Where Does Air Quality Matter? New Evidence from the Housing Market

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The most recent version of this paper can be found here.

Abstract

Estimating the value of improved environmental quality is of central interest to policymakers weighing the costs and benefits of environmental regulations. Under the standard hedonic valuation approach, researchers estimate the demand for environmental improvements from changes in housing prices. However, in a general equilibrium setting with elastic housing supply, amenity improvements may yield an expansion of the housing market (the 'quantity' effect), muting the capitalization of the amenity into housing prices (the 'price' effect), such that inferring benefits solely from price changes underestimates the true willingness-to-pay. We demonstrate how the elasticity of the local housing market affects valuations of amenity changes in the context of local air quality improvements induced by the Clean Air Act's $PM_{2.5}$ standards. We present consistent empirical evidence that the price capitalization of air quality improvements is substantially lower in places with more elastic housing markets, as increased demand is absorbed by expansions in housing supply. We present a model of spatial equilibrium of local prices, populations, and wages as functions of local amenities. Estimates from the model suggest that willingness-to-pay for air quality improvements are larger than those produced by the standard hedonic approach.

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1 Introduction

The hedonic approach to estimating the economic benefits of non-market amenities frequently relies on the housing market to infer the implicit price function (Harrison and Rubinfeld, 1978; Smith and Huang, 1995; Chay and Greenstone, 2005; Bayer et al., 2009). In an influential paper on the valuation of air quality, Chay and Greenstone (2005) exploit the structure of the Clean Air Act (CAA) to provide evidence on the capitalization of improved air quality into housing values, and use this evidence to infer the marginal willingness to pay (MWTP) for cleaner air. In a partial equilibrium setting in which housing markets cannot respond to outward shifts in demand induced by air quality improvements, changes in housing prices might provide an appropriate estimate of the marginal benefits of these improvements. Indeed, implicit in the canonical hedonic valuation model is the assumption that MWTP for an amenity is fully captured in price (and wage) changes, or that housing supply is entirely inelastic and unable to respond to outward shifts in demand via increases in quantity. However, in general equilibrium environments in which housing supply is elastic, amenity improvements may yield an expansion of the housing market (the 'quantity' effect), muting the capitalization of the amenity into housing prices (the 'price' effect), such that inferring benefits from price changes alone could yield an estimate of willingness to pay that is biased towards zero.

Recent advances in the urban economics literature suggest that housing supply constraints shape how well individuals are able to sort across place.[1] Increased demand for places with relatively inelastic housing supply – due to local land use regulations or geographical barriers to construction – tends to manifest through increases in housing prices and relatively modest changes in population. In contrast, places with fewer constraints to new development can absorb increased demand via additional housing units, such that demand shifts yield muted price responses. Consider Los Angeles, California, with relatively inelastic housing supply, and Atlanta, Georgia, with relatively elastic housing supply. Both experienced large improvements in air quality over the 2000-2010 decade following the introduction of the $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS). Over this decade, $PM_{2.5}$ concentrations fell by 31 percent in Los Angeles and by 26 percent in Atlanta. Over this same period, Los Angeles experienced a 72 percent increase in (real) housing prices and about a 5 percent increase in the number of housing units. Meanwhile, Atlanta experienced only a 5 percent increase in (real) housing prices and about a 32 percent increase in the number of housing units. What role did local housing supply constraints play in mediating the relationship between local amenity shifts and price changes? What does this imply for subsequent estimates of the marginal benefits of air quality improvements?

In this paper, we present evidence that plausibly exogenous air quality improvements (regulation-induced reductions in $PM_{2.5}$ concentrations) generate both price *and* quantity effects, with the rel-

[1] See, for example, Katz and Rosen (1987); Glaeser and Gyourko (2003, 2005, 2018); Glaeser et al. (2005); Gyourko et al. (2008); Glaeser and Ward (2009); Saiz (2010); Kahn et al. (2010); Gyourko and Molloy (2015); Ganong and Shoag (2017); Baum-Snow et al. (2018); Hsieh and Moretti (2019); Baum-Snow (2023).

ative strength of each depending on the elasticity of local housing supply. Census tracts with relatively inelastic housing supply experience relatively large price responses to air quality improvements compared to tracts with relatively elastic housing supply. This is consistent with either taste-based sorting – individuals with a higher MWTP for air quality choose to live in more tightly regulated markets – or, with the hypothesis that housing supply constraints mediate the relationship between amenities and housing prices (Baum-Snow, 2023). We provide reduced-form empirical evidence, supported by a spatial equilibrium model of local labor and housing markets, for the latter explanation. This indicates that price changes will not fully capitalize the benefits of amenity improvements in situations when quantities are not explicitly fixed.

To isolate the causal relationship between air quality and local prices and population sizes, we exploit the introduction of the 1997 $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS), which went into effect in 2005.[2] Following the implementation of these 1997 standards, areas designated as 'nonattainment' were legally required to reduce $PM_{2.5}$ concentrations, while 'attainment' areas, with $PM_{2.5}$ concentrations below the regulatory ceiling, were not. Instrumenting for Census-tract-level changes in average $PM_{2.5}$ concentrations with area nonattainment status in 2005, we estimate the effect of declining $PM_{2.5}$ concentrations on housing prices and various indicators for quantity between 2000 and 2010. We show how the price and quantity effects differ across elastic and inelastic housing market, where housing supply elasticity is measured both at the metropolitan statistical area (MSA) level and the Census-tract level.

Consistent with existing literature, we find that the 1997 standards yielded substantial decreases in average $PM_{2.5}$ concentrations in nonattainment areas. Being in a nonattainment area in 2005 leads to 1.5-$\mu g/m^3$ reduction in average $PM_{2.5}$ concentrations between 2000-2010. Given that the average $PM_{2.5}$ concentration in nonattainment tracts was 15.4-$\mu g/m^3$, this implies that nonattainment status yields about a 10-percent decline in average $PM_{2.5}$ concentrations across metro-area Census tracts in the sample. These air quality improvements are met with large increases in housing prices as measured by the tract-level housing price index (HPI): A CAA-induced 1-unit decline in average $PM_{2.5}$ concentrations yields about a 5 percent increase in local housing prices over the 2000-2010 period across all metropolitan tracts (i.e., when housing supply elasticities are not considered). We find that air quality improvements yield larger housing price increases inelastic-supply housing markets (a 7.2 percent increase) compared to elastic-supply housing markets (a statistically insignificant 2.8 percent increase). Measuring quantity changes for fixed geographic units is less straightforward than measuring price changes. Census tract boundaries are changed periodically to account for population flows, and cities can expand outward to accommodate increased demand. Thus, the number of housing units or population head counts might inadequately capture quantity movements. For these reasons, we use the change in population density as our primary measure of quantity effects at the tract level. We find that a decline in the aver-

[2] Other research exploiting the introduction of the NAAQS standards regulating $PM_{2.5}$ to understand the effects of these regulations on exposure to air pollution include Jha et al. (2019); Currie et al. (2020); Sager and Singer (2022).

age tract-level $PM_{2.5}$ concentration between 2000 and 2010 yields a larger increase in population density in elastic tracts compared to inelastic tracts. These results are reinforced by an alternative specification in which we instead instrument for the change in tract-level $PM_{2.5}$ concentrations with the predicted change caused by upwind coal plant closures.

The reduced-form evidence is consistent with our stylized model of how demand shifts manifest in places with different levels of housing supply constraints, indicating that classic hedonic valuation techniques might underestimate MWTP in the presence of elastic housing supply. Motivated by this insight, we attempt produce estimates of willingness-to-pay for air quality improvements that account for heterogeneous housing supply elasticities across space. We develop a Rosen-Roback-style model of spatial equilibrium that provides expressions for local housing prices, populations, and wages as functions of local levels of air pollution. This enables us to understand how prices and quantities simultaneously respond to changes in amenities, allowing for local housing supply constraints to mediate these relationships. Numerous studies have applied the logic of Rosen (1979) and Roback (1982) to estimate the benefits of amenity improvements. Typically, these studies assume a fixed supply of housing, implying that amenity changes are fully capitalized in price changes.[3] By relaxing this assumption of fixed supply, our model allows for housing supply to expand according to demand and local supply constraints. Estimating the model using county-level data on changes in $PM_{2.5}$ concentrations caused by the NAAQS standards as well as neighboring and upwind coal plant closures, we find MWTP for $PM_{2.5}$ reductions on the order of \$10,000-\$16,000 per unit decline. A back-of-the-envelope extrapolation based on the number of housing units in nonattainment areas implies a WTP of \$466 billion for reductions in $PM_{2.5}$ in the first decade of the 21st century. While we caution against interpreting this estimate at face value, we believe it is constructive to compare it with an equivalent estimate extrapolated from price changes alone. Consistent with theoretical predictions, the estimated MWTP for air quality improvements is between 13 and 90 percent larger based on the spatial equilibrium model estimation than an equivalent extrapolation based on price capitalization in a classic quasi-experimental environment.

This paper makes two important contributions to the literature. First, we provide quasi-experimental evidence that housing supply constraints influence the ability for housing prices to fully capitalize local air quality improvements. In relatively elastic markets, prices are less responsive to amenity improvements. This reduced-form evidence indicates that researchers should be attentive to the elasticity of the market in question (typically housing) when estimating the MWTP for amenity improvements. The canonical hedonic model, in assuming a fixed supply of housing, might yield an underestimate of the value of local amenity improvements in a general equilibrium setting in which there exists a quantity margin in addition to a price margin. In other words, price changes alone will not serve as a sufficient statistic for estimating the marginal benefits of amenity changes

[3] In the canonical hedonic model, the implicit price of an amenity includes *both* the positive price differential as well as the negative wage differential.

in the presence of elastic supply. Second, we extend the Rosen-Roback model of spatial equilibrium to allow for quantity changes in response to amenity improvements. Developing and estimating this model using county-level data on price, quantity, wage, and air quality changes, we illustrate how researchers can recover MWTP for air quality improvements in the presence of both price and quantity effects. This model provides guidance on how the hedonic framework can be adapted to measure MWTP for amenities in general equilibrium settings, accounting for the elasticity of local housing supply.

The rest of this paper is organized as follows. Section 2 presents a stylized model of supply and demand for air quality improvements, demonstrating how demand shifts yield both price and quantity effects in elastic settings. We describe our data and methodological approach to estimating the price and quantity effects in Sections 3 and 4, with results detailed in Section 5. Section 7 presents a spatial equilibrium model for air quality improvements, with model estimation results provided in Section 7.3. Section 8 concludes.

2 A stylized model of supply and demand

To illustrate how the canonical hedonic model might underestimate the value of air quality improvements when the quantity of housing can expand to absorb increased demand, we present the following stylized example of housing supply and demand. This exposition is highly consistent with that presented in Baum-Snow (2023). Consider two locations: one with relatively inelastic housing supply, and one with relatively elastic housing supply. Housing supply might be inelastic because there exist various geographical barriers to construction, or because local zoning and land use regulations make construction relatively costly. At time $t = 0$, demand for these locations is given by D(Amenity$_0$), with price P_0 and quantity Q_0 in Figure 1.

Now, imagine that demand for these locations shifts outward due to an exogenous increase in local amenities, such as an improvement in air quality. This improvement is reflected by the shift from D(Amenity$_0$) to D(Amenity$_1$) in Figure 1a. The inelastic housing market, relatively constrained in its ability to produce new housing units, will experience this demand shift predominantly as a price increase, with prices increasing from P_0 to $P_{1,\text{inelastic}}$. The location with more elastic housing supply will respond to this demand shift by expanding its housing stock to accommodate newcomers, such that the price effect is relatively attenuated and the quantity effect is relatively large. In the extreme example in which housing supply is perfectly inelastic, the entire effect of the demand shift will manifest as a price increase, from P_0 to $P_{1,\text{inelastic}}$ in Figure 1b.

This is a highly simplified example, but it illustrates the important role that housing supply elasticities plays in determining how well amenity changes are capitalized into housing prices, and thus how well price changes reflect MWTP. If individuals are randomly sorted into inelastic and elastic housing markets such that the WTP for improved air quality is constant across locations (i.e., there is no self-selection based on preferences for air quality), a hedonic evaluation of the benefits of cleaner air based exclusively on price capitalization would produce different estimates in the elastic housing market compared to the inelastic housing market. By neglecting the demand shift that manifests as an increase in the quantity margin (via greater numbers of housing units or population head counts), the evaluation would underestimate the true MWTP in more elastic housing markets.

We are not the first to raise concerns regarding the assumption of fixed housing supply implicit in the canonical hedonic model. Many scholars have acknowledged this issue and provided helpful direction for conducting hedonic valuation methods in general equilibrium environments. For example, Sieg et al. (2004) provide a structural model of Tiebout sorting, demonstrating how individuals re-optimize in response to large changes in amenities, and illustrating the large differences between partial- and general-equilibrium estimates of MWTP in the case of sorting-induced endogenous local attribute changes. Here, we leave aside the issue of endogenous local amenity changes and focus instead on how local housing supply characteristics affect the capacity for housing prices to adjust and for individuals to sort more generally. More recently, Banzhaf (2021) shows that price changes associated with improved air quality include both amenity demand (WTP) *and* changes in the hedonic price function, especially over longer time horizons. That is, amenity shocks can influence the equilibrium hedonic price function for an entire housing market (including untreated units), such that there may exist price changes not directly attributable to local amenity improvements. In our exposition, the ex-post price function in a difference-in-differences setting can represent a completely different *quantity* of housing – and thus a fundamentally different housing market – when housing supply is relatively elastic. We do not address the issue of indirect price effects treated in Banzhaf (2021), but rather show that even the direct price effect captured by typical hedonic methods is an insufficient statistic for MWTP when there also exists a quantity margin. In Section 7, we develop and estimate a spatial equilibrium model that incorporates this quantity margin, offering a novel method scholars may use to recover MWTP when housing supply is not explicitly fixed.

3 Data

Our primary empirical analysis leverages changes in tract-level air pollution, housing prices, and population densities in metropolitan area Census tracts over the 2000-2010 period. We also consider changes over shorter (2000-2007) and longer (2000-2016) time horizons, as well as county-level changes in air quality and housing characteristics. To implement this analysis, we construct a data set of tract- and county-level characteristics between 2000 and 2016 using several sources, detailed below.

3.1 Air pollution data

Fine-grain air pollution data have recently been produced for the entire U.S. using a combination of satellite data, pollution monitors, land use characteristics, and chemical air transport models (van Donkelaar et al., 2019). We aggregate the gridded air pollution data to the Census-tract and county levels. Our primary independent variable of interest is the long-difference change in average annual $PM_{2.5}$ concentrations in a given Census tract between 2000 and 2010. We also consider this change over the 2000-2007 and 2000-2016 periods in order to elucidate the differences between short- (partial equilibrium) and longer-term (general equilibrium) adjustments. We supplement the main Census-tract-level analyses with county-level variation in air quality, and calculate a county's average annual $PM_{2.5}$ concentration based on the average of all Census tracts within the county in that year.

3.2 Housing price, quantity, and demographic data

We combine the air quality data with local housing, economic, and demographic data retrieved from the decennial Census, the American Community Survey (ACS), and the Federal Housing Finance Agency (FHFA). Our two main outcome variables of interest are the tract's housing price index (HPI) in the final year of the period (where 2000 is the base year of the index) and the long-difference change in the natural log of the tract's population density over the period.[4] The HPI, retrieved from the FHFA, is a weighted, repeat-sales index capturing movements in prices of single-family homes whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac. It provides a measure of housing price appreciation in a given tract (or county) holding the underlying quality of housing stock relatively constant.

Measuring quantity adjustments with fixed geographic units is less straightforward than the measurement of price adjustments. Census tract boundaries are modified (and new tracts defined) periodically to account for population adjustments, such that the geographic unit is designed to have relatively consistent populations over time. Cities grow outward as well as upward, and thus comparisons of the number of individuals living within a consistent city boundary across time will fail to incorporate the contribution of sprawl to larger numbers of residents or housing units. Counties offer a relatively tractable geographic unit from which to measure quantity adjustments, but offer less precision for exploring the importance of housing supply elasticities, as rural and urban tracts within a given county will have largely different housing supply constraints. Given these limitations, we measure tract-level quantity adjustments using the change the natural log of population density over the given period.[5] We supplement this with a county-level analysis using the change in the natural log of total housing units. In the primary tract-level analysis, we assign all characteristics to Census tracts using the consistent tract boundaries as defined by the

[4]For the 2000-2010 period, the outcome variable is the tract's 2010 HPI. For the 2000-2016 period, we consider the 2016 HPI. Both are indexed to 2000, such that the HPI in 2000 is 100 for all tracts.

[5]We are not the first to explore the impact of changes in local amenities on population density. Other papers that consider this outcome variable include Banzhaf and Walsh (2008) and Greenstone and Gallagher (2008).

