(\tilde{y}_1, p_2, g_2) \\ V(\tilde{y}_2, p_2, g_2) - V(\tilde{y}_2, p_3, g_3) \\ \int_{\underline{y}}^{\tilde{y}_1} h(p_1, y) f(y)\,\mathrm{d}y - S^1(p_1) \\ \int_{\tilde{y}_1}^{\tilde{y}_2} h(p_2, y) f(y)\,\mathrm{d}y - S^2(p_2) \\ \int_{\tilde{y}_2}^{\overline{y}} h(p_3, y) f(y)\,\mathrm{d}y - S^3(p_3) \end{pmatrix}$$

The Jacobian of $\boldsymbol{F}$ with respect to $\boldsymbol{\theta}$ is

$$\frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}} = \begin{pmatrix} V_y^{11} - V_y^{12} & 0 & V_p^{11} & -V_p^{12} & 0 \\ 0 & V_y^{22} - V_y^{23} & 0 & V_p^{22} & -V_p^{23} \\ H^{11} & 0 & X^1 & 0 & 0 \\ -H^{21} & H^{22} & 0 & X^2 & 0 \\ 0 & -H^{32} & 0 & 0 & X^3 \end{pmatrix}$$

By Lemma 1, the Jacobian determinant is strictly negative.

$$\begin{aligned} \det \frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}} = {} & H^{21}H^{32}V_p^{12}V_p^{23}X^1 + H^{11}H^{32}V_p^{11}V_p^{23}X^2 + H^{11}H^{22}V_p^{11}V_p^{22}X^3 \\ & + \left(X^1X^2X^3(V_y^{22} - V_y^{23}) - H^{32}V_p^{23}X^1X^2\right)(V_y^{11} - V_y^{12}) \\ & - \left(H^{21}V_p^{12}X^1 + H^{22}V_p^{22}X^1 + H^{11}V_p^{11}X^2\right)(V_y^{22} - V_y^{23})X^3 < 0 \end{aligned}$$

As this determinant is non-zero, the Jacobian is non-singular and we can invoke the implicit function theorem to write $\boldsymbol{\theta}$ as a function of $\boldsymbol{g}$ such that $\boldsymbol{F}(\boldsymbol{\theta}^*(\boldsymbol{g}),\boldsymbol{g}) = \mathbf{0}$. (For clarity of notation going forward, I omit stars from variables at their equilibrium value.)

Differentiating the equilibrium condition with respect to g_2 yields

$$\frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}} \cdot \frac{\partial \boldsymbol{\theta}}{\partial g_2} = -\frac{\partial \boldsymbol{F}}{\partial g_2}$$

$$\begin{pmatrix} V_y^{11} - V_y^{12} & 0 & V_p^{11} & -V_p^{12} & 0 \\ 0 & V_y^{22} - V_y^{23} & 0 & V_p^{22} & -V_p^{23} \\ H^{11} & 0 & X^1 & 0 & 0 \\ -H^{21} & H^{22} & 0 & X^2 & 0 \\ 0 & -H^{32} & 0 & 0 & X^3 \end{pmatrix} \begin{pmatrix} \partial \tilde{y}_1/\partial g_2 \\ \partial \tilde{y}_2/\partial g_2 \\ \partial p_1/\partial g_2 \\ \partial p_2/\partial g_2 \\ \partial p_3/\partial g_2 \end{pmatrix} = \begin{pmatrix} V_g^{12} \\ -V_g^{22} \\ 0 \\ 0 \\ 0 \end{pmatrix}$$

Solving for $\partial \boldsymbol{\theta}/\partial g_2$ yields

$$\frac{\partial \boldsymbol{\theta}}{\partial g_2} = \left(\det \frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}}\right)^{-1} \cdot$$
$$\begin{bmatrix} -H^{22}X^1X^3V_p^{22}V_g^{22}\left(\frac{V_g^{12}}{V_g^{22}} - \frac{V_p^{12}}{V_p^{22}}\right) + V_g^{12}X^1X^2X^3\left(V_y^{22} - V_y^{23}\right) - H^{32}V_g^{12}V_p^{23}X^1X^2 \\ -H^{21}X^1X^3V_p^{22}V_g^{22}\left(\frac{V_g^{12}}{V_g^{22}} - \frac{V_p^{12}}{V_p^{22}}\right) - V_g^{22}X^1X^2X^3\left(V_y^{11} - V_y^{12}\right) + H^{11}V_g^{22}V_p^{11}X^2X^3 \\ H^{11}H^{22}X^3V_p^{22}V_g^{22}\left(\frac{V_g^{12}}{V_g^{22}} - \frac{V_p^{12}}{V_p^{22}}\right) - H^{11}V_g^{12}X^2X^3\left(V_y^{22} - V_y^{23}\right) + H^{11}H^{32}V_g^{12}V_p^{23}X^2 \\ -H^{11}H^{22}X^3V_g^{22}V_p^{11} - H^{21}H^{32}V_g^{12}V_p^{23}X^1 + H^{22}V_g^{22}X^1X^3\left(V_y^{11} - V_y^{12}\right) + H^{21}V_g^{12}X^1X^3\left(V_y^{22} - V_y^{23}\right) \\ -H^{21}H^{32}X^1V_p^{22}V_g^{22}\left(\frac{V_g^{12}}{V_g^{22}} - \frac{V_p^{12}}{V_p^{22}}\right) - H^{32}V_g^{22}X^1X^2\left(V_y^{11} - V_y^{12}\right) + H^{11}H^{32}V_g^{22}V_p^{11}X^2 \end{bmatrix}$$

The Jacobian determinant is negative and, using Lemmata 1 and 2, it is clear upon inspection that the signs of $\partial \boldsymbol{\theta}/\partial g_2$ are consistent with the statement of the proposition.

