

Where does Air Quality Matter?

New Evidence from the Housing Market

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The most recent version of this paper can be found [here](#).

Abstract

Under the classic hedonic valuation approach, the demand for environmental improvements is often estimated from changes in housing prices. We show that when housing supply is elastic, amenity improvements may yield an expansion of the housing market (the ‘quantity’ effect), muting the capitalization of the amenity into housing prices (the ‘price’ effect). We demonstrate this in the context of local air quality improvements induced by the Clean Air Act’s (CAA) $PM_{2.5}$ standards. The price capitalization of air quality improvements is higher in places with relatively inelastic housing supply, while quantity responses are larger in places with relatively elastic housing supply. A simple spatial equilibrium model demonstrates that the reduced-form hedonic valuation coefficient reflects the willingness to pay for an amenity attenuated in proportion to the local housing supply elasticity. Incorporating housing supply elasticities into the classic hedonic regression framework increases the estimated marginal benefits of CAA-induced reductions in $PM_{2.5}$ by up to over 100 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; Sager and Singer, 2022). In a partial equilibrium setting in which housing stock 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 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 introduction 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 about a 3 percent increase in its total population. Meanwhile, Atlanta experienced only a 5 percent increase in housing prices in real terms and about 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 marginal benefits of air quality improvements? How can researchers estimate MWTP for amenity shifts in settings with elastic supply?

In this paper, we present evidence that plausibly exogenous improvements in air quality induced by the CAA generate both price *and* quantity effects, with the relative strength of each depending on the elasticity of local housing supply. A reduction in average annual PM_{2.5} concentrations yields larger price increases in Census tracts with relatively inelastic housing supply,

whereas it yields larger population increases in Census tracts with relatively elastic housing supply. 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. We present a simple spatial equilibrium model which incorporates this intuition. Our model shows that when housing is elastically supplied, the reduced-form effect of a pollution reduction is an attenuated estimate of willingness to pay, where the attenuation is proportional to the local housing supply elasticity. Using this framework and incorporating estimates of local housing supply elasticities from the literature, we provide new estimates of the MWTP for reduced $PM_{2.5}$ concentrations. We find that incorporating measures of housing supply elasticity into the classic hedonic regression framework substantially increases the estimated marginal benefits of reductions in $PM_{2.5}$.

To isolate the causal relationship between air quality and local prices and population sizes, we exploit the introduction of the 1997 $PM_{2.5}$ National Ambient Air Quality Standards (NAAQS), which went into effect in 2005.¹ Following the implementation of these 1997 standards, areas designated as ‘nonattainment’ were legally required to reduce $PM_{2.5}$ concentrations, while ‘attainment’ areas, with $PM_{2.5}$ concentrations below the regulatory ceiling, were not. Instrumenting for Census-tract-level changes in average $PM_{2.5}$ concentrations with area nonattainment status in 2005, we estimate the effect of declining $PM_{2.5}$ concentrations on housing prices (the ‘price’ effect) and population sizes (the ‘quantity’ effect) between 2000 and 2010. We then examine how price and quantity effects of these air quality improvements differ across inelastic- and elastic-supply areas based on housing supply elasticity estimates from [Saiz \(2010\)](#) and [Baum-Snow and Han \(2024\)](#).

We find that regulation-induced air quality improvements are met with large increases in housing prices: Across all tracts in our sample, a CAA-induced 1-unit decline in average $PM_{2.5}$ concentrations 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

¹Other research exploiting the introduction of the NAAQS standards regulating $PM_{2.5}$ to understand the effects of these regulations on exposure to air pollution include [Bento et al. \(2015\)](#); [Jha et al. \(2019\)](#); [Currie et al. \(2020\)](#); [Sager and Singer \(2022\)](#).

increases in the most inelastic-supply housing markets (an 8.7 percent increase) compared to the most elastic-supply housing markets (a statistically insignificant 2.5 percent decrease).

