Crawford School of Public Policy
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Willingness to pay for clean air:

Evidence from diesel vehicle registration restrictions in Japan

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Abstract

This paper documents the effect of diesel vehicle registration restrictions introduced in Japan in 2001 in reducing suspended particulate matter (SPM) concentrations. The focus is on Aichi and Mie prefectures, home to a number of municipalities that were required to implement these restrictions in 2001. The paper then uses this intervention to estimate the causal effect of air pollution on land values. We obtain estimates of the elasticity of residential land prices with respect to SPM concentration of between –0.4 and –1.0. The revealed willingness to pay for the improvements in air quality induced by the intervention in Aichi and Mie is estimated at about US$7 billion. We also find evidence that net in-migration appears to be a key mechanism via which clean air was capitalized into higher land values. The results are robust to a number of estimation approaches and sample restrictions.

Keywords:
Vehicle registration restrictions, urban air pollution, hedonic pricing

JEL Classification:
Q53, Q58, R48

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1. Introduction

Motor vehicles are a major source of urban air pollution around the world. Exposure to high concentrations of vehicular air pollution leads to a wide range of health problems, including decreased lung function, increased risk of respiratory symptoms, and premature death. Poor air quality also has adverse implications for the long-term growth of local economies through channels such as hindering human capital formation (Bharadwaj et al., 2017) and labor force participation (Viard and Fu, 2015).

Old-vehicle scrappage programs have been introduced in many countries in order to improve urban air quality. The reason for targeting old vehicles is that they account for a disproportionate share of vehicular emissions. Vehicles from older model years have less sophisticated and more worn-out pollution-control equipment. Removing the most polluting vehicles from the road via a vehicle scrappage program has the potential to make an important contribution to improving air quality.

Under a related but distinct approach, in June 2001 a diesel vehicle replacement program was introduced in designated municipalities in Japan under the Automobile NOx/PM Law (ANPL), with the aim of reducing ambient pollution concentrations of suspended particulate matter (SPM). The program banned diesel vehicles that did not meet set emission standards from registering in designated municipalities after certain grace periods. Registration restrictions were introduced in a staggered way over 2004–2015, determined by the first year of registration of the vehicle. Non-compliant vehicles were not required to be scrapped, but data from the Ministry of Economy, Trade and Industry (2008) suggest that about 70% of vehicles replaced under the ANPL were indeed scrapped.

The ANPL has been controversial because it imposed costs on the owners of non-compliant vehicles, especially truck companies for which replacements are expensive. Arimura and Iwata (2008) calculated that the aggregate cost of vehicle replacements under the ANPL was about US$8 billion across all designated municipalities in Japan. Opponents also argue that the program infringed property rights. Little has been known about the economic benefits, making it difficult to evaluate the ANPL program in a holistic way. Existing evidence has been limited as to whether the ANPL was effective in reducing pollution (Ministry of Internal Affairs and Communications, 2004; Iwata and Arimura, 2009; Nishitateno and Burke, 2020).

The goal of this paper is to estimate the revealed willingness to pay (WTP) for improvements in air quality induced by the ANPL program, with a focus on the two prefectures of Aichi and Mie, where some municipalities became ANPL-designated in 2001. We draw on a hedonic pricing model applied to a property-level panel dataset for 1995–2015. Using a matching approach to draw a control group from elsewhere in Japan with highly similar average pre-trends in residential land prices, we attempt to estimate the implicit price of air quality by identifying the extent to which reduced SPM concentration led to residential land price increases. This allows us to obtain an estimate of the gradient of the hedonic pricing schedule, which we use to estimate the economic benefits of the program. We also explore whether net in-migration has been a channel via which the benefits of cleaner air have been capitalized into higher land prices.

A key issue in the hedonics literature is that single-equation estimates of the association between air pollution and property values may be biased upward by omitted variables (Parmeter and Pope, 2013). To address this potential endogeneity we exploit the policy-induced variation in air pollution in the study area. We do so by instrumenting the temporal variation in SPM concentration with each municipality's time-space-varying designation status under the ANPL. Our instrumental variable (IV) approach is attractive because: (i) the program was geographically-focused and had a clear cut-off year, allowing for a difference-in-difference analysis that compares municipalities subject to the program with those that were not, and (ii) the mandatory nature of the program eliminates concerns about self-selection into vehicle retirements, which has been an issue in the evaluation of scrappage programs.

The first-stage results suggest that the ANPL program led to a 17% reduction in annual mean SPM concentration in the designated municipalities of Aichi and Mie prefectures on average over the years 2001–2015, relative to the control group. A significant effect on air pollution kicked in a year after the intervention started and persisted over subsequent years of the sample. The time pattern of the effect on air pollution is similar to what we go on to observe for the time pattern of the effect on land prices, consistent with a transmission mechanism affecting land prices via air quality.

Our IV estimates suggest that the elasticity of the average residential land price with respect to SPM concentration is between –0.4 and –1.0. This is larger than prior estimates of between –0.1 and –0.6 for the United States (Chay and Greenstone, 2005; Hanna, 2007; Bayer et al., 2009; Bento et al., 2015). We also find that municipalities that were subject to the ANPL experienced a 4.6% greater increase in the births- and deaths-adjusted population over 2001–2015, suggesting that municipal net in-migration was a channel through which the capitalization of clean air into residential land prices occurred. Based on the hedonic results, the estimated WTP for the improvements in air quality in Aichi and Mie induced by the program was about US$6.8 billion.

The paper contributes to the hedonics literature through the use of a quasi-experimental identification strategy. The approach is similar to those of Chay and Greenstone (2005) and Bento et al. (2015), who employed non-attainment status based on the US federal air quality standard as an IV. However it differs in some distinctive ways. We use a longitudinal panel dataset that enables us to examine the time patterns of the effects on air pollution and residential land prices in an event-study setup. The paper is also the first to provide evidence on whether in-migration is a relevant mechanism via which clean air is capitalized into residential land prices.

The paper also contributes to the literature that evaluates the effects of vehicle scrappage programs and related interventions. There is often no clear distinction between the treatment and control groups in these studies, as the program is typically applied to an entire country or state. The existing literature mostly focuses on analyzing determinants of scrappage decisions (Alberini et al., 1995, 1996) and estimating the extent to which vehicle scrappage is attributable to a program (Mian and Sufi, 2012; Sandler, 2012; Li et al., 2013; Antweiler and Gulati, 2015; Grigolon et al., 2016; Hoekstra et al., 2017). In contrast, our study utilizes a geographical control group and provides estimates of economic benefits.

Bans on diesel vehicles have been on the agenda since the *dieselgate* scandal of 2015, especially in European cities. In February 2018, a German court ruled that Stuttgart can ban diesel cars from driving in downtown areas to improve air quality (Bennhold, 2018). The mayors of Paris, Madrid, and Athens have agreed to outlaw diesel vehicles from city centers by 2025. The United Kingdom has also considered the introduction of a diesel scrappage scheme (Butcher, 2018). Japan's geographically-focused diesel vehicle replacement program offers a potential model, and one that appears to be effective in reducing pollution and providing benefits to the local area.

2. Diesel vehicle replacement program

In June 1992, Japan introduced an Automobile NOx Control Law to reduce ambient concentrations of nitrogen oxide (NOx) in designated areas in Tokyo, Saitama, Chiba, Kanagawa, Osaka, and Hyogo prefectures. The law was amended in June 2001 to also target SPM in response to growing health concerns pertaining to air pollution in metropolitan areas. Some municipalities in Aichi and Mie also became designated in June 2001 as a result of lawsuits claiming that SPM was responsible for health damages. The law was renamed the Automobile NOx/PM Law (ANPL).

