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

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Abstract

The hedonic valuation approach often estimates demand for amenities from housing prices. We show that when housing supply is elastic, increased demand is met through quantity expansions, attenuating price capitalization and biasing hedonic estimates downward. Consistent with this, we find that declines in $PM_{2.5}$ concentrations yield larger price effects in markets with inelastic housing supply and larger quantity effects in elastic markets. A spatial equilibrium model demonstrates that the traditional hedonic price coefficient reflects demand for an amenity attenuated by the supply elasticity. Incorporating elasticities into the hedonic framework increases the estimated benefits of $PM_{2.5}$ reductions by over 12 percent.

Keywords: hedonic valuation, air pollution, population mobility, housing, public policy

JEL Codes: H4, J18, Q5, Q53, R11

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1 Introduction

The hedonic valuation approach to estimating the economic benefits of non-market amenities such as environmental quality frequently relies on the housing market to infer the implicit price function of the amenity (Harrison and Rubinfeld, 1978; Smith and Huang, 1995; Chay and Greenstone, 2005; Bayer et al., 2009; Bento et al., 2015; Currie et al., 2015). In a partial equilibrium setting in which the quantity of housing is fixed, the responsiveness of housing prices to outward demand shifts induced by amenity improvements offers an appropriate estimate of the marginal benefits of the improvement. Indeed, implicit in many empirical applications of the canonical hedonic valuation model is the assumption that marginal willingness to pay (MWTP) for an amenity is fully capitalized into prices, or that supply is perfectly inelastic. However, in general equilibrium settings in which supply is elastic, the housing market may expand to accommodate increased demand (the 'quantity' effect). In this case, the capitalization of the amenity into housing prices (the 'price' effect) will be attenuated, and the standard hedonic price parameter will no longer serve as a sufficient statistic for MWTP. Rather, it will provide an underestimate of the true parameter.

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 implementation of the Clean Air Act's (CAA) $PM_{2.5}$ 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 housing prices in real terms and a 3 percent increase in its total population. Meanwhile, Atlanta experienced only a 5 percent increase in housing prices in real terms and a 24 percent increase in its total population. What role did local housing supply constraints play in mediating the relationship between local amenity shifts and price changes, and what does this imply for subsequent estimates of the benefits of air quality improvements? How can researchers estimate MWTP for amenity shifts in elastic-supply settings?

In this paper, we present evidence that plausibly exogenous improvements in air quality induced by the CAA yield larger price effects in inelastic-supply markets and larger quantity effects in elastic-supply markets, and we detail a novel method to incorporate supply elasticities into the hedonic framework. To isolate the causal relationship between air quality and local prices and population sizes, we exploit the introduction of the CAA's 1997 $PM_{2.5}$ NAAQS, which went into effect in 2005.[1] Following the implementation of these 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. We exploit differential pollution reductions induced by these regulations and heterogeneous supply elasticities across cities and neighborhoods to examine how supply constraints mediate both price and quantity effects.

Instrumenting for Census-tract-level changes in average $PM_{2.5}$ concentrations with area nonattainment status, we find that a 1-unit decline in average $PM_{2.5}$ concentrations induced by the CAA NAAQS yields about a 5.8 percent increase in local housing prices, as measured by the tract-level housing price index (HPI). This is equivalent to an increase of about $6,570 per home in 2000 dollars. Grouping Census tracts into eight bins of housing supply elasticity based on the estimates from Saiz (2010), we find that air quality improvements yield much larger housing price increases in the most inelastic-supply markets (an 8.7 percent increase) compared to the most elastic-supply markets (a statistically insignificant 2.5 percent decrease). In contrast, the largest quantity effects are observed in the most elastic-supply Census tracts. The same regulation-induced decline in $PM_{2.5}$ yields a 5.7 percent increase in population counts in the most elastic-supply housing markets, compared to a statistically insignificant 0.3 percent decrease in the most inelastic-supply

[1] Other research exploiting the introduction of new NAAQS regulations to understand their effects on air pollution concentrations, differential pollution exposure, and other outcomes include Bento et al. (2015); Jha et al. (2019); Sager and Singer (2022); Currie et al. (2023).

housing markets. Using neighborhood-level elasticity parameters from Baum-Snow and Han (2024) and examining within-labor market variation in price and quantity effects yields similar conclusions.

Our reduced-form evidence is consistent with the economic intuition that housing supply constraints mediate the relationship between demand shocks and housing prices. This indicates that price changes will not fully capitalize the benefits of amenity improvements in situations when quantities are not explicitly fixed. Motivated by this insight, we develop a simple Rosen-Roback-style model of spatial equilibrium (Rosen, 1979; Roback, 1982) that provides expressions for local housing prices and population sizes as functions of local levels of air pollution. The model enables us to interpret the coefficients from a standard hedonic regression in the presence of both price and quantity responses to changes in local amenities. Specifically, the model implies that when supply is perfectly inelastic, the standard hedonic price coefficient is a sufficient statistic for MWTP. However, in the presence of quantity margins (i.e., when supply is elastic), the coefficient from a standard hedonic model is the MWTP for the amenity improvement, attenuated in proportion to the elasticity of housing supply. Guided by the parameters in the model, we provide new estimates of MWTP that incorporate the local housing supply elasticity measured at both the metropolitan statistical area (MSA)- (Saiz, 2010) and the Census-tract level (Baum-Snow and Han, 2024). This approach produces MWTP estimates of about \$7,360 to \$14,384 per unit of pollution reduction (per household), which is on the order of 12 to 117 percent larger than the estimate produced by the standard hedonic approach (\$6,570 per household). Therefore, incorporating supply elasticities into the hedonic regression framework substantially increases the estimated benefits of environmental improvements in elastic-supply settings.

This paper makes two important contributions to the literature. First, we build on the canonical work of Chay and Greenstone (2005) – *Does Air Quality Matter? Evidence from the Housing Market* – and subsequent literature exploiting the CAA regulatory structure to study air pollution (Grainger, 2012; Bento et al., 2015; Jha et al., 2019; Sanders et al., 2020; Sager and Singer, 2022; Bishop et al., 2023; Currie et al., 2023), by providing quasi-experimental evidence that housing supply constraints influence how well housing prices capitalize local air quality improvements. Areas in which supply is more inelastic, due to regulatory constraints or geographic barriers to construction, experience the strongest price effects of regulation-induced pollution improvements. This is consistent with recent advances in the urban economics literature showing that housing supply constraints shape price effects and sorting behavior (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). Our reduced-form evidence indicates that places with relatively elastic housing markets may accommodate demand shifts via increases in housing supply, which may attenuate the price effects of such demand shifts. This implies that the elasticity of the market in question (typically housing) should be considered when estimating the MWTP for amenity improvements.

Second, we contribute to the extensive empirical and theoretical literature on hedonic valuation by adapting the framework to account for variation in housing supply elasticities. Many studies exploit the price capitalization of environmental improvements to infer the marginal benefits of these changes (Harrison and Rubinfeld, 1978; Smith and Huang, 1995; Chay and Greenstone, 2005; Bayer et al., 2009; Currie et al., 2015; Bento et al., 2015; Keiser and Shapiro, 2019; Sager and Singer, 2022), but implicit in this approach is the assumption that supply is perfectly inelastic. This assumption likely fails in general equilibrium settings when markets can expand to accommodate demand shifts. Prior work has raised other general equilibrium concerns, such as shifts in price functions over time and the impact of endogenous sorting on non-treated areas (e.g., Sieg et al., 2004; Kuminoff and Pope, 2014; Banzhaf, 2021).[2] Our paper advances this tradition by exam-

[2]For example, Sieg et al. (2004) provide a structural model demonstrating how individuals re-optimize in response to large amenity changes and find large differences between partial- and general-equilibrium

ining a new source of bias and explicitly incorporating a place-specific housing supply elasticity parameter into the traditional hedonic framework. In doing so, we present new evidence on how the price capitalization of pollution reduction varies with local housing supply constraints, and we detail a new method through which researchers can incorporate elastic housing supply — and the resulting quantity effect — into the hedonic valuation approach.

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 price and quantity effects in Sections 3 and 4, with reduced-form results detailed in Section 5. Section 6 presents a spatial equilibrium model for air quality improvements and new estimates of MWTP that incorporate the supply elasticity parameter. Section 7 concludes.

2 A stylized depiction of the housing market and amenity improvements

We first illustrate how the canonical hedonic model might underestimate the value of air quality improvements when housing stock can expand to absorb increased demand by offering a simple graphical depiction. This exposition is similar to that presented in Baum-Snow (2023). We build on this stylized example using a richer model of spatial equilibrium in Section 6.

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 (Quigley and Raphael, 2005; Saiz, 2010;

MWTP estimates in the case of sorting-induced endogenous local attribute changes. More recently, Banzhaf (2021) builds on Kuminoff and Pope (2014) and others to show that price changes associated with improved air quality include both amenity demand 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.

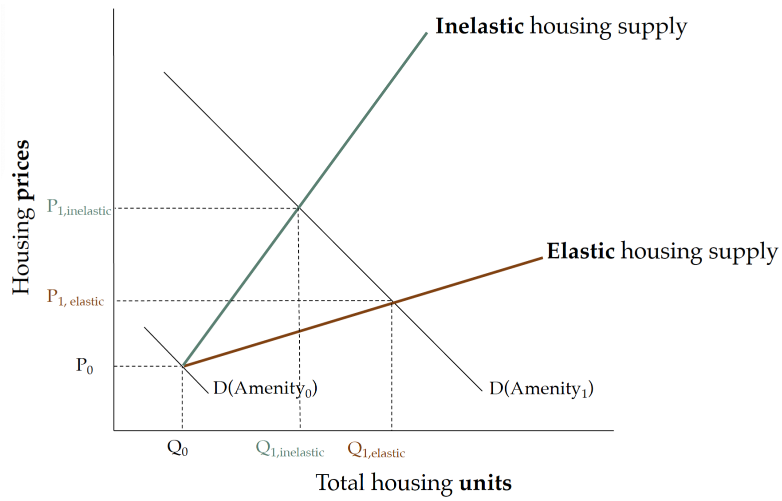
Gyourko and Molloy, 2015). At time $t = 0$, demand for these locations is given by D(Amenity$_0$), with price P_0 and quantity Q_0 in Figure 1.

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 — $Q_{1,\text{elastic}}$ reflects a larger outward shift in housing units than $Q_{1,\text{inelastic}}$. 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 the setting in which the typical hedonic method is assumed to take place.