The proportionality of $\partial \tilde{y}_1/\partial g_2$ and $\partial p_1/\partial g_2$ follows from

$$\frac{-X^1}{H^{11}} \frac{\partial p_1}{\partial g_2} = \frac{\partial \tilde{y}_1}{\partial g_2}$$

□

Proposition 2.

$$\frac{\partial \tilde{y}_1}{\partial g_2} > 0$$

if and only if

$$\frac{M(\tilde{y}_2, p_2, g_2)}{M(\tilde{y}_1, p_2, g_2)} > R^* \tag{6}$$

where R^* depends on $(\tilde{y}_2, g_2, g_3, p_2, p_3)$.

Proof. Re-write $\partial \tilde{y}_1 / \partial g_2$ as

$$\frac{\partial \tilde{y}_1}{\partial g_2} = \left(\det \frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}} \right)^{-1} X^1 X^2 X^3 V_g^{12} \left[H^{22} \frac{V_p^{22}}{X^2} \left(\frac{M^{22}}{M^{12}} - 1 \right) + \left(V_y^{22} - V_y^{23} \right) - H^{23} \frac{V_p^{23}}{X^3} \right]$$

where $M^{ij} = M(\tilde{y}_i, p_j, g_j)$. Then

$$\begin{aligned} & \frac{\partial \tilde{y}_1}{\partial g_2} > 0 \\ \Leftrightarrow & H^{22} \frac{V_p^{22}}{X^2} \left(\frac{M^{22}}{M^{12}} - 1 \right) + \left(V_y^{22} - V_y^{23} \right) - H^{23} \frac{V_p^{23}}{X^3} > 0 \\ \Leftrightarrow & \frac{M^{22}}{M^{12}} > 1 + \frac{H^{23} \frac{V_p^{23}}{X^3} + V_y^{23} - V_y^{22}}{H^{22} \frac{V_p^{22}}{X^2}} = R^* \end{aligned}$$

□

Recall from Definition 4 that X^j is the derivative of excess housing demand in j with respect to price; H^{2j} is amount of housing demanded by $\tilde{y}_2$ in j; and $V_p^{2j} = V_p(\tilde{y}_2, p_j, g_j)$, the derivative of $\tilde{y}_2$'s indirect utility in j with respect to price. Thus, R^* depends on the $\tilde{y}_2$'s utility tradeoffs in $j = 2$ versus $j = 3$.

Proposition 3. *The comparative statics for g_1 are g_3 are*

$$\frac{\partial \tilde{y}_1}{\partial g_1} > 0; \quad \frac{\partial \tilde{y}_2}{\partial g_1} > 0; \quad \frac{\partial p_1}{\partial g_1} > 0; \quad \frac{\partial p_2}{\partial g_1} < 0; \quad \frac{\partial p_3}{\partial g_1} < 0;$$

$$\frac{\partial \tilde{y}_1}{\partial g_3} < 0; \quad \frac{\partial \tilde{y}_2}{\partial g_3} < 0; \quad \frac{\partial p_1}{\partial g_3} < 0; \quad \frac{\partial p_2}{\partial g_3} < 0; \quad \frac{\partial p_3}{\partial g_3} > 0;$$

Proof. Following the proof of Proposition 1,

$$\frac{\partial \boldsymbol{\theta}}{\partial g_1} = \left(\det \frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}}\right)^{-1} \cdot \begin{bmatrix} H^{22}V_g^{11}V_p^{22}X^1X^3 + H^{32}V_g^{11}Y_p^{23}X^1X^2 - V_g^{11}X^1X^2X^3\left(V_y^{22} - V_y^{23}\right) \\ H^{21}V_g^{11}V_p^{22}X^1X^3 \\ -H^{11}H^{22}V_g^{11}V_p^{22}X^3 - H^{11}H^{32}V_g^{11}V_p^{23}X^2 + H^{11}V_g^{11}X^2X^3\left(V_y^{22} - V_y^{23}\right) \\ H^{21}H^{32}V_g^{11}V_p^{23}X^1 - H^{21}V_g^{11}X^1X^3\left(V_y^{22} - V_y^{23}\right) \\ H^{21}H^{32}V_g^{11}V_p^{22}X^1 \end{bmatrix}$$