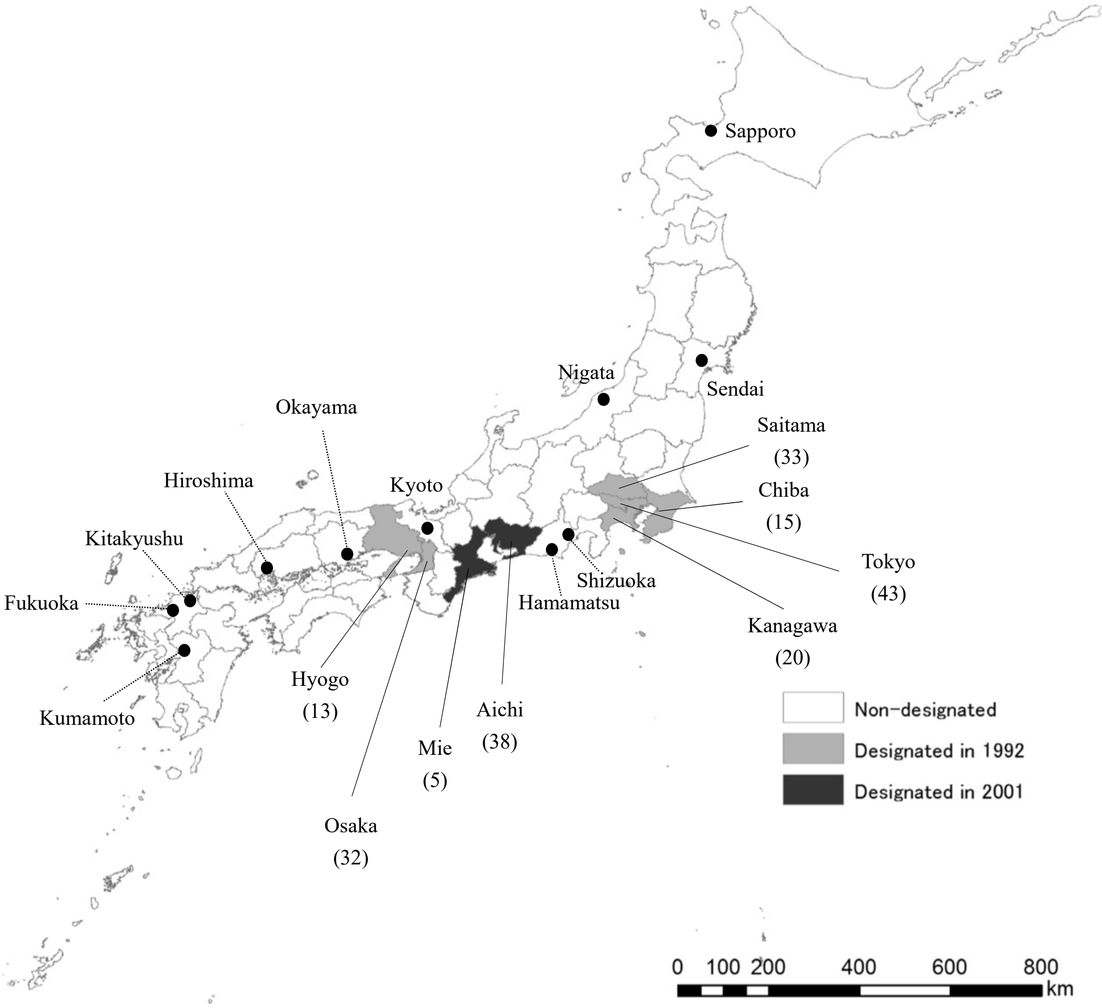

Figure 1. Designated areas under the Automobile NOx/PM Law

Notes: The number in the brackets stands for the number of designated municipalities. Designated municipalities in Aichi and Mie are defined as the treatment group in the analysis in this paper. Dots show the 11 municipalities used for the control group.

The ANPL stipulated that all monitors in the designated areas shown in Figure 1 must meet the national air quality standard for SPM, which involves keeping the 98th-percentile of the daily-mean SPM concentration below 0.10 mg/m^3 throughout the year. As of 2015, 197 municipalities in 8 prefectures (Tokyo, Saitama, Chiba, Kanagawa, Osaka, Hyogo, Aichi, and Mie) had been designated, covering 57% of the total area of the 8 prefectures. The designation was assigned to municipalities that violated the SPM standard at least once over the past 8 years, plus surrounding municipalities (Ministry of Environment, 2001). Once imposed, no designation has been lifted.

A diesel vehicle replacement program was a key component of the ANPL. Diesel is popular for trucks and buses due to superior performance in terms of fuel efficiency, durability, horsepower, and fuel expenses. There had been quite low turnover of trucks and buses in Japan, meaning that the fleets included some old vehicles. As of 2000, diesel vehicles accounted for 87% of SPM emissions from motor vehicles and 43% of anthropogenic SPM emissions in designated areas (Ministry of Environment, 2002).

The ANPL stipulated the SPM emission performance standard for targeted vehicles – trucks, buses, special-use vehicles, and diesel passenger cars – in designated areas. The emission standards for trucks, buses, and special-use vehicles were 0.055 g/km for vehicles with a gross weight of less than 1.7 tons, 0.06 g/km for 1.7–2.5 tons, 0.175 g/kWh for 2.5–3.5 tons, and 0.49 g/kWh for more than 3.5 tons. The emission standard for diesel passenger vehicles was 0.055 g/km regardless of weight. These standards have remained unchanged. They are based on the emission ratings at the time of vehicle production. Targeted vehicles are labeled non-compliant if their SPM emission ratings at the time of production exceeded the ANPL emission standards.

Vehicle registration restrictions were introduced in a staggered way over 2004–2015, with requirements determined by vehicle type and the first year of vehicle registration (Appendix 1). The compliance years were set such that older vehicles have shorter grace periods. To illustrate, in 2004 non-compliant standard trucks first registered in 1998 or earlier were not allowed to be registered in designated areas, while the compliance year for those registered in 2002 was 2012. Owners of vehicles that were found to be non-compliant could be sentenced to up to six months in jail or required to pay a fine of up to US$2,700. Nationally, approximately 2.6 million non-compliant vehicles were removed from the designated areas under the program.

3. Sample

3.1. Data

Our main data source is the National Land Numerical Information (NLNI) dataset compiled by the Ministry of Land, Infrastructure, Transport and Tourism (MLITT). This provides digitized geographical information on factors such as topography, land use, public facilities, roads, and railroads. Land values and attributes are recorded on an annual basis by property, enabling us to construct a longitudinal panel dataset at the property level and to control for various neighborhood variables. All neighborhood control variables are measured within 1 km of each property using geographical coordinate systems.

We use the residential land price (not including the value of the dwelling) per square meter (yen/m^2), based on assessments by qualified real estate appraisers, as the outcome variable. A sample of properties was chosen by the MLITT so that the land price represents the average price in the surrounding areas. Given that assessors' evaluations are informed by recent transaction records in the area around the property, assessed values have been widely used as a proxy of market values in the Japanese context (Tabuchi, 1996; Nakagawa et al., 2009).

Although real estate transaction prices are publicly available from the Land General Information System, we do not use these for several reasons.[1] First, they are only available from 2006 onwards, well after the intervention started. Second, transaction data are rarely recorded over time for a given property, limiting our analysis to either pooled cross-sectional property data or panel data aggregated to the municipality level. Third, information on property attributes is missing from the available transaction data, including the address of each property. This makes it difficult to closely couple the observations with the air pollution and neighbourhood data.

Assessed values may include valuation errors (Shimizu and Nishimura, 2006). In particular, it is known that assessed land values tend to lag market values by 1–2 years on average (Hidano et al., 1995; Inoue et al., 2016), a particularly relevant issue given that we focus on temporal variation. We examined the extent to which the use of one- and two-year leads of the residential land price affects our IV estimates, finding that the baseline estimates remain similar (results available on request).[2]

Another important data source for the study is Environmental GIS data compiled by the National Institute for Environmental Studies (NIES). These data provide comprehensive information on ambient concentrations of targeted pollutants, including SPM, at the monitoring-station level. The sample is limited to monitors that operated for at least 70% of the year. We proxy the ambient pollution level at the property by the reading at the nearest pollution monitor.

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[1] https://www.land.mlit.go.jp/webland_english/servlet/MainServlet.

[2] To examine the correlation between the assessed and transaction values, we also collected data on real estate transaction prices over 2006–2015 in the municipalities under consideration from the Land General Information System (n = 248,780). We regressed the log of the transaction price (yen/m^2) on the log of the municipality-average assessed land value (yen/m^2), controlling for year dummies. This provided an elasticity of 0.98, significantly different from zero at the 1% level (n = 248,780, R^2 = 0.23). Similarly, we regressed the log of the assessed land value on the log of the municipality-average transaction price with year dummies, finding an elasticity of 1.05, significantly different from zero at the 1% level (n = 23,007, R^2 = 0.48). We also regressed the difference between the log of the assessed land value and the log of the municipality-average transaction price on ANPL designation status over the same time period, controlling for year dummies. We found a coefficient for the ANPL designation status of –0.07 (p value = 0.159). This provides no significant evidence that measurement error is systemically different between the treatment and control groups.

Information on earthquakes and weather are from the Japan Meteorological Agency. Annual data on socioeconomic variables are from the System of Social and Demographic Statistics of the Ministry of Internal Affairs and Communications (MIAC). The definitions and data sources are listed in Appendix 2.

The sample period throughout the analysis is 1995–2015. We exclude years prior to 1995 because the coverage of properties and air pollution monitoring stations was limited in those early years, and to avoid the influence of overconfidence and speculation during Japan's real estate bubble period of the 1980s and early 1990s.

3.2. Treatment and control groups

We focus on the effects of the ANPL in the 42 designated municipalities in Aichi and Mie prefectures – the 2001 ANPL designation group. Effects for the 1992 designation group are not analyzed, as 1992 fell prior to the 1995–2015 sample period. Annual data are available for 1,055 properties in the treatment group, with the data being balanced (i.e. available for every year) for 675 of these properties.

For the control group we sought non-designated municipalities that are at a similar level of urbanization as the treatment group, using the list of major cities under the Japan Local Autonomy Law. As of 2015, 20 municipalities were classed as major cities under this law, including Nagoya (the largest city in the treatment group) and 11 non-designated municipalities: Sapporo, Sendai, Nigata, Hiroshima, Okayama, Hamamatsu, Shizuoka, Kyoto, Kitakyusyu, Fukuoka, and Kumamoto. Major cities are those that have more than 500,000 residents, less than 10% of employment in primary industry, and adequate urban infrastructure. The control group "pool" comprises of 11 non-designated municipalities with data available for 1,494 properties (1,020 being balanced). As will be discussed below, we trim this control group using a matching approach to ensure highly similar pre-trends.