2010 Census. Baseline tract-level covariates are retrieved from the 2000 Census.[6] Population densities for years 2000 and 2010 are derived from the decennial Census. 2016-level characteristics are based on those from the 2012-2016 5-year ACS samples, while 2007-level characteristics are from the 2005-2009 5-year ACS samples. County-level demographic data are retrieved from these same sources.

3.3 Housing supply restriction and elasticity data

We incorporate various measures of housing supply constraints defined at the tract- and metropolitan-area levels. In all cases, we use these measures to define tracts as either 'elastic' or 'inelastic', rather than using the elasticity estimates themselves. Our primary measure of local housing supply elasticity is drawn from Saiz (2010), who provides housing supply estimates at the metropolitan area level for cities with over 500,000 persons in 2000. These elasticity estimates incorporate geographic constraints to development, a determinant of exogenously undevelopable land in the area, as well as local land use regulations determined from the 2005 Wharton Regulation Survey.[7] We limit our sample to metro-area tracts with non-missing Saiz (2010) elasticity estimates. These estimates range from 0.6 (Miami, Florida) to 5.45 (Wichita, Kansas). We consider a tract as being in an 'inelastic' market if its metropolitan-area elasticity is less than 1 (8,230 tracts), and in an 'elastic' market otherwise (18,347 tracts).[8]

We supplement this elasticity measure with estimates of tract-level housing supply elasticities from Baum-Snow and Han (2023).[9] These estimates are identified using labor demand shocks in commuting destinations from residential locations. The authors then estimate the change in local housing quantity resulting from shifts in local housing prices, conditional on tract-specific observables. Tract-level housing supply elasticities vary based on the tract's distance to the central business district, land availability, topographical features, and land use regulations. These tract-level elasticities are primarily meant for comparison *within* metropolitan areas rather than *across*, and thus we combine these tract-level elasticity measures with the Saiz (2010) measure to produce a characterization of a Census tract's elasticity that is comparable across metropolitan areas. To do so, we first split tracts into two, equal-sized groups *within* a metropolitan area, defining tracts as

[6]As detailed in Section 4, these include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied.

[7]Saiz (2010) uses the measure of local land use regulations from the Wharton Residential Land Use Regulation Index (WRLURI), constructed by Gyourko et al. (2008). This regulatory index provides an aggregate measure of the restrictiveness of local land use regulations in 293 metropolitan areas in the U.S.

[8]This aggregate measure is based on 11 subindexes, which include a local political pressure index, state political involvement index, state court involvement index, local zoning approval index, local project approval index, local assembly index, supply restrictions index, density restrictions index, open-space index, exactions index, and approval delay index.

[9]Baum-Snow and Han (2023) provide several housing supply elasticity estimates. We use the housing units supply elasticities estimated based on their quadratic finite mixture model, which are the authors' preferred estimates. This model allows parameters governing tract supply elasticities to flexibly differ between metropolitan areas as functions of developable land, regulation, and developed land. We use the elasticity estimates from the 2021 version of this working paper, which produces nearly identical groupings of tracts as the estimates in more recent versions of the paper.

within-city inelastic if they are in the bottom 50% of tract-level elasticities and within-city elastic if they are in the top 50%. We then use the metropolitan-area bifurcation above, characterizing a city as inelastic if its Saiz (2010) elasticity is less than 1 and elastic otherwise. This produces four groups of Census tracts: elastic tracts in elastic metros (N=9,970), inelastic tracts in inelastic metros (N=4,485), elastic tracts in inelastic metros, and inelastic tracts in elastic metros. We focus on the first two groups, investigating whether the price and quantity response to air quality improvements differs between especially inelastic tracts within tight markets and relatively elastic tracts within looser markets.

4 Methodological approach

To illustrate the role that housing supply constraints play in shaping how well the housing market capitalizes air quality improvements, we estimate the relationship between reductions in $PM_{2.5}$ concentrations and a tract's HPI and change in log population density over the relevant period. Our empirical approach is similar to that in Chay and Greenstone (2005), with a few notable deviations. Most importantly, we use this framework to separately identify both price *and* quantity effects in both inelastic and elastic housing markets. This allows us to elucidate the extent to which housing supply constraints mediate the price capitalization of air quality improvements. Second, advances in air pollution monitoring and housing price databases allow us to conduct our main analysis at the Census tract (rather than county) level. This finer geographic unit provides much greater precision in detecting the co-movements of air pollution and housing prices. Finally, we apply the framework to a more contemporary regulation-induced air quality improvement, such that resulting estimates are of immediate relevance to current policy discussions regarding the strengthening (or relaxation) of ambient air pollution standards.

Consider the following long-difference equation:

$$\Delta y_i = \beta_0 + \beta_1 \Delta PM2.5_i + \mathbb{X}_i' \gamma + \delta_d + \varepsilon_i \tag{1}$$

Where Δy_i is the dependent variable in tract i (the 2010 HPI and long-difference change in log population density), $\Delta PM2.5_i$ is the long-difference change in average $PM_{2.5}$ concentrations in tract i, $\mathbb{X}_i'$ reflects tract-level covariates, and δ_d represents Census division fixed effects. The inclusion of Census division fixed effects absorbs secular trends in price and population movements that differ across regions. Tract-level covariates include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Estimating equation 1 using Ordinary Least Squares, β_1 measures the association between a one-unit change in average tract-level $PM_{2.5}$ concentrations and the change in the tract's price or population density between 2000 and 2010. Our primary analysis considers these long-difference changes over the 2000-2010 period, but we supplement this by documenting these relationships over longer-term (2000-2016) and shorter-term (2000-2007) periods.

In order to determine whether the relationship between air quality improvements and associated price and quantity changes differs depending on the elasticity of local housing supply, we estimate a slightly modified version of equation 1, where we interact the primary explanatory variable ($\Delta PM2.5_i$) with an indicator for being in an 'inelastic' or 'elastic' housing market, where elasticity is defined at both the tract-level and by metropolitan area, as described above:

$$\Delta y_i = \beta_0 + \beta_1 \left(\Delta PM2.5_i \times \mathbf{1}[in_i = 0]\right) + \beta_2 \left(\Delta PM2.5_i \times \mathbf{1}[in_i = 1]\right) + \mathbb{X}_i'\gamma + \delta_d + \varepsilon_i \tag{2}$$

Here, $in_i = 1$ if tract i is in an inelastic housing market, and $in_i = 0$ otherwise, where these two groups are collectively exhaustive of all Census tracts in the sample used for the primary analysis.[10] β_1 measures the relationship between a $PM_{2.5}$ concentrations and outcomes in elastic tracts, while β_2 measures this relationship in inelastic tracts. We can then consider the null hypothesis that $\beta_1 = \beta_2$ to determine whether the price (or quantity) effect is significantly different in inelastic and elastic housing markets.[11]

4.1 Causal inference: Clean Air Act

Many unobserved characteristics covary with both air pollution and the central outcomes of interest, introducing bias in the estimation of the pollution-price or pollution-population gradient. The issue of misspecification in the traditional hedonic price model is well-known, and researchers have used a wide variety of quasi-experimental solutions to address it.[12] Here, we exploit the introduction of the Clean Air Act (CAA) 1997 $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS), which went into effect in 2005. The annual air quality standard for $PM_{2.5}$ set by the regulation was 15 micrograms per cubic meter ($\mu g/m^3$), based on the three-year average of annual mean $PM_{2.5}$ concentrations.[13] In December of 2004, EPA issued official designations for the 1997 $PM_{2.5}$ standards, classifying areas as in nonattainment if they violated the 1997 annual standard over a three-year period. These areas are displayed in blue in Figure 2. Following this designation, states with nonattainment areas were required to submit to the EPA state implementation plans (SIPs) identifying how nonattainment areas would meet $PM_{2.5}$ standards, and meet these standards by 2010. The observed decline in $PM_{2.5}$ concentrations between 2000 and 2010 is shown in Figure 3. A comparison of Figures 2 and 3 suggests that while much of the country experienced air quality improvements over the 2000-2010 period, many of the areas with the greatest improvements (e.g., Southern California, Northern Georgia, and the Central Atlantic region) were those that were in nonattainment in 2005. Currie et al. (2020) document that the 1997 NAAQS greatly improved air quality in newly regulated areas, indicating that the standards were relevant to the

[10]We prefer this strategy to estimating equation 1 separately for the two groups of tracts, as inelastic and elastic metros tend to be concentrated in different areas of the country. Elastic metros tend to be more common in the Midwest and Sunbelt, while inelastic metros are more common on the coasts.

[11]In analyses using the combined tract- and metro-level elasticities, we interact $\Delta PM2.5_i$ with an indicator variable for each of the four categories. We then test equality of the coefficients on $\Delta PM2.5_i$ interacted with an indicator for being in an elastic tract in an elastic metro and $\Delta PM2.5_i$ interacted with an indicator for being in an inelastic tract in an inelastic metro.

[12]See, for example, Chay and Greenstone (2005); Bayer et al. (2009); Lee and Taylor (2019); Banzhaf (2021).

[13]The regulation also imposed a daily standard of 65 $\mu g/m^3$.

differential reduction in $PM_{2.5}$ seen in Figure 3.

Following Chay and Greenstone (2005), who instrumented for changes in county-level TSP concentrations from 1970-1980 with mid-decade nonattainment status, we instrument for tract-level changes in average $PM_{2.5}$ concentrations with a dummy variable indicating whether the tract was in a nonattainment status area in 2005.[14] The central identifying assumption is that, conditional on observable characteristics, nonattainment status is exogenous to expected outcomes. In this setting, this would be violated if places which were designated as nonattainment were on differential price or quantity trajectories than those in attainment, or if nonattainment status has a direct impact on outcomes that is distinct from its impact that occurs through pollution reductions (e.g., employment effects). While we do not see significant differences in 2000-level covariates between tracts in nonattainment and attainment areas, there are notable differences in population density and price pre-trends between the two groups of tracts. These characteristics are presented in Columns 1-3 of Table 1. We consider the 1990-2000 change in log population density and the 1995 HPI (where 2000=100) as the primary indicators of possible pre-trends.[15] Because the HPI is indexed to 2000-level prices, a higher value in 1995 reflects *less* price appreciation between 1995 and 2000. Thus, Table 1 indicates that nonattainment tracts were growing more slowly – both in terms of population and prices – prior to the period of analysis. Without adjusting for these pre-trends, this instrumental variable strategy would thus likely yield an underestimate of the change in prices and quantities attributable to regulation-induced declines in $PM_{2.5}$ concentrations.

To address these pre-trends, we estimate each attainment tract's propensity score for treatment based on the 1995 HPI and the 1990-2000 change in log population density using the four nearest neighbors to treatment (nonattainment) tracts. We impose common support by dropping treatment observations whose propensity score is higher than the maximum or less than the minimum propensity score of the control group (attainment) observations. We then weight the observations using the weights generated in this matching process. This yields a slightly smaller sample, as tracts that perform as poor matches to the treatment group are dropped from the analysis.[16] Weighting observations by the weights produced in this PSM process mollifies these differential pre-trends, as seen in Columns 4-6 of Table 1. The identifying assumption is now that nonattainment tracts and their propensity-matched attainment tracts would have experienced the same change in prices and population densities over time in the absence of the regulation. This strategy is similar to that in Sager and Singer (2022), who demonstrate how failing to match control (attainment) and treatment (nonattainment) tracts on the pre-period outcomes of interest can substantially alter the coefficient estimates when using NAAQS nonattainment status as an instrument for

[14] In specifications in which we instrument for tract-level pollution declines with nonattainment status, we cluster standard errors on county, as nonattainment "areas" tended to align with county boundaries. We use robust standard errors for the county-level analyses.

[15] We consider the 1995 HPI rather than the 1990 HPI because a large share of tracts (37%) have missing values for 1990. Still, we lose some observations by considering the 1995 value (8.3% of tracts have missing 1995 values).

[16] This process also drops all tracts with missing 1995 HPI values. This essentially amounts to restricting the sample to larger metro areas.

changes in $PM_{2.5}$ concentrations.[17] Ultimately, weighting observations by the weights produced in the PSM process described here has little substantive impact on the estimates presented in this paper.

Restricting the sample to Census tracts with non-missing HPI values, non-missing elasticity estimates, and positive weights produced by the PSM technique yields a sample of 22,879 Census tracts.[18] Including all 2000-level covariates, division fixed effects, and weighting by the weights produced in this matching process, the first-stage F-statistic on the nonattainment instrument is about 70.[19] Table 2 shows this first-stage relationship, and indicates that nonattainment status is associated with about a 1.4-$\mu g/m^3$ decline in $PM_{2.5}$ concentrations over the 2000-2010 period, relative to an average $PM_{2.5}$ concentration of 15.4 $\mu g/m^3$ in 2000 among nonattainment tracts in the sample.[20] Nonattainment tracts classified as inelastic based on their metropolitan area's Saiz (2010) elasticity began the period with higher average $PM_{2.5}$ concentrations than those classified as elastic (17.2 $\mu g/m^3$ versus 14.5 $\mu g/m^3$). These values, as well as descriptive statistics on the central outcome variables and changes in $PM_{2.5}$ concentrations over the 2000-2010 period, are shown in Table 3.[21]

While our strategy addresses endogeneity concerns around air quality, it does not address potential selection across elastic and non-elastic places. Conditional on observable characteristics, individuals may still sort into elastic or inelastic housing markets based on their underlying preferences for air quality. If sorting into elastic vs. inelastic locations arises due to unobservable taste dispersion, then the underlying MWTP for pollution reductions are expected to differ across housing markets.[22] Individuals living in relatively inelastic markets (e.g., the coasts) might differ

[17] Sager and Singer (2022) are primarily interested in the effect of nonattainment status on subsequent changes in $PM_{2.5}$ concentrations, and thus match on pre-treatment levels of $PM_{2.5}$. They show how this yields a smaller estimated effect of nonattainment status on subsequent pollution, but a larger estimated effect of nonattainment on housing prices. Given that we are primarily interested in changes in housing prices and population densities as outcomes, the matching strategy we outline here better addresses the concerns related to differential counterfactual trends between nonattainment and attainment tracts.

[18] Restricting the sample to tracts with positive PSM weights yields a loss of 3,698 tracts.

[19] The residualized first-stage relationship between nonattainment status and the change in $PM_{2.5}$ concentrations between 2000 and 2010 is shown in Figure 5.

[20] Table 2 also displays the reduced-form relationship between nonattainment status and the central outcome variables of interest, indicating that nonattainment status is associated with a 7.4 percent increase in housing prices and a statistically insignificant change in population density.

[21] This implies that a 1-unit reduction in $PM_{2.5}$ concentrations represents a smaller *percent* change in inelastic tracts compared to elastic tracts. This could produce differential price effects in inelastic and elastic markets independent of differential housing supply constraints. If prices respond more to larger relative (i.e., percent) improvements in air quality, elastic tracts should experience larger price effects in response to a 1-unit improvement. Alternatively, if individuals are willing to pay more for air quality improvements at higher initial levels of pollution, inelastic tracts should experience larger price effects. However, the evidence on taste-based sorting suggests that the opposite is likely the case. Chay and Greenstone (2005) provide "modest evidence" that MWTP for pollution reductions is *lower* in communities with relatively high pollution levels, consistent with preference-based sorting, whereby individuals living in places with initially *low* levels of air quality have higher MWTP for incremental pollution reductions. We do not take a stand on which of these effects (if either) dominates, but if preference-based sorting is at play, this would bias our estimates toward finding a *larger* price effect in elastic markets, with lower initial $PM_{2.5}$ concentrations.

[22] Note that this is different from the issue of endogenous or taste-based sorting often discussed in the canonical hedonic setting (which remains an issue here). Individuals with higher MWTP might choose to live in places with initially

from individuals living in relatively elastic markets (e.g., the sunbelt) in ways that correlated with their preferences for air quality. We include a rich set of observable tract-level covariates ($\mathbb{X}_i'$) in our regression to address these concerns. However, we are unable to rule out that self-selection could drive some variations in the price response to pollution reductions. While this is a limitation when interpreting the MWTP estimates, we do not believe that it obstructs the broader conceptual point that market constraints matter for the capitalization of amenity improvements.

As discussed in Bishop et al. (2020), a central challenge to interpreting the estimates produced by this instrumental variable approach, which is an application of a more general class of difference-in-differences hedonic valuation techniques, is that price functions may change over time. Kuminoff and Pope (2014), Banzhaf (2021), and others show that the MWTP estimate produced in the typical difference-in-differences framework combines information on two hedonic price functions (pre and post treatment) and thus may be biased. Our setting overlaps with the Great Recession and associated housing crisis, which fundamentally altered the price functions in housing markets across the United States. While this would complicate the MWTP estimate produced from price capitalization in the canonical setting for the reasons discussed by Kuminoff and Pope (2014) and Banzhaf (2021), the central goal of our reduced-form exercise is not to produced unbiased estimates of MWTP based on price capitalization. Rather, it is to elucidate another, distinct source of bias in the canonical framework: the assumption of fixed quantities. Our empirical approach demonstrates how price capitalization differs depending on the elasticity of the local housing market, or its capacity to absorb increased demand. We then offer a novel strategy to recover MWTP in the presence of both price and quantity margins in Section 7.