We estimate the quantity effect based on the change in log population counts within consistent (2010) Census tract boundaries. While the price effect of air quality improvements is largest in the most inelastic-supply places, we find that the CAA-induced decline in $PM_{2.5}$ concentrations yields the largest quantity effect in the most elastic-supply Census tracts. A regulation-induced 1-unit decline in average $PM_{2.5}$ concentrations over the 2000–2010 period yields about a 5.7 percent increase in population in the most elastic-supply housing markets, compared to a statistically insignificant 0.3 percent increase in the most inelastic-supply housing markets. The conclusion that the price (quantity) response to improved air quality is greater in relatively inelastic (elastic) locations is largely robust to alternative definitions of housing supply elasticity and quantity outcomes, different empirical specifications, as well as matching observations according to pre-regulation price and quantity trends.

The reduced-form evidence is consistent with the economic intuition that housing supply constraints should modify the price and quantity effects of demand shifts, and it indicates that the classic hedonic valuation technique will likely underestimate MWTP in elastic-supply settings when price effects are attenuated by simultaneous quantity effects. Motivated by this insight, we develop a simple Rosen-Roback-style model of spatial equilibrium 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 indeed 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 housing supply elasticity into the hedonic regression framework substantially increases the

estimated benefits of environmental improvements.

This paper makes two important contributions to the literature. First, we build the literature exploiting the CAA regulatory structure to study air pollution (Chay and Greenstone, 2005; Grainger, 2012; Bento et al., 2015; Jha et al., 2019; Currie et al., 2020; Sanders et al., 2020; Sager and Singer, 2022; Bishop et al., 2023), and we provide 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 extending the Rosen-Roback model of spatial equilibrium (Rosen, 1979; Roback, 1982) to allow for a quantity response to amenity improvements in addition to price capitalization. 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; Bento et al., 2015; Keiser and Shapiro, 2019; Sager and Singer, 2022). Our model provides guidance on how the hedonic framework can be adapted to measure MWTP for amenities in general equilibrium settings, accounting for the elasticity of local housing supply. Our model shows that in the presence of quantity effects, the reduced-form effects of air quality improvements will underestimate the MWTP for air quality. In these cases, the true MWTP can be recovered by incorporating a measure of housing supply elasticity into the traditional hedonic price capitalization approach. Specifically, the traditional price capitalization regression coefficient reflects MWTP attenuated by the housing supply elasticity. Incorporating measures of local housing supply elasticity into the hedonic framework produces estimates of MWTP up to over

100% larger than estimates based solely on price capitalization.

The rest of this paper is organized as follows. Section 2 presents a stylized model of supply and demand for air quality improvements, demonstrating how demand shifts yield both price and quantity effects in elastic settings. We describe our data and methodological approach to estimating the price and quantity effects in Sections 3 and 4, with results detailed in Section 5. Section 6 presents a spatial equilibrium model for air quality improvements, with model estimation results provided in Section 6.2. Section 7 concludes.