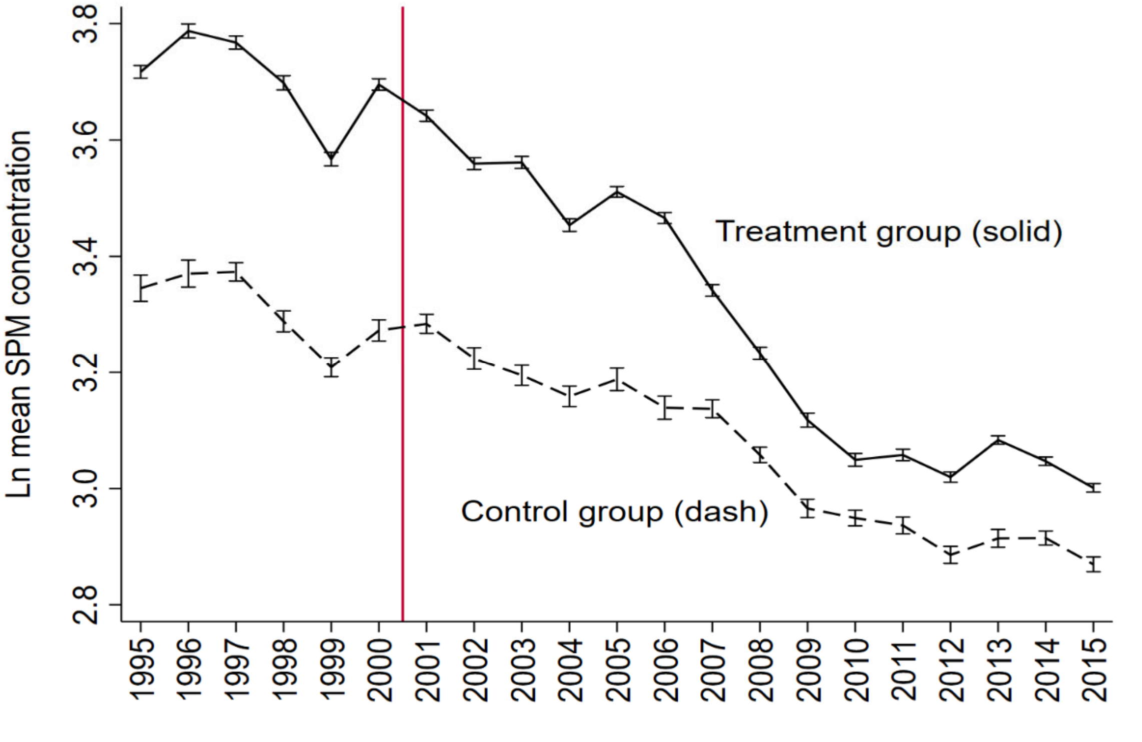
There are two additional justifications for our choice of the control group pool. First is comparability in terms of road traffic. According to the 2010 National Traffic Census compiled by the MLITT, the average daily traffic volumes on roads, including both road directions, were 21,929 and 21,321 for the treatment and control group pools, respectively. The Census also shows that the average driving speeds were 30 km per hour for both groups.

Second, the 11 control municipalities are geographically distant from the designated municipalities in Aichi and Mie. This is important given potential geographical spillovers, as compliant vehicles could be driven outside designated areas. Although it is not reported here, we carefully examined the extent and scope of spatial leakages of the intervention, finding that neighboring municipalities benefited from the intervention *vis-à-vis* more distant municipalities.

Figure 2 shows the trends for the log annual mean ambient concentration of SPM and the log annual mean residential land price in the treatment and control group pools. Overall, the SPM and price trends for the pre-treatment period are similar for the treatment and control group pools.[3] Statistical tests fail to reject the null hypotheses that the slopes of the linear time trends are the same for the two groups for the pre-treatment period. In contrast, we see divergent trends in SPM and land prices for the treatment and control group pools in the post-intervention period.

[3] That the pre-trends are similar after controlling for the variables included in our estimation is also seen in Appendix 3, which plots the residuals for the log pollution and land price variables from regressions that control for property attributes, neighborhood variables, earthquake/weather variables, socioeconomic variables, property fixed effects, and year fixed effects.

Panel A. Ln SPM concentration



Panel B. Ln residential land prices

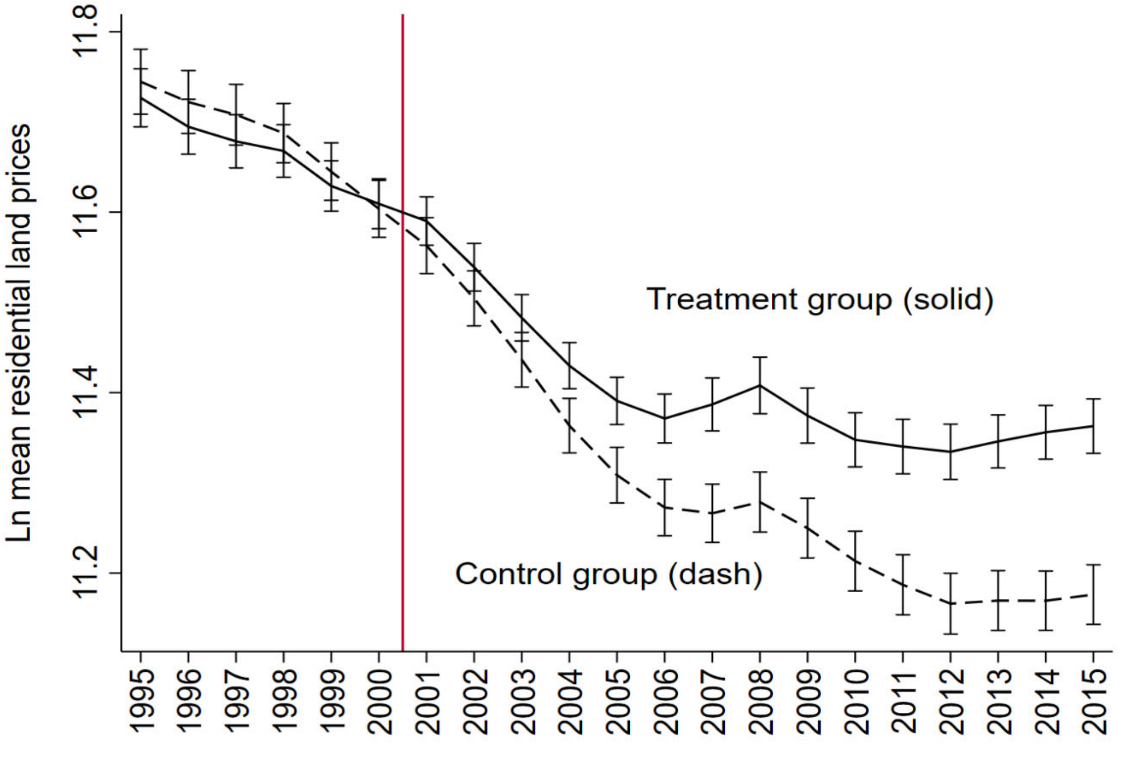


Figure 2. Time trends of mean SPM concentration and residential land prices

Notes: The vertical bands represent the 95% confidence intervals. The treatment group covers 42 designated municipalities in Aichi and Mie prefectures. The control group pool is from 11 non-designated municipalities.

However, the two log mean land price series in Figure 2 cross over just prior to the policy being introduced, providing some evidence of a potential pre-trend threat. To address this issue, we proceeded to select a final control group that is comparable to the treatment group in the pre-treatment growth rate of land values. Specifically, we calculated the percentage change in land price between 1995 and 2000 for each property, then computed the average for the treatment group and the control group pool. The average changes were –10% and –12%, respectively. To equate these, we ordered the control properties by percentage price change and sequentially excluded control properties until the average price change for the control group became –10%. The resultant control group has 1,004 control properties. As will be presented in Figure 3, an event-study analysis confirms that there are no noticeable differences in pre-trends for the air pollution and residential land price variables between the treatment and final control groups.

3.3. Descriptive statistics

Table 1 shows the sample averages during the pre- and post-intervention periods, and their differences, for the treatment and final control groups. We use municipality-level data on the earthquake/weather and socioeconomic variables for data availability reasons. We see that average residential land prices declined by about 26% in the designated municipalities, relative to 39% in the control group (a difference of +13 percentage points). Average annual mean SPM concentration fell by 44% in the designated municipalities, relative to 26% in the control group (a difference of –18 percentage points). Larger reductions in the treatment group can also be observed for the other SPM variables, such as the number of days exceeding the national standard. Thus, simple difference-in-difference calculations provide evidence of treatment effects.

Simple interpretations might be misleading because the initial conditions prior to the policy and time-series trends for other factors are not taken into account. As can be seen in Table 1, the sample means during the pre-intervention periods are quite similar for property attributes, neighborhood variables, earthquake/weather variables, and socioeconomic variables between the treatment and control groups. The averages for these variables also show similar temporal changes. However, we see noticeable differences in some variables, such as the vehicle ownership rate. In addition, we see differential temporal changes in the building-area ratio, areas of parks, unemployment rate, and vehicle ownership rates. We control for all variables listed in Table 1 in our estimations.