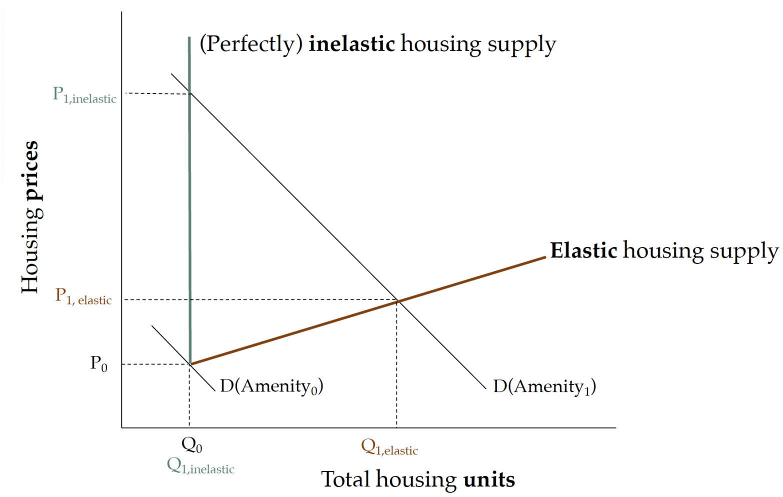
Consider Los Angeles, California, and Atlanta, Georgia. Both cities were in nonattainment areas based on the 1997 $PM_{2.5}$ NAAQS. Nonattainment status was announced in December of 2004 and took effect in 2005. Both cities experienced large improvements in air quality over the 2000 to 2010 period, in part thanks to this designation. Between 2000 and 2010, $PM_{2.5}$ concentrations fell by 31 percent in Los Angeles and by 26 percent in Atlanta. Los Angeles has many regulatory and geographic constraints that limit new residential construction, and thus it has quite inelastic housing supply. Atlanta, on the other hand, has relatively elastic housing supply.[3] Over the 2000–2010 decade, Los Angeles experienced a 72 percent increase in (real) housing prices and about a 3 percent increase in its total population. Meanwhile, Atlanta experienced only a 5 percent increase in (real) housing prices and about a 24 percent increase in its total population. Of course, these price and population trajectories are not solely reflective of the impact of

[3]In Saiz (2010), the estimated metro-level housing supply elasticity in Los Angeles is 0.63, compared to 2.55 in Atlanta.

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



(a)



(b)

Notes: This figure reflects a stylized depiction of supply and demand for two locations: one with inelastic housing supply (in teal), and one with elastic housing supply (in brown). An amenity improvement is reflected in the outward shift in demand from $D(Amenity_0)$ to $D(Amenity_1)$. Panel b is identical to panel a, but the inelastic housing market has perfectly inelastic housing supply.

regulation-induced air quality improvements, but the stark contrast across the two places is consistent with the basic economic logic illustrated in Figure 1.

This is a highly stylized exposition of supply and demand, but it illustrates the important role that housing supply elasticities play in determining how well amenity changes are capitalized into housing prices, and thus how well price changes reflect MWTP. While taste-based sorting may result in different estimates of MWTP across place, basic economic theory offers an alternative explanation: supply constraints dictate the relative price and quantity effects of demand shifts. In places with perfectly inelastic supply, demand shifts will be perfectly capitalized into housing prices. As supply is more elastic, housing stock will expand to accommodate increased demand, attenuating the price capitalization. Even 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 will produce larger estimates in the inelastic housing market compared to the elastic housing market. By neglecting the demand shift that manifests as an increase in the quantity margin, the evaluation would underestimate the true MWTP in more elastic housing markets.

3 Data

Our empirical analysis leverages changes in tract-level air pollution, housing prices, and population counts in over 25,000 metropolitan-area Census tracts over the 2000-2010 period. We construct a data set of tract-level characteristics between 2000 and 2010 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. Three of the major data projects offering these satellite-derived pollution estimates include Meng et al. (2019), Di et al. (2016), and van Donkelaar et al. (2019). We aggregate the gridded air pollution data from van Donkelaar et al. (2019) to the Census-tract level, although our conclusions are insensitive to using alternative data sets. 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.

3.2 Housing price, population, and demographic data

We combine the air quality data with local housing, population, 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 2010 (where 2000 is the base year of the index) and the long-difference change in the natural log of the tract's population between 2000 and 2010. Population counts in 2000 and 2010 are based on the decennial Census, retrieved from the Social Explorer database.[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 holding the underlying quality of housing stock relatively constant. Because Census tract boundaries are modified (and new tracts defined) periodically to account for population adjustments, we assign all characteristics to Census tracts using consistent 2010 tract boundaries. Baseline tract-level covariates are based on estimates from the 2000 Census, retrieved from the Social Explorer database.

[4] We consider the change in population counts as our primary measure of quantity adjustments for consistency with the model described in Section 6, rather than the stylized depiction in Section 2. Supply constraints may promote increased crowding within existing housing units, which could differentially influence population counts and the number of housing units. Our conclusions are robust to instead considering the change in housing units as well as the change in population density, following Banzhaf and Walsh (2008) and Greenstone and Gallagher (2008). They are also robust to transforming the price index into a variable reflecting differences in logs, as well as transforming the population change to reflect a percent change.

3.3 Housing supply restriction and elasticity data

We incorporate various measures of housing supply constraints defined at both the tract- and metropolitan-area levels. 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.[5] We limit our sample to metro-area tracts in the contiguous United States with non-missing Saiz (2010) elasticity estimates (and non-missing HPI estimates), resulting in a sample of 25,843 Census tracts housing over one-third of the U.S. population. Elasticity estimates range from the most inelastic of 0.6 (Miami, Florida) to the most elastic of 5.45 (Wichita, Kansas). To elucidate how price capitalization varies across elasticity, we group tracts into eight equal-sized bins based on their Saiz (2010) elasticities. Each bin includes about 3,230 Census tracts.

We supplement this metro-level measure with tract-level housing supply elasticity estimates from Baum-Snow and Han (2024).[6] These estimates are identified using labor demand shocks in commuting destinations from residential locations. 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 metro areas rather than across. To provide a

[5] As discussed in Saiz (2010), unlike predetermined geographic features such as oceans, lakes, and mountains, zoning and other land-use regulations are endogenous to prices. Saiz (2010) thus endogenizes the regulatory component of housing supply elasticity in the model used to estimate elasticities. The measure of regulatory intensity is based on the Wharton Residential Land Use Regulation Index, constructed by Gyourko et al. (2008). This regulatory index provides an aggregate measure of the restrictiveness of local land use regulations 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.

[6] Baum-Snow and Han (2024) offer several elasticity estimates. We use the authors' "preferred" quadratic finite mixture model estimates. We use the elasticity estimates from the 2021 working paper version, which produces nearly identical groupings of tracts as the estimates in the published version of the paper.

tract-level measure of housing supply elasticity that is comparable across metropolitan areas, we take the simple average of metro-level (Saiz, 2010) and tract-level (Baum-Snow and Han, 2024) supply estimates, but our conclusions are similar when using more sophisticated methods of combining these parameters.[7] This value ranges from the most inelastic of 0.25 (Census tract 186.10 in San Diego, California) to the most elastic of 3.17 (Census tract 100.04 in Wichita, Kansas). We again group tracts into eight equal-sized bins based on this average value.

3.4 Summary statistics and an application to air quality improvements

Table 1 presents the central summary statistics for the 25,843 Census tracts that form the basis of our analysis. Across all tracts in the sample, the average $PM_{2.5}$ concentration was $13\mu g/m^3$ in 2000, and the average change over the 2000–2010 decade was a decline of $3\mu g/m^3$. Over this decade, home prices increased by an average of 32.7% and population counts increased by an average of 10.8 log points. Table 1 also presents statistics in each of the eight bins of metro-level housing supply elasticity, based on the measure in Saiz (2010). Bin 1, the most inelastic group of Census tracts, started the period with the highest average concentrations of $PM_{2.5}$ and experienced the largest subsequent declines over the decade. Column 6 shows the average metro-level elasticity in each bin, while column 7 describes the average metro/tract-level elasticity taken by simple mean of the measures from Saiz (2010) and Baum-Snow and Han (2024).

In Section 2, we showed that outward demand shifts should yield larger price growth in markets with more inelastic supply and larger population growth in markets with more elastic supply. While the statistics in Table 1 are purely descriptive, they are consistent with this stylized exposition. Housing prices tended to grow more in the most inelastic housing markets, while population counts tended to grow more in the most elastic hous-

[7] The tract-level elasticity estimates from Baum-Snow and Han (2024) are smaller in magnitude than those in Saiz (2010). This results from differences in the study periods as well as the nature of demand shocks used for identification. The elasticity parameters in Saiz (2010) are estimated over the 1970–2000 period, while those in Baum-Snow and Han (2024) are estimated between 2000 and 2010.

Table 1: Summary statistics for primary outcome & independent variables

	(1) $PM_{2.5}$ conc. (2000)	(2) Med. home value (2000)	(3) $\Delta PM_{2.5}$ 2000–10	(4) 2010 HPI (2000=100)	(5) Δln(pop) 2000-10	(6) Metro-level elasticity	(7) Metro/tract elasticity
Full sample: (N=25,843)							
mean	13.0	113,260	-3.0	132.7	10.8	1.6	0.9
(sd)	(3.4)	(63,842)	(1.8)	(28.8)	(27.7)	(0.9)	(0.5)
8 bins of Saiz (2010) elasticity							
1 (most	15.0	161,813	-4.4	155.8	4.8	0.6	0.4
inelastic)	(4.9)	(87,929)	(2.5)	(25.6)	(19.0)	(0.0)	(0.1)
2	12.7	147,508	-2.9	138.4	7.4	0.8	0.5
	(2.5)	(80,922)	(1.3)	(24.4)	(24.3)	(0.0)	(0.1)
3	13.1	97,863	-3.6	126.8	12.3	1.0	0.6
	(4.5)	(41,315)	(2.3)	(20.4)	(28.0)	(0.1)	(0.1)
4	12.2	105,208	-2.8	121.7	7.9	1.3	0.8
	(2.7)	(47,300)	(1.6)	(34.8)	(24.6)	(0.1)	(0.1)
5	12.7	113,858	-3.5	148.1	9.8	1.6	0.9
	(2.6)	(54,065)	(1.1)	(31.5)	(27.5)	(0.0)	(0.1)
6	12.2	90,808	-2.5	129.9	15.0	2.0	1.2
	(3.4)	(40,335)	(1.7)	(21.1)	(33.5)	(0.2)	(0.1)
7	14.0	92,350	-2.6	117.3	14.1	2.5	1.4
	(2.4)	(43,426)	(1.4)	(20.7)	(29.0)	(0.1)	(0.1)
8 (most	12.2	83,502	-1.6	120.0	17.9	3.4	1.9
elastic)	(2.2)	(35,861)	(1.2)	(16.1)	(33.2)	(0.6)	(0.3)

Median home value is based on Census estimates retrieved from Social Explorer and is reported in 2000-level (nominal) dollars. 2000-level $PM_{2.5}$ concentrations and its change are based on the values reported in van Donkelaar et al. (2019). The 2010 housing price index (HPI) is retrieved from FHFA. Change in ln(population) is based on estimates from the Census, retrieved from the Social Explorer database, and is multiplied by 100 for ease of interpretation. Metro-level elasticity refers to the elasticity derived in Saiz (2010), while metro/tract elasticity refers to the average elasticity across Saiz (2010) and Baum-Snow and Han (2024).

ing markets over the 2000 to 2010 period. One goal of our empirical analysis is to explore the extent to which these diverging growth patterns are attributable to CAA-induced reductions in $PM_{2.5}$ concentrations.