5 Results: Price and quantity effects of air quality improvements

This section presents the central quasi-experimental evidence on the price and quantity effects of air quality improvements across metropolitan Census tracts. Section 5.1 offers our primary empirical results for the differential effect of these improvements in inelastic and elastic Census tracts over the 2000 to 2010 period. We illustrate how price responses differ across various lengths of time in section 5.2, showing that prices are relatively more responsive under short time horizons. We detail and provide evidence using an alternative quasi-experimental design that exploits proximate and upwind coal plant closures in section 6. Additional robustness checks are reported in Appendix A. We find consistent evidence that housing prices capitalize improvements in air quality across U.S. Census tracts over the 2000-2010 period, with this price effect mediated by the elasticity of local housing supply. This suggests that housing supply constraints matter when estimating the MWTP for amenity improvements, and motivates the creation of a tractable model for benefit estimation in Section 7 that explicitly incorporates the capacity for markets to accommo-

low levels of pollution reduction. Banzhaf and Walsh (2008) show that individuals with greater MWTP might endogenously sort *in response to* air quality improvements, such that individuals living in newly clean areas have different MWTP than those elsewhere.

date increased demand via increases in quantity.

5.1 Central estimates: Heterogeneity by housing supply elasticity

Table 4 shows the OLS and nonattainment status IV results for relationship between declining $PM_{2.5}$ concentrations and the two main outcome variables across all metropolitan Census tracts, without taking housing supply elasticities into consideration. Our primary specification indicates that a CAA-induced 1-unit ($\mu g/m^3$) decline in average annual $PM_{2.5}$ concentrations yields a 5.2 percent increase in local housing prices in 2010 relative to 2000 levels, as indicated in column 4. The IV estimates for housing prices are substantially larger, and more precise, than the OLS estimates. This is consistent with the evidence presented in Chay and Greenstone (2005) and Sager and Singer (2022), as well as other hedonic estimates of the benefits of air quality improvements. The IV estimate for the effect of pollution declines on population density are statistically indistinguishable from zero.[23]

Next, we consider heterogeneity in the effect of air quality improvements across relatively inelastic and elastic housing markets. We find that air quality improvements yield larger housing price increases in tracts defined by inelastic housing markets, relative to elastic housing markets. Panel A of Table 5 reports the estimated coefficients β_1 and β_2 in equation 2, where we instrument for the change in average annual $PM_{2.5}$ concentrations with nonattainment status. The first row shows the estimated effect of regulation-induced pollution reductions in tracts classified as 'elastic' based on the Saiz (2010) measure, and the second row indicates this effect for those classified as 'inelastic'. Our preferred estimates in column 2, which include Census division fixed effects and baseline tract-level covariates, imply that a 1-unit decline in annual $PM_{2.5}$ concentrations yields a (statistically insignificant) 2.8 percent increase in housing prices in tracts in relatively elastic metro areas, compared to a much more precise 7.2 percent increase in housing prices in inelastic areas. In all specifications, we can reject the null hypothesis that the coefficient on $\Delta PM_{2.5}$ is the same for elastic and inelastic tracts at standard confidence levels. The estimates in column 2 imply that a 1-unit decline in $PM_{2.5}$ yields nearly three times the housing price impact in inelastic markets compared to elastic markets.[24] The conclusion that housing prices are more sensitive to pollution declines in inelastic markets compared to elastic markets is largely robust to the choice of specification and method for defining elasticity. Appendix Table C2 presents our central estimates when grouping Census tracts according to four categories of housing supply constraints based on both their tract-

[23] We multiply the change in log population density by 100 for ease of interpretation. The OLS estimates suggest that density declines with pollution declines. This is consistent with previous evidence of a strong correlation between pollution and economic activity.

[24] Elastic tracts in nonattainment areas began the period with slightly lower levels of annual $PM_{2.5}$ emissions (14.5 $\mu g/m^3$ in elastic tracts versus 17.2 in inelastic tracts), such that a 1-unit decline reflects about a 6.9 percent decline in emissions in elastic tracts compared to 5.8 percent decline in inelastic tracts. Thus, in percentage terms, a *smaller* amenity improvement yields a much *larger* price increase in inelastic markets. The implied elasticity of housing prices with respect to pollution is thus about -0.41 in elastic tracts, compared to -1.24 in inelastic tracts. The implied elasticity reported in Sager and Singer (2022) is -1.1. Chay and Greenstone (2005) estimate that the implied elasticity of housing prices with respect to TSP concentrations is between -0.2 and -0.35.

and metro-level elasticities. The results are quantitatively similar when additionally considering the *within*-metro tract-level elasticities based on Baum-Snow and Han (2023). A 1-unit NAAQS-induced decline in $PM_{2.5}$ concentrations yields a statistically insignificant 3 percent increase in housing prices in elastic tracts in elastic metros, compared to a more precise 7.3 increase in prices in inelastic tracts in inelastic metro areas.

The quantity response to pollution declines is less consistent across specifications, but our estimates are suggestive that quantity responses (measured as the change in population density) are indeed stronger in elastic markets compared to inelastic markets. Table 5, columns 3 and 4, shows the estimated effect of a NAAQS-induced 1-unit decline in $PM_{2.5}$ concentrations on the change in the log population density between 2000 and 2010. Our preferred specification (column 4) indicates that a 1-$\mu g/m^3$ decline in average annual $PM_{2.5}$ concentrations yields a 1.4 percent increase in population density in elastic tracts, compared to a statistically insignificant 0.4 percent increase in inelastic tracts. That pollution declines yield larger population density increases in tracts characterized by relatively elastic housing markets would be consistent with the stylized example provided in Figure 1a, where the expansion of housing supply attenuates the price response. This suggests that explicitly incorporating both price and quantity effects might be necessary for generating credible estimates of MWTP.

5.2 Short- and long-run impacts of air quality improvements on housing prices and population changes

A housing market may be relatively inelastic if there exist substantial geographical or regulatory barriers to construction, but it may also be relatively inelastic over shorter time horizons, as housing units cannot be built in the very short run. Thus, we expect the price response to air quality improvements to be larger in the short run, and relatively more attenuated in the long run. Indeed, we find that the housing price effects of NAAQS-induced declines in $PM_{2.5}$ concentrations are smaller in magnitude in the long run (2000-2016) and larger in the short run (2000-2007). The IV estimates for the effect of a change in average annual $PM_{2.5}$ concentrations across three different periods are displayed in Table 5. Columns 2 and 4 display the primary specification for housing prices and population densities, respectively.[25] While price effects in elastic tracts appear statistically insignificant in all specifications, the effect of a 1-unit decline in $PM_{2.5}$ shrinks over time in inelastic tracts.[26] This provides additional suggestive evidence that the elasticity of the local housing market matters for price capitalization: Even housing markets characterized by substantial legal or geographical constraints to construction are not perfectly inelastic over longer time horizons. In these settings, the MWTP estimated based on price capitalization alone will be biased to the extent that it does not incorporate the quantity margin. Over progressively longer

[25] Changes in log population density are statistically noisy in all periods, and we refrain from offering any firm conclusions regarding the quantity effect of air quality improvements over differing time horizons. However, the stylized model above indicates that if housing supply is relatively more elastic over longer time horizons, population effects should be larger in the long run.

[26] The sample size differs slightly over time as some tracts have missing HPI values in various years.

time horizons, we expect the magnitude of this bias to grow. In circumstances in which researchers evaluate relatively immediate price changes in response to amenity improvements, there will be little resulting bias in using price changes to estimate MWTP.[27]

6 Additional reduced-form evidence: Coal plant closure instrument

This section details a central robustness check used to support our primary quasi-experimental analysis. Here, we rely on an alternative instrumental variable specification in which we instrument for the change in average annual tract-level $PM_{2.5}$ concentrations with the predicted change induced by coal plant closures in other Census tracts. Section 6.1 details the methodological approach, and section 6.2 provides the estimates produced using this strategy. Additional robustness checks are detailed in Appendix A.

6.1 Coal plant closure instrument: methodological approach

To supplement our primary quasi-experimental evidence exploiting the NAAQS, we instead instrument for the observed change in $PM_{2.5}$ concentrations with the change in concentrations due to decommissioned or retired coal units as predicted by InMap, a chemical air transport model. Similar 'wind' instruments and strategies have been used to study the effects of air pollution in other empirical settings (Sullivan, 2017; Keiser et al., 2018; Hernandez-Cortes et al., 2022). We identify coal units that were retired between 2006 and 2016, as well as relevant emissions characteristics of these coal units (annual NOx and SO_2 emissions), from Burney (2020). Between 2006 and 2016, 333 coal units went offline. In many cases, units are phased out before their ultimate retirement. To generate the counterfactual emissions that would have occurred had these coal units continued to operate, we take the average of emissions between 2005 and the final year in which the unit operated. We combine this with unit-specific smoke stack characteristics from EIA's Form 860.[28]

We input the location of the 333 coal units that closed over this period, their average annual emissions, and stack characteristics to InMap. InMap then generates an estimate of annual $PM_{2.5}$ concentrations attributable to these coal units across the U.S. using a long-range transport model and information about secondary pollutant formation. We aggregate these emissions estimates to U.S. Census tracts and counties. This variable thus provides an estimate of the total change in annual $PM_{2.5}$ concentrations due to coal plant closures in upwind or neighboring the location. We use the

[27] Depending on the empirical setting, estimating very short-run price changes may be more or less feasible. In this setting, the standards were not implemented until 2005, and states were given a three-year window under which to develop plans to reduce $PM_{2.5}$ concentrations in nonattainment areas. Ambient air quality changes in a relatively gradual manner, and may or may not be immediately salient, such that studying extremely short-run price responses (i.e., when housing supply is perfectly inelastic) is typically infeasible.

[28] Burney (2020) uses different facility and unit IDs from those in the EIA data, and we were unable to perfectly match all units in the Burney (2020) data to their associated stack characteristics. When unable to assign unit-specific emissions to unit-specific stack characteristics, we assigned the unit in the Burney (2020) dataset to the average of stack characteristics at the associated facility.

InMap predicted concentration as an instrument for the actual, observed changes in $PM_{2.5}$ over the 2000-2016 period. Figure 4 depicts the change in PM2.5 concentrations predicted by InMap based on the coal plant closures over 2000–2016. We also consider the 2000-2010 period, instrumenting for the actual change in average $PM_{2.5}$ concentrations with the change predicted by coal plant closures occurring between 2006 and 2009. However, only 51 coal units closed before 2010.

Causal inference here relies on the assumption that coal plant closures are not driven by unobservable place characteristics that are endogenous to price and population changes. This could be violated if, for example, the fastest growing (price or population) locations were more likely to pressure local regulators to decommission coal plants. In this case, price increases following coal plant closures would not be directly attributable to the coal plant closure itself, but these other local characteristics. Alternatively, the closing of a coal plant must only affect local prices and quantities through its impact on air pollution. If a plant's closure makes a place more or less attractive for other reasons – perhaps because of a reduced dis-amenity associated with the visibility of plant operations or its negative impact on local employment demand – the exclusion restriction would not be satisfied. To address these concerns, we omit tracts that are within 5 kilometers of a coal plant that closed over 2006–2016. In county-level specifications, we omit counties in which a coal unit ceased operation during this period. The effect of a change in $PM_{2.5}$ concentrations is thus identified off of coal plant closures in relatively distant locations.

Table 7 presents the first-stage relationship between the change in average annual tract-level $PM_{2.5}$ concentrations between 2000 and 2016 predicted by coal plant closures and those observed in the data. Column 3, which includes division fixed effects and tract-level covariates, implies that a 1-unit increase in $PM_{2.5}$ concentrations caused by upwind and neighboring coal plants that closed during the 2006-2016 period is associated with a 1.3-unit decline in *observed* $PM_{2.5}$ concentrations. The first-stage F-statistic is 995 in our preferred specification.

6.2 Results: Coal plant closures

Table 8 shows the estimated relationship between tract-level pollution concentrations, housing prices, and population densities for all tracts in the sample between 2000–2016, using the coal plant closure instrument for changes in $PM_{2.5}$ concentrations. Here, we weight observations by total housing units in 2000 rather than the weights produced using propensity score matching, leaving a slightly larger sample than that used for the primary specifications (25,263 tracts). Consistent with the results leveraging air quality improvements induced by the Clean Air Act NAAQS, the preferred (IV) specifications in columns 4 and 8 imply that a 1-unit decline in average annual $PM_{2.5}$ concentrations yield a strongly significant 5.1 percent increase in housing prices and statistically insignificant 0.35 percent increase in population density.

Differentiating these estimated effects according to whether tracts are in 'elastic' or 'inelastic' metros, we see similar patterns as those shown in Table 5. Panel B of Table 8 reports these results. A

1-unit decline in $PM_{2.5}$ concentrations induced by coal plant closures yields a 6.5 percent increase in housing prices in tracts in elastic metros, compared to an 8.6 percent increase in inelastic metros. As with the Clean Air Act instrument, the results for changes in population density are relatively noisy. If anything, it appears that declining pollution levels caused by upwind coal plant closures yield *decreases* in population density in tracts in relatively inelastic metro areas. This could be the case if, for instance, the closure of coal plants suppressed local job opportunities and instigated out-migration as a result. Individuals may commute much farther than 5 kilometers to work at local coal plants, such that omitting tracts within 5 kilometers of these operations does not adequately address this issue. Appendix Table C3 shows the primary estimates omitting tracts within different sized "donuts" around closed coal plants. The price effect is attenuated when omitting tracts of greater distance to coal plants, while the impact on population density becomes more negative, though it remains statistically insignificant at standard confidence levels. In all cases, the price effect is larger (i.e., more negative) among tracts in inelastic markets, and the population effect larger among tracts in elastic markets.

7 A spatial equilibrium model for air-quality improvements

The empirical evidence that air quality improvements yield larger price increases in markets characterized by relatively inelastic housing supply is consistent with the stylized model presented in Section 2. In markets in which housing supply is not perfectly inelastic, the stylized model indicates that there should be some type of quantity adjustment in addition to these price adjustments, such that price changes alone may not provide a sufficient statistic upon which to evaluate the benefits of improved air quality. However, the classic hedonic model does not provide an obvious way to incorporate this quantity margin when estimating MWTP for amenity changes. To address this, we develop a spatial equilibrium model for air-quality improvements that provides expressions for local population, wages, and housing prices as a function of local amenities. This model builds on the long line of research which extends the logic of Rosen (1979) and Roback (1982) to estimate the benefits of amenity improvements.[29] We estimate the model in Section 7.3 to derive estimates of MWTP for air quality improvements which account for the effects of heterogeneous housing supply elasticities on the price and quantity margins.

7.1 Spatial equilibrium model

Assume that there are a large number of places indexed by j. All workers inelastically supply one unit of labor to their local labor market earning a wage of W_j. Assume that there is only one type of worker, such that all workers have the same marginal productivity (and hence face the

[29]Our model is most similar to Glaeser and Tobio (2007), who present a Rosen-Roback framework that uses changes in population, income, and housing prices to assess the sources of growth in the Sunbelt. Bartik et al. (2019) also use the concept of spatial equilibrium to infer MWTP for amenity changes. Other related extensions include Diamond (2016) and Bieri et al. (2023), among others.

same wage, W_j).[30] Workers consume one unit of a local good (housing) with a price R_j and they consume a tradable good X with price of 1. They also gain utility from local amenities, S_j.

Worker i's indirect utility is given by:

$$V_{ij} = W_j + S_j - R_j + \varepsilon_{ij} \tag{3}$$

where ε_{ij} reflects worker i's idyosyncratic preferences for place j.

There are a total of N_j workers in place j, and $\sum_j N_j = N_{total}$. Inverse supply of the local good (housing) is given by:

$$R_j = \bar{R} + \rho_j \ln N_j \tag{4}$$

where the number of housing units in place j is assumed to be equal to the number of workers, N_j, assuming that all workers consume one unit of housing. The parameter ρ_j characterizes the elasticity of the supply of housing (Moretti, 2011). It will be influenced by place-specific characteristics such as geographic characteristics and local land use regulations. In locations with substantial geographic barriers to development and restrictive regulations, ρ_j will be large. In locations with relatively loose regulatory codes and few geographic constraints, ρ_j will be very small. In the extreme example in which housing supply is perfectly inelastic and the supply curve is vertical, ρ_j will be infinite.