Table 1—Descriptive statistics

	Treatment group			Control group		
	Before	After	Diff.	Before	After	Diff.
Land price						
Residential land price (log)	11.66	11.40	–0.26	11.65	11.26	–0.39
Air pollution						
Ambient concentration of SPM (log)						
Annual mean	3.70	3.26	–0.44	3.31	3.05	–0.26
Hourly maximum	5.65	5.26	–0.39	5.20	5.12	–0.08
98th-percentile daily average	4.54	4.10	–0.44	4.16	3.95	–0.21
Days exceeding the national standard	7	1	–6	1	1	0
Property attributes						
Wooden house, %	82	79	–3	89	88	–1
Number of floors	2	2	0	2	2	0
Water, %	100	100	0	100	100	0
Gas, %	76	81	5	74	77	3
Sewage, %	53	75	22	82	93	11
Distance to train station, km	1.6	1.7	0.1	2.5	2.5	0
Building-area ratio, %	25	55	30	33	53	20
Floor-area ratio, %	167	179	12	144	154	10
Neighborhood variables						
Bullet trains, %	8	8	0	13	15	2
Expressways, %	14	22	8	18	22	4
Number of estate developments	0.3	0.3	0	0.3	0.3	0
Number of local heritages	1.0	1.1	0.1	0.6	0.8	0.2
Areas of parks, km^2	74	75	1	75	86	11
Earthquake/weather variables						
Earthquake, %	0	0	0	0	0.03	0.03
Temperature, degree Celsius	16	16	0	14	15	1
Precipitation, millimeters	136	136	0	126	128	2
Sunlight duration, hours	177	177	0	154	157	3
Wind, meters per second	3	3	0	3	3	0
Socioeconomic variables						
Population per hectare	34	35	1	37	39	2
Population aged above 65 years, %	13	19	6	14	20	6
Per capita income, million yen	3.8	3.6	–0.2	3.6	3.3	–0.3
Unemployment rate, %	3.8	4.4	0.6	4.9	6.0	1.1
Vehicle ownership rate per 1000 people	481	459	–22	395	380	–15
Fiscal soundness, %	1	1	0	0.7	0.8	0.1

Notes: This table presents the sample averages during the pre- and post-intervention periods and their differences for the treatment and control groups. The pre- and post-intervention periods are 1995–2000 and 2001–2015, respectively. The treatment group is 42 designated municipalities with 1,055 properties. The control group is 11 non-designated municipalities with 1,004 properties. Land values, air pollution, property attributes, and neighborhood variables are based on the property-level data. Earthquake/weather and socioeconomic variables are based on the municipality-level data.

4. Empirical strategy

4.1. Instrumental variable approach

Drawing on the hedonic pricing model proposed by Rosen (1974), we proceed to estimate the implicit price of air quality embedded in residential land values. The land price can be expressed as $P(\boldsymbol{z}) = P(z_1, z_2, \dots \dots, z_n)$, with $\boldsymbol{z}$ being a vector of attributes such as land characteristics, neighborhood factors, and environmental amenities (including air quality). The first-order condition in the hedonic setup is that the marginal willingness to pay (MWTP) for air quality will equal the marginal rate of substitution between air quality and the numeraire good, holding all other attributes fixed.

We first pursue single-equation estimation of the MWTP for air quality:

$$(1) \qquad P_{i,t} = \alpha + \theta Q_{i,t} + \gamma \boldsymbol{W}_{i,t} + \omega_i + \rho_t + u_{i,t}$$

where i and t are property and year, respectively. P is the log residential land price. Q is log ambient SPM concentration. $\boldsymbol{W}$ is a vector of property attributes, neighbourhood variables, earthquake/weather variables, and socioeconomic variables. ω is property fixed effects to account for time-invariant factors that are relevant for land values (e.g., topography). ρ is a vector of year fixed effects to control for any national-level changes during our sample period such as consumption tax hikes and altered land use rules. u is an error term. θ captures the capitalization of a one-unit reduction in air pollution into residential land prices, providing the average gradient of the hedonic pricing schedule.

A key issue in identifying θ is that pollution levels are not randomly assigned, which introduces a source of potential estimation bias; it is well documented in the hedonics literature that single-equation estimation can lead to substantial underestimates of the MWTP for clean air due to omitted variables (Smith and Huang, 1995; Chay and Greenstone, 2005). In the context of the current study, changes in local economic conditions seem to be highly relevant as potential sources of bias. For example, factory closures might improve air quality but devalue surrounding residential areas. Newly-built commercial facilities such as shopping malls might act as an attraction, resulting in an increase in land values and also emissions from road transport. The controls for the municipality-level socioeconomic factors (e.g., unemployment rates) in our estimation are unlikely to absorb all such local effects.

To address the potential endogeneity problem, we employ an IV approach utilizing the time-space-varying designation status of the ANPL. Our IV is an interaction of a dummy variable indicating the post-intervention period ($Post_t$) with a dummy variable indicating if the property is located in a treated area ($Treated_i$). Under assumptions, the IV estimator captures the average causal response to a unit change in SPM concentration for the treated areas (Angrist and Imbens, 1995). The IV estimates can thus be interpreted as the MWTP for air quality.

The first-stage and reduced-form equations are expressed as follows:

(2) $Q_{i,t} = \beta + \pi(Treated_i \times Post_t) + \sigma \boldsymbol{W}_{i,t} + \omega_i + \rho_t + \varepsilon_{i,t}$

(3) $P_{i,t} = \sigma + \delta(Treated_i \times Post_t) + \gamma \boldsymbol{W}_{i,t} + \omega_i + \rho_t + \epsilon_{i,t}$

π captures the average difference in log SPM concentration before and after the intervention for treated areas relative to untreated areas, other things equal. δ captures the average difference in log residential land prices before and after the intervention for treated areas relative to untreated areas.

4.2. Assumptions

A key assumption is that air quality improvements are the only channel via which the instrument influences temporal differences in residential land prices between the treated and untreated areas, and that no omitted variables are correlated with both land prices and treatment status. A concern, though, is that the ANPL intervention might have affected land values through other channels, such as the state of the local economy. For example, the ANPL program imposed replacement costs on the owners of non-compliant vehicles, perhaps affecting the demand for residential property.

Another assumption is that, in the absence of the program, trends in air quality and land prices for the treatment group would be the same as for the control group. The long time horizon in our data heightens this issue of potential confounders. Our estimates might also pick up some unobservable shocks in local economies.

In order to address the above concerns, we take four approaches. First, as mentioned, we control for a set of time-varying factors listed in Table 1 (property attributes, neighborhood variables, earthquake/weather variables, and socioeconomic variables). The second approach is to use a matched control group with common pre-trends for air pollution and land values, as discussed above. Third, we report an estimate that controls for municipality-specific time trends as a robustness check. Fourth, we implement a permutation test to assess whether our baseline estimate is abnormal in terms of the distribution of placebo estimates based on random assignments of the treatment. Details are reported in Section 5.

4.3. Standard errors

Our use of a property-level panel raises two concerns. First, model errors for properties in the same municipality might be correlated due to common shocks such as local government policies. Second, model errors might be serially correlated over time. Failure to adjust for within-cluster correlations may lead to misleadingly small standard errors.

The simplest approach is a clustering adjustment. The conventional approach is to cluster the standard errors at the level at which the treatment is applied (Bertrand et al., 2004). We thus report robust standard errors clustered by municipality. The number of clusters is 53, which is sufficient for the standard cluster adjustment to be reliable (Angrist and Pischke, 2009).

5. Results

5.1. Baseline estimates

Table 2 reports the estimation result for the first-stage equation (2). Column 1 finds a point estimate for ANPL designation status of –0.18. This is significantly different from zero at the 1% level, with the 95% confidence interval ranging from –0.27 to –0.10. The *F* statistic on the instrument exceeds 17, allowing us to reject the null hypothesis of the Stock-Yogo weak instrument test of 10% maximal IV size. The result suggests that designation under the ANPL led to a reduction in annual mean ambient concentration of SPM of 17% on average over the years 2001–2015 for designated municipalities in Aichi and Mie prefectures.[4]

Table 2—First-stage estimates

Dependent variables:	Ln ambient concentration of SPM measured by:			Days exceeding national standard
	Annual mean	Hourly maximum	98th-percentile daily average	
	(1)	(2)	(3)	(4)
Treated × Post	–0.183***	–0.358***	–0.225***	–5.953***
	(0.043)	(0.088)	(0.039)	(0.877)
Cragg-Donald *F* statistic	2,094	1,686	3,683	6,916
R^2	0.73	0.57	0.73	0.48
Year fixed effects	Yes	Yes	Yes	Yes
Property fixed effects	Yes	Yes	Yes	Yes
Property attributes	Yes	Yes	Yes	Yes
Neighborhood variables	Yes	Yes	Yes	Yes
Earthquake/weather variables	Yes	Yes	Yes	Yes
Socioeconomic variables	Yes	Yes	Yes	Yes
Properties	2,059	2,059	2,059	2,059
Municipalities	53	53	53	53
Observations	38,711	38,711	38,711	38,711