4 Methodological approach

In this section, we outline our approach to estimating the relationship between regulation-induced air quality improvements (i.e., declines in $PM_{2.5}$ concentrations) and subsequent price and population growth. Our general approach follows Chay and Greenstone (2005) and subsequent research by instrumenting for mid-period CAA nonattainment status to estimate the effect of air quality improvements on local outcomes. Unlike existing literature, the central goal of our empirical analysis is to use this framework to examine heterogeneity in price and quantity effects across places with varying housing supply elasticities.

We begin with the following long-difference equation:

$$\Delta y_j = \beta_0 + \beta_1 \Delta PM2.5_j + \mathbb{X}_j' \gamma + \delta_d + \varepsilon_j \tag{1}$$

Where Δy_j is the long-difference change in the outcome variable in tract j between 2000 and 2010, $\Delta PM2.5_j$ is the long-difference change in average $PM_{2.5}$ concentrations in tract j over the same period, $\mathbb{X}_j'$ reflects tract-level covariates, and δ_d represents Census division fixed effects. We focus on two outcome variables: the tract's 2010 HPI (indexed to 2000, such that it reflects the percent change in housing prices), and the 2000–2010 change in the natural log of tract population. The inclusion of Census division fixed effects absorbs secular trends in price and population movements that differ across regions. Our conclusions are largely robust to alternative levels of geographic controls (e.g., region). 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. These covariates are meant to capture observable demographic, educational, economic, and housing market characteristics that might influence housing prices or population growth as well as pollution concentrations, although the point estimates are quite stable across specifications (i.e., omitting control variables). We cluster standard errors at the county level. When estimating equation 1 using Ordinary Least Squares (OLS), 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 housing price or population between 2000 and 2010, after conditioning on observable covariates.

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 $\Delta PM2.5_j$ with a binned value of the tract's housing supply elasticity, e_j. We allow for eight, equal-sized bins and estimate the following:

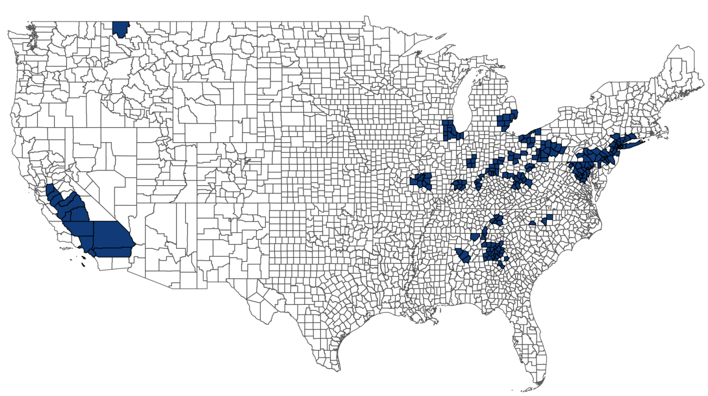
$$\Delta y_j = \sum_{q=1}^{8} \beta_q \left(\Delta PM2.5_j \times \mathbf{1}[e_j = q]\right) + \mathbb{X}_j' \gamma + \delta_d + \varepsilon_j \tag{2}$$

Tracts in the lowest quantile ($e_j = 1$) are the most inelastic and tracts in the highest quantile ($e_j = 8$) are the most elastic. The eight bins are collectively exhaustive of all Census tracts in the sample. Our central method for grouping tracts into bins relies on the metro-level elasticities in Saiz (2010). We also group tracts into eight equal-sized bins based on the average of this value and the tract-level elasticity estimated in Baum-Snow and Han (2024), as described in Section 3. The conclusions are insensitive to the number of quantiles, q. In equation 2, β_1 measures the relationship between a change in $PM_{2.5}$ concentrations and the outcome of interest in the most inelastic quantile, β_2 measures this relationship in the second-most inelastic quantile, etc., and β_8 measures this relationship in the most elastic quantile. Again, our outcomes of focus are the 2010 HPI and the 2000–2010 change in the natural log of the population. A comparison of the point estimates across bins reveals how the 'price' and 'quantity' effect of air quality improvements differs across places with varying housing supply constraints.

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 has been addressed using a wide variety of quasi-experimental solutions.[8] Following Currie et al. (2023) and others, 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, to isolate regulation-induced changes in $PM_{2.5}$ concentrations over the 2000–2010 decade. 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.[9] In December of 2004, EPA issued official designations for the 1997 $PM_{2.5}$ standards, classifying areas as 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, based on the estimates provided by van Donkelaar et al. (2019), is shown in Figure 3.

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

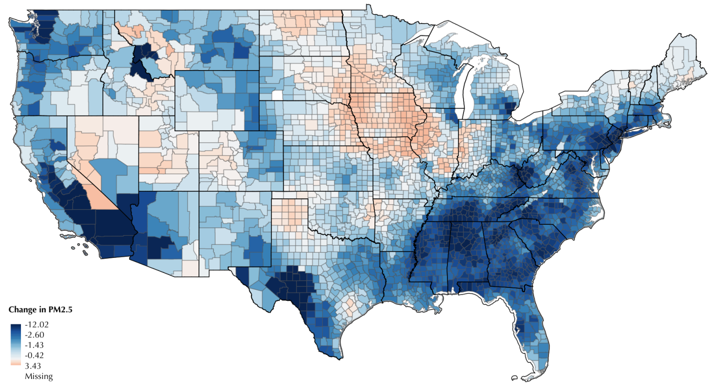


Notes: Areas classified as nonattainment under the 1997 NAAQS (as announced in December 2004) are indicated in blue. Source: U.S. Environmental Protection Agency (EPA).

A comparison of Figures 2 and 3 indicates that while much of the country experienced air quality improvements over the 2000-2010 period, many of the areas with the

[8] See, for example, Chay and Greenstone (2005); Bayer et al. (2009); Lee and Taylor (2019); Banzhaf (2021).
[9] The regulation also imposed a daily standard of 65 $\mu g/m^3$.

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 the estimates provided by van Donkelaar et al. (2019).

greatest improvements (e.g., Southern California, Northern Georgia, and the Central Atlantic region) were those that were in nonattainment in 2005. Indeed, Currie et al. (2023) document that the 1997 NAAQS greatly improved air quality in newly regulated areas.[10] We leverage these differential regulation-induced air quality improvements across place by instrumenting for $\Delta PM2.5_j$ in equations 1 and 2 with a dummy variable indicating whether the tract was in a nonattainment status area in 2005.[11] Note that the regression coefficient on the change in $PM_{2.5}$ concentrations, β_1 in equation 1 or β_q in equation 2, will be negative if the regulation-induced declines in $PM_{2.5}$ concentrations (i.e., air quality improvements) yield increased housing prices or population counts.

The typical identifying assumption in this IV approach is that conditional on observable characteristics, nonattainment status is exogenous to expected outcomes. In this setting, this would be violated if places that 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

[10] In Appendix Figure A1, we reproduce a version of the first-stage event study in Currie et al. (2023) using our sample of metro-area Census tracts and the pollution data from van Donkelaar et al. (2019). The figure reveals extremely similar patterns in pollution changes across tracts in attainment versus nonattainment areas in the years prior to, but not after, the new standards took effect, when nonattainment tracts experienced relative declines in pollution concentrations.

[11] We cluster standard errors by county, as nonattainment "areas" tended to align with county boundaries.

pollution reductions (e.g., employment effects). In the Supplemental Appendix, we interrogate pre-period trends in population counts and housing prices, and we demonstrate that our conclusions are robust to matching attainment and nonattainment tracts in a similar spirit as Sager and Singer (2022). This strategy produces quantitatively similar estimates as our primary specification. However, we note that the central goal of our analysis is not simply to estimate the price capitalization of air quality improvements, but to characterize how this capitalization differs across tracts with varying degrees of housing market constraints. We further demonstrate that the conclusions are similar when examining heterogeneity in capitalization effects across tracts *within* counties. This approach absorbs the average effect as well as any differential trends that might exist at the county level.

Restricting the sample to Census tracts with non-missing HPI values and non-missing elasticity estimates yields a sample of 25,843 Census tracts. The first-stage F-statistic on the nonattainment instrument is about 70. Table 2 shows this first-stage relationship, and indicates that nonattainment status is associated with about a 1.7-$\mu g/m^3$ decline in $PM_{2.5}$ concentrations over the 2000 to 2010 period, relative to an average $PM_{2.5}$ concentration of 13.0 $\mu g/m^3$ in 2000 across the entire sample (Table 1). Table 2 also displays the reduced-form relationship between nonattainment status and the outcomes of interest, indicating that nonattainment status is associated with a 9.2 percent increase in housing prices and a statistically insignificant and small (0.08 log points) increase in population. Table 1 showed that tracts classified as the most inelastic based on their metropolitan area's Saiz (2010) elasticity began the period with higher average $PM_{2.5}$ concentrations of more elastic tracts. This implies that a 1-unit reduction in $PM_{2.5}$ concentrations represents a smaller percent change in inelastic tracts compared to elastic tracts.[12]

[12]This could produce differential price effects in inelastic and elastic markets independent of differential housing supply constraints. If housing prices are more responsive to larger relative (i.e., percent) improvements in air quality, elastic tracts should experience larger price effects in response to a 1-unit improvement. 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. Both of these phenomena would result in larger price effects in elastic markets.

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), 2000-10	
Nonattainment	-1.685***	-1.574***	10.289**	9.196**	-0.506	0.081
	(0.209)	(0.187)	(4.831)	(4.367)	(1.742)	(1.290)
Controls		✓		✓		✓
Division FE	✓	✓	✓	✓	✓	✓
F-stat (nonatt)	64.76	70.47				
R-squared	0.487	0.512	0.371	0.430	0.037	0.119
Observations	25,843	25,843	25,843	25,843	25,843	25,843

Standard errors, in parentheses, are clustered by 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. Nonattainment status refers to the 1997 NAAQS standards, which went into effect in 2005.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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 arises due to unobservable taste dispersion, then the underlying MWTP for pollution reductions should differ across housing markets. Individuals living in relatively inelastic markets (e.g., the coasts) might differ from individuals living in relatively elastic markets (e.g., the sunbelt) in ways that are correlated with their preferences for air quality. We include a rich set of observable tract-level covariates ($\mathbb{X}'_j$) in our regression to address these concerns. However, we are unable to rule out that self-selection could drive some variation in the price response to pollution reductions. While this is a limitation in our analysis, it does not obstruct the broader conceptual point that market constraints influence the capitalization of amenity improvements.