We assume that workers are identical and face an inverse labor demand curve given by:

$$W_j = A_j - \alpha \ln N_j \tag{5}$$

where A_j is a local productivity shifter and α is the slope of the inverse labor demand curve.

Assume that ε_{ij} follows a Type 1 Extreme Value distribution. In equilibrium, the marginal worker is indifferent between place j and all other places $-j$. The number of workers living in place j can be written in terms of the probability that worker i chooses to live in place j, scaled by the number of workers (N_{total}):[31]

$$N_j = N_{total} \frac{\exp\left(W_j + S_j - \bar{R}\right) N_j^{-\rho_j}}{\sum_k \exp\left(W_k + S_k - R_k\right)} \tag{6}$$

We can write log population (lnN_j), wages (W_j) and housing prices (R_j), as functions of amenity value S_j and take the long difference in each variable over time.[32]

[30] We do not explicitly model mobility costs. Bayer et al. (2009) provide a careful treatment of this issue, showing that the failure of individuals to move to areas experiencing air quality improvements could be partially due to mobility frictions. Failing to account for these migration costs would downwardly bias estimates of the disutility associated with pollution.

[31] This is based on the conditional logit setup from McFadden (1973), used in a variety of settings in urban economics (see, for example, Diamond 2016).

[32] For brevity, we have omitted time subscripts in these expressions. We assume that W_j, N_j, A_j, S_j, R_j, and $\bar{R}$ may vary across time, while other parameters are assumed to be time-invariant.

$$\ln N_j = \frac{1}{1+\rho_j+\alpha}(A_j + S_j - \bar{R}) + C_1 \tag{7}$$

$$W_j = \frac{1+\rho_j}{1+\rho_j+\alpha}A_j - \frac{\alpha}{1+\rho_j+\alpha}(S_j - \bar{R}) - C_2 \tag{8}$$

$$R_j = \frac{\rho_j}{1+\rho_j+\alpha}(A_j + S_j) + \frac{1+\alpha}{1+\rho_j+\alpha}\bar{R} + C_3 \tag{9}$$

where C_1, C_2, and C_3 are constants. The derivations of these expressions can be found in Appendix B.1. In Appendix B.1, we further derive long difference expressions for population ($\Delta \ln N_j$), wages (ΔW_j), and housing prices(ΔR_j):

$$\Delta \ln N_j = \frac{1}{1+\rho_j+\alpha}(\Delta A_j + \Delta S_j + \Delta\bar{R}) \tag{10}$$

$$\Delta W_j = \frac{1+\rho_j}{1+\rho_j+\alpha}\Delta A_j - \frac{\alpha}{1+\rho_j+\alpha}(\Delta S_j - \Delta\bar{R}) \tag{11}$$

$$\Delta R_j = \frac{\rho_j}{1+\rho_j+\alpha}(\Delta A_j + \Delta S_j) + \frac{1+\alpha}{1+\rho_j+\alpha}\Delta\bar{R} \tag{12}$$

Now, let productivity A_j and amenity value S_j be linear functions of local pollution concentrations X_j. The long difference over time ΔA_j and ΔS_j are given by:

$$\Delta A_j = \varphi_1 \Delta X_j + \tilde{\mu_j} \tag{13}$$

$$\Delta S_j = \gamma_1 \Delta X_j + \tilde{\nu_j} \tag{14}$$

Where $\tilde{\mu_j}$ and $\tilde{\nu_j}$ are unobservable determinants of ΔA_j and ΔS_j, respectively. Importantly, $\tilde{\mu_j}$ and $\tilde{\nu_j}$ are not orthogonal to air quality improvements ΔX_j, as unobserved characteristics may covary with both air quality improvements and productivity and amenity improvements.

Plugging equations 13 and 14 into the long difference expressions for population (equation 10), wages(equation 11), and housing prices (equation 12), we can write the central parameters as functions of ΔX_j:

$$\Delta \ln N_j = \frac{1}{1+\rho_j+\alpha}\Delta\bar{R} + \frac{\varphi_1+\gamma_1}{1+\rho_j+\alpha}\Delta X_j + \xi_j^n \tag{15}$$

$$\Delta W_j = \frac{\alpha}{1+\rho_j+\alpha}\Delta \bar{R} + \frac{(1+\rho_j)\varphi_1 - \alpha\gamma_1}{1+\rho_j+\alpha}\Delta X_j + \xi_j^w \tag{16}$$

$$\Delta R_j = \frac{1+\alpha}{1+\rho_j+\alpha}\Delta \bar{R} + \frac{\rho_j(\varphi_1+\gamma_1)}{1+\rho_j+\alpha}\Delta X_j + \xi_j^r \tag{17}$$

where $\xi_j^n = \frac{\tilde{\mu_j}+\tilde{\nu_j}}{1+\rho_j+\alpha}$, $\xi_j^w = \frac{(1+\rho_j)\tilde{\mu_j}-\alpha\tilde{\nu_j}}{1+\rho_j+\alpha}$, and $\xi_j^r = \frac{\rho_j(\tilde{\mu_j}+\tilde{\nu_j})}{1+\rho_j+\alpha}$.

7.2 GMM estimation

We jointly estimate the full model using a nonlinear simultaneous-equations GMM estimator. For estimation purposes, we allow ρ_j (characterizing inverse local housing supply elasticity) to take on one of two values: $\rho_j = \rho_1$ for places j in the set of 'inelastic' housing markets I and $\rho_j = \rho_2$ for places j in 'elastic' housing markets:

$$\rho_j = \begin{cases} \rho_1 \text{ if } j \in I \\ \rho_2 \text{ if } j \notin I \end{cases}$$

To implement the GMM estimator, we derive the following equations by rearranging equations 15, 16, and 17, and replacing ρ_j with $\rho_j = \rho_1 \cdot \mathbb{1}_{j\in I} + \rho_2 \cdot \mathbb{1}_{j\notin I}$:

$$\xi_j^n = \Delta \ln N_j - \frac{1}{1+\rho+\alpha}\Delta \bar{R} - \frac{\varphi_1+\gamma_1}{1+\rho+\alpha}\Delta X_j \tag{18}$$

$$\xi_j^w = \Delta W_j - \frac{\alpha}{1+\rho+\alpha}\Delta \bar{R} - \frac{(1+\rho)\varphi_1 - \alpha\gamma_1}{1+\rho+\alpha}\Delta X_j \tag{19}$$

$$\xi_j^r = \Delta R_j - \frac{1+\alpha}{1+\rho+\alpha}\Delta \bar{R} - \frac{\rho(\varphi_1+\gamma_1)}{1+\rho+\alpha}\Delta X_j \tag{20}$$

where ξ_j^n, ξ_j^w, and ξ_j^r are functions of $\tilde{\mu}_j$ and $\tilde{\nu}_j$, and are endogenous to air quality improvements ΔX_j. Unobserved characteristics of place j may vary with both changes in population, wages and housing prices, as well as air quality improvements. To address endogeneity concerns, we need a set of instruments, $\mathbf{Z}$, that is mean independent of $\tilde{\mu}_j$ and $\tilde{\nu}_j$, such that the expectation of the error term is mean zero conditional on the instrument: $E[\tilde{\mu}_j|\mathbf{Z}] = 0$ and $E[\tilde{\nu}_j|\mathbf{Z}] = 0$. This implies $\mathbf{Z}$ is also mean independent of ξ_j^n, ξ_j^w and ξ_j^r:

$$E[\xi_j^n|\mathbf{Z}] = 0$$
$$E[\xi_j^w|\mathbf{Z}] = 0$$
$$E[\xi_j^r|\mathbf{Z}] = 0$$

In practice, we construct a vector of instruments $\mathbf{Z}$, that include the county's nonattainment status under the CAA, the predicted change in PM2.5 from upwind coal plants that closed between 2006 and 2009, as well as a constant. The identifying assumption is that non-attainment status and upwind coal plant closures are uncorrelated with unobserved shocks to population, wages and housing prices. This results in nine moment conditions—i.e. each of the three instruments times the three error terms. Full details of instrument construction and moment conditions are specified in Appendix B.3.

Conditional on the instruments $\mathbf{Z}$, equations 18, 19, and 20 jointly solve the local general equilibrium problem of how wages, housing prices, and population sizes respond to an exogenous change in air quality. The four endogenous variables are: $\Delta \ln N_j$, ΔR_j, and ΔW_j, and ΔX_j. $\Delta \bar{R}$ reflects the average change in construction costs (housing prices) across all places, which is observed in the data. To reduce the number of parameters to estimate, we calculate the slope of the inverse labor demand curve, α, using estimates from the literature, as detailed in Appendix B.2. This leaves four unknown parameters to estimate:

- Labor productivity parameter (φ_1)
- The marginal willingness-to-pay (MWTP) for amenity improvement (γ_1)
- The elasticity of local housing supply in inelastic places (ρ_1)
- The elasticity of local housing supply in elastic places (ρ_2)

The full model is estimated using a standard two-step GMM procedure, using county-level data on population, wage, price, and pollution changes between 2000 and 2010, rather than tract-level data, for which accurate, publicly available wage data are not available. Wages (average annual pay) are retrieved from the Quarterly Census on Employment and Wages (QCEW). We inflate all wage and price data to 2018 dollars using the January CPI-U, so that all changes are expressed in real terms. The level change in housing price (ΔR_j) is calculated based on the county's median, owner-occupied home value in 2000 and the county's 2010 HPI (indexed to 2000 levels), as described in Appendix B.2. Median home values and all population counts are retrieved from the Decennial Census. We limit our analysis to counties with non-missing HPI values, leaving a final sample of 2,395 counties. Our central estimates define counties as elastic if they are historically low-regulation states and inelastic if they historically high-regulation states, as defined by Ganong and Shoag (2017). The details of this bifurcation are explained in Appendix A, and the states that compose the relevant categories can be found in Appendix Table C4.

7.3 Model estimation results

The main GMM estimates are presented in Table 6. All dollar values are expressed in $1,000s, such that the γ term reflects the MWTP for $PM_{2.5}$ expressed in thousands. The estimates in column 1 thus indicate that, across all counties, the MWTP for a 1-unit reduction of $PM_{2.5}$ is approximately

$13,840. When we allow the housing supply parameter, ρ, to vary according to whether the county is in a high-regulation (inelastic) or low-regulation (elastic) state, we estimate MWTP ranging from approximately $9.9 to $16.7 thousand per unit of pollution reduction.

The estimates presented in columns 2 and 3 are based off of a split sample, where the model is estimated using only historically low-regulation states (column 2) or high-regulation states (column 3). While this allows ρ to differ between the two sets of counties, it also allows γ to differ, and thus MWTP. Taken literally, these estimates suggest that MWTP for 1 unit of pollution reduction is about $2,000 *higher* in low-regulation states compared to high-regulation states. This could be explained by taste-based sorting, where individuals select into a given type housing market based on their tastes for air quality. Alternatively, it could be explained by the fact that 1 unit of pollution reduction represents a larger *percent* change in pollution reduction in low-regulation states compared to high-regulation states.

Contrasting these figures to those produced using traditional hedonic methods, we see that estimates delivered from the canonical model typically imply a lower MWTP for air quality. Table 4 showed that a Clean-Air-Act-induced 1-unit reduction in $PM_{2.5}$ yielded a 5.2 percent increase in housing prices across all metropolitan Census tracts in the sample. The average home value in a nonattainment tract in was $168,624 in 2000 (adjusted 2018 dollars), meaning that home values increased by roughly $8,768 as a result of a 1-unit decline in $PM_{2.5}$ concentrations over a ten-year period. There were about 35 million housing units in nonattainment areas in 2000. Extrapolating from these price effects alone implies a WTP for air quality improvements on the order of $300 billion.[33]

The MWTP parameters expressed in Table 6 are between 13 and 90 percent higher than the average NAAQS-induced price increase estimated from Table 4. Extrapolating from the estimate in column 1, based on the full sample of U.S. counties with non-missing HPI values (i.e., all metro counties) implies a WTP for air quality improvements on the order of $466 billion. This value is about 50 percent larger than that derived from the reduced-form evidence on price capitalization. We caveat that these estimates, however, are not directly comparable, as they rely on different geographic units (and hence slightly different samples), as well as differing estimation methods. Still, the large difference in resulting estimates illustrates the importance of incorporating the capacity for adjustments *beyond* price capitalization when estimating the benefits of air quality improvements.

[33] Chay and Greenstone (2005) estimate that a 1-unit decline in TSP concentrations caused a $2,400 increase in housing prices in nonattainment counties. With approximately 19 million households in nonattainment counties, they extrapolate a WTP for TSP reductions in the late 1970s of approximately $45 billion (in 2001 dollars).

8 Conclusion and discussion

Many applications of the hedonic approach exploit price capitalization in the housing market to estimate the benefits of local amenities. Implicit in these applications is the assumption that the supply of housing is fixed, or perfectly inelastic. In circumstances in which the market can expand in order to accommodate increased demand arising from amenity improvements, there will be a quantity response to these amenity changes in addition to this price response. We expect that this quantity margin will be larger, and the concurrent price capitalization smaller, in places characterized by relatively elastic housing supply. Thus, MWTP estimates based on price changes alone may be biased to the extent that the observed price changes are attenuated by expansions in supply.

The empirical evidence presented in this paper suggests that housing supply constraints do indeed mediate the relationship between improvements in local amenities and housing prices growth. We exploit the implementation of the 1997 NAAQS for $PM_{2.5}$, which took effect in 2005, to show that exogenous improvements in air quality lead to a larger increase in housing prices in inelastic housing markets relative to elastic housing markets. This reduced-form result is consistent across a wide range of specifications and empirical strategies. That price capitalization is larger in relatively constrained housing markets indicates either that individuals living in inelastic markets have stronger preferences for cleaner air, or that price changes alone are insufficient to measure demand for clean air. Consistent with a stylized model of supply and demand for amenity improvements, we find modest evidence that exogenous improvements in air quality lead to larger quantity changes in elastic housing markets relative to inelastic housing markets. That is, prices *and* quantities adjust in response to amenity improvements.

Motivated by this empirical evidence, we develop a spatial equilibrium model of local labor and housing markets, which allows for improvements in environmental amenities to generate both price *and* quantity effects. The model provides expressions for housing prices, population head counts, and wages as functions of local amenities, with these relationships mediated by the elasticity of local housing supply. We estimate the model using county-level changes in $PM_{2.5}$ concentrations induced by NAAQS regulations as well as neighboring and upwind coal plant closures. Consistent with the notion that price changes will underestimate benefits in the presence of supply shifts, the resulting MWTP for air quality from this estimated model is larger than that based on price capitalization alone. Taken together with the reduced-form estimates, we find broad evidence that the canonical hedonic model will tend to underestimate the value of local air quality improvements in the presence of a quantity response, with the resulting bias in canonical estimates depending on the elasticity of local housing supply.

A key limitation of the analysis presented in this paper is that we do not account for heterogeneity in preferences for cleaner air. If individuals with a higher MWTP for air quality select into cities with more inelastic local housing supply, then some of the heterogeneity in the price effects could be explained by this taste-based sorting. Nevertheless, we show that price effects should conceptually be larger in places with relatively inelastic housing supply, independent of self-selection. We provide reduced-form evidence that is consistent with this conceptual prediction using a variety of specifications and empirical settings. Given the distribution of true MWTP in the population, we show that prices alone may be an insufficient statistic for recovering the MWTP in situations when local housing markets are not perfectly inelastic.

Importantly, our critique of the canonical hedonic approach is limited to situations in which researchers *cannot* plausibly take advantage of extremely short-run price responses to amenity changes. Housing supply may indeed be fixed, or perfectly inelastic, under very immediate time horizons. In situations in which there is an extremely abrupt and salient change in local amenities, and researchers have the capacity to estimate concurrent price changes, there will be little or no bias of the form we discuss in this paper because there exists no quantity margin. However, over progressively larger time horizons, new homes can be constructed and supply can expand to accommodate increased demand. The capacity for new construction depends upon the elasticity of local housing supply. Here, we show that explicitly accounting for this quantity margin is essential to producing unbiased estimates of MWTP. Over the past several decades, much progress has been made in elucidating and addressing the biases in the canonical hedonic method. In this paper, we present one commonly overlooked source of bias emerging when the assumption of fixed quantities does not hold, and present a model of spatial equilibrium that can be used to estimate MWTP in this situation. We anticipate that much more progress will be made in developing tractable methods to deal with this source of bias and the credibility of resulting estimates going forward.