Notes: Columns 1–4 show the estimation results for the first-stage equation (2) with different air pollution variables. All variables listed in Table 1 are controlled for: property attributes, neighborhood variables, earthquake/weather variables, and socioeconomic variables. See Appendix 2 for definitions and data sources. All specifications use property-level panel data for 1995–2015. Standard errors are robust to heteroscedasticity and clustered at the municipality level. The null of a weak instrument is rejected if the *F* statistic on the instrument exceeds the Stock–Yogo critical value (16.38).
***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

We also find that the average treatment effects on the hourly maximum and the 98th-percentile daily average SPM concentration are reductions of about 30% and 20%,

[4] The formula $100 * [\exp(\text{coefficient}) - 1]$ is applied to log-linear coefficients to calculate the exact percentage change.

respectively (Columns 2 and 3). The point estimate for the 98th-percentile daily average is of particular interest as it allows us to assess the extent to which the intervention contributed to the ultimate target of the ANPL: all monitors in the designated areas meeting the national SPM standard. The estimate suggests that the intervention on average led to around 14 monitors that had previously violated the national standard becoming compliant during the years 2001–2015. This amounts to all of the total reduction in non-attained monitors for designated municipalities in Aichi and Mie prefectures.

Column 4 of Table 2 uses the days exceeding the national standard for SPM as a dependent variable. The point estimate is –6, different from zero at the 1% significance level. The 95% confidence interval ranges from –8 to –4. This suggests that the intervention decreased the days per year for which the daily average SPM concentration exceeded 0.10 mg/m^3 by 6 on average.

Table 3 presents the main results. Column 1 reports the single-equation results of equation (1), which provides an elasticity of residential land prices with respect to annual mean SPM concentrations of only –0.04. Ignoring the potential for endogenous pollution might well have caused this estimate to be biased upward.

Column 2 of Table 3 reports IV estimates that are quite different to the single-equation estimates.[5] The point estimate for SPM concentration is –0.62, significant at the 5% level, with the 95% confidence interval ranging from –1.12 to –0.13. Together with the first-stage results, the IV estimates suggest that the ANPL caused residential land prices for the treatment group to increase by about 11% on average relative to the control group. This is similar to what is observable from the reduced-form equation (3), which directly examines the program’s effects on residential land prices (Column 3).

Based on the estimates above, we calculate the benefit of the ANPL by taking the difference between mean land prices in year-2015 yen in the treated and counterfactual areas. Converting into US$ using the 2015 current exchange rate and bringing all flows to year-2015 terms using a discount rate of 3%, we obtain an estimate of the benefit of the intervention of US$8 per square meter in 2015 dollars. The annual survey on property tax indicates that the total taxable land area for residences in the treatment group was 859 million square meters as of 2015. This implies that the revealed WTP for the reduction in SPM concentration caused by the intervention under the ANPL was approximately US$6.8 billion for the designated municipalities in Aichi and Mie prefectures.

[5] The base of Table 3 shows that contrasting results between single-equation and IV estimation are also observed when other pollution variables are used.

Table 3—Baseline estimates

Dependent variable: Ln residential land price			
Estimation methods:	Single-equation	IV	Reduced-form
	(1)	(2)	(3)
Ln annual mean SPM	–0.041*	–0.617**	
	(0.024)	(0.249)	
Treated × Post			0.113***
			(0.032)
R^2	0.82	0.65	0.83
Year fixed effects	Yes	Yes	Yes
Property fixed effects	Yes	Yes	Yes
Property attributes	Yes	Yes	Yes
Neighborhood variables	Yes	Yes	Yes
Earthquake/weather variables	Yes	Yes	Yes
Socioeconomic variables	Yes	Yes	Yes
Properties	2,059	2,059	2,059
Municipalities	53	53	53
Observations	38,711	38,711	38,711
Estimated coefficients for other air pollution variables:			
Ln hourly maximum SPM	–0.009	–0.316***	-
Ln 98th-percentile daily average SPM	–0.042*	–0.504***	-
Days exceeding national standard	–0.002	–0.019***	-

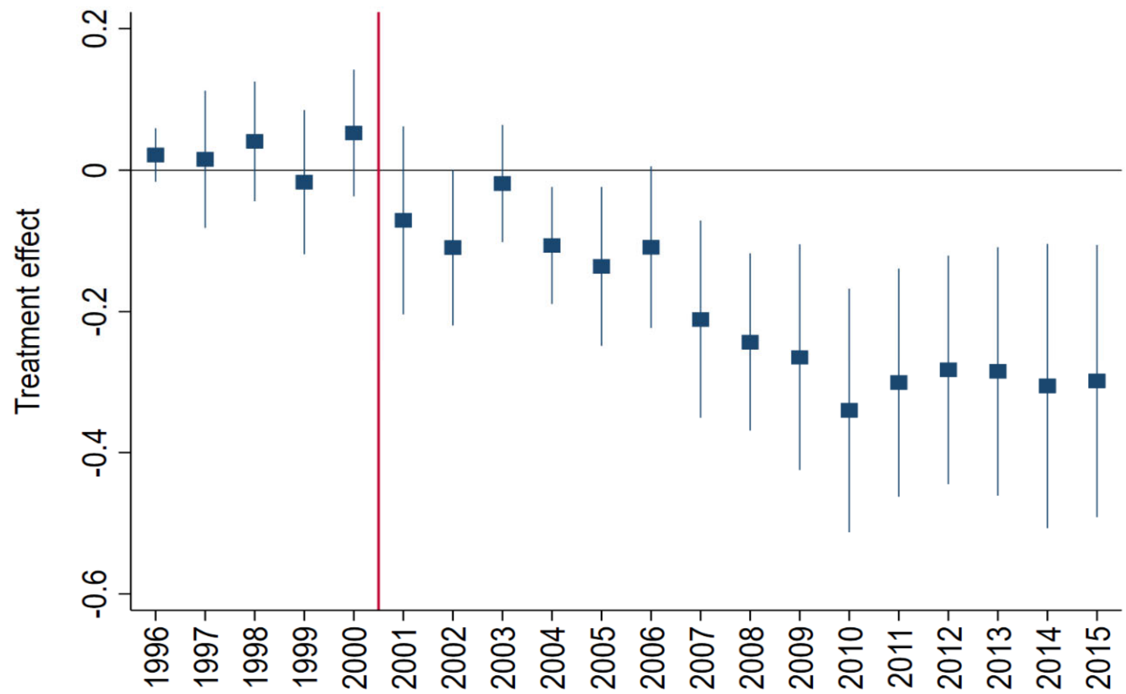
Notes: Columns 1 and 2 present results for single equation and IV estimation of equation (1). Column 3 presents the estimation results for the reduced-form equation (3). See the notes of Table 2 for property attributes, neighbourhood variables, earthquake/weather variables, and socioeconomic variables. All specifications use property-level panel data for 1995–2015. Standard errors are robust to heteroscedasticity and clustered at the municipality level.
***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

5.2. Additional analysis

Dynamics of the treatment effects.—The specifications in equations (2) and (3) provide no indication of the dynamics of the intervention effects: how quickly air pollution and land values changed after the law was enacted, and whether impacts increased, stabilized, or declined over time. Following a standard event-study setup we now estimate the time patterns of the treatment effects on SPM concentration and residential land prices by interacting year dummies for all years other than 1995 with the ANPL designation variable $Treated_i$. The other elements are identical to equations (2) and (3).

Figure 3 shows the results. Interestingly, the time patterns of the effects on residential land prices mirror the dynamics of the effects on air pollution, consistent with an air quality transmission mechanism. Panel A suggests that the effects on SPM concentration kicked in after one year and peaked in 2010 (in point estimate terms). The effect persisted in subsequent years. Mean SPM was about 37% lower in 2010 relative to 1995 as a result of the treatment based on the point estimate. In point-estimate terms, this was the peak proportional effect during the treatment period. Panel B shows that the effects on land prices also kicked in during 2001, then increased gradually thereafter.