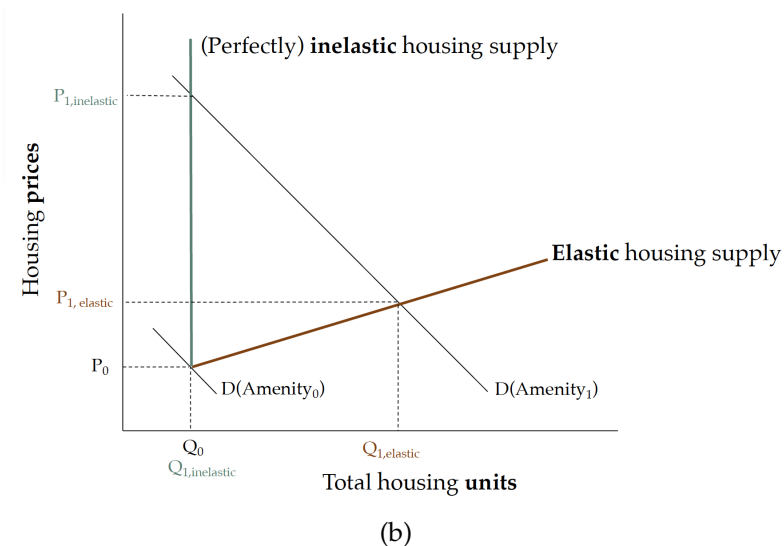
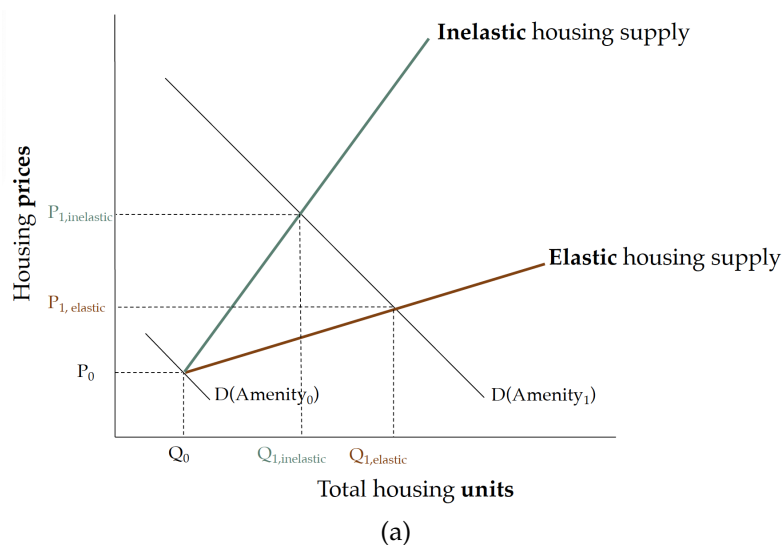
2 A stylized depiction of the housing market and amenity improvements

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. At time $t = 0$, demand for these locations is given by $D(\text{Amenity}_0)$, 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 $D(\text{Amenity}_0)$ to $D(\text{Amenity}_1)$ 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

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



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.

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} National Ambient Air Quality Standards (NAAQS), which went into effect in 2005. Both experienced large improvements in air quality over the 2000–2010 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.² 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 regulation-induced air quality improvements, but the stark contrast across the two places is consistent with the basic economic theory 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.

We are not the first to raise concerns regarding the assumption of fixed housing supply im-

²In Saiz (2010), the estimated metro-level housing supply elasticity in Los Angeles is 0.63, compared to 2.55 in Atlanta.

plicit in the canonical hedonic model. Many scholars have acknowledged this issue and provided helpful direction for conducting hedonic valuation methods in general equilibrium environments. For example, [Sieg et al. \(2004\)](#) provide a structural model of Tiebout sorting, demonstrating how individuals re-optimize in response to large changes in amenities, and illustrating the large differences between partial- and general-equilibrium estimates of MWTP in the case of sorting-induced endogenous local attribute changes. Here, we leave aside the issue of endogenous local amenity changes and focus instead on how local housing supply characteristics affect the capacity for housing prices to adjust and for individuals to sort more generally. More recently, [Banzhaf \(2021\)](#) shows that price changes associated with improved air quality include both amenity demand (WTP) and changes in the hedonic price function, especially over longer time horizons. That is, amenity shocks can influence the equilibrium hedonic price function for an entire housing market (including untreated units), such that there may exist price changes not directly attributable to local amenity improvements. In our exposition, the ex-post price function in a difference-in-differences setting can represent a completely different *quantity* of housing – and thus a fundamentally different housing market – when housing supply is relatively elastic. We do not address the issue of indirect price effects treated in [Banzhaf \(2021\)](#), but rather show that even the direct price effect captured by typical hedonic methods is an insufficient statistic for MWTP when there also exists a quantity margin. In Section 6, we back out MWTP incorporating this quantity margin, offering a simple method scholars may use to recover MWTP when housing supply is not explicitly fixed.