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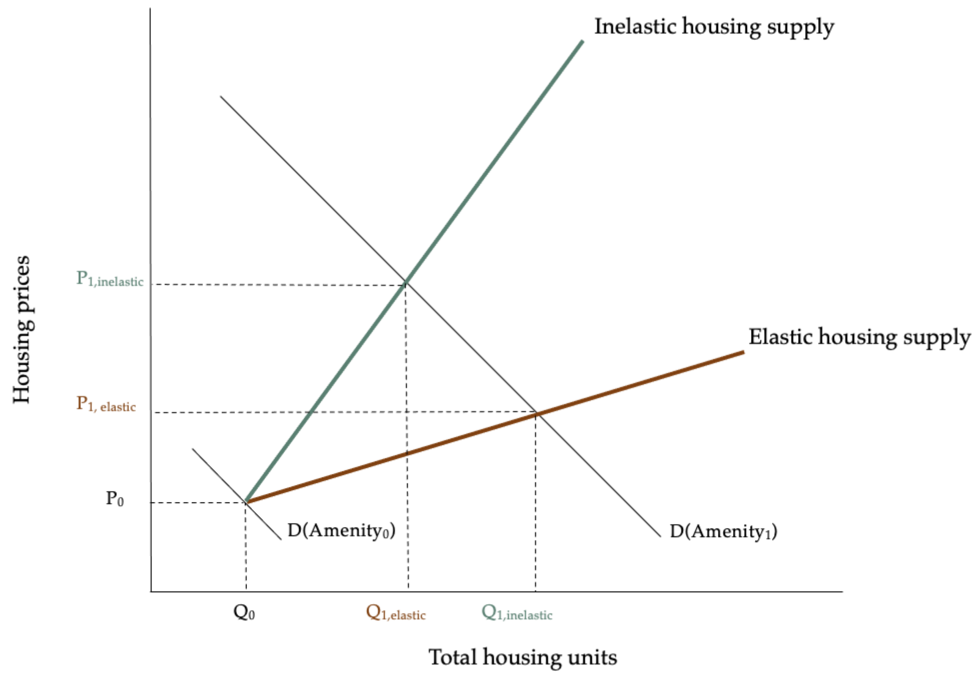
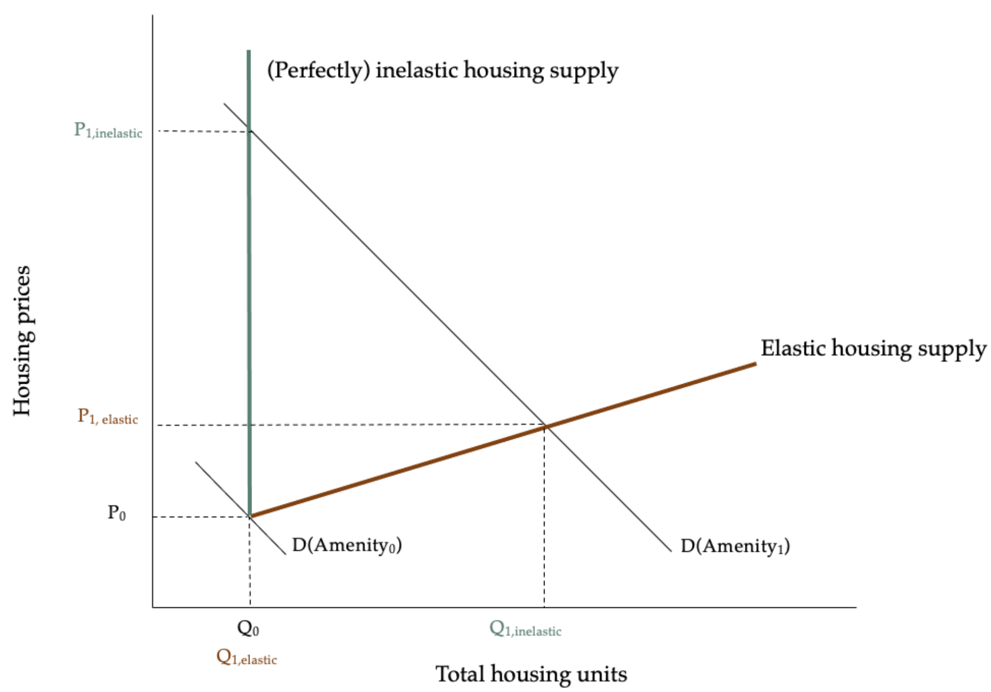
Figures

Figure 1: Effect of demand shift in (in)elastic markets

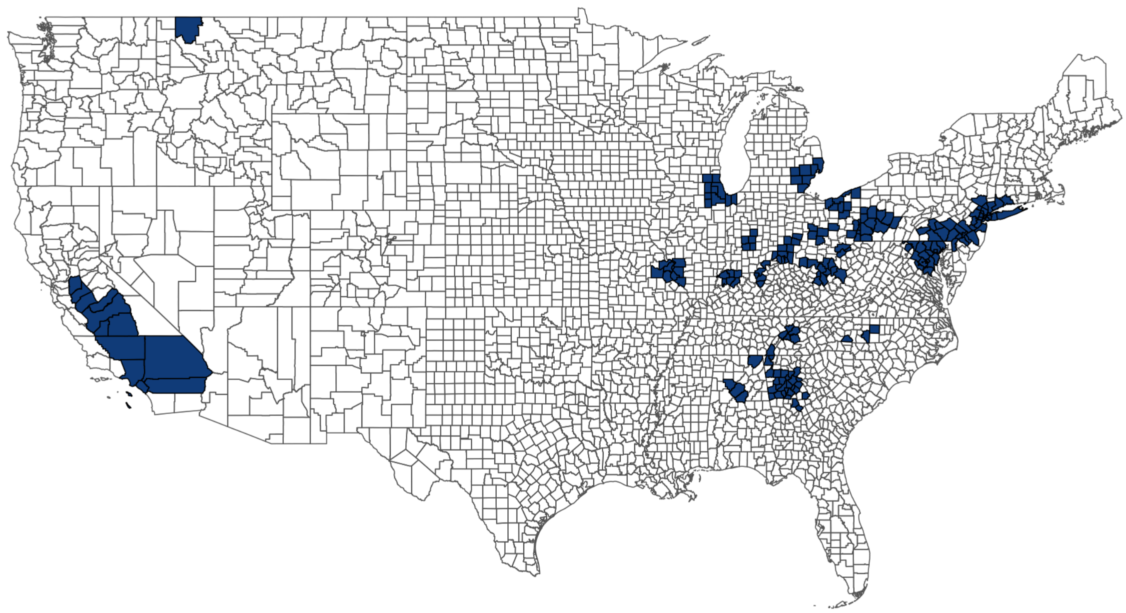


(a)



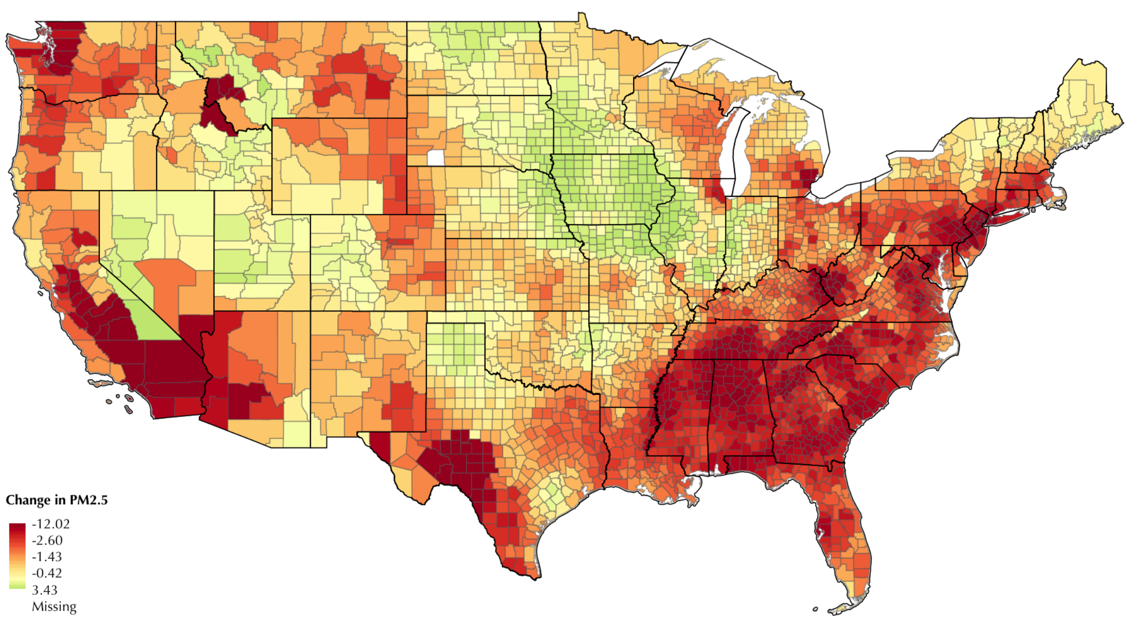
(b)

Figure 2: NAAQS $PM_{2.5}$ nonattainment areas



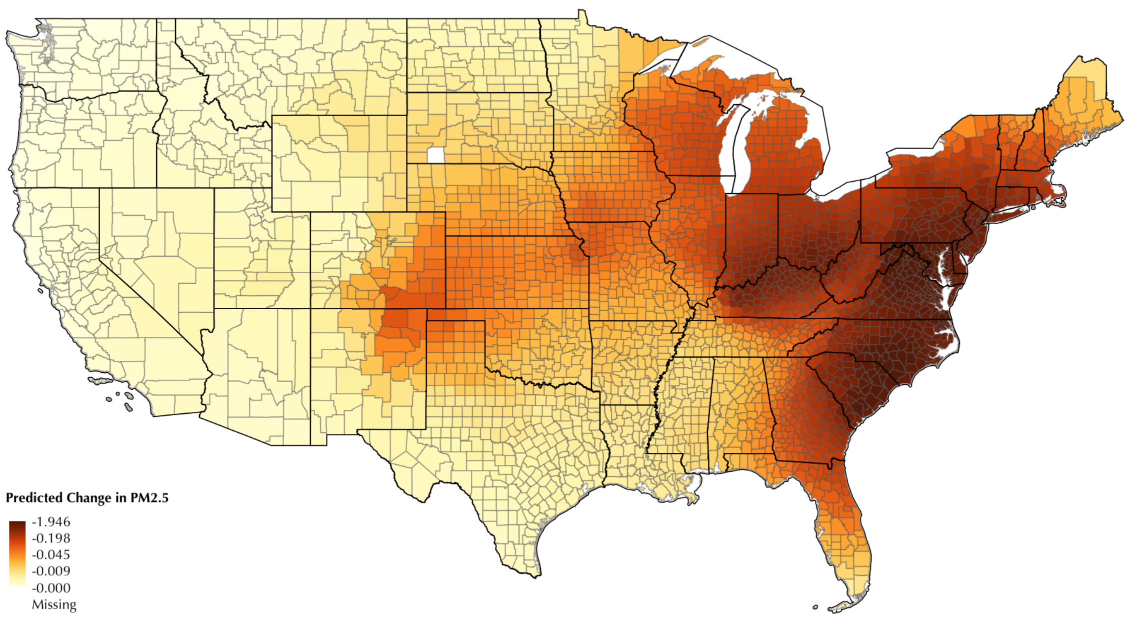
Notes: Areas classified as nonattainment under the 1997 NAAQS (announced in December 2004) are indicated in blue.

Figure 3: Change in average annual $PM_{2.5}$ concentrations, 2000-2010



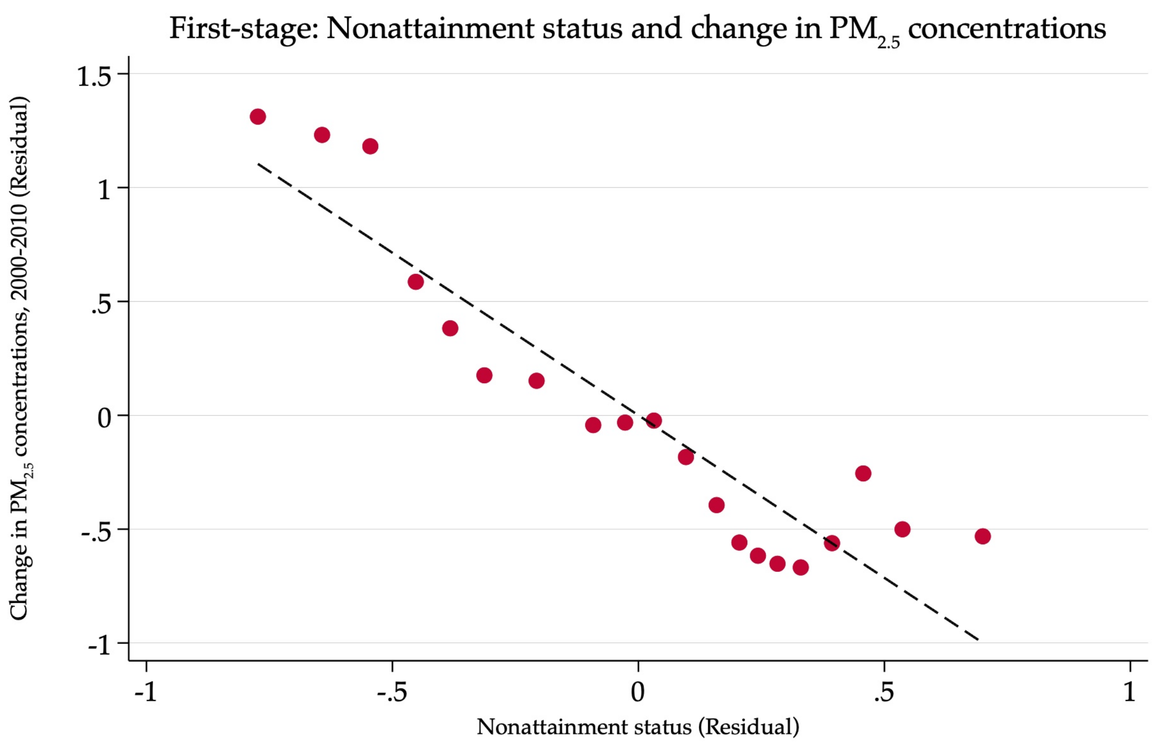
Notes: Figure reflects the change in average annual $PM_{2.5}$ concentrations between 2000 and 2010, where annual $PM_{2.5}$ concentrations are based on those provided by van Donkelaar et al. (2019).

Figure 4: Predicted change in $PM_{2.5}$ concentrations based on InMap, 2000-2016



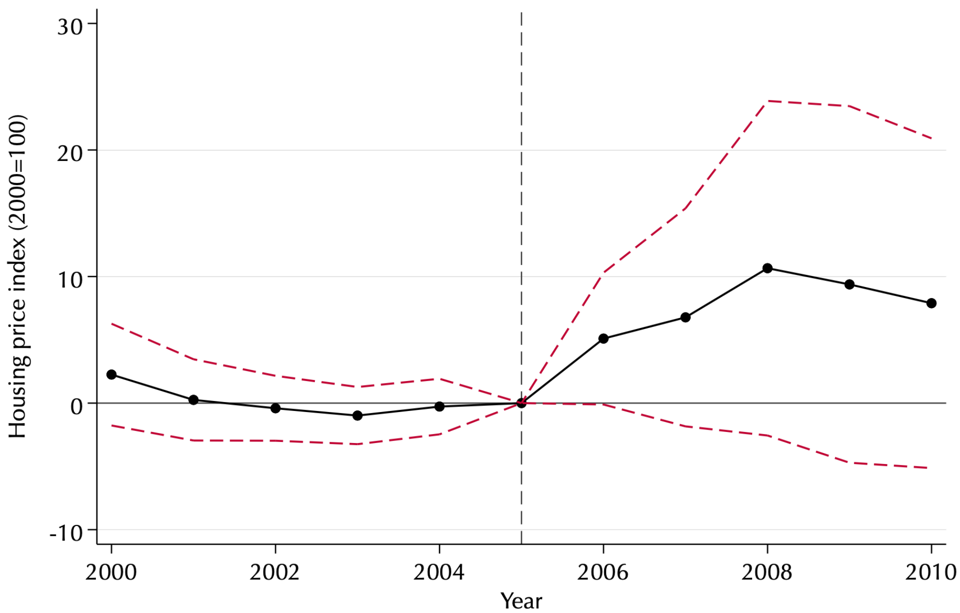
Notes: Figure reflects the predicted change in $PM_{2.5}$ concentrations between 2000 and 2016 attributable to coal plant closures, as predicted by the InMap chemical air transport model.