Panel A. Ln SPM concentration



Panel B. Ln residential land price

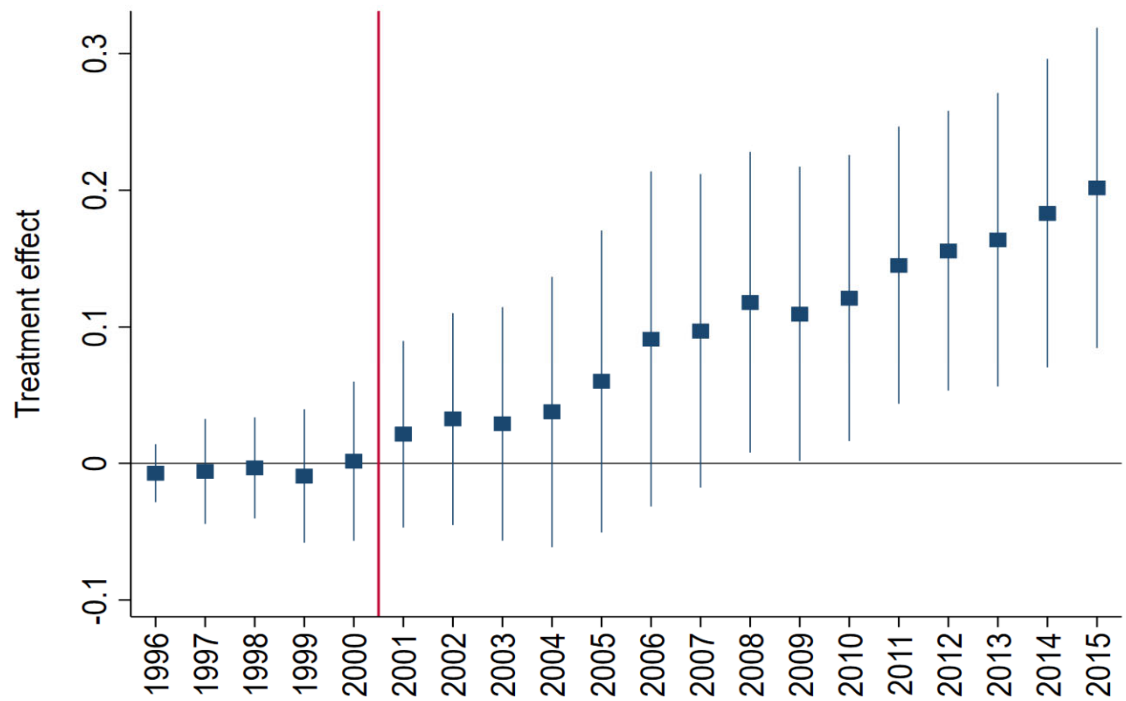


Figure 3. Event-study analysis

Notes: This figure presents the time pattern of pre- and post-treatment effects on log SPM and the log residential land price. The squares show the point estimates and the vertical bands represent the 95% confidence intervals. Standard errors are robust to heteroscedasticity and clustered at the municipality level.

Another important finding is that there are no noticeable effects during the pre-intervention period, increasing the confidence with which the parallel trends assumption can be made. Pre-treatment effects on air pollution are statistically indistinguishable from zero (Panel A of Figure 3). Panel B also indicates that the pre-trends of residential land price between the treatment and control groups appear to be common. In both cases, joint significance tests cannot fail to reject the null hypothesis that the event-study coefficients are zero for 1996–2000.

Robustness.— Our baseline IV estimate suggests that the land price-pollution elasticity is about –0.62 (Column 2 of Table 3). Table 4 explore if this estimate is robust to different estimation approaches. First of all, there are many possible alternative ways of constructing the control group using matching based on pre-trends. For example, we could restrict the control properties within a certain range around the average proportional pre-treatment period price change of the treatment group (–10%), such as between –15% and –5%. Column 1 reports the result in this case. We find that the main result remains unchanged. The results also remain similar even when different ranges are used.

Column 2 of Table 4 presents a specification that includes municipality-specific time trends. The point IV estimate is –0.38 (significantly different from zero at the 10% significance level), which is smaller in absolute value than the baseline result. Column 3 reports a specification in which the control group is restricted to four major cities – Sendai, Shizuoka, Hamamatsu, Fukuoka – that violated the SPM standard at least once over 1993–2000, but that were not designated as no lawsuits had been lodged in those municipalities. Although the point IV estimate is larger in absolute value, the main conclusion still holds.

Our analysis has proxied the pollution concentration at the property level by the reading at the nearest air monitoring station. The nearest monitoring station is quite far from some properties; indeed, the mean distance is 10 km. Column 4 of Table 4 represents the results for samples restricted to properties for which the nearest monitor is within 5 km. The point estimate remains similar to our baseline results.

The baseline estimate might be affected by changes in sample composition, although we have controlled for panel fixed effects. In Column 5 of Table 4 we restrict the sample to a balanced sample of 1,604 properties. The point estimate remains similar.

Table 4—Robustness checks

Dependent variable: Ln residential land price	Alternative matching based on similar pre-trends	Municipality-specific time trends	Control group: Polluted cities	Properties with the nearest monitor within 5 km	Balanced sample
	(1)	(2)	(3)	(4)	(5)
Ln annual mean SPM	–1.024***	–0.379*	–0.830**	–0.519**	–0.625**
	(0.368)	(0.227)	(0.415)	(0.221)	(0.251)
R^2	0.37	0.81	0.42	0.71	0.65
First-stage results					
Treated × Post	–0.150***	–0.024***	–0.160***	–0.184***	–0.188***
	(0.048)	(0.007)	(0.053)	(0.044)	(0.043)
Cragg-Donald *F* statistic	910	654	881	1,677	1,923
R^2	0.79	0.79	0.79	0.74	0.65
Properties	1,436	2,059	1,279	1,631	1,604
Municipalities	53	53	46	52	51
Observations	25,890	38,711	22,843	30,649	33,684

Notes: Columns 1–5 present results for IV estimation of equation (1). All specifications control for year fixed effects, property fixed effects, property attributes, neighborhood variables, earthquake/weather variables, and socioeconomic variables. Standard errors are robust to heteroscedasticity and clustered at the municipality level. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Placebo tests.—There is some uncertainty over the ability of our control group to reproduce the counterfactual of how the treated municipalities would have evolved in the absence of the treatment. One way to assess this uncertainty is to use permutation inference, where the distribution of test statistics is computed under random permutations of the sample units' assignments to the treatment and control groups (Abadie et al., 2010; Cunningham et al., 2019). Specifically, we test if under the hypothesis of no treatment effects the estimated effect of air pollution on land values falls into the 95% confidence interval of the mean of the placebo effects.

We first randomly assign the treatment to all municipalities in the sample. The random assignments are then repeated so that in total we have 1,000 randomized samples. We then re-estimated equation (1) in IV form for each sample. Note that the treatment period (from the year 2001) remains unchanged. The distribution of the placebo estimates is presented in Figure 4. The vertical line shows our baseline IV estimate (–0.62). The mean of the placebo estimates is –0.09 with a 95% confidence interval from –0.15 to –0.02 (i.e., the standard error of the mean is 0.035). Our baseline estimate falls outside this range.

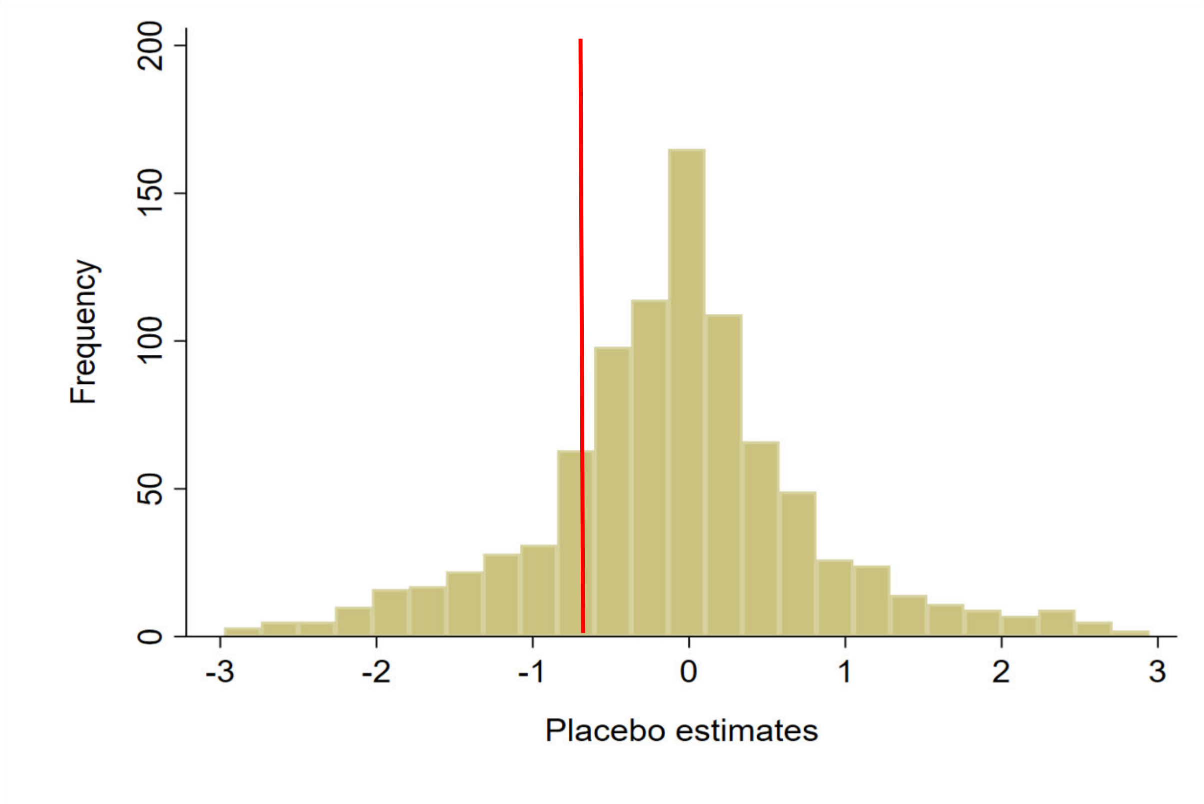


Figure 4. Permutation tests

Notes: This figure presents the histogram of IV estimates of θ for equation (1), based on random assignments of the treatment. The vertical line shows our baseline IV estimate (–0.62). The number of samples is 1,000, the mean is –0.092, and the 95% confidence interval of the mean ranges from –0.151 to –0.034.