As discussed in Bishop et al. (2020), another challenge 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 the associated housing crisis, which fundamentally altered the price functions in housing markets across the United States. While this complicates 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 to interrogate a different, distinct source of bias in the canonical framework: the assumption of fixed quantities. Our empirical approach leverages variation in local housing supply elasticities to illuminate how price capitalization and quantity effects of air quality improvements differ based on these market constraints.[13] We present a theoretical strategy to recover MWTP in the presence of price and quantity margins in Section 6.

5 Results: Price and quantity effects of air quality improvements

This section presents our central reduced-form results on the price and quantity effects of air quality improvements. Section 5.1 presents point estimates on these effects across all 25,843 metro-area Census tracts in our sample with non-missing HPI values and non-missing elasticity estimates.[14] We show in the Supplemental Appendix that these results are largely robust to alternative weighting schemes that explicitly address potential pre-trends in the central outcome variables. In Section 5.2, we demonstrate how price and quantity effects differ depending on the elasticity of local housing supply. These results suggest that housing supply constraints are relevant to the price capitalization of amenity improvements, and motivate the creation of a tractable model for benefit estimation in Section 6 that explicitly incorporates the capacity for markets to accommodate increased demand via increases in quantity.

[13]We further demonstrate that our conclusions are robust to examining variation in price and quantity effects within individual counties, thus absorbing any differential impacts of the Great Recession across labor markets.

[14]We illustrate how price responses differ across various lengths of time in the Supplemental Appendix, showing that prices are relatively more responsive under short time horizons.

5.1 Price and quantity impacts of air quality improvements

We first examine the price and population response to changes in average annual $PM_{2.5}$ concentrations over the 2000 to 2010 period without differentiating housing markets according to local housing supply constraints. Table 3 shows the OLS and nonattainment status IV coefficient estimates of β_1 in equation 1, detailing the relationship between changes in average annual $PM_{2.5}$ concentrations and tract-level housing prices and population sizes across the 25,843 metropolitan Census tracts. The change in the natural log of the population has been multiplied by 100 to facilitate interpretation as an approximation of the percent change in the population. The point estimate from our primary specification including all tract-level controls (column 4) indicates that a CAA-induced 1-unit (μg/m^3) decline in average annual $PM_{2.5}$ concentrations yields a 5.8 percent increase in tract-level housing prices in 2010 relative to 2000 levels. 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 other hedonic price evaluations of the demand for air quality improvements. The positive OLS coefficients in columns 5 and 6 imply that population *declines* with pollution declines, which is consistent with the fact that there is a strong correlation between pollution and economic activity. When we instrument for declining pollution levels with regulatory designations (columns 7 and 8), this relationship becomes statistically indistinguishable from zero.

One might be concerned that nonattainment tracts were on different trajectories than attainment tracts independent of their regulatory status, which may confound the interpretation of the estimates presented above. Using a similar IV strategy as here, Sager and Singer (2022) demonstrate that matching nonattainment to attainment tracts based on pre-regulation pollution levels produces attenuated estimates of the pollution effects of nonattainment status (i.e., the first stage), but it increases estimates of price capitalization in response to regulation-induced pollution declines. In the Supplemental Appendix, we show that the price and quantity impacts of regulation-induced pollution declines pre-

Table 3: 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(population), 2000-2010			
	OLS		IV		OLS		IV	
$\Delta PM_{2.5}$, '00-10	-1.551	-0.984	-6.108**	-5.843**	1.608***	0.880**	0.301	-0.051
	(1.438)	(1.316)	(2.664)	(2.750)	(0.488)	(0.418)	(1.030)	(0.818)
Controls		✓		✓		✓		✓
Division FE	✓	✓	✓	✓	✓	✓	✓	✓
Observations	25,843	25,843	25,843	25,843	25,843	25,843	25,843	25,843

Standard errors, in parentheses, are clustered by 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. Columns 3, 4, 7, and 8 instrument for change in $PM_{2.5}$ with NAAQS nonattainment status, as described in text. 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

sented in Table 3 are robust to alternative weighting schemes where we match nonattainment and attainment tracts according to pre-trends in price and population changes and weight observations according to the weights produced in this matching process. Below, we present the results from a specification that controls for county fixed effects, which will additionally absorb any unobserved county-level attributes that may differentially influence price and population trajectories across labor markets.

5.2 Price and quantity impacts by housing supply elasticity

The primary goal of our empirical analysis is to examine heterogeneity in the effect of air quality improvements across more inelastic or elastic housing markets. To do so, we estimate equation 2 for the 25,853 Census tracts in our sample, grouping tracts into eight bins of metro-level elasticity according to the values in Saiz (2010), where bin 1 is the most inelastic and bin 8 is the most elastic. Figure 4 reports the estimated coefficients β_q in equation 2 (and 95 percent confidence intervals), where we instrument for the change in average annual $PM_{2.5}$ concentrations over the 2000 to 2010 period with nonattainment status. The top panel (a) reports the coefficient estimates for HPI (the 'price' effect), and the bottom panel (b) reports the coefficient estimates for population changes (the 'quantity' effect). The estimates in each panel are estimated from a single regression that includes controls for 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, the share of occupied housing units that are renter-occupied, and division fixed effects, with standard errors clustered by county.

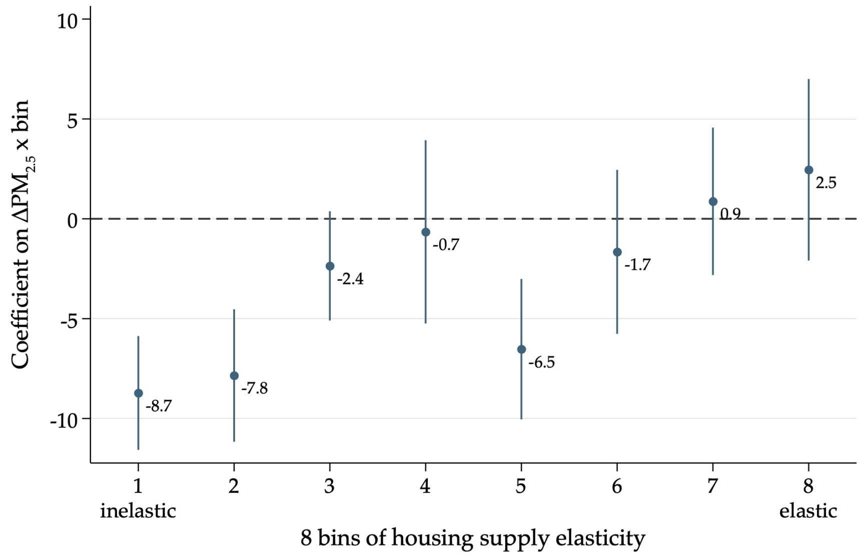
We find that regulation-induced air quality improvements yield larger housing price increases in tracts defined by inelastic housing markets, and larger population increases in tracts defined by elastic housing markets, consistent with the stylized model presented in Section 2. The leftmost point estimate in the top panel of Figure 4 implies that a 1-unit decline in annual $PM_{2.5}$ concentrations produces an 8.7 percent increase in housing prices in the most inelastic tracts, compared to a (statistically insignificant) 2.5 percent decline in housing prices in the most elastic tracts. There is a clear relationship between supply elasticities and price capitalization, with housing prices increasing the most in response to regulation-induced pollution declines in the most inelastic tracts.[15] The implied elasticity of housing prices with respect to $PM_{2.5}$ changes is about -1.3 in the most inelastic tracts, compared to -0.75 across all metro-area Census tracts in the sample.[16]

The bottom panel of Figure 4 — showing the quantity effect — displays a somewhat striking mirror-image version of the price effect. Regulation-induced pollution declines yield the largest population increases in the most elastic Census tracts. The rightmost point estimate in the bottom panel implies that a 1-unit decline in annual $PM_{2.5}$ concentrations produces about a 5.7 percent increase in population in the most elastic tracts.

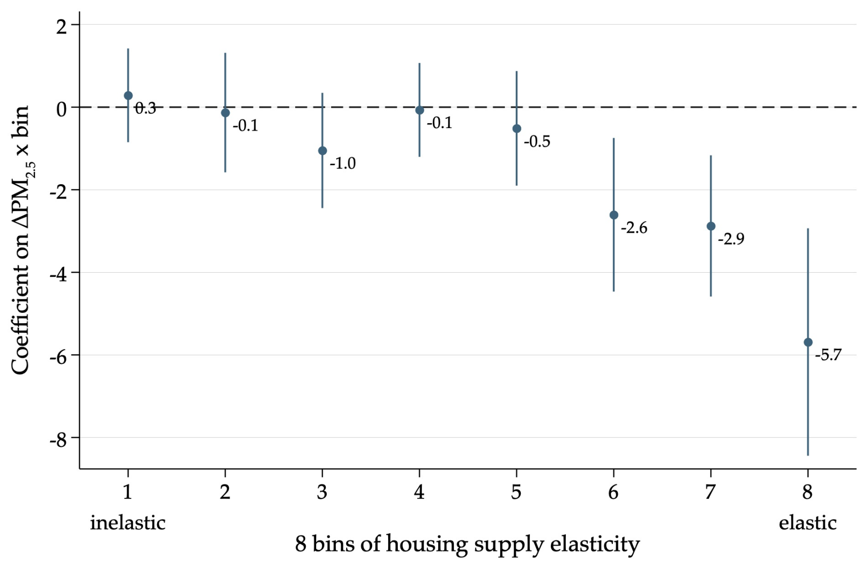
[15]The most inelastic bin of tracts began the period with higher levels of annual $PM_{2.5}$ emissions than other bins (15 μg/m^3 in the most inelastic tracts versus 13 μg/m^3 across all tracts in the sample), such that a 1-unit decline reflects about a 6.7 percent decline in emissions in inelastic tracts compared to 7.7 percent decline across all tracts. Thus, in percentage terms, a *smaller* pollution decline yields a much *larger* price increase in inelastic markets.

[16]The implied elasticity of housing prices with respect to $PM_{2.5}$ changes reported in Sager and Singer (2022) is -1.1. Sager and Singer (2022) estimate the elasticity over a slightly shorter time horizon such that prices should be more responsive to changes in air quality, and thus the elasticity estimates in both papers are quite comparable. For reference, Chay and Greenstone (2005) estimate that the implied elasticity of housing prices with respect to TSP concentrations is between -0.2 and -0.35.