Figure 5: First-stage relationship between nonattainment status and $\Delta PM_{2.5}$, 2000-2010



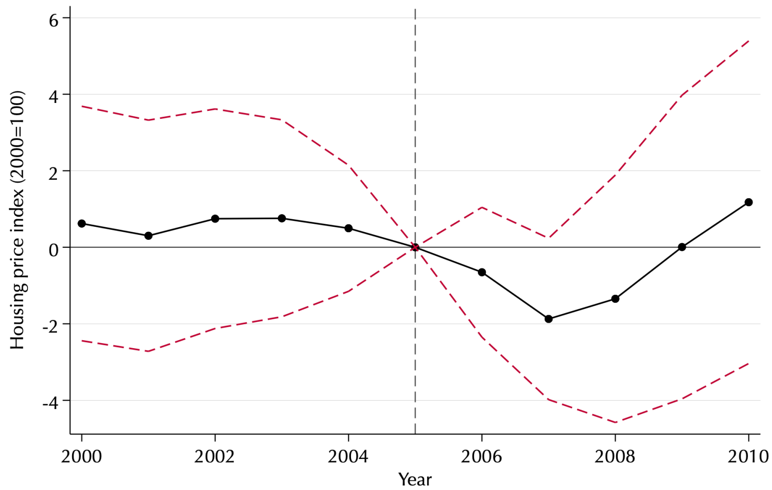
Notes: Figure plots the residualized change in average annual $PM_{2.5}$ concentrations between 2000 and 2010 on a tract's residualized nonattainment status in 2005. Variables are residualized on all 2000-level covariates included in the analysis (share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied), as well as Census division. Regressions are weighted using the weights produced in PSM, described in text.

Figure 6: Effect of $PM_{2.5}$ NAAQS on housing prices in newly regulated Census tracts

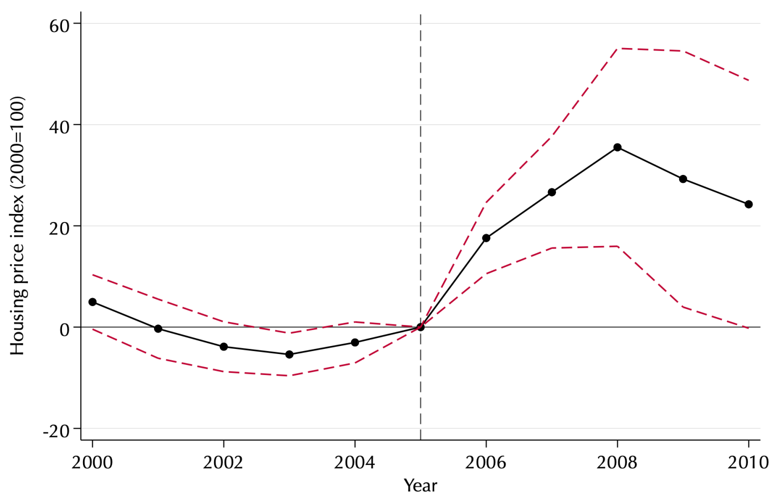


Notes: This figure plots the event-study coefficient estimates from equation 21, where the dependent variable is the HPI in a given Census tract. Regressions are weighted by weights produced by PSM and control for state-by-year fixed effects and tract-level covariates. The dashed lines represent 95% confidence intervals. Standard errors are clustered by county.

Figure 7: Effect of $PM_{2.5}$ NAAQS on housing prices in newly regulated Census tracts, by metro-level housing supply elasticity



(a) Tracts in **elastic** metro areas



(b) Tracts in **inelastic** metro areas

Notes: This figure plots the event-study coefficient estimates from equation 21, where the dependent variable is the HPI in a given Census tract. Regressions are weighted by weights produced by PSM and control for state-by-year fixed effects and tract-level covariates. The dashed lines represent 95% confidence intervals. Standard errors are clustered by county. Tracts are defined as elastic or inelastic based on their metropolitan area's elasticity estimated in Saiz (2010) .

Tables

Table 1: Nonattainment and attainment tract characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Housing-unit-weighted			**PSM-weighted**		
	Attain.	Non.	(1)-(2)	Attain.	Non.	(4)-(5)
ln(med. hh income)	10.846	10.880	-0.033	10.868	10.905	-0.037
	(0.015)	(0.023)		(0.012)	(0.027)	
adult college share	31.387	30.577	0.809	31.359	30.639	0.720
	(0.720)	(1.160)		(0.698)	(1.443)	
non-Hisp. white share	75.996	71.647	4.349	78.637	70.858	7.779
	(1.601)	(4.381)		(1.533)	(5.279)	
renter-occ. housing rate	29.581	28.984	0.597	26.542	27.456	-0.913
	(0.636)	(1.747)		(0.500)	(1.956)	
vacancy rate	5.492	4.719	0.774*	5.139	4.381	0.758**
	(0.234)	(0.326)		(0.176)	(0.260)	
1995 HPI	77.856	81.473	-3.617***	81.522	81.450	0.072
	(0.944)	(0.774)		(0.699)	(0.748)	
Δln(pop dens), ’90-2000	27.845	18.209	9.636***	18.551	17.978	0.573
	(2.279)	(1.935)		(1.078)	(2.062)	
$PM_{2.5}$ concentration, 2000	11.064	15.359	-4.294***	11.034	15.417	-4.383***
	(0.166)	(0.501)		(0.181)	(0.576)	
Observations	14,754	11,823		11,650	11,229	

Sample in columns 1-3 includes all metro tracts with non-missing values for HPI and elasticity. Means are weighted by total housing units in 2000. Sample in columns 4-6 includes all metro tracts with non-missing values for HPI and elasticity with positive weights produced by PSM. Means are weighted by these PSM weights. Standard errors, clustered on county, are in parentheses.
*** p<0.01, ** p<0.05, * p<0.1

Table 2: First stage and reduced form: Nonattainment status

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ PM2.5, 2000-10		2010 HPI (2000=100)		Δ ln(pop dens), 2000-10	
Nonattainment	-1.587***	-1.430***	9.566**	7.395*	-1.025	-0.400
	(0.177)	(0.171)	(4.366)	(3.829)	(1.434)	(1.084)
Controls		✓		✓		✓
Division FE	✓	✓	✓	✓	✓	✓
F-stat (nonatt)	80.72	70.27				
R-squared	0.500	0.530	0.387	0.437	0.034	0.105
Observations	22,879	22,879	22,879	22,879	22,879	22,879

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by the weights produced in PSM, described in text.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: Summary statistics for primary outcome & independent variables

	(1) Mean	(2) SD	(3) p25	(4) p50	(5) p75
Full sample: (N=22,879)					
$PM_{2.5}$ concentration, 2000	13.23	3.44	10.89	13.07	15.01
Median home value, 2000	159,199	82,204	106,067	139,421	184,603
ln(pop density), 2000	7.67	1.34	6.99	7.96	8.58
ΔPM2.5, 2000-2010	-3.09	1.87	-4.04	-2.94	-1.84
2010 HPI	133.80	29.18	115.37	131.89	152.18
Δln(pop density), 2000-2010	8.89	22.66	-2.89	2.53	12.31
Nonattainment tracts: (N=11,229)					
$PM_{2.5}$ concentration, 2000	15.42	3.10	13.76	14.93	16.25
Median home value, 2000	168,624	85,482	112,218	150,411	198,209
ln(pop density), 2000	7.89	1.30	7.25	8.11	8.76
ΔPM2.5, 2000-2010	-3.88	2.04	-4.76	-3.57	-2.51
2010 HPI	135.34	35.90	109.50	132.41	162.34
Δln(pop density), 2000-2010	7.50	20.48	-2.98	2.13	10.67
Elastic tracts: (N=15,729)					
$PM_{2.5}$ concentration, 2000	12.64	2.73	10.80	12.82	14.60
Median home value, 2000	142,686	64,127	100,273	128,691	165,493
ln(pop density), 2000	7.43	1.29	6.71	7.76	8.36
ΔPM2.5, 2000-2010	-2.70	1.46	-3.75	-2.74	-1.65
2010 HPI	128.71	28.70	111.13	127.17	146.52
Δln(pop density), 2000-2010	9.79	23.46	-3.08	2.85	14.22
Nonattainment elastic tracts: (N=7,290)					
$PM_{2.5}$ concentration, 2000	14.46	2.05	13.44	14.54	15.45
Median home value, 2000	151,917	73,042	103,272	133,832	178,139
ln(pop density), 2000	7.59	1.25	6.93	7.87	8.45
ΔPM2.5, 2000-2010	-3.25	1.45	-4.30	-3.31	-2.20
2010 HPI	128.32	36.87	102.10	124.22	156.09
Δln(pop density), 2000-2010	7.90	20.66	-3.48	2.11	12.25
Inelastic tracts: (N=7,150)					
$PM_{2.5}$ concentration, 2000	14.66	4.43	11.05	13.98	16.42
Median home value, 2000	199,345	104,478	135,713	174,830	229,387
ln(pop density), 2000	8.26	1.25	7.74	8.51	9.07
ΔPM2.5, 2000-2010	-4.04	2.36	-5.10	-3.32	-2.38
2010 HPI	146.18	26.51	126.56	142.74	165.22
Δln(pop density), 2000-2010	6.69	20.42	-2.46	1.97	8.62
Nonattainment inelastic tracts: (N=3,939)					
$PM_{2.5}$ concentration, 2000	17.19	3.85	14.70	16.08	20.73
Median home value, 2000	199,543	97,396	140,056	176,945	228,714
ln(pop density), 2000	8.45	1.22	7.89	8.68	9.26
ΔPM2.5, 2000-2010	-5.04	2.43	-7.41	-4.57	-3.10
2010 HPI	148.32	29.97	122.04	148.47	171.61
Δln(pop density), 2000-2010	6.76	20.14	-2.11	2.15	8.31

Summary statistics are weighted by the weights produced in PSM, described in text. Change in population density is multiplied by 100 for ease of interpretation. Tracts are defined as inelastic if they have a Saiz (2010) elasticity of less than 1, and elastic otherwise.

Table 4: Price and population responses to $\Delta PM_{2.5}$, 2000-2010

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2010 HPI (2000=100)				Δ ln(pop density), 2000-2010			
	OLS		IV		OLS		IV	
$\Delta PM_{2.5}$, '00-10	-1.414	-0.520	-6.028**	-5.173*	1.756***	1.128***	0.646	0.280
	(1.341)	(1.183)	(2.655)	(2.776)	(0.399)	(0.368)	(0.899)	(0.771)
Controls		✓		✓		✓		✓
Division FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	22,879	22,879	22,879	22,879	22,879	22,879	22,879	22,879

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by the weights produced in PSM, described in text. Columns 3, 4, 7, and 8 instrument for change in $PM_{2.5}$ with nonattainment status. The outcome variable in columns 5 through 8 has been multiplied by 100 for ease of interpretation.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 5: IV estimates: Effect of $\Delta PM_{2.5}$ on prices and quantities, by metro-level elasticity

	(1)	(2)	(3)	(4)
	HPI (2000=100)		Δln(population density)	
		Panel A: **2000-2010**		
$\Delta PM_{2.5}{}^{2000\text{-}10}$x **Elastic**	-2.767	-2.604	-0.932	-1.389**
	(2.418)	(2.448)	(0.892)	(0.676)
$\Delta PM_{2.5}{}^{2000\text{-}10}$ x **Inelastic**	-6.982***	-7.082***	-0.001	-0.435
	(2.313)	(2.541)	(0.960)	(0.686)
P-val(In=Elastic)	0.000	0.000	0.041	0.017
Observations	22,879	22,879	22,879	22,879
		Panel B: **2000-2007**		
$\Delta PM_{2.5}{}^{2000\text{-}07}$x **Elastic**	-4.259	-2.618	-0.008	-0.014
	(6.970)	(6.391)	(0.010)	(0.010)
$\Delta PM_{2.5}{}^{2000\text{-}07}$ x **Inelastic**	-20.867***	-17.269***	-0.004	-0.008
	(2.767)	(3.010)	(0.007)	(0.006)
P-val(In=Elastic)	0.003	0.003	0.682	0.569
Observations	22,818	22,818	17,016	17,016
		Panel C: **2000-2016**		
$\Delta PM_{2.5}{}^{2000\text{-}16}$x **Elastic**	-2.083	-0.658	-0.069	-0.253
	(2.766)	(2.382)	(0.821)	(0.666)
$\Delta PM_{2.5}{}^{2000\text{-}16}$ x **Inelastic**	-6.491**	-4.680**	0.464	0.360
	(2.559)	(2.244)	(0.853)	(0.658)
P-val(In=Elastic)	0.000	0.000	0.080	0.023
Observations	22,182	22,182	22,879	22,879
Controls	-	✓	-	✓
Division fixed effects	✓	✓	✓	✓

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by the weights produced in PSM, described in text. We instrument for change in $PM_{2.5}$ with nonattainment status. Tracts are defined as elastic or inelastic based on their metropolitan area's elasticity estimated in Saiz (2010). The outcome variable in columns 3 and 4 has been multiplied by 100 for ease of interpretation.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 6: GMM estimates of model parameters

	(1)	(2)	(3)	(4)	(5)
	Estimate single ρ for all counties			Allow for two values of ρ	
ρ (Housing supply parameter)	853.26**				
	(406.23)				
ρ_1 (HS parameter, inelastic)			1,032.04	586.30***	804.69***
			(863.53)	(184.64)	(214.15)
ρ_2 (HS parameter, elastic)		343.11		604.26***	399.25***
		(230.13)		(195.69)	(92.83)
φ (Labor productivity parameter)	-0.99*	-1.18	-0.80	-1.97***	-2.30***
	(0.57)	(1.20)	(0.64)	(0.57)	(0.46)
γ (MWTP for pollution reduction)	-13.32***	-11.90**	-9.92***	-16.53***	-16.73***
	(2.97)	(5.89)	(3.14)	(2.69)	(1.79)
Observations	2,395	1,393	1,002	2,395	2,395
Model	All metro counties	Low-reg states	High-reg states	Interact rho with dummy	6 equations, 4 unknowns

See text for model details. Estimates in column (1) are based off of all counties with non-missing HPI values, with no differentiation between elastic and inelastic markets. Those in column 2 and 3 are based off of a restricted sample including only counties in low-regulation (elastic) states and high-regulation (inelastic) states, respectively, as defined by Ganong and Shoag (2017). Estimates in column 4 allow ρ to take on one of two values using the three equations outlined in the text. Those in column 5 are based off of six equations with four unknown parameters, with three equations including only inelastic counties (high-regulation states) and three equations including only data from elastic counties (low-regulation states).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7: First stage: Predicted Δ $PM_{2.5}$ from upwind coal plant closures

	(1)	(2)	(3)
		Δ PM2.5, 2000-16	
Predicted Δ $PM_{2.5}$, 2000-16	-1.650***	-1.395***	-1.363***
	(0.025)	(0.040)	(0.043)
Controls	-	-	✓
Fixed effects	-	✓	✓
F-stat (nonatt)	4210	1206	994.4
R-squared	0.086	0.282	0.334
Observations	25,236	25,236	25,236

Robust standard errors are in parentheses. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by number of housing units in 2000.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 8: Effect of $\Delta PM_{2.5}$ on prices and quantities, 2000-2016 (IV Estimates)
Coal plant closure specifications

	(1)	(2)	(3)	(4)
	2016 HPI (2000=100)		Δ ln(pop density), 2000-2016	
	Panel A: **Full sample**			
$\Delta PM_{2.5}^{2000\text{-}16}$	-6.164***	-5.051***	-0.650	-0.374
	(0.840)	(0.840)	(0.448)	(0.458)
Controls	-	✓	-	✓
Division fixed effects	✓	✓	✓	✓
Observations	25,236	25,236	25,236	25,236
	Panel B: **By metro-level elasticity**			
$\Delta PM_{2.5}^{2000\text{-}16}$x **Elastic**	-7.348***	-6.513***	-0.357	0.039
	(0.768)	(0.771)	(0.412)	(0.419)
$\Delta PM_{2.5}^{2000\text{-}16}$ x **Inelastic**	-9.489***	-8.594***	0.174	0.628
	(0.666)	(0.694)	(0.366)	(0.383)
P-val(In=Elastic)	0.000	0.000	0.000	0.000
Controls	-	✓	-	✓
Division fixed effects	✓	✓	✓	✓
Observations	25,236	25,236	25,236	25,236

Robust standard errors are in parentheses. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by number of housing units in 2000. Change in $PM_{2.5}$ is instrumented with the change predicted by upwind coal plant closures. Tracts are defined as elastic or inelastic based on their metropolitan area's elasticity estimated in Saiz (2010). The outcome variable in columns 3 and 4 has been multiplied by 100 for ease of interpretation.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix

A Robustness to alternative specifications

The conclusion that housing prices are more sensitive to air quality improvements in markets characterized by relatively inelastic housing supply is largely insensitive to the choice of empirical specification or definition of local housing supply elasticity. That is, housing prices do less to "capitalize" pollution declines in more elastic markets, such that a classic hedonic analysis conducted in setting with elastic supply will likely yield a lower bound estimate of MWTP compared to one conducted in an inelastic setting. Here, we outline the methodology and results from several alternative specifications.