and

$$\frac{\partial \boldsymbol{\theta}}{\partial g_3} = \left(\det \frac{\partial \boldsymbol{F}}{\partial \boldsymbol{\theta}}\right)^{-1} \cdot \begin{bmatrix} -H^{22}V_g^{23}V_p^{12}X^1X^3 \\ -H^{11}V_g^{23}V_p^{11}X^2X^3 - H^{21}V_g^{23}V_p^{12}X^1X^3 + V_g^{23}X^1X^2X^3\left(V_y^{11} - V_y^{12}\right) \\ H^{11}H^{22}V_g^{23}V_p^{12}X^3 \\ H^{11}H^{22}V_g^{23}V_p^{11}X^3 - H^{22}V_g^{23}X^1X^3\left(V_y^{11} - V_y^{12}\right) \\ -H^{11}H^{32}V_g^{23}V_p^{11}X^2 - H^{21}H^{32}V_g^{23}V_p^{12}X^1 + H^{32}V_g^{23}X^1X^2\left(V_y^{11} - V_y^{12}\right) \end{bmatrix}$$

Again following the methods used in Proposition 1, we get the sign of each element of these vectors. □

B Firm Data Construction

B.1 Geocoding

The accurate geocoding of pollution sources is obviously critical when analyzing the effect these sources have on the surrounding population. Administrative records on the latitude and longitude of each smoke stack operated by the firm would be the ideal data. Regulators often collect this data for the explicit purpose of dispersion modeling, and though SCAQMD does collect this data, they are unavailable for public use (SCAQMD 2015b). In lieu of direct geographic data for each smoke stack, I follow the literature and simply geocode the firms' street addresses, taking care to use the actual operating address of the firm and not a corporate or mailing address which are often listed in databases. For large firms and firms that match to interpolated street addresses instead of parcel centroids, I double-checked the coordinates using satellite photos from Google Maps to make sure the geographic point that represents the firm is reasonably close to the actual smoke stacks.[22]

B.2 Facility ID

SCAQMD assigns each facility an ID number; however, a facility may have more than one ID number in the data, both over time and cross-sectionally. This is primarily a concern when matching firms to the NEI, as described in Appendix B.3. It might also affect the pattern of firm behavior described by Figure 5, though this figure is only descriptive and not used in any calculations.

A facility's ID can change under a number of circumstances: the facility is sold, changes its name, or some part of its address changes. For the most part, these changes occur for superficial reasons, e.g., a zip code or street suffix is changed. To construct unique facility ID's, I flagged every pair of facilities less than 400 meters apart and visually inspected satellite photos and emissions data for every cluster of neighboring facilities. First, firms were merged if they occupied the same or neighboring parcels and shared breaks in their time series of emissions. For example, Facility A emits 25 tons per quarter from 1994 to 1999Q3 and then is missing from the data, while Facility B, located at the same parcel of land as A, enters the data in 1999Q4 and begins emitting 25 tons per quarter. Facilities were also merged if they had similar names and occupied the same or neighboring parcels of land. These merges were verified by checking whether or not the firms appeared separately in the NEI.

B.3 Stack Data from the NEI

Data for each firm's smoke stacks is taken from the National Emissions Inventory (NEI) from 1999 and 2002. Besides the smoke stack parameters, the NEI also has data on firm's name, address, SIC, and the equipment's SSC, and the estimated emissions by pollutant for each stack.[23] It also includes the ID number assigned to the facility by state-level

22. This is potentially important because the firm's "store-front" address right on the street is often at the edge of the property, far away from the smoke stacks. Using unchecked street addresses can introduce significant errors (1–2 km) for firms that occupy large parcels of land.

23. The Source Classification Codes (SCC) for point pollution sources are a hierarchical index used by the EPA that categorize pollution-generating equipment by combustion type, fuel type, and size. It is analogous

regulators. For SCAQMD firms, this "state ID" consists of a county code, an air basin code, an air district code, and the SCAQMD-assigned facility ID. Using this reconstructed ID, I was able to match most facilities in the SCAQMD emissions data to the NEI using either their own facility ID or an ID from a facility I had previously matched to it as described in section B.2. I used the 2002 NEI data whenever possible, falling back to the 1999 database when necessary. For facilities whose ID's did not match either dataset, I tried to match them using firm address and name. Firms that still did not match were almost all small firms that had ceased to exist before the NEI 1999 data was collected. These firms should have little impact on the overall results and were dropped. For matched facilities, I verified that individual stacks were not duplicated.

Many of the stack parameters in the NEI are flagged as imputed values. The imputation process was not well documented, so I re-imputed them using the median stack parameters from all non-imputed stacks in the SIC and SCC group. Finally, when passing the stack parameters to AERMOD, I weighted each stack according to its reported emissions in the NEI.

to the hierarchical SIC and NAICS industry codes.