Sorting.—If there is heterogeneity across individuals in preferences regarding clean air, individuals would likely self-select their location such that those with the highest distaste for air pollution would be more likely to live in the least polluted areas. In this case, the land price-pollution gradient could be non-linear, causing θ to differ from the average MWTP in the sub-population in the treated areas (Chay and Greenstone, 2005; Bento et al., 2015).

To address this issue, we draw on the random coefficients regression model specified by Chay and Greenstone (2005):

$$(4) \quad P_{i,t} = \bar{\theta}Q_{i,t} + \varphi\hat{\varepsilon}_{i,t} + \vartheta\left(Q_{i,t} \times \hat{\varepsilon}_{i,t}\right) + \sigma\boldsymbol{W}_{i,t} + \omega_i + \rho_t + \mu_{i,t}$$

where $\hat{\varepsilon}_{i,t}$ is the residuals from the first-stage equation (2). Under some assumptions, estimation of equation (4) provides (i) a consistent estimate of MWTP in the subpopulation ($\bar{\theta}$), (ii) the extent of omitted variables bias in the single-equation estimation shown in equation (1) (φ), and (iii) the extent of self-selection biases arising from taste sorting (ϑ). As the IV estimates are more negative than the single-equation results, we expect $\varphi > 0$. The sign and significance of ϑ is of interest. $\vartheta > 0$ supports self-selection biases from taste sorting.

Table 5 presents the results. Columns 1, 2, and 3 use the annual mean, hourly maximum, and 98$^{\text{th}}$-percentile daily average SPM concentrations as $Q_{i,t}$, respectively. We find that the point estimates of $\bar{\theta}$ are –0.61, –0.32, and –0.50, which are quite similar to the IV estimates in Table 3. Thus our IV estimation appears to do a reasonable job of absorbing both sources of bias.

The Table 5 results indicate that φ is positive and statistically significant, implying that omitted variables bias in the single-equation estimation is substantial. We also find that ϑ is indistinguishable from zero for all specifications, implying that self-selection bias from taste sorting might not be a major issue. We conclude that our log-linear approximation of the MWTP for air quality is a suitable approach.

Table 5—Examination of heterogeneity in preferences for air quality

Dependent variable: Ln residential land price.	(1)	(2)	(3)
Ln annual mean SPM	–0.608***		
	(0.166)		
Ln hourly maximum SPM		–0.316***	
		(0.088)	
Ln 98th-percentile daily average SPM			–0.501***
			(0.135)
First stage residual	0.648***	0.318***	0.530**
	(0.212)	(0.095)	(0.205)
First stage residual × Ln annual mean SPM	–0.015		
	(0.026)		
First stage residual × Ln hourly maximum SPM		0.001	
		(0.004)	
First stage residual × Ln 98th-percentile daily average SPM			–0.006
			(0.027)
R^2	0.83	0.83	0.83
Properties	2,059	2,059	2,059
Municipalities	53	53	53
Observations	38,711	38,711	38,711

Notes: This table reports the estimation results for equation (4), using property-level panel data for 1995–2015. All specifications control for year fixed effects, property fixed effects, property attributes, neighborhood variables, earthquake/weather variables, and socioeconomic variables. Standard errors are robust to heteroscedasticity and clustered at the municipality level.
***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Migration.— Tiebout (1956) hypothesized that people vote with their feet to find the community that provides their optimal bundle of taxes and public goods. Research has gone on to explore the extent to which households adjust their locations in response to air quality improvements. In California, Kahn (2000) found that the population of counties that experienced a 10-day reduction in the annual number of high ozone days over 1980–1994 grew by 8% more than they would have otherwise. Banzhaf and Walsh (2008) found that the population in a half-mile diameter with reduced exposure to polluting facilities increased by 6% more than otherwise over 1990–2000.

In the same spirit we test the hypothesis that the populations of municipalities that experienced a larger reduction in SPM concentration grew faster than those of other municipalities. We use a municipality-level dataset to estimate the following specification:

$$(5) \quad P_{c,t} = \alpha + \varphi Q_{c,t} + \gamma \boldsymbol{D}_{c,t} + \omega_c + \rho_t + u_{c,t}$$

where c and t stand for municipality and year, and P is the log births- and deaths-adjusted population. To focus on temporal changes in population due to inter-municipality migration, this variable was constructed by subtracting the annual number of births and adding the annual number of deaths for January–December from the population as of October for each year. This population stock variable thus varies due to net migration. Q is the log annual mean

SPM concentration. ***D*** is a vector of municipality-level controls such as earthquake strikes, temperature, precipitation, daylight, wind, unemployment rate, and per capita income. ω and ρ are municipality- and year-fixed effects. We analyze a similar panel dataset (50 municipalities for 1995–2015) using the same estimation methods (single equation, IV, and reduced-form) as in the earlier analysis.

Table 6 presents the results, which are quite consistent with the analysis of the air pollution-residential land price gradients. Column 1 shows that single-equation estimation yields no significant relationship between SPM concentration and this measure of population. In contrast, the IV estimate in Column 2 finds a significant effect. The elasticity of population with respect to SPM concentration is estimated as –0.36, differing from zero at the 1% significance level. Column 3 reports the reduced-form estimates, which show that municipalities that were subject to the ANPL intervention experienced a 4.6% greater increase in this measure of population over 2001–2015 relative to other municipalities, all else equal.

Table 6—Estimated effects of SPM concentration and ANPL designation on temporal population changes

Dependent variable: Ln population (excluding deaths and births)			
Estimation methods:	Single-equation	IV	Reduced-form
	(1)	(2)	(3)
Ln annual mean SPM	0.018	–0.359**	
	(0.023)	(0.170)	
Treated × Post			0.045***
			(0.015)
R^2	0.56	0.39	0.56
Year fixed effects	Yes	Yes	Yes
Municipality fixed effects	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Municipalities	50	50	50
Observations	1,037	1,037	1,037

Notes: Columns 1 and 2 show the results for single-equation and IV estimations of Equation (5), using a municipality-level panel dataset for 1995–2015. Column 3 shows the reduced-form results where we regress the log population on IV, all else equal. Control variables include earthquake strikes, precipitation, temperature, daylight duration, wind, unemployment rate, and per capita income. Standard errors are robust to heteroscedasticity and clustered at the municipality level.
***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

6. Conclusion

This paper examined the environmental and welfare impacts of a diesel vehicle replacement program implemented in Japan under the Automobile NOx/PM Law (ANPL). The results suggest that the intervention led to a 17% reduction in annual mean ambient concentration of SPM in the designated municipalities in Aichi and Mie prefectures on average for the years 2001–2015. An examination of effects on residential land prices provides an estimate of the revealed willingness to pay of about US$7 billion. We also found evidence of migration to areas that experienced pollution reductions under the ANPL. This may well have been a key mechanism via which the capitalization of cleaner air into residential land prices occurred.

A feature of the ANPL is that a regulation-based approach was followed: owners of polluting vehicles were required to replace their vehicles earlier than they may have been intending. This contrasts to incentive-based programs such as the 2009 US Cash-for-Clunkers scheme. The sizable environmental and welfare benefits of the ANPL in the treated areas suggest that regulation-based programs can indeed be effective and economically justifiable.

While we have aimed to be relatively comprehensive, not all benefits can be captured in a hedonic study such as this. We have focused on benefits that have been reflected in increases in residential land prices. Commercial land prices may also have increased, but this has not been captured. Our estimate of the benefits of the intervention may thus represent a lower bound.

The ANPL has not required non-compliant vehicles to be scrapped, leading to some clunkers being exported overseas, which may have adversely affected air quality in the importing countries. Empirical evidence on clunker and pollution leakage effects to overseas jurisdictions has been quite limited (Davis and Kahn, 2010). Examination of leakage across borders due to the ANPL is an interesting avenue for future research.

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Appendix 1. ANPL compliance by the first year of registration

Initial registration year	Trucks		Buses		Special-use vehicles		Diesel passenger cars	
	Standard	Small	Standard	Small	Standard	Small	Standard	Small
1988 or before	2004	2004	2005	2004	2004	2004	2005	2005
1989	2004	2004	2005	2005	2005	2005	2005	2005
1990	2005	2004	2005	2005	2005	2005	2005	2005
1991	2005	2005	2006	2005	2005	2005	2005	2005
1992	2005	2005	2006	2005	2005	2005	2005	2005
1993	2005	2005	2006	2006	2006	2006	2005	2005
1994	2006	2005	2007	2006	2006	2006	2005	2005
1995	2006	2006	2008	2006	2006	2006	2005	2005
1996	2006	2006	2009	2007	2007	2007	2006	2006
1997	2007	2006	2010	2008	2008	2008	2007	2007
1998	2008	2007	2011	2009	2009	2009	2008	2008
1999	2009	2008	2012	2010	2010	2010	2009	2009
2000	2010	2009	2013	2011	2011	2011	2010	2010
2001	2011	2010	2014	2012	2012	2012	2011	2011
2002	2012	2011	2015	2013	2013	2013	2012	2012

Source: Iwata and Arimura (2009).