A.1 Event-study design

Nonattainment status for the 1997 NAAQS was announced in December 2004 and implemented in 2005. While this implementation did not yield instantaneous reductions in emissions, we might expect the housing market to respond relatively quickly to anticipated improvements in air quality, such that we can exploit annual changes in housing prices surrounding the nonattainment status designation as an event study.[34] Here, we consider the relationship between nonattainment status and tract-level changies in $PM_{2.5}$ and housing prices as the central relationships of interest, rather than the instrumented effect of changes in $PM_{2.5}$ on housing prices, given the nature of the event-study specification. Following Currie et al. (2020), we estimate an event-study model of the form:

$$y_{it} = \sum_{t=2000}^{t=2010} \beta_t \left(\mathbf{1}[Nonattain_i] \times \mathbf{1}[year_t \geq 2005]\right) + \mathbb{X}_i'\gamma + \rho_t + \varepsilon_{it} \tag{21}$$

where y_{it} reflects the housing price index for tract i in year t. This is regressed on a series of interaction terms indicating whether the tract is in an area designated as nonattainment for the NAAQS standard ($\mathbf{1}[Nonattain_i] = 1$) interacted with a dummy for each year before and after the regulations went into place. Rather than interact these terms with an indicator for whether the tract is in an inelastic or elastic market to understand the potentially mediating role of housing supply, we estimate 21 separately for tracts in inelastic and elastic markets, as well as all tracts in the sample. We include state-year fixed effects ρ_t and cluster standard errors on county.[35] The coefficients of interest, β_t, compares the housing price changes of tracts that were newly regulated under the $PM_{2.5}$ standard to those that that were in compliance, before and after the regulations went into place. The identifying assumption is that the housing prices in newly regulated tracts would have trended similarly to the unregulated tracts in the absence of the standards. To address any possible pre-trends, we again weight observations by the weights produced in a modified version

[34]We cannot conduct a similar exercise for tract-level changes in measures of population sizes (density, number of housing units, etc.) because there do not exist reliable, annual estimates of these characteristics at the tract level.

[35]State-year fixed effects are intended to absorb any state-level changes that coincide with the introduction of the new standards.

of the matching process described for the primary analysis. Here, we match control (attainment) tracts to treated (nonattainment) tracts on state as well as on their 2005-level HPI (indexed to 2000). We conduct this matching process separately for tracts in inelastic and elastic markets when we estimate regression coefficients in the split sample.

Figures 6 and 7 show the event-study coefficient estimates from equation 21, for all tracts in the sample (Figure 6) and separately by metro-level elasticity (Figure 7). Visually, we see little evidence of differential trends in housing prices in the years leading up to the new standards. Across all tracts in the sample, housing prices appear to increase following the implementation of these standards in 2005. However, figure 7 indicates that this effect is entirely driven by tracts in inelastic metro areas. There is no visual evidence of an increase in housing prices in newly regulated tracts in elastic metro areas.

In a similar spirit as Currie et al. (2020), our regression coefficients are estimated from the difference-in-difference analog to equation 21:

$$y_{it} = \beta_0 + \beta_1 \left(\mathbf{1}[Nonattain_i] \times \mathbf{1}[year_t \geq 2005]\right) + \beta_2 \left(\mathbf{1}[Nonattain_i]\right) + \mathbb{X}_i'\gamma + \rho_t + \varepsilon_{it} \tag{22}$$

Here, β_1 provides an estimate of the average difference in housing prices in the five years after the standards were implemented relative to the five years before, comparing nonattainment and attainment tracts. Table C5 reports the estimated coefficients in all tracts (columns 1 and 4), tracts in elastic metros (columns 2 and 5) and tracts in inelastic metros (columns 3 and 6). As indicated by the event-study figures, the reduced-form effect of nonattainment status on housing prices is substantial, but only in tracts in inelastic metros, where nonattainment designation yields about a 24 percent increase in housing prices.

A.2 Alternative weighting schemes

The primary estimates weight tract-level observations by the weights produced in the nearest neighbor matching exercise where attainment tracts are matched to nonattainment tracts on the 1995 HPI and the 1990-2000 change in log population density. Unlike the difference-in-differences specification above, the central estimates do not conduct this matching exercise separately in inelastic and elastic tracts. When investigating the potentially distinct effect of NAAQS-induced $PM_{2.5}$ reductions on tract-level outcomes across inelastic and elastic metro areas, it might be more appropriate to estimate attainment tracts' propensity for treatment *within* their given housing supply group. Nonattainment tracts in inelastic markets might differ from their attainment counterparts in ways that are distinct from how nonattainment and attainment tracts differ in elastic markets. Thus, we reestimate the primary analysis, but apply weights produced in a PSM exercise where attainment and nonattainmnet tracts are matched in exactly the same method as before, but within their given metropolitan-area housing supply group (i.e., elastic or inelastic).

Table C6 shows the central estimates of equation 2, instrumenting for the change in $PM_{2.5}$ with nonattainment status, using alternative weighting schemes. The estimates produced when separately matching attainment and nonattainment tracts in elastic and inelastic markets (columns 3 and 7) are quite similar to those produced when matching all tracts (columns 2 and 6). Of course, if nonattainment status were truly randomly assigned, none of these considerations would be relevant, and the matching exercise would have no substantive impact on the estimates. Indeed, weighting by the initial number of tract housing units (columns 4 and 8) or omitting weights entirely (columns 1 and 5) produces extremely similar estimates, indicating that the choice of weighting scheme does not substantively affect the conclusions.

A.3 County-level analysis

Census tract boundaries are designed and modified to have relatively consistent populations to one another and across time, making it difficult to detect changing quantity margins within individual Census tracts. To address this, our tract-level data set is constructed using consistent 2010 Census tract boundaries, and we consider the change in the natural log of a tract's population density as the primary outcome variable capturing quantity movements rather than outcomes like the change in the log of total housing units or population head counts, which are likely more prone to measurement error associated with imputation to the consistent 2010 tract boundaries. Still, we conduct the analysis at the county level to ensure that quantity estimates are not affected by this specification decision.

Our county-level analysis proceeds similarly as our tract-level analysis. We estimate the modified version of equation 2 over the 2000-2010 period:

$$\Delta y_i = \beta_0 + \beta_1 \left(\Delta PM2.5_i \times \mathbf{1}[in_i = 0]\right) + \beta_2 \left(\Delta PM2.5_i \times \mathbf{1}[in_i = 1]\right) + \mathbb{X}_i'\gamma + \delta_r + \varepsilon_i \tag{23}$$

where i now indexes county. We include the same vector of 2000-level covariates ($\mathbb{X}_i'$) as before. Rather than include Census division fixed effects, we follow the county-level analysis in Chay and Greenstone (2005) and include region fixed effects, δ_r. The two main outcome variables include the county's HPI in 2010 (indexed to 2000) and the change in the natural log of housing units. We weight all observations by the number of housing units in 2000.[36]

In order to bifurcate tracts based on the elasticity of local housing supply, our tract-level analysis uses the Saiz (2010) and Baum-Snow and Han (2023) measures of local housing supply. Counties have a much larger geographic footprint than Census tracts, and typically include multiple metropolitan areas, and thus we rely on alternative methods for bifurcating counties into elastic and inelastic markets. We use three primary methods for defining these categories.

First, we rely on the historical groupings of states defined by Ganong and Shoag (2017), which

[36]The pre-trends in housing prices and housing units are balanced across attainment and nonattainment counties in our sample. Weighting by the weights produced in propensity score matching has little quantitative impact on the estimates.

categorize states as having historically high or low levels of regulatory constraints to construction. Their measure of a state's historical tendency to regulate land use is based on the number of land use cases per capita around 1965. We classify counties as "inelastic" if they are in high-regulation states, and "elastic" if they are in low-regulation states. This leaves a sample of 2,398 county-level observations with non-missing 2010 HPI values.

Second, we categorize counties as "inelastic" if they are located in states along the coasts, and "elastic" if they are in states in the South and Sunbelt of the United States. Other work has documented that housing supply is relatively more elastic in the latter group compared to the former (Glaeser and Tobio, 2007; Glaeser et al., 2006). We omit the "heartland" and central U.S. from this sample, leaving a sample of 1,170 county-level observations. The states that compose the groupings for these first two methods are listed in Table C4.

Finally, we create a county-level measure of housing supply elasticity based on the measures provided by Saiz (2010) and Baum-Snow and Han (2023). A county's elasticity is defined as follows:

$$\text{County elasticity} = \left(\frac{\text{avg. tract-level elasticity in county}}{\text{avg. tract-level elasticity in MSA}} \right) \times (\text{MSA-level elasticity})$$

Such that the county elasticity reflects a combination of the elasticity measures within its metropolitan areas and Census tracts. We then define a county as "inelastic" if it is in the most inelastic quartile of counties, and "elastic" otherwise. This yields a much smaller sample than the other two categorizations (413 observations), as it omits all counties without large metropolitan areas. Still, these 413 counties represented almost 60 percent of the U.S. population in 2000.

Table C7 shows central estimates for county-level price and quantity responses to NAAQS-induced declines in average annual $PM_{2.5}$ concentrations between 2000 and 2010. Across all methods for defining "inelastic" versus "elastic" counties, price responses appear larger in more constrained markets. For example, column 1 implies that a 1-unit decline in $PM_{2.5}$ concentrations between 2000-2010 yielded about a 3.5 percent increase in housing prices in counties in high-regulation (inelastic) states, as defined by Ganong and Shoag (2017), compared to a statistically insignificant 1.7 percent increase in housing prices in low-regulation (elastic) states. Quantity responses are much less consistent across specifications, but tend to indicate that pollution reductions yield larger increases in housing units in counties in less constrained (and hence more elastic) markets. In many specifications, NAAQS-induced declines in $PM_{2.5}$ concentrations yield *declines* in housing units in more constrained markets. This could be the case for a number of reasons. If price increases are so large that they thwart future developments, the quantity response we do see could pick up both the direct effects of pollution reductions on demand as well as the indirect effects driven by these price responses. If the new standards suppressed economic activity in local communities, we might also expect declines in local population (and hence reduced demand for new housing units).

Consistent with the estimates produced by the primary empirical strategy, these results indicate that housing prices are more responsive to pollution reductions in places defined by relatively inelastic housing markets. This again indicates that evaluating MWTP based on price changes alone could yield different estimates depending on the elasticity of the market considered.

B Model estimation details

B.1 Model derivation

The total number of workers in place j is given by (equation 6):

$$N_j = N_{total} \frac{\exp\left(W_j + S_j - \bar{R}\right) N_j^{-\rho_j}}{\sum_k \exp\left(W_k + S_k - R_k\right)}$$

Now, we can write (log) population, wages and housing prices as functions of amenity value S_j:

- Population (equation 7):

$$\ln N_j = \frac{1}{1+\rho_j+\alpha}(A_j + S_j - \bar{R}) + C_1$$

- Wages (equation 8):

$$W_j = \frac{1+\rho_j}{1+\rho_j+\alpha} A_j - \frac{\alpha}{1+\rho_j+\alpha}(S_j - \bar{R}) - C_2$$

- Housing prices (equation 9):

$$R_j = \frac{\rho_j}{1+\rho_j+\alpha}(A_j + S_j) + \frac{1+\alpha}{1+\rho_j+\alpha}\bar{R} + C_3$$

where C_1, C_2, and C_3 are constants.

To arrive at these three expressions, we take the log of equation B.1:

$$\ln N_j = \left(W_j + S_j - \bar{R}\right) - \rho_j \ln N_j + \ln\left(\frac{N_{total}}{\sum_k \exp\left(W_k + S_k - R_k\right)}\right)$$

Let $C = \ln\left(\frac{N_{total}}{\sum_k \exp(W_k + S_k - R_k)}\right)$:

$$\ln N_j = \left(W_j + S_j - \bar{R}\right) - \rho_j \ln N_j + C$$

$$\rightarrow$$

$$(1+\rho_j)\ln N_j = W_j + S_j - \bar{R} + C$$

$$\rightarrow$$

$$\ln N_j = \frac{1}{1+\rho_j}\left(W_j + S_j - \bar{R} + C\right)$$

Inverse labor demand is $W_j = A_j - \alpha \ln N_j$. Plugging this in above:

$$\ln N_j = \frac{1}{1+\rho_j}\left(A_j - \alpha \ln N_j + S_j - \bar{R} + C\right)$$
$$\rightarrow$$
$$\ln N_j = -\frac{\alpha}{1+\rho_j}\ln N_j + \frac{1}{1+\rho_j}\left(A_j + S_j - \bar{R} + C\right)$$
$$\rightarrow$$
$$\frac{1+\rho_j+\alpha}{1+\rho_j}\ln N_j = \frac{1}{1+\rho_j}\left(A_j + S_j - \bar{R} + C\right)$$
$$\rightarrow$$
$$\ln N_j = \frac{1}{1+\rho_j+\alpha}\left(A_j + S_j - \bar{R}\right) + C_1$$

Which is the expression in equation 7, where $C_1 = \frac{1}{1+\rho_j+\alpha}C$.

Now, plugging in this expression for $\ln N_j$ into the equation $W_j = A_j - \alpha \ln N_j$:

$$W_j = A_j - \alpha\left(\frac{1}{1+\rho_j+\alpha}\left(A_j + S_j - \bar{R} + C\right)\right)$$
$$\rightarrow$$
$$W_j = \frac{1+\rho_j}{1+\rho_j+\alpha}A_j - \frac{\alpha}{1+\rho_j+\alpha}(S_j - \bar{R}) - C_2$$

Which is the expression in equation 8, where $C_2 = -\frac{\alpha}{1+\rho_j+\alpha}C$.

Finally, plugging in the expression $\ln N_j$ into the equation $R_j = \bar{R} + \rho_j \ln N_j$:

$$R_j = \bar{R} + \rho_j\left(\frac{1}{1+\rho_j+\alpha}\left(A_j + S_j - \bar{R} + C\right)\right)$$
$$\rightarrow$$
$$R_j = \frac{\rho_j}{1+\rho_j+\alpha}\left(A_j + S_j\right) + \frac{1+\alpha}{1+\rho_j+\alpha}\bar{R} + C_3$$

Which is the expression in equation 9, where $C_3 = \frac{\rho_j}{1+\rho_j+\alpha}C$.

Taking the long difference of equations 7, 8, and 9 over time, assuming that C_1, C_2, and C_3 are time-invariant:[37]

- Population:

$$\Delta \ln N_j = \frac{1}{1+\rho_j+\alpha}(\Delta A_j + \Delta S_j + \Delta \bar{R})$$

- Wages:

$$\Delta W_j = \frac{1+\rho_j}{1+\rho_j+\alpha}\Delta A_j - \frac{\alpha}{1+\rho_j+\alpha}(\Delta S_j - \Delta \bar{R})$$

[37]We have omitted time subscripts in these expressions for brevity, but we assume that only W_j, N_j, A_j, S_j, R_j, and $\bar{R}$ may vary across time. All parameters with a Δ should have a time subscript.

- Housing prices:
$$\Delta R_j = \frac{\rho_j}{1+\rho_j+\alpha}(\Delta A_j + \Delta S_j) + \frac{1+\alpha}{1+\rho_j+\alpha}\Delta \bar{R}$$

Let productivity A_j and amenity value S_j be linear functions of local pollution concentrations X_j:

$$A_j = \varphi_0 + \varphi_1 X_j + \mu_j$$
$$S_j = \gamma_0 + \gamma_1 X_j + \nu_j$$

Taking the long difference of the above equations over time, letting φ_0 and γ_0 be time-invariant produces equations 13 and 14:

$$\Delta A_j = \varphi_1 \Delta X_j + \tilde{\mu_j}$$
$$\Delta S_j = \gamma_1 \Delta X_j + \tilde{\nu_j}$$

Plugging these equations into the long difference expressions for population, wages, and housing prices, above, we arrive at equations 15, 16, and 17.

B.2 Parameterizing the model

To reduce the number of paramaters to estimate, we rely on estimates from the literature and initial wages in the data to parameterize α. We also plug in a value for $\Delta \bar{R}$ using the average change housing prices observed in the data. Below, we outline the construction of these variables.