Figures and Tables

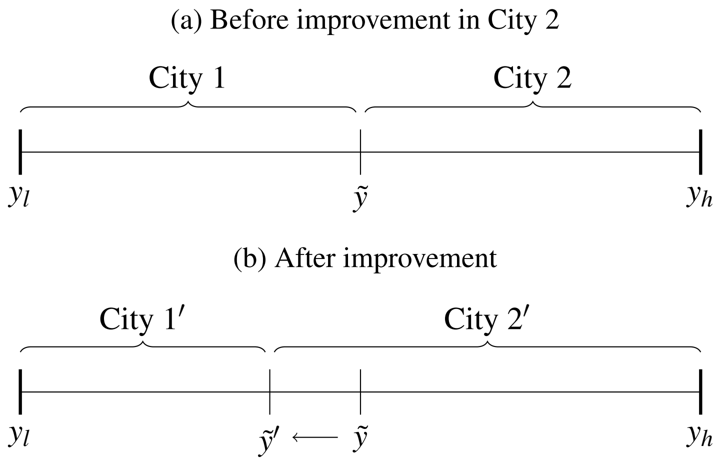


Figure 1: Shock to a Two-community Equilibrium

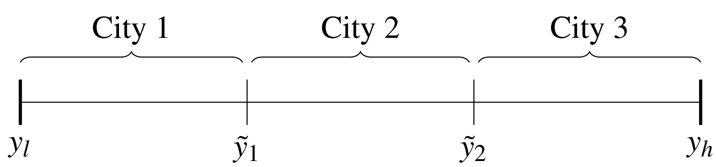


Figure 2: A Three-community Equilibrium

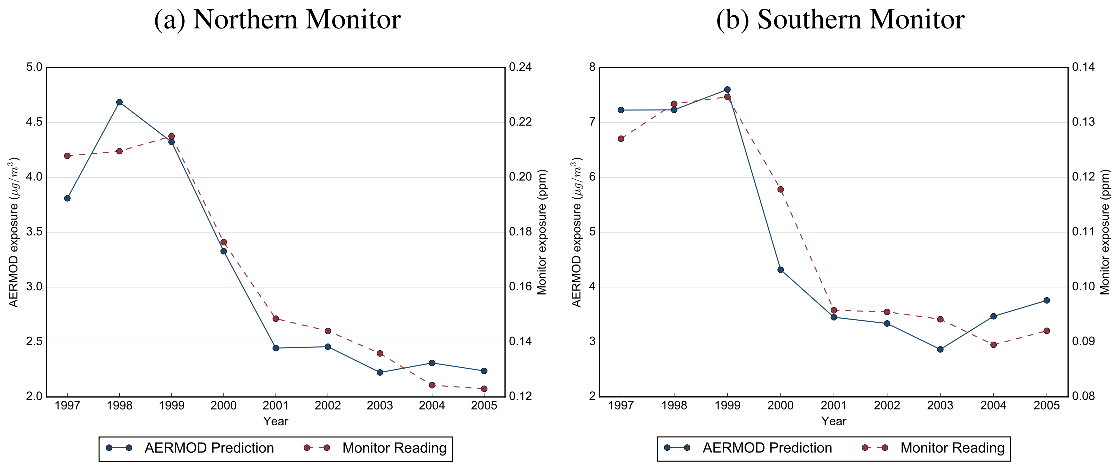


Figure 3: AERMOD and Pollution Monitor Readings Over Time

Notes: Figures plot exposure to NO_x as predicted by AERMOD (solid lines) at the two monitor locations shown in Figure 6a, as well as the actual monitor readings for each location (dashed lines). Plotted values are the fourth quarter average for the given year for reasons of atmospheric chemistry, see Section 3.1.

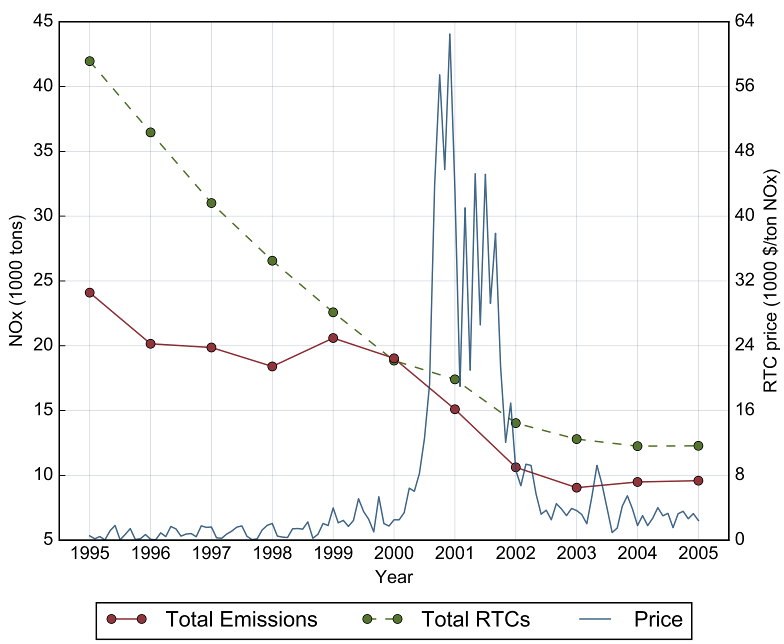
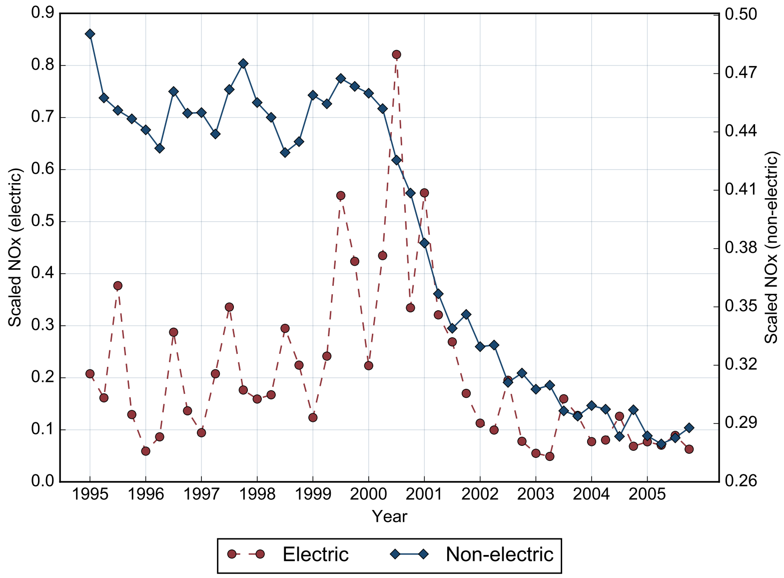