Appendix 2. Variable descriptions

I. DEPENDENT VARIABLES (time-varying)

- *Residential land price*: Property-level assessment value of land used for residence, yen/m^2. Ministry of Land, Infrastructure, Transport and Tourism (MLITT).
- *Population*: Municipality-level population adjusted for births and deaths. Ministry of Internal Affairs and Communications (MIAC).

II. EXPLANATORY VARIABLES (time-varying)

a. Air quality:

- *SPM concentration*: Ambient concentration of suspended particulate matter (SPM) measured by annual mean, 98^{th}-percentile of daily average, and hourly maximum. Unit: $\mu g/m^3$. National Institute for Environmental Studies (NIES).
- *Days exceeding the national standard*: Number of days per year that daily average SPM concentration exceeded 0.10 $\mu g/m^3$. NIES.

b. Property attributes:

- *Wood*: Dummy variable, equal to 1 if house is wooden. MLITT.
- *Floors*: Number of floors. MLITT.
- *Water*: Dummy variable, equal to 1 if water is available. MLITT.
- *Gas*: Dummy variable, equal to 1 if gas is available. MLITT.
- *Sewage*: Dummy variable, equal to 1 if sewage is available. MLITT.
- *Train station*: Distance to the nearest train station, meters. MLITT.
- *Building-area ratio*: Ratio of building area to land area, %. MLITT.
- *Floor-area ratio*: Ratio of total floor area to land area, %. MLITT.

c. Neighborhood variables:

- *Bullet trains*: Dummy variable, equal to 1 if a bullet train line is located within 1 km. MLITT.
- *Expressways*: Dummy variable, equal to 1 if an expressway is located within 1 km. MLITT.
- *Estate developments*: Number of estate developments within 1 km. MLITT.
- *Parks*: Total area of parks located within 1 km, m^2. MLITT.
- *Local heritages*: Total number of cultural properties designated by prefectural governments within 1 km. MLITT.

d. Earthquake/weather variables:

- *Earthquakes*: Dummy variable, equal to 1 if an earthquake with magnitude above 6.1 occurred in the prefecture where a property is located during the year. Japan Meteorological Agency (JMA).
- *Temperature*: Average temperature during the year at the municipality level, degrees Celsius. JMA.

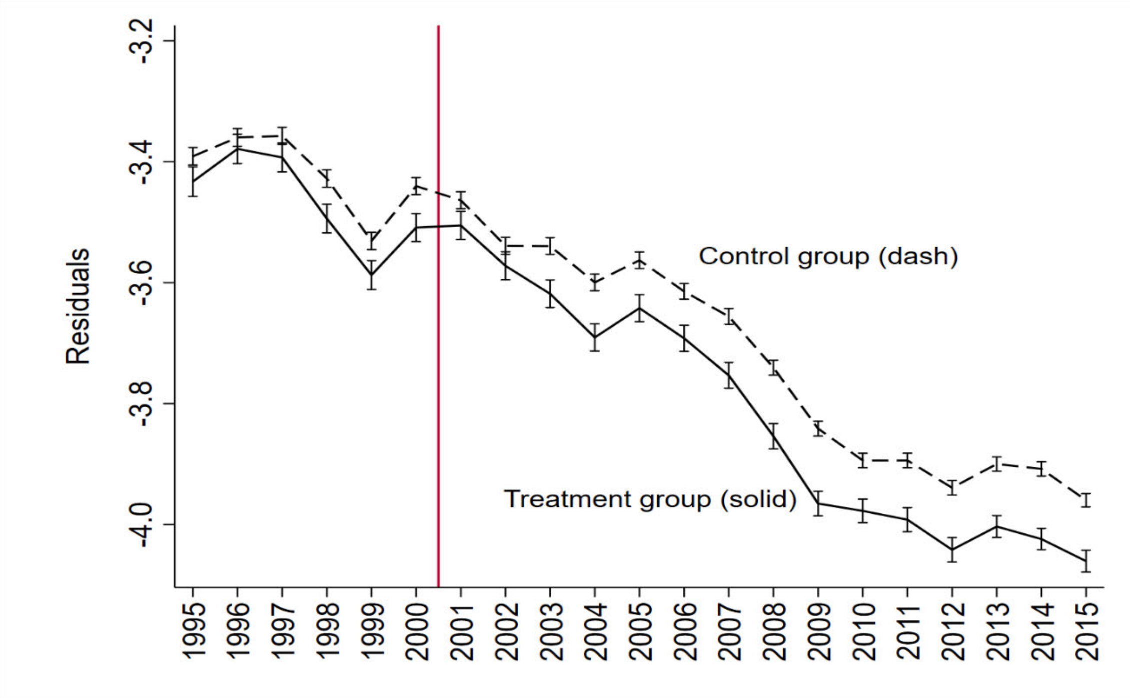
- *Wind*: Average wind velocity during the year at the municipality level, meters per second. JMA.
- *Precipitation*: Total precipitation during the year at the municipality level, millimeters. JMA.
- *Daylight*: Average duration of sunshine during the year at the municipality level, hours. JMA.

e. Socioeconomic variables:

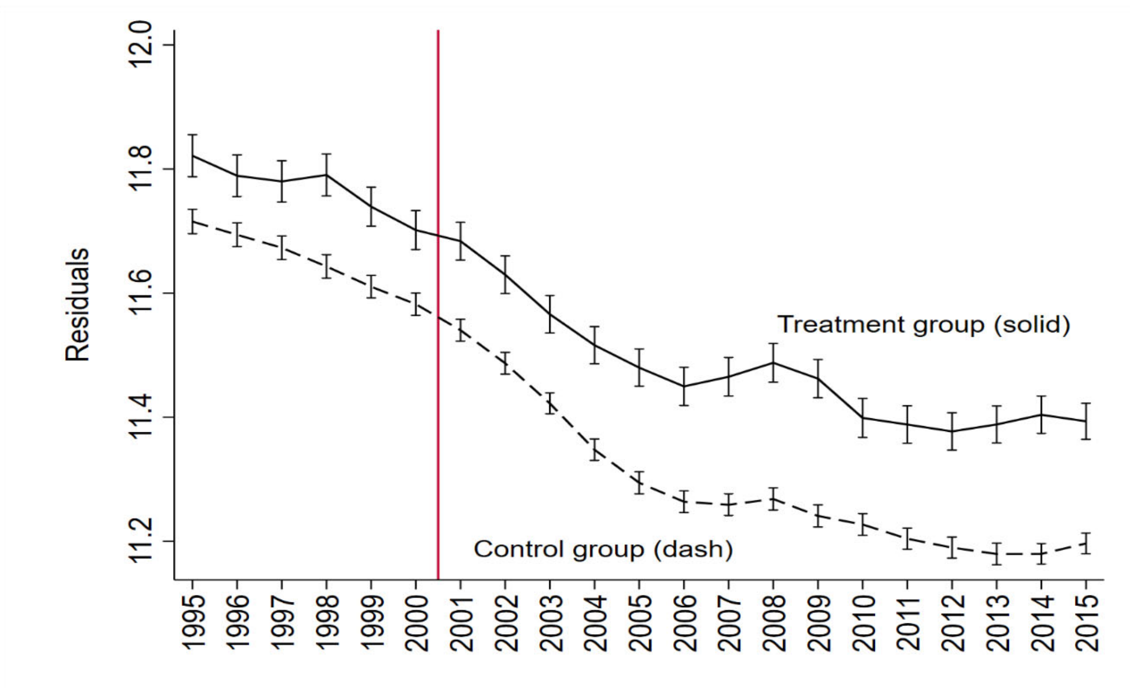
- *Population density*: Annual number of people who reside in a given municipality for more than three months divided by the municipal area, hectare. MIAC.
- *Population aged above 65 years*: (Annual number of people aged 65 years who reside in a given municipality for more than three months divided by the total municipal population) × 100, %. MIAC.
- *Per capita income*: Total taxable income divided by total number of taxpayers in a given municipality, thousand yen. MIAC.
- *Unemployment rate*: (Number of people unemployed divided by total municipal labor force) × 100, %. MIAC.
- *Vehicle ownership rate per 1000 people*: (Number of passenger cars and trucks registered as of March in a given year divided by total municipal population) × 1000. MIAC.
- *Fiscal soundness*: (Municipal fiscal balance divided by municipal fiscal revenues including tax revenues, subsidy of tax allocated to local government and municipal board) × 100, %. MIAC.

Appendix 3. Residuals

Panel A. Ln SPM concentration



Panel B. Ln residential land prices



Notes: Panel A plots the residuals from a regression of the log annual mean SPM concentration on a vector of property attributes, neighborhood variables, earthquake/weather variables, socioeconomic variables, property fixed effects, and year fixed effects. Panel B plots the residuals for log residential land prices with the same controls. The vertical bands represent the 95% confidence intervals.