We are interested in estimating $\alpha = \frac{\Delta W_j}{\Delta \ln N_j}$, or $\alpha = \frac{\Delta W_j}{\% \Delta N_j}$ so we must first translate the elasticity of local labor demand, η^{LD}, into a semi-log elasticity, α. To do this, consider the following:

$$\frac{1}{\eta^{LD}} = \frac{\% \Delta W}{\% \Delta N}$$
$$\Rightarrow \frac{1}{\eta^{LD}} = \frac{\frac{\Delta W}{W}}{\% \Delta N}$$
$$\Rightarrow \frac{1}{\eta^{LD}} = \frac{\Delta W}{\% \Delta N} \cdot \frac{1}{W}$$
$$\Rightarrow \frac{1}{\eta^{LD}} = \alpha \cdot \frac{1}{W}$$
$$\Rightarrow \alpha = \frac{1}{\eta^{LD}} \cdot W$$

Estimates of the short-run, own-wage elasticity of labor demand ($\eta^{LD} = \frac{\% \Delta N}{\% \Delta W}$) range (in absolute value) from about 0.15 to 0.75, and center around 0.5.[38] As seen in Table B1, the average annual wage across U.S. counties in the sample (those with non-missing HPI values) was \$48,420 in 2000 (in 2018 dollars).[39] Letting η^{LD}=0.5 and plugging in this initial wage W from the data, we arrive at the central value for α used to estimate the model: $\alpha = \frac{48.4}{0.5} = 96.8$ (in thousands).[40]

We estimate $\Delta\bar{R}$ using the average change housing prices observed in the data. The change in an individual county j's housing price (ΔR_j) is given by:

$$\Delta R_j^{2000-2010} = \left(R_j^{2000} \times \frac{HPI_j^{2010}}{100} \right) - R_j^{2000}$$

Where HPI_j^{2010} is county j's housing price index in 2010 (indexed such that 2000=100). We then take the weighted average of ΔR_j across all counties in the sample to estimate $\Delta\bar{R}$, where observations are weighted by the number of housing units in the county in 2000. As seen in Table B1, this value is 68.79 for all counties in the sample.

[38]See p.101 here

[39]Data on wages are retrieved from the Quarterly Census of Employment and Wages, county high-level annual data sets. We inflate all wage and price data to 2018 dollars using the January CPI-U. The average across counties is weighted by the number of housing units in 2000.

[40]The results are insensitive to a range of estimates for α based on an own-wage elasticity of labor demand between 0.15 and 0.75.

Table B1: Summary statistics for primary county-level outcome & independent variables used in model estimation

	(1) Mean	(2) SD	(3) p25	(4) p50	(5) p75
Full sample: (N=2,399)					
$PM_{2.5}$ concentration, 2000	12.06	3.14	9.91	11.89	14.13
Δ $PM_{2.5}$, 2000-10	-2.60	1.67	-3.58	-2.51	-1.42
Average annual pay ($1,000s), 2000	48.42	12.31	39.35	46.57	55.22
Δ Average annual pay ($1,000s), 2000-10	1.52	3.35	0.15	1.65	3.04
Δ ln(housing units), 2000-10	8.66	11.06	1.58	6.27	13.91
Median home value ($1,000s), 2000	184.95	92.68	123.64	159.91	225.40
Δ Housing price ($1,000s), 2000-10	68.79	68.82	27.23	45.52	88.07
Elastic counties (low regulation): (N=1,393)					
$PM_{2.5}$ concentration, 2000	11.35	2.67	9.80	11.63	13.29
Δ $PM_{2.5}$, 2000-10	-1.98	1.45	-3.15	-1.86	-0.96
Average annual pay ($1,000s), 2000	44.68	10.17	36.83	42.83	50.93
Δ Average annual pay ($1,000s), 2000-10	1.47	3.74	-0.21	1.59	3.33
Δ ln(population), 2000-10	10.47	11.95	2.49	8.31	18.00
Median home value ($1,000s), 2000	141.59	47.36	111.16	132.74	164.31
Δ Housing price ($1,000s), 2000-10	36.77	40.71	22.49	32.40	46.69
Inelastic counties (high regulation): (N=1,002)					
$PM_{2.5}$ concentration, 2000	12.50	3.34	9.97	12.27	14.75
Δ $PM_{2.5}$, 2000-10	-2.98	1.68	-4.01	-2.81	-1.90
Average annual pay ($1,000s), 2000	50.71	12.86	41.72	48.80	57.72
Δ Average annual pay ($1,000s), 2000-10	1.49	2.97	0.32	1.69	2.82
Δ ln(population), 2000-10	7.51	10.31	1.41	5.47	11.33
Median home value ($1,000s), 2000	212.65	103.59	134.80	186.49	275.47
Δ Housing price ($1,000s), 2000-10	88.66	74.57	33.06	63.73	131.43

Summary statistics are weighted by the number of housing units in the county in 2000. All price and wage values were adjusted to 2018 inflation-adjust dollars using the January CPI-U. Population changes have been multiplied by 100 for ease of interpretation. Δ Housing price is calculated using the 2010 HPI and 2000-level median home values, as described in text. Counties are defined as elastic if they are in "low-regulation" states and inelastic if they are in "high-regulation" states, as defined by Ganong and Shoag (2017).

B.3 Derivation of the GMM estimator

To derive the GMM estimator, first let the error term in equation 15, 16, 17 be defined as ξ_j^n, ξ_j^w, ξ_j^r:

$$\xi_j^n = \frac{\tilde{\mu_j} + \tilde{\nu_j}}{1 + \rho + \alpha}$$

$$\xi_j^w = \frac{(1 + \rho)\tilde{\mu_j} - \alpha\tilde{\nu_j}}{1 + \rho + \alpha}$$

$$\xi_j^r = \frac{\rho(\tilde{\mu_j} + \tilde{\nu_j})}{1 + \rho + \alpha}$$

Let there be a vector of instruments, $\mathbf{Z} = \begin{bmatrix} 1 & Z_1 & Z_2 \end{bmatrix}'$, that is mean independent of $\tilde{\mu}_j$ and $\tilde{\nu}_j$, such that the expectation of the error term is mean zero conditional on the instrument:

$$E[\tilde{\mu}_j | \mathbf{Z}] = 0 \tag{24}$$

$$E[\tilde{\nu}_j | \mathbf{Z}] = 0 \tag{25}$$

Recall that $\xi_j^n = \frac{\tilde{\mu_j} + \tilde{\nu_j}}{1 + \rho_j + \alpha}$, $\xi_j^w = \frac{(1 + \rho_j)\tilde{\mu_j} - \alpha\tilde{\nu_j}}{1 + \rho_j + \alpha}$, and $\xi_j^r = \frac{\rho_j(\tilde{\mu_j} + \tilde{\nu_j})}{1 + \rho_j + \alpha}$. This implies the following conditional moment restrictions:

$$E[\xi_j^d | \mathbf{Z}] = 0$$

$$E[\xi_j^w | \mathbf{Z}] = 0$$

$$E[\xi_j^r | \mathbf{Z}] = 0$$

To go from a conditional moment restriction to an unconditional moment restriction, let:

$$E[\xi_j^d \mathbf{Z}] = 0, d \in (n, w, r)$$

Combining these conditions, we have nine empirical moments:

$$\mathbf{m_j} = \begin{bmatrix} \xi_j^n \cdot \mathbf{Z} \\ \xi_j^w \cdot \mathbf{Z} \\ \xi_j^r \cdot \mathbf{Z} \end{bmatrix}$$

The orthogonality conditions are summarized as $E[\mathbf{m_j}] = 0$. The sample analog is:

$$\mathbf{g} = \frac{1}{J} \sum_{j=1}^{J} \mathbf{m_j}$$

The parameters to estimate are given by the following vectors:

$$\boldsymbol{\beta} = (\rho, \varphi_1, \gamma_1)$$

The two-step GMM estimator is implemented by furst estimating $\hat{\boldsymbol{\beta}}^0$ as followsL

$$\hat{\boldsymbol{\beta}}^0 = \arg\min_{\beta} \mathbf{g}'\mathbf{g}$$

This estimate is then used to form the following weight matrix:

$$\hat{W}^0 = \frac{1}{J}\sum_{j=1}^{J} \mathbf{m_j}(\hat{\boldsymbol{\beta}}^0) \cdot \mathbf{m'_j}(\hat{\boldsymbol{\beta}}^0)$$

Next, $\hat{\boldsymbol{\beta}}$ is re-estimated as follows:

$$\hat{\boldsymbol{\beta}}^{GMM} = \arg\min \mathbf{g}'(\hat{W}^0)^{-1}\mathbf{g}$$

C Additional tables

Table C2: Effect of $\Delta PM_{2.5}$ on prices and quantities, 2000-2010, by tract- and metro-level elasticity

	(1)	(2)	(3)	(4)
	2010 HPI (2000=100)		Δ ln(pop density), '00-10	
$\Delta PM_{2.5}$ x **Elastic** tract in elastic metro	-2.697	-3.038	-4.049***	-3.782***
	(2.716)	(2.674)	(1.107)	(0.818)
$\Delta PM_{2.5}$ x **Inelastic** tract in inelastic metro	-7.181***	-7.286***	0.363	-0.202
	(2.324)	(2.550)	(0.742)	(0.531)
$\Delta PM_{2.5}$ x Elastic tract in inelastic metro	-6.692***	-6.977***	-1.462	-1.568
	(2.369)	(2.547)	(1.388)	(1.010)
$\Delta PM_{2.5}$ x Inelastic tract in elastic metro	-2.802	-2.347	0.896	0.012
	(2.227)	(2.279)	(0.794)	(0.619)
P-val(In=Elastic)	0.000	0.000	0.000	0.000
Controls	-	✓	-	✓
Division FE	✓	✓	✓	✓
Observations	22,879	22,879	22,879	22,879

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by the weights produced in PSM, described in text. We instrument for change in $PM_{2.5}$ with nonattainment status. Tracts are defined as elastic or inelastic based on metropolitan elasticity in Saiz (2010) and tract-level elasticity in Baum-Snow and Han (2022). The outcome variable in columns 3 and 4 has been multiplied by 100 for ease of interpretation.
*** p<0.01, ** p<0.05, * p<0.1

Table C3: Effect of $\Delta PM_{2.5}$ on prices and quantities, 2000-2016, by metro-level elasticity
Omitting tracts proximate to coal plants

	(1)	(2)	(3)	(4)	(5)	(6)
	2016 HPI (2000=100)			Δ ln(pop density), 2000-2016		
$\Delta PM_{2.5}^{2000\text{-}16}$x **Elastic**	-6.513***	-5.319***	-0.146	0.039	-0.069	-0.676*
	(0.771)	(0.736)	(0.556)	(0.419)	(0.423)	(0.399)
$\Delta PM_{2.5}^{2000\text{-}16}$ x **Inelastic**	-8.594***	-7.811***	-3.920***	0.628	0.516	-0.170
	(0.694)	(0.663)	(0.528)	(0.383)	(0.385)	(0.358)
P-val(In=Elastic)	0.000	0.000	0.000	0.000	0.000	0.000
Controls	✓	✓	✓	✓	✓	✓
Division fixed effects	✓	✓	✓	✓	✓	✓
Sample	>5km	>10km	>25km	>5km	>10km	>25km
Observations	25,236	24,205	21,318	25,236	24,205	21,318

Robust standard errors are in parentheses. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by number of housing units in 2000. Change in $PM_{2.5}$ is instrumented with the change predicted by upwind coal plant closures. Tracts are defined as elastic or inelastic based on their metropolitan area's elasticity estimated in Saiz (2010). The outcome variable in columns 4, 5, and 6 has been multiplied by 100 for ease of interpretation. The final row indicates the sample used for the analysis, referring to the size of the "donut" around closed coal plants, below which tracts were dropped from the sample.
*** p<0.01, ** p<0.05, * p<0.1

Table C4: "Elastic" & "Inelastic" state categorization schemes

Ganong and Shoag (2017) categorization		**Coast/Sunbelt categorization**	
Elastic	*Inelastic*	*Elastic*	*Inelastic*
Low-regulation states	High-regulation states	Sunbelt states	Coastal states
Alabama	Arkansas	Alabama	California
Arizona	California	Arizona	Connecticut
Indiana	Colorado	Arkansas	Maine
Iowa	Connecticut	Florida	Massachusetts
Kansas	Delaware	Georgia	New Hampshire
Kentucky	Florida	Louisiana	New Jersey
Maine	Georgia	Mississippi	New York
Michigan	Idaho	Nevada	Oregon
Minnesota	Illinois	New Mexico	Pennsylvania
Mississippi	Louisiana	North Carolina	Rhode Island
Nebraska	Maryland	Oklahoma	Vermont
New Mexico	Massachusetts	South Carolina	Washington
North Carolina	Missouri	Tennessee	
North Dakota	Montana	Texas	
Oklahoma	Nevada		
South Carolina	New Hampshire		
South Dakota	New Jersey		
Tennessee	New York		
Texas	Ohio		
Utah	Oregon		
Virginia	Pennsylvania		
West Virginia	Rhode Island		
Wisconsin	Vermont		
Wyoming	Washington		

Table displays two of the methods in which counties are defined as "inelastic" or "elastic." The categorizations listed in the first two columns are based on states' historical tendencies to regulate land use as measured by Ganong and Shoag (2017). Those in the second two columns define states as "elastic" if they are in the Sunbelt, and "inelastic" if on the coasts. States in which all counties have missing HPI values are omitted in both categorization schemes.

Table C5: Reduced-form effect of nonattainment status on housing prices, diff-in-diff estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	HPI (2000=100)					
	All	Elastic	Inelastic	All	Elastic	Inelastic
Nonattain×Post	6.977	0.632	21.356***	6.416	-0.967	24.149***
	(9.154)	(6.676)	(7.631)	(3.967)	(1.807)	(5.084)
Controls	✓	✓	✓	✓	✓	✓
Year fixed effects	✓	✓	✓			
State-year fixed effects				✓	✓	✓
Observations	145,143	91,774	44,217	145,143	91,774	44,217

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by the weights produced in PSM, described in text.
*** p<0.01, ** p<0.05, * p<0.1

Table C6: Effect of $\Delta PM_{2.5}$ on prices and quantities, 2000-2010, alternative weighting schemes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	2010 HPI (2000=100)				Δ ln(pop density), 2000-2010			
$\Delta PM_{2.5}{}^{'00\text{-}10}$x **El**	-3.435	-2.604	-1.996	-3.553	-1.818**	-1.389**	-1.361*	-1.655***
	(2.406)	(2.448)	(2.484)	(2.436)	(0.730)	(0.676)	(0.698)	(0.567)
$\Delta PM_{2.5}{}^{'00\text{-}10}$x **In**	-7.727***	-7.082***	-6.858***	-7.611***	-0.674	-0.435	-0.484	-0.630
	(2.538)	(2.541)	(2.604)	(2.500)	(0.699)	(0.686)	(0.725)	(0.555)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓	✓	✓
Weighting	None	PSM	PSM2	Units	None	PSM	PSM2	Units
Observations	26,577	22,879	22,499	26,577	26,577	22,879	22,499	26,577

Standard errors, in parentheses, are clustered on county. Controls include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations in columns 1 and 5 are unweighted. Those in columns 2 and 6 are weighted by the weights produced in PSM, described in text. Those in columns 3 and 7 are weighted by the weights produced in PSM, separately matching attainment/nonattainment tracts in inelastic and elastic metros. Those in columns 4 and 8 are weighted by total housing units in 2000. We instrument for change in $PM_{2.5}$ with nonattainment status. Tracts are defined as elastic or inelastic based on their metropolitan area's elasticity estimated in Saiz (2010). The outcome variable in columns 5 through 8 has been multiplied by 100 for ease of interpretation.
*** p<0.01, ** p<0.05, * p<0.1

Table C7: Effect of $\Delta PM_{2.5}$ on prices and quantities, 2000-2010, county-level estimates

	(1)	(2)	(3)	(4)	(5)	(6)
	Low- vs. high-reg		Sunbelt vs. coasts		County-level elasticity	
	HPI	ΔUnits	HPI	ΔUnits	HPI	ΔUnits
$\Delta PM_{2.5}^{2000\text{-}10}$x **Elastic**	-1.746	0.823	2.473	-3.416***	-3.595*	-0.424
	(2.151)	(0.709)	(1.603)	(0.938)	(2.054)	(0.736)
$\Delta PM_{2.5}^{2000\text{-}10}$x **Inelastic**	-3.452**	1.179**	-5.800***	0.619	-5.358***	1.475**
	(1.518)	(0.585)	(1.410)	(0.626)	(1.832)	(0.618)
P-val(In=Elastic)	0.222	0.407	0.000	0.000	0.146	0.000
Controls	✓	✓	✓	✓	✓	✓
Region FE	✓	✓	✓	✓	✓	✓
Observations	2,398	2,398	1,170	1,170	413	413

Robust standard errors are in parentheses. Controls include the share of the county population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied. Observations are weighted by county-level housing units in 2000. We instrument for change in $PM_{2.5}$ with nonattainment status. The outcome variable in columns 2, 4, and 6 refers to the change in the natural log of housing units between 2000 and 2010. It has been multiplied by 100 for ease of interpretation.

*** p<0.01, ** p<0.05, * p<0.1