Figure 4: RECLAIM Market

Notes: "Total RTCs" is the number of RTCs expiring in the calendar year. "Price" is the average of all arms-length transactions in a month across all RTC vintages.

(a) Quarterly



(b) Annual

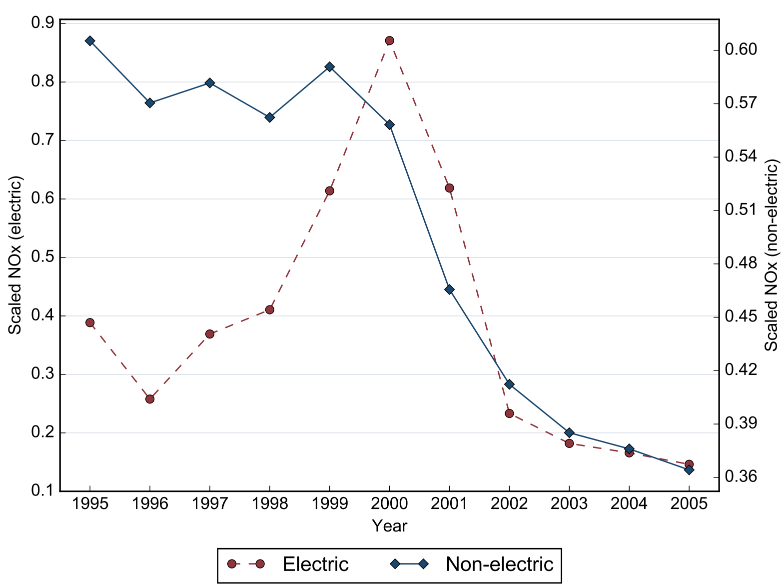
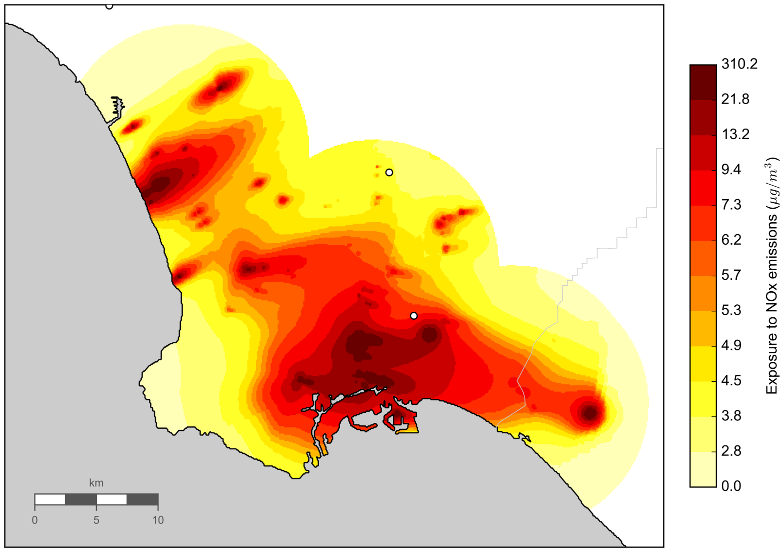


Figure 5: Scaled Emissions by Firm Type

Notes: Firm emissions are scaled by firm's own maximum emissions. Sample is restricted to firms that operated in at least 8 quarters.