Figure 4: Price and population response to changes in $PM_{2.5}$, by metro-level elasticity



(a) Outcome: 2010 HPI (2000=100)



(b) Outcome: Δln(population), 2000-10

Notes: Figure shows the point estimates and 95 percent confidence intervals of the regression coefficient β_q on change in tract-level $PM_{2.5}$ concentrations over the 2000–2010 period interacted with the tract's metro-level elasticity quantile based on Saiz (2010). Tracts are broken into 8 quantiles, where 1 is the most inelastic. The point estimates in each sub-figure are produced from a single regression, which includes controls for 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, the share of occupied housing units that are renter-occupied, and division fixed effects. Standard errors are clustered by county. We instrument for the change in $PM_{2.5}$ with NAAQS nonattainment status, as described in text. The outcome variable in the bottom panel has been multiplied by 100 for ease of interpretation.

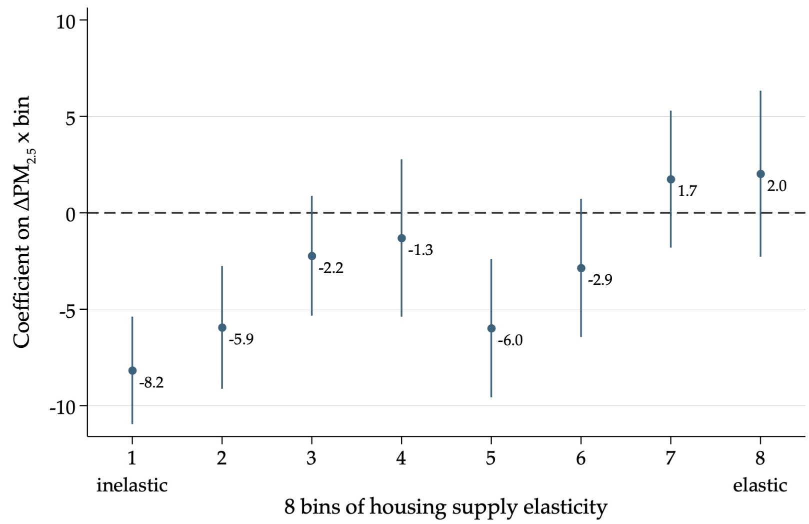
Moving rightward from the leftmost estimate, indicating a statistically indistinguishable quantity effect in the most inelastic Census tracts, there is a clear downward trend in the coefficient estimate. Population responses to pollution decline increase as places are characterized by more elastic housing markets. Together, panels a and b of Figure 4 are suggestive that regulation-induced declines in $PM_{2.5}$ concentrations yield both price and quantity effects, with the relative strength of these margins dictated by local housing supply elasticities.

We note that the grouping of Census tracts into eight bins of metro-level elasticity estimates is meant for expositional purposes — there is nothing special about these cut-offs, and the relationship is quite similar using different thresholds (e.g., using four quantiles or ten quantiles). We also note that there exists heterogeneity in supply constraints within metropolitan areas, and not just across. In Figure 5, we replicate the analysis above but incorporate tract-level elasticity estimates from Baum-Snow and Han (2024) using the average of their tract- and metro-level elasticity estimates from Baum-Snow and Han (2024) and Saiz (2010). This produces extremely similar patterns to those observed in Figure 4. With the exception of bin 5, the most supply-constrained tracts experience the largest price capitalization of pollution declines. Concurrently, the most elastic-supply tracts experience the largest population increases in response to pollution declines.[17]

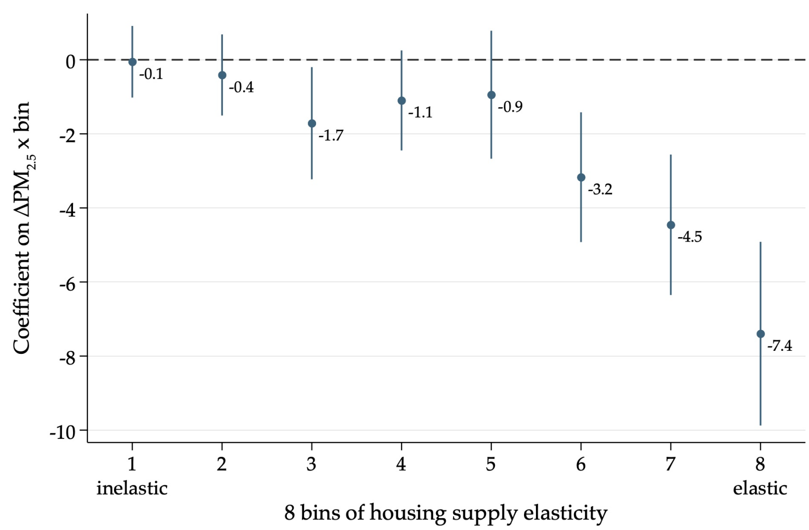
To further interrogate the heterogenous price and quantity effects of these pollution reductions, we present the point estimates from a modified version of equation 2 which controls for county fixed effects. Here, we group tracts into eight equal-sized bins based only on the tract-level elasticity estimates from Baum-Snow and Han (2024), which are primarily meant for comparison within labor markets rather than across. This specification will absorb the average effect of regulation-induced pollution improvements and

[17]Housing markets may be relatively more inelastic in shorter-run settings, as one cannot build new housing units immediately, even in elastic-supply places. Similarly, even inelastic-supply locations become relatively elastic over long enough time horizons. In the Supplemental Appendix, we consider how price capitalization changes over progressively longer long-difference settings. As expected, we find that price capitalization attenuates over progressively longer time horizons.

Figure 5: Price and population response to changes in $PM_{2.5}$, by tract- and metro-level elasticity



(a) Outcome: 2010 HPI (2000=100)



(b) Outcome: Δln(population), 2000-10

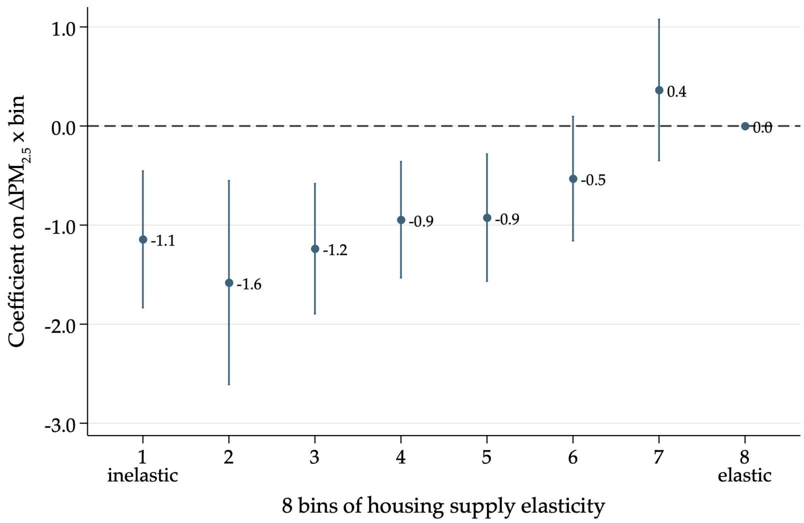
Notes: Figure shows the point estimates and 95 percent confidence intervals of the regression coefficient β_q on the change in tract-level $PM_{2.5}$ concentrations over the 2000–2010 period interacted with the tract's elasticity quantile, based on the average of tract- (Baum-Snow and Han, 2024) and metro- (Saiz, 2010) level elasticities. Tracts are broken into 8 quantiles, where 1 is the most inelastic. The point estimates in each sub-figure are produced from a single regression, which includes controls for 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, the share of occupied housing units that are renter-occupied, and division fixed effects. Standard errors are clustered by county. We instrument for the change in $PM_{2.5}$ with NAAQS nonattainment status, as described in text. The outcome variable in the bottom panel has been multiplied by 100 for ease of interpretation.

identify variation in the price or quantity effect within counties based on the tract-level supply elasticity. Additionally, the inclusion of county fixed effects will absorb any non-regulation-induced price or population trends occurring at the labor market level over this period that could confound the interpretation of the baseline results. Because the average effect is absorbed by the county fixed effect, we omit one bin from the regression specification, such that the coefficients reflect the difference in the effect compared to the most elastic quantile of tracts (bin 8). Figure 6 presents these results.

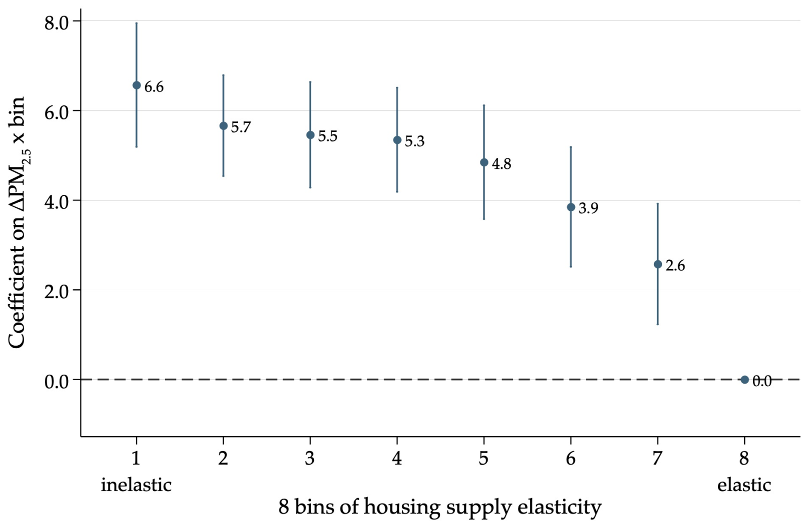
The top panel of Figure 6 shows that the regulation-induced decline in $PM_{2.5}$ concentrations produces larger housing price increases in more inelastic tracts within a given county. The bottom panel displays the opposite relationship for population changes, such that the most elastic tracts experience the largest population declines in response to pollution reductions. These point estimates are not directly comparable to those in Figures 4 and 5, as they display the change in the treatment effect across different groups of tracts within a county relative to the most elastic quantile, rather than the treatment effect itself which is absorbed by the county fixed effect. However, they are consistent with the conclusion that the price and quantity effects of pollution improvements vary across locations with different housing supply elasticities.

The relationships described in this section are consistent with the basic economic theory that housing market constraints play a role in determining the price and quantity effects of demand shifts. What is less clear is what this implies for hedonic estimates of the marginal benefits of pollution reductions, or amenity changes more broadly. If price capitalization were the sufficient statistic necessary for estimating MWTP, the coefficient estimates in the top panels of Figures 4 and 5 imply that the benefits of $PM_{2.5}$ reductions are larger in inelastic-supply places. However, the quantity effects in the bottom panels of these figures indicate that other margins of adjustment likely attenuate the price capitalization in elastic-supply places, biasing MWTP estimates toward zero. In the following section, we present a simple spatial equilibrium model that allows us to interpret

Figure 6: Within-county price and population effects, by tract-level elasticity



(a) Outcome: 2010 HPI (2000=100)



(b) Outcome: Δln(population), 2000-10

Notes: Figure shows the point estimates and 95 percent confidence intervals of the regression coefficient β_q on the change in tract-level $PM_{2.5}$ concentrations over the 2000–2010 period interacted with the tract's elasticity quantile, based on estimates in Baum-Snow and Han (2024). Tracts are broken into 8 quantiles, where 1 is the most inelastic. The point estimates in each sub-figure are produced from a single regression, which includes county fixed effects. Bin 8 is omitted from the regression. Standard errors are clustered by county. We instrument for the change in $PM_{2.5}$ with NAAQS nonattainment status, as described in text. The outcome variable in the bottom panel has been multiplied by 100 for ease of interpretation.

the reduced-form price coefficient as MWTP modified by local housing supply elasticities. This model offers a way to estimate MWTP for pollution reductions in the presence of quantity effects.