(a) Exposure to NO_x Emissions



(b) Fraction of Block Group with Low Income

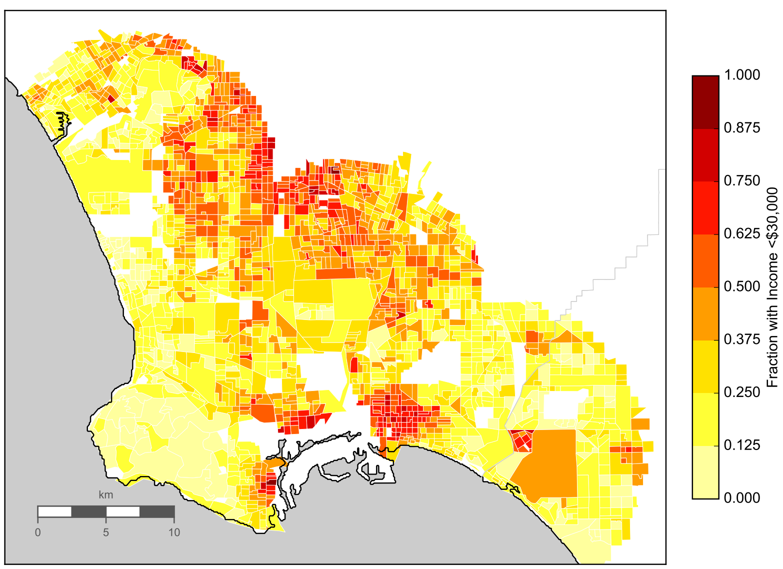


Figure 6: Exposure to Pollution and Block Group Income in 2000

Notes: Sub-figure (a) plots the average exposure to industrial NO_x emissions Sub-figure (b) plots the fraction of each block group's households with household income less than $30,000.

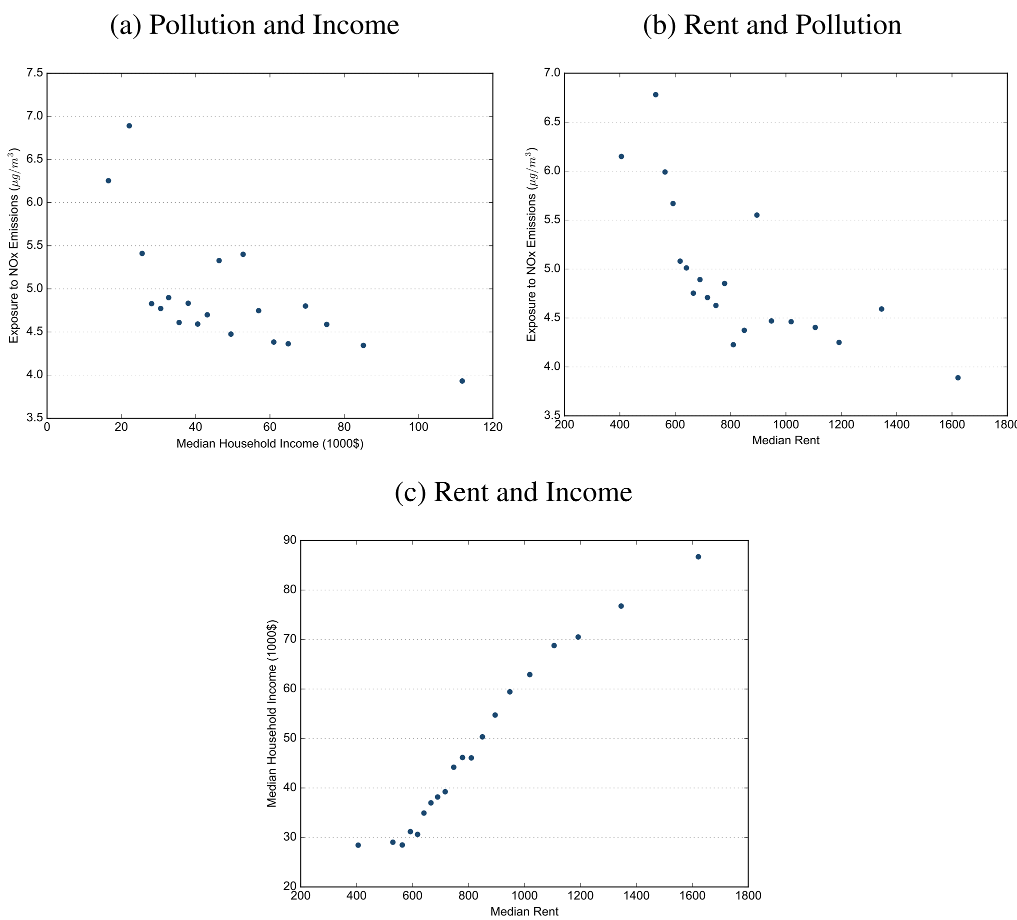
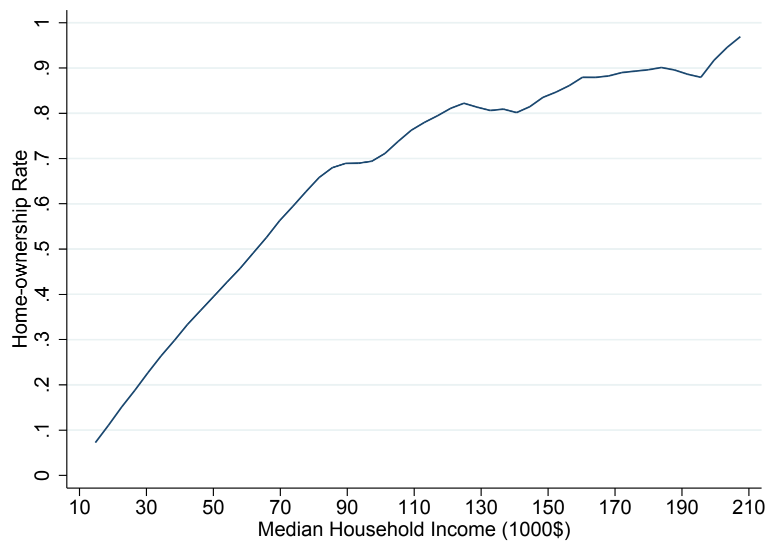


Figure 7: Neighborhood Stratification by Income, Rent, and Pollution in 2000

Notes: Figures are binned scatterplots of the listed variables. Each point is the y- and x-variable average within 20 quantile bins of the x-axis variable.