6 A model for air-quality improvements

That pollution declines yield larger price increases in places characterized by relatively inelastic housing markets, and greater population increases in places characterized by relatively elastic housing markets is consistent with the basic logic of supply and demand presented in Section 2. However, the presence of a quantity margin poses a problem for hedonic valuation, as the expansion of the market may attenuate the price capitalization of demand shifts. To make progress towards incorporating this quantity margin into the hedonic method, we develop a simple spatial equilibrium model for air-quality improvements. This model builds on the long line of research that extends the logic of Rosen (1979) and Roback (1982) to estimate demand for amenities.[18] We show that when housing supply is perfectly inelastic, the hedonic price coefficient is a sufficient statistic for estimating MWTP. When housing is elastically supplied, MWTP can be estimated by incorporating a measure of the housing supply elasticity into the traditional hedonic price capitalization approach.

6.1 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. We assume that there is one type of worker, such that all workers have the same marginal productivity

[18] 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. Our model builds on others like Chattopadhyay (1999) and Bajari and Kahn (2005) by using housing price data with assumptions about utility to estimate MWTP, but we advance this tradition by explicitly incorporating elastic housing supply and the relevant quantity margin in demand estimation.

(and hence face the same wage, W_j).[19] 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:

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

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:

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

where the number of housing units in place j is equal to the number of workers, N_j, such that each worker consumes one unit of housing. The parameter ρ_j is the inverse elasticity of the supply of housing (Moretti, 2011). It is influenced by place-specific qualities 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 ample developable land, ρ_j will be very small. In the extreme case in which housing supply is perfectly inelastic and the supply curve is vertical, ρ_j will be infinite.

Assume that ε_{ij} follows a Type 1 Extreme Value distribution. The number of workers living in place j can be written in terms of the probability that worker i chooses to live in

[19] 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.

place j, scaled by the number of workers (N_{total}):[20]

$$N_j = N_{total} \frac{\exp\left(W_j + S_j - \bar{R}\right) N_j^{-\rho_j}}{\sum_k \exp\left(W_k + S_k - \ln R_k\right)} \tag{5}$$

Writing log population ($\ln N_j$) and housing prices (R_j) as functions of amenity value S_j and taking the long difference in each variable over time produces:[21]

$$\Delta \ln N_j = \frac{1}{1+\rho_j}(\Delta W_j + \Delta S_j + \Delta \bar{R}) \tag{6}$$

$$\Delta \ln R_j = \frac{\rho_j}{1+\rho_j}(\Delta W_j + \Delta S_j) + \frac{1}{1+\rho_j}\Delta \bar{R} \tag{7}$$

We allow amenity value S_j to be a linear function of local pollution concentrations X_j:

$$S_j = \gamma_0 + \gamma_1 X_j + \nu_j \tag{8}$$

Taking the long difference of this expression over time produces:

$$\Delta S_j = \gamma_1 \Delta X_j + \tilde{\nu_j} \tag{9}$$

where $\tilde{\nu_j}$ is an unobservable determinant of ΔS_j.[22]

We assume that wages are orthogonal to local pollution concentrations X_j, but ex-

[20] This is based on the conditional logit setup from McFadden (1973), used in a variety of settings in urban economics such as Diamond (2016).

[21] These expressions are produced by first taking the natural log of equation 5 and letting $C_1 = \ln\left(\frac{N_{total}}{\sum_k \exp(W_k + S_k - \ln R_k)}\right)$ to get $\ln N_j = \frac{1}{1+\rho_j}\left(W_j + S_j - \bar{R}\right) + C_1$. Plugging this expression into the inverse housing supply expression (equation 4) and simplifying produces:

$$\ln R_j = \frac{\rho_j}{1+\rho_j}\left(W_j + S_j\right) + \frac{1}{1+\rho_j}\bar{R} + C_2$$

where $C_2 = \frac{\rho_j}{1+\rho_j}C_1$. Taking the long difference of these expressions over time produces equations 6 and 7. For brevity, we have omitted time subscripts in these expressions. We assume that W_j, N_j, S_j, R_j, and $\bar{R}$ may vary across time, while other parameters are assumed to be time-invariant.

[22] γ_0 is assumed to be time-invariant. $\tilde{\nu_j}$ is not orthogonal to air quality improvements ΔX_j, as unobserved characteristics may covary with both air quality and amenity improvements.

tending the model to allow local pollution concentrations to influence local productivity produces similar conclusions.[23] Plugging equation 9 into the expressions for population (equation 6) and housing prices (equation 7), we can write the central parameters as functions of ΔX_j:

$$\Delta \ln N_j = \frac{1}{1+\rho_j}(\Delta \bar{R} + \Delta W_j) + \frac{\gamma_1}{1+\rho_j}\Delta X_j + \xi_j^n \tag{10}$$

$$\Delta \ln R_j = \frac{\rho_j}{1+\rho_j}\Delta W_j + \frac{1}{1+\rho_j}\Delta \bar{R} + \frac{\rho_j \gamma_1}{1+\rho_j}\Delta X_j + \xi_j^r \tag{11}$$

where $\xi_j^n = \frac{\tilde{\nu_j}}{1+\rho_j}$ and $\xi_j^r = \frac{\rho_j \tilde{\nu_j}}{1+\rho_j}$.

Equations 10 and 11 demonstrate how local population counts and housing prices respond to local pollution concentrations. The marginal willingness to pay (MWTP) for air pollution changes is given by the parameter γ_1. These expressions demonstrate a central insight from the stylized model presented earlier. The price and quantity effects of a pollution decline are both modified by ρ_j, the inverse housing supply elasticity. Even if γ_1 is constant across locations, such that there is no self-selection to inelastic or elastic places based on preferences for clean air, an exogenous shift in local pollution concentrations will yield larger housing price changes in places with inelastic housing supply, and larger population count changes in places with elastic housing supply.

6.2 MWTP for amenity improvements from reduced-form estimates

Let $\hat{\beta}_R$ and $\hat{\beta}_N$ be the estimated causal effect of a 1-unit improvement in $PM_{2.5}$ concentrations (ΔX_j) on the change in housing prices ($\Delta \ln R_j$) and change in population ($\Delta \ln N_j$), respectively. From the model, we see that $\hat{\beta}_R$ — the housing price capitalization of air quality improvements — reflects the MWTP scaled by the expression $\frac{\rho_j}{1+\rho_j}$:

[23] Empirically, we find little evidence that wages respond to local pollution concentrations in this context.

$$\hat{\beta}_R = \frac{\rho_j}{1+\rho_j} \cdot \gamma_1$$

Recall that ρ_j is the inverse housing supply elasticity, i.e., $\frac{d \ln R_j}{d \ln N_j}$. This implies that when housing supply is perfectly inelastic (i.e., as $\rho_j \to \infty$), the coefficient from a typical hedonic price regression thus offers a sufficient statistic for MWTP, γ_1, because $lim_{\rho_j \to \infty}$ $\frac{\rho_j}{1+\rho_j} = 1$. However, when housing supply is not perfectly elastic (i.e., $\frac{\rho_j}{1+\rho_j} < 1$), the coefficient from this regression will reflect MWTP attenuated by $\frac{\rho_j}{1+\rho_j}$. This attenuation will be more severe when housing supply is very elastic, such that ρ_j is very small.

The model expressions reveal two reduced-form methods that researchers may use to estimate MWTP in settings with elastic housing supply. First, if the housing supply elasticity is a known parameter, its inverse can be used to define ρ_j for each unit of observation. The price capitalization of the amenity change ΔX_j interacted with the term $\frac{\rho_j}{1+\rho_j}$ then offers an estimate of γ_1. Similarly, if ρ_j is constant across units of observation, one can back out γ_1 by dividing the classic hedonic price coefficient $\hat{\beta}_R$ by $\frac{\rho}{1+\rho}$.

Second, when ρ_j is unknown but does not vary substantially across observations, both price and quantity margins can be used to back out both ρ_j and γ_1. That is, when ρ_j is unknown, one needs the additional parameter $\hat{\beta}_N$ to calculate MWTP:

$$\hat{\beta}_N = \frac{\gamma_1}{1+\rho_j}$$

The ratio of $\hat{\beta}_R$ and $\hat{\beta}_N$ offers the inverse housing supply elasticity parameter:

$$\rho_j = \frac{\hat{\beta}_R}{\hat{\beta}_N}$$

Intuitively, because the exogenous shock to air quality acts as a demand shifter that moves both prices and population counts, it can be leveraged to estimate the housing supply elasticity and γ_1.[24] Do note that ρ_j typically varies across place j, and thus this strategy is most appropriately used in settings in which housing supply constraints do not vary substantially across observations and a quantity margin can plausibly be identified.

In summary, the classic hedonic price coefficient $\hat{\beta}_R$ is a sufficient statistic for ρ_j only when housing supply is perfectly inelastic. When supply is not perfectly inelastic and ρ_j is known, one can calculate MWTP, γ_1, as the hedonic price regression coefficient on $\frac{\rho_j}{1+\rho_j}\Delta X_j$. When ρ_j is unknown and it does not vary substantially across observations, it can be calculated as the ratio of $\hat{\beta}_R$ and $\hat{\beta}_N$ and used to back out the MWTP parameter, γ_1.

6.3 MWTP estimates that incorporate elastic housing supply

Informed by the model expressions derived above, this section presents estimates of MWTP for $PM_{2.5}$ reductions which account for housing supply elasticities. We rely on the first method to estimate MWTP, γ_1, as housing supply constraints vary substantially across tracts in our sample. This approach leverages elasticity estimates from the literature to define the inverse elasticity ρ_j. Following equation 11, we regress 2000–2010 price changes on the change in $PM_{2.5}$ multiplied by $\frac{\rho_j}{1+\rho_j}$:

$$\Delta y_j = \beta_0 + \beta_{MWTP} \cdot \frac{\rho_j}{1+\rho_j} \Delta PM2.5_j + \mathbb{X}_j'\gamma + \delta_d + \varepsilon_j \qquad (12)$$

where we impute ρ_j from the literature in one of three ways: ρ_j is defined as (i) the inverse of metro-level elasticity from Saiz (2010), (ii) the inverse of tract-level elasticity from Baum-Snow and Han (2024), or (iii) the inverse of the average of the two elasticity estimates. The outcome variable Δy_j reflects the tract's 2010 HPI, indexed to 2000 levels. This percent change in housing prices serves as a proxy for the change in log housing prices, $\Delta \ln R_j$, as defined in the model. As before, we instrument for the change in tract-level

[24]When housing is supplied elastically, the MWTP for the amenity can be estimated as:

$$\gamma_1 = \hat{\beta}_R + \hat{\beta}_N$$

where $\hat{\beta}_R$ and $\hat{\beta}_N$ are the dollar-value equivalents of price and population changes in percent.