(a) Home-ownership rate



(b) House Price Windfall

Figure 8: Home-ownership and Price Windfall by Income

Notes: Plots are the result of local linear regressions using an Epanechnikov kernel with bandwith of 5. Sample is Census 2000 block groups, weighted by population. In subplot B, the dashed line is the gain to owners of units occupied by a household with the given income, and the solid line is the gain to residents.

Table 1: House Summary Statistics

	Never Sold	Sold Once		Repeat Sales	
		Pre	Post	Pre	Post
Sale Price		394,839	541,228	420,912	603,347
		(284,955)	(357,514)	(304,854)	(396,748)
Lot Size	6,544	6,617	6,381	6,245	6,010
	(6,662)	(7,173)	(6,793)	(5,567)	(4,926)
Square Feet	1,537	1,611	1,534	1,574	1,492
	(651)	(722)	(690)	(710)	(656)
Year Built	1950	1952	1950	1951	1950
	(15.24)	(15.61)	(15.77)	(16.97)	(16.79)
Bedrooms					
1	0.01	0.01	0.01	0.01	0.02
2	0.23	0.22	0.24	0.25	0.27
3	0.48	0.48	0.49	0.49	0.49
4	0.22	0.23	0.21	0.21	0.19
5+	0.05	0.05	0.05	0.04	0.03
Bathrooms					
1	0.34	0.29	0.33	0.31	0.35
2	0.47	0.47	0.46	0.45	0.45
3	0.13	0.16	0.13	0.15	0.13
4+	0.03	0.04	0.04	0.05	0.04
Sold in Quarter					
1		0.19	0.22	0.20	0.21
2		0.28	0.27	0.29	0.28
3		0.28	0.28	0.28	0.27
4		0.25	0.24	0.24	0.23
Times Sold				2.14	
				(0.38)	
Total Properties	275,218	84,041		19,545	

Notes: Summary statistics from regression sample as described in Section 4.1. Table lists sample means with standard deviations given in parentheses.

Table 2: Block Group Summary Statistics

	Total		Mean	
	2000	2005/9	2000	2005/9
Population	2,775,700	2,811,468	1,435	1,454
			(814)	(867)
Households	950,591	952,008	492	492
			(322)	(332)
Pop. Density (pop/mi^2)			13,423	13,518
			(8,389)	(8,815)
Household Income (BG Median)			49,292	64,211
			(23,411)	(32,920)
Population over age 25	1,717,881	1,796,814	888	929
			(505)	(564)
Educational Attainment (count)				
Less than High School	458,399	384,055	237	199
			(221)	(209)
High School Grad	830,050	895,603	429	463
			(269)	(294)
More than High School	429,432	517,156	222	267
			(262)	(312)
Educational Attainment (fraction)				
Less than High School			0.28	0.22
			(0.22)	(0.19)
High School Grad			0.48	0.50
			(0.13)	(0.14)
More than High School			0.24	0.28
			(0.19)	(0.21)
Race/Ethnicity (count)				
White (non-Hispanic)	852,136	787,815	441	407
			(468)	(466)
Hispanic	1,030,236	1,147,634	533	593
			(546)	(601)
Black	507,488	468,462	262	242
			(380)	(378)
Race/Ethnicity (fraction)				
White (non-Hispanic)			0.34	0.32
			(0.31)	(0.30)
Hispanic			0.34	0.38
			(0.26)	(0.28)
Black			0.19	0.17
			(0.25)	(0.24)

Notes: Number of block groups is 1,934. Block groups with fewer than 400 people in 2000 are excluded from regression sample and so are excluded here. Data for 2000 comes from the 2000 Census. Data for 2005/9 comes from the 2005–2009 ACS 5-year sample and is labeled “2005” elsewhere. All educational attainment variables are restricted to people who are at least 25 years old. Income is denominated in nominal dollars. Standard deviations in parentheses.

Table 3: Firm Summary Statistics by Industry

	Petroleum Refining	Electric Services	Other Industries	Crude Petroleum and Natrual Gas	Steam and Air-Conditioning Supply	Secondary Smelting and Refining	Other Industrial Inorganic Chemicals	Gypsum Products	All Firms
Mean Emissions (tons)									
1998	524.8	212.6	16.8	31.1	38.8	45.5	39.7	33.7	62.0
2002	380.9	56.1	11.1	8.9	5.7	24.8	37.0	8.8	33.2
Median Emissions (tons)									
1998	332.4	120.0	4.8	5.7	14.5	41.0	34.5	28.7	7.2
2002	255.6	42.2	2.9	1.4	3.7	22.4	43.6	9.3	4.1
Industry Share of Total Emissions (percent)									
1998	42.6	28.8	18.9	3.6	2.1	1.6	1.4	0.9	100.0
2002	56.1	13.8	23.9	1.9	0.6	1.6	1.8	0.4	100.0
Mean Smoke Stack Characteristics									
Height (m)	25.1	37.4	12.3	7.1	19.1	10.6	28.4	19.6	14.9
Diameter (m)	1.3	3.6	0.8	0.4	0.9	0.7	0.9	1.2	1.0
Velocity (m/s)	8.6	20.1	10.8	14.2	12.5	12.5	11.9	9.5	11.7
Temp. (°C)	292.8	231.0	223.0	351.5	191.6	120.9	251.0	271.2	233.7
Mean Dist. to Weather Monitor (km)	7.0	7.5	6.3	6.2	6.8	5.2	6.1	5.9	6.4
No. of Firms	9	15	150	14	6	4	4	3	205

Notes: Sample of firms is those within 20 km of sample area shown in Figure 6a.

Table 4: Effect on Block Group Median Monthly Rent

	(1)	(2)	(3)	(4)
Aermod_pre×post	0.0031*	0.0031**		
	[0.0018]	[0.0015]		
Aermod			-0.0124	-0.0126**
			[0.0076]	[0.0063]
Method	OLS	OLS	2SLS	2SLS
Weighted by	Pop.	Renters	Pop.	Renters
R^2	0.9331	0.9536		

Notes: N=3,162. Outcome is log of median rent. Excluded instrument in 2SLS regressions is aermod_pre × post. Rents with error codes ($0) or top codes ($2,001) are dropped from the sample. Sample and controls are otherwise the same as in Table 5, plus an interaction of median rent in 2000 with post. Sample average of aermod_pre is 6.781. Standard errors, clustered by tract, in brackets: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Effect of Pollution on Block Group Demographics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	ln Income	ln Pop.	ln H-holds	ln H. Units	% Low Inc	% Mid Inc	% High Inc
	A. OLS with Controls						
Aermod	0.0020	-0.0012	0.0014	0.0059	0.0029	0.0021	-0.0050*
	[0.0050]	[0.0054]	[0.0043]	[0.0041]	[0.0027]	[0.0018]	[0.0027]
	B. Reduced Form						
Aermod_pre×post	0.0036	-0.0025*	-0.0024*	-0.0030**	-0.0028***	-0.0001	0.0029***
	[0.0026]	[0.0014]	[0.0014]	[0.0015]	[0.0008]	[0.0007]	[0.0010]
	C. 2SLS						
Aermod	-0.0143	0.0100*	0.0096*	0.0121**	0.0113***	0.0004	-0.0116***
	[0.0108]	[0.0056]	[0.0056]	[0.0058]	[0.0035]	[0.0026]	[0.0043]

Notes: N=3,870. Sample periods are 2000 and 2005–2009 using data from the 2000 Census and 2005–2009 ACS, respectively. Regressions include block group fixed effects and 10-km grid–post dummies. Year-2000 demographic controls, interacted with "post", include: population, number of households, number of housing units, ln median household income, number of people at least 25 years old, fraction without a high school diploma, fraction with diploma but no college, fraction white (non-Hispanic), fraction Hispanic, fraction black. All educational attainment variables are restricted to the sample of people who are at least 25 years old. Block groups with fewer than 400 people in 2000 are dropped. Sample average of aermod_pre is 6.222. Standard errors, clustered by tract, in brackets: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Change in Population by Household Income

	(1) log Low Inc	(2) log Mid Inc	(3) log High Inc
Aermod_pre×post	-0.0142**	-0.0034	0.0060
	[0.0062]	[0.0033]	[0.0039]
R^2	0.9200	0.9052	0.9438
N	3,786	3,834	3,846

Notes: Low income is households with less than $30,000 income, mid is $30-60,000, and high is $60,000 or more. Block groups with zero households of the given income group in either year are dropped. Sample and other control variables the same as in Table 5.

Table 7: Change in Demographics by Initial Neighborhood Income

	(1) ln Income	(2) ln Pop.	(3) ln H-holds	(4) ln H. Units	(5) % Low Inc	(6) % Mid Inc	(7) % High Inc
Aermod_pre×post×							
% Low Income in 2000	0.022***	-0.025**	-0.027**	-0.023**	-0.010***	0.004	0.007*
	[0.008]	[0.011]	[0.011]	[0.012]	[0.003]	[0.003]	[0.004]
% Mid Income in 2000	-0.012	0.023	0.028**	0.019	0.006	-0.005	-0.001
	[0.013]	[0.015]	[0.014]	[0.015]	[0.005]	[0.004]	[0.006]
% High Income in 2000	0.000	-0.004	-0.006	-0.004	-0.003	0.000	0.003
	[0.010]	[0.007]	[0.007]	[0.006]	[0.003]	[0.003]	[0.005]

Notes: Low income is households with less than $30,000 income, mid is $30-60,000, and high is $60,000 or more. Sample and other control variables the same as in Table 5.