$PM_{2.5}$ concentrations between 2000 and 2010 with NAAQS nonattainment status. We again include tract-level covariates $\mathbb{X}'_j$, division fixed effects δ_d, and cluster errors at the county level. When estimating equation 12 in this IV setting, β_{MWTP} reflects the reduced-form estimate of average MWTP for an additional unit decline in $PM_{2.5}$ induced by the CAA, accounting for heterogeneous supply elasticities across Census tracts.

Table 4: Price response to air-quality improvements, scaled by housing supply elasticity

	(1)	(2)	(3)	(4)
		2010 HPI		
Δ $PM_{2.5}$, 2000-10	-5.843**			
	(2.750)			
$\frac{\rho_j}{1+\rho_j} \times \Delta$ $PM_{2.5}$, 2000-10		-12.69**	-6.498**	-9.722**
		(4.952)	(3.033)	(4.042)
Controls	✓	✓	✓	✓
Division FE	✓	✓	✓	✓
Elasticity used to calc. ρ_j	Baseline (no interaction)	Metro-level	Tract-level	Metro- and tract- average
Observations	25,843	25,843	25,843	25,843

Standard errors, in parentheses, are clustered by 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. In columns 2–4, we interact Δ $PM_{2.5}$ with $\frac{\rho_j}{1+\rho_j}$, a measure of the inverse housing supply elasticity in tract j. In column 2, this is defined as the inverse of the metro-level elasticity provided by Saiz (2010). In column 3, ρ_j is the inverse of the tract-level elasticity provided by Baum-Snow and Han (2024). In column 4, we take the average of the metro- and tract-level elasticities and define ρ_j as the inverse of this value. We instrument for the primary independent variable (Δ $PM_{2.5}$ between 2000 and 2010, or that scaled by ρ_j) with NAAQS nonattainment status, as described in text.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In Table 4, we present the IV coefficient estimates of β_{MWTP} from equation 12 using these three different methods of characterizing ρ_j, as well as the standard hedonic approach. Column 1 reproduces the estimate from Table 3 reflecting the reduced-form effect of a 1-unit change in $PM_{2.5}$ on tract-level HPI, without incorporating any measure of housing supply elasticity. A 1-μg/m^3 decline in $PM_{2.5}$ concentrations yields a 5.8% increase in housing prices, or an increase of $6,570 over the 2000-level median home value in the sample. Thus, the standard hedonic price capitalization approach would imply a MWTP of about \$6,570 per household for a 1-unit improvement in air pollution. Extrapolating from the first-stage coefficient from Table 2 (1.574), this implies that the NAAQS-induced pollution reductions were valued at about \$10,000 per household. Again, this estimate implicitly assumes that housing supply is perfectly inelastic, such that the housing price change is a sufficient statistic for estimating MWTP.

Columns 2–4 of Table 4 present estimates of MWTP that account for local housing supply elasticities. The primary independent variable in these specifications is the change in $PM_{2.5}$ concentrations over the 10-year period times $\frac{\rho_j}{1+\rho_j}$. Imputing ρ_j from housing supply elasticities drawn from the literature, we find that the average β_{MWTP} ranges from 6.5 to 12.7 percent, which translates to about \$7,360 to \$14,384 per household per unit of pollution reduction. Extrapolating from the first-stage coefficient as before, this implies that the NAAQS-induced pollution reductions were valued at about \$11,500 to \$22,600 per household. Consistent with theoretical predictions, these estimates of MWTP are larger — on the order of about 12 to 117 percent larger — than the estimate induced from the standard hedonic price coefficient. That the metro-level elasticity (column 2) produces larger estimates than the tract-level elasticity (column 3), with the estimate produced by the average measure (column 4) falling in between is explained by the relatively larger elasticities estimated by Saiz (2010) compared to Baum-Snow and Han (2024).[25] Given that the smaller (i.e., more inelastic) tract-level estimates in Baum-Snow and Han (2024) are produced from more recent demand shocks, and because the metro-level estimates do not allow for heterogeneous supply elasticities across neighborhoods, the more conservative estimates produced in column 3 may be particularly relevant.[26] The differences in estimates produced using these alternative elasticity parameters highlight the notion that the bias implicit in the classic hedonic approach will be more severe as the market in

[25]As discussed above, the differences in the magnitude of the elasticity estimates can be attributed to differences in the study period and the nature of the demand shocks used for identification.

[26]The tract-level elasticities provide finer geographic detail but do not fully capture differences in elasticities between metro areas. Therefore, both estimates provide valuable insights, and we do not consider one to be inherently preferable to the other.

question is more supply-elastic.

We caveat that this exercise requires that the housing supply elasticity is a known, exogenous parameter. We draw from existing tract- and metro-level elasticity estimates derived from alternative identification strategies to impute ρ_j, but the considerable variation in β_{MWTP} displayed in Table 4 highlights the underlying variation in supply elasticity estimates themselves. As progress continues to be made in quantifying credible housing supply elasticities across finer geographic scales (Baum-Snow and Han, 2024), we anticipate new opportunities to incorporate this parameter into the hedonic valuation approach.

7 Conclusion and discussion

Many applications of the hedonic valuation approach exploit price capitalization in the housing market to estimate demand for amenities. Implicit in these applications is the assumption that the supply of housing is fixed, or perfectly inelastic, such that price capitalization is a sufficient statistic for MWTP. However, in elastic-supply settings, markets can expand to accommodate increased demand. This quantity adjustment serves to attenuate concurrent price adjustments, such that price capitalization offers a downward-biased estimate of MWTP.

The empirical evidence presented in this paper suggests that housing supply constraints do indeed mediate the relationship between improvements in local amenities and housing price growth. We exploit the implementation of the 1997 CAA NAAQS for $PM_{2.5}$, which took effect in 2005, to show that regulation-induced improvements in air quality lead to larger housing price increases in inelastic housing markets relative to elastic housing markets. This 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 that these regulation-induced air quality improvements lead to larger quantity changes (i.e., population increases) in elastic housing markets relative to inelastic housing markets.

Motivated by this empirical evidence, we develop a spatial equilibrium model that allows for amenity changes to generate both price *and* quantity effects. Our model provides a new interpretation of the reduced-form effect of air quality improvements on housing prices: this effect is an estimate of the MWTP scaled by the local housing supply elasticity. Based on this insight, we provide new estimates of MWTP using CAA-induced reductions in $PM_{2.5}$ concentrations, as well as measures of local housing supply elasticities from the literature. We find that the resulting MWTP for air quality improvements is at least 12 percent larger than the estimate produced based on price capitalization alone. We show that the canonical hedonic price coefficient will tend to underestimate the value of amenity improvements in the presence of a quantity margin, with the resulting bias more severe in more elastic-supply settings.

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 more inelastic-supply cities, then some of the heterogeneity in the price effects could be explained by 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 consistent with this prediction using a variety of specifications. In addition, our critique of the canonical hedonic approach is limited to situations in which housing supply is not explicitly fixed and those 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. However, in many general equilibrium, elastic-supply contexts, the hedonic approach may continue to be an attractive technique for evaluating the benefits of amenity improvements. For these cases, we provide a simple framework that allows researchers to estimate willingness to pay for amenity improvements, accounting for variations in housing supply elasticity across space.

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Supplemental Appendix

Supplemental appendix material for "Where Does Air Quality Matter? New Evidence from the Housing Market" by Eleanor Krause and Tridevi Chakma

A Event-study first stage

Following Currie et al. (2023), we estimate the following event-study specification to further interrogate the first-stage relationship between nonattainment status and tract-level $PM_{2.5}$ concentrations:

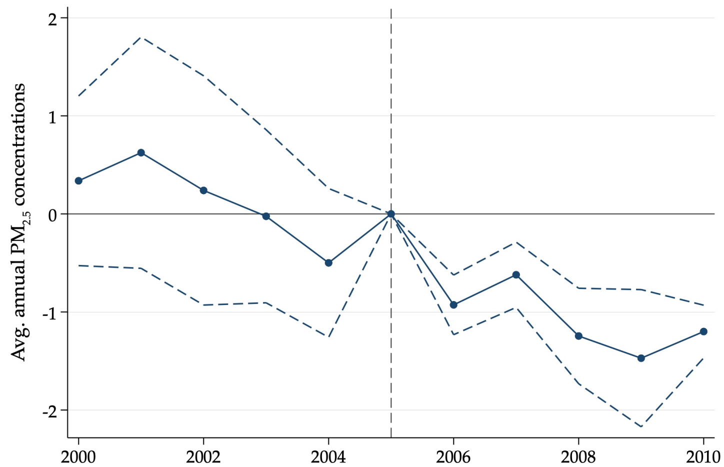
$$PM_{jct} = \sum_{t=2000}^{2010} \beta_t \left(\mathbf{1}[Nonattain_c = 1] \times \mathbf{1}[year_t = t] \right) + \phi_c + \rho_t + \epsilon_{jct} \tag{13}$$

where PM_{jct} is the average $PM_{2.5}$ concentration in tract j in county c in year t, regressed on a series of interaction terms for whether the tract is in a newly designated nonattainment county $\mathbf{1}[Nonattain_c] = 1$ interacted with a dummy for each year before and after the regulation went into place (2005). Regressions include county fixed effects ϕ_c and year fixed effects ρ_t, and standard errors are clustered by county. Figure A1 displays the coefficient estimates, showing statistically indetectable differences in pollution changes across tracts in attainment versus nonattainment areas in the years prior to the 2005 regulation took effect. These trends are quite similar to those in Currie et al. (2023), who use pollution data from Di et al. (2016) and estimate differences in individual-level pollution exposure using administrative data.

B Pre-trends and alternative weighting schemes

While we do not observe significant differences in 2000-level covariates between tracts in nonattainment and attainment areas, we note nonattainment tracts were growing more slowly in terms of population and price changes in the years leading up to our empirical setting. These characteristics are presented in Columns 1-3 of Table B1. We consider

Figure A1: First-stage effect of nonattainment status on $PM_{2.5}$ concentrations (Event-study)



Notes: Figure plots the event-study coefficients from equation 13, where the outcome is the Census tract's average annual $PM_{2.5}$ concentrations ($\mu g/m^3$), based on estimates from van Donkelaar et al. (2019). The regression controls for county and year fixed effects. 95-percent confidence intervals are reflected by dashed lines. Errors are clustered by county.

the 1990-2000 change in log population and the 1995 HPI (where 2000=100) as the primary indicators of possible pre-trends.[1] Because the HPI is indexed to 2000-level prices, a higher value in 1995 reflects *less* price appreciation between 1995 and 2000. Thus, Table B1 indicates that nonattainment tracts experienced slower population and price growth than nonattainment tracts prior to 2000. If nonattainment tracts would have grown more slowly over the 2000–2010 period in the absence of regulation-induced pollution reductions, our primary IV strategy would provide a lower bound estimate on the change in prices and quantities attributable to the regulation.

The central goal of our primary empirical analysis is not to identify the causal effect of regulation-induced pollution reductions on housing prices and population counts, but rather to elucidate how price and quantity changes differ across markets with different supply elasticities. However, in this section, we show that the baseline estimates of the

[1]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 (8.5% of tracts have missing 1995 values).

Table B1: Nonattainment and attainment tract characteristics

	(1)	(2)	(3)	(4)	(5)	(6)
	Unweighted			PSM-weighted		
	Attain.	Non.	(1)-(2)	Attain.	Non.	(4)-(5)
2000-level covariates						
ln(med. hh income)	10.867	10.895	-0.028	10.866	10.905	-0.039
	(0.015)	(0.027)		(0.012)	(0.028)	
adult college share	31.323	30.276	1.047	31.332	30.654	0.678
	(0.712)	(1.397)		(0.695)	(1.455)	
non-Hispanic white share	75.507	70.572	4.935	78.302	70.738	7.563
	(1.705)	(5.165)		(1.523)	(5.302)	
renter-occupied housing rate	27.666	27.691	-0.024	26.575	27.466	-0.891
	(0.646)	(1.942)		(0.510)	(1.969)	
vacancy rate	5.330	4.502	0.829**	5.208	4.379	0.829**
	(0.215)	(0.269)		(0.185)	(0.262)	
Other characteristics						
1995 HPI	78.215	81.425	-3.210***	81.541	81.425	0.116
	(0.980)	(0.752)		(0.732)	(0.752)	
Δln(population), '90-2000	30.746	18.303	12.442***	18.884	18.077	0.806
	(2.801)	(2.084)		(1.148)	(2.083)	
$PM_{2.5}$ concentration, 2000	11.051	15.434	-4.383***	11.075	15.455	-4.381***
	(0.171)	(0.558)		(0.181)	(0.575)	
Observations	14,107	11,736		11,263	11,144	

Sample in columns 1-3 includes all metro tracts with non-missing values for HPI and elasticity. Sample in columns 4-6 includes all metro tracts with non-missing values for HPI and elasticity with positive weights produced by PSM. Means in columns 4-6 are weighted by these PSM weights. Standard errors, clustered by county, are in parentheses. Non. refers to nonattainment tracts, based on whether the tract was in an area designated as nonattainment under the 1997 NAAQS standards, which went into effect in 2005. 2000-level covariates are retrieved from the U.S. Census. HPI is retrieved from the FHFA and is indexed to 2000 levels (2000=100).
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

price and quantity effects of regulation-induced $PM_{2.5}$ declines are robust to alternative weighting schemes in which we explicitly match attainment and nonattainment tracts based on pre-period price and quantity changes.

First, we estimate each attainment tract's propensity score for treatment (i.e., receiving nonattainment status) based on the 1995 HPI and the 1990-2000 change in log population. We use these outcome changes because they precede the long-difference (2000–2010) setting. The 1995 HPI is again indexed to 2000 levels, such that it represents the price change from 1995–2000. We use the 1995 HPI rather than the 1990 value, as the

1990 value is missing for a large share (37%) of tracts in our primary sample.[2] The 1990 population estimates are retrieved from the U.S. Census. We do this propensity score matching (PSM) using the four nearest neighbors to treatment (nonattainment) tracts and then weight the observations using the weights generated in this matching process. 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. This yields a slightly smaller sample than that used in our primary analysis, as tracts that perform as poor matches to the treatment group are dropped from the analysis. Weighting observations by the weights produced in this PSM process mollifies the differential pre-trends observed earlier, as seen in Columns 4-6 of Table B1.

Because we are primarily interested in housing price capitalization, the second and third weighting strategies focus on differential housing price trends across nonattainment and attainment tracts. In the second strategy, we employ a similar method as the first, but match attainment and nonattainment tracts on only 1995 HPI, again imposing 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. Finally, we note that housing prices grew dramatically and heterogeneously across the United States in the run-up to the Great Recession and associated housing crisis. Nonattainment status was announced in December of 2004, and thus it may be more appropriate to address potentially heterogeneous housing price trends in the years immediately preceding nonattainment designation. Thus, in the third weighting strategy, we match attainment and nonattainment tracts based on their 2005 HPI, where 2000 is still this base year. This amounts to matching tracts based on their 2000–2005 price appreciation. We again impose common support. In all strategies, we match control and treatment observations using the four nearest neighbors, although the conclusions are relatively insensitive to the precise matching strategy used.

[2] The 1995 HPI is also missing for many tracts in our primary sample, although the share is much smaller (8.5%). This process will drop all tracts with missing 1995 values.

The identifying assumption is that nonattainment tracts and their propensity-matched attainment tracts would have experienced the same changes in prices (or prices and populations) over time in the absence of the regulation. While impossible to test this counterfactual explicitly, weighting observations such that nonattainment and attainment tracts have common pre-trends in these outcomes attenuates concerns that the observed "effect" of regulatory-induced pollution declines is driven by differential trajectories. The strategy outlined here 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 changes in $PM_{2.5}$ concentrations.[3]

Table B2 shows the point estimates of β_1 in equation 1 describing the relationship between NAAQS-induced changes in tract-level $PM_{2.5}$ concentrations and price and population changes over the 2000 to 2010 period, using the alternative weighting schemes described in this section. As before, we instrument for the change in $PM_{2.5}$ with NAAQS nonattainment status announced in December 2004. In columns 1 and 2, we reproduce the central estimates (without weighting) from Table 3. In columns 3 through 8 of Table B2, we weight by the weights produced in PSM, described above. Columns 3 and 4 match on 1995 HPI and 1990-2000 population changes. Columns 5 and 6 match on 1995 HPI only, and columns 7 and 8 match on 2005 HPI.

The point estimates in odd-numbered columns reflect the price effect, and the point estimates in even-numbered columns reflect the population effect, of regulation-induced changes in $PM_{2.5}$ concentrations using these different weighting schemes. The price capitalization is quite similar across these various strategies, while population changes remain small and statistically insignificant across specifications. We also note that using

[3]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 counts as outcomes, the matching strategy we outline here better addresses the concerns related to differential counterfactual trends between nonattainment and attainment tracts.

Table B2: Price and population responses to $\Delta PM_{2.5}$, 2000-2010 (alternative weighting schemes)

	(1) 2010 HPI	(2) $\Delta\ln(pop)^{'00\text{-}10}$	(3) 2010 HPI	(4) $\Delta\ln(pop)^{'00\text{-}10}$	(5) 2010 HPI	(6) $\Delta\ln(pop)^{'00\text{-}10}$	(7) 2010 HPI	(8) $\Delta\ln(pop)^{'00\text{-}10}$
Δ $PM_{2.5}$, 2000-10	-5.843**	-0.051	-4.964*	0.136	-6.238**	0.594	-5.285*	-0.662
	(2.750)	(0.818)	(2.779)	(0.759)	(2.697)	(0.813)	(2.734)	(0.794)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
Division FE	✓	✓	✓	✓	✓	✓	✓	✓
Weight	none	none	'95 HPI & $\Delta\ln(pop)^{'90\text{-}00}$	'95 HPI & $\Delta\ln(pop)^{'90\text{-}00}$	'95 HPI	'95 HPI	'05 HPI	'05 HPI
Observations	25,843	25,843	22,407	22,407	20,835	20,835	23,714	23,714

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. We instrument for change in $PM_{2.5}$ with NAAQS nonattainment status, as described in text. The outcome variable in columns 2, 4, 6, and 8 has been multiplied by 100 for ease of interpretation. In columns 3 through 8, we weight observations by the weights produced in PSM, where we match nonattainment and attainment tracts on the variables indicated in the "weight" row using the 4 nearest neighbors and imposing common support.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

these alternative weighting schemes to estimate equation 2 produces similar results as those in Figure 4. The conclusion that housing prices are more sensitive to air quality improvements in markets characterized by relatively inelastic housing supply, and that population sizes respond more in elastic-supply locations, 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, where population changes are the more relevant margin of adjustment to demand shifts.

C Short- and long-run impacts of air quality improvements on housing prices

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 that the price capitalization of air quality improvements will 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 larger in magnitude in

Table C3: Price capitalization of air quality improvements over time

	(1)	(2)	(3)	(4)
	HPI in year X (2000=100)			
	X=2008	2010	2013	2016
Δ $PM_{2.5}$, 2000-X	-6.301**	-5.843**	-3.964**	-2.657
	(2.690)	(2.750)	(1.688)	(2.454)
Controls	✓	✓	✓	✓
Division FE	✓	✓	✓	✓
Observations	25,749	25,843	25,669	24,855

Standard errors, in parentheses, are clustered by 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. We instrument for change in $PM_{2.5}$ between 2000 and the year indicated (X) with NAAQS nonattainment status, as described in text.
*** p<0.01, ** p<0.05, * p<0.1

the short run (2000–2008) and smaller in the longer run (2000–2013 and 2000–2016).

Table C3 presents the point estimates capturing the effect of the regulation-induced change in average annual $PM_{2.5}$ concentrations on tract-level price changes over different long-difference periods. In each column, we instrument for the change in average annual $PM_{2.5}$ concentrations between 2000 and the year indicated with nonattainment status. The outcome variable is defined as the HPI in the year indicated, relative to 2000 levels. Thus, column 1 shows the price capitalization between 2000 and 2008, column 2 shows the price capitalization between 2000 and 2010 (our primary setting), column 3 shows the price capitalization between 2000 and 2013, and column 4 shows the price capitalization between 2000 and 2016.[4] The specification used to produce the estimates is identical to our central analysis, but the primary independent variable and outcome variable are adjusted to reflect the relevant time horizon. The price effect of regulation-induced pollution reductions becomes increasingly attenuated over time.

Consistent with basic economic theory, in very short-run settings, prices appear more responsive to demand shifts. A 1-$\mu g/m^3$ regulation-induced decline in average annual

[4] We select 2008 as our "short-run" setting because states were given a three-year window to develop plans to reduce $PM_{2.5}$ concentrations in nonattainment areas following implementation in 2005.

$PM_{2.5}$ concentrations yields about a 6.3 percent increase in housing prices between 2000 and 2008, which declines to a statistically indistinguishable 2.7 percent increase in housing prices between 2000 and 2016. 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 could be biased to the extent that it does not incorporate the quantity margin. Over progressively longer 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.[5]

[5]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.