3 Data

Our primary empirical analysis leverages changes in tract-level air pollution, housing prices, and population densities in 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 pollu-

tion 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. We also consider this change over the 2000–2007, 2000–2013, and 2000–2016 periods in order to elucidate the differences between short- (partial equilibrium) and longer-term (general equilibrium) adjustments.

3.2 Housing price, quantity, and demographic data

We combine the air quality data with local housing, economic, and demographic data retrieved from the decennial Census, the American Community Survey (ACS), and the Federal Housing Finance Agency (FHFA). Our two main outcome variables of interest are the tract’s housing price index (HPI) in the final year of the period (where 2000 is the base year of the index) and the long-difference change in the natural log of the tract’s population over the period.³ The HPI, retrieved from the FHFA, is a weighted, repeat-sales index capturing movements in prices of single-family homes whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac. It provides a measure of housing price appreciation in a given tract (or county) holding the underlying quality of housing stock relatively constant.

Measuring quantity adjustments with fixed geographic units is less straightforward than the measurement of price adjustments. Census tract boundaries are modified (and new tracts defined) periodically to account for population adjustments, such that the geographic unit is designed to have relatively consistent populations over time. Cities grow outward as well as upward, and thus comparisons of the number of individuals living within a consistent city boundary across time will fail to incorporate the contribution of sprawl to larger numbers of residents or housing units. Counties offer a relatively tractable geographic unit from which to measure quantity adjustments but offer less precision for exploring the importance of housing supply elasticities, as rural and urban tracts within a given county will have largely different housing supply constraints. With these limitations in mind, we measure tract-level quantity adjustments using the change in the natural log of the population over the given period, and we assign all characteristics to Census tracts using the consistent tract boundaries as defined by the 2010 Census.⁴ Baseline tract-level

³For the 2000–2010 period, the outcome variable is the tract’s 2010 HPI. For the 2000–07, 2000–13 and 2000–16 periods, we consider the 2007, 2013, or 2016 HPI, respectively, indexed to 2000, such that the HPI in 2000 is 100 for all tracts.

⁴Supply constraints may promote increased crowding within existing housing units. Our conclusions are robust to

covariates are retrieved from the 2000 Census.⁵ Population counts for years 2000 and 2010 are derived from the decennial Census.

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.⁶ 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 reflecting 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).⁷ 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 elasticity measure with estimates of tract-level housing supply elasticities from [Baum-Snow and Han \(2024\)](#).⁸ These estimates are identified using labor demand shocks in commuting destinations from residential locations. The authors then estimate the change in local housing quantity resulting from shifts in local housing prices, conditional on tract-specific observables. Tract-level housing supply elasticities vary based on the tract’s distance to the central

instead estimating the effect on the change in the number of housing units as well as the change in population density, following [Banzhaf and Walsh \(2008\)](#) and [Greenstone and Gallagher \(2008\)](#).

⁵As detailed in Section 4, these include the share of the tract population that is non-Hispanic white, the share of adults with a college degree, median household income, the share of housing units that are occupied, and the share of occupied housing units that are renter-occupied.

⁶[Saiz \(2010\)](#) uses the measure of local land use regulations from the Wharton Residential Land Use Regulation Index (WRLURI), constructed by [Gyourko et al. \(2008\)](#). This regulatory index provides an aggregate measure of the restrictiveness of local land use regulations in 293 metropolitan areas in the U.S.

⁷This aggregate measure is based on 11 subindexes, which include a local political pressure index, state political involvement index, state court involvement index, local zoning approval index, local project approval index, local assembly index, supply restrictions index, density restrictions index, open-space index, exactions index, and approval delay index. These indices are summarized using factor analysis. The final aggregated index is increasing in the restrictiveness of regulations and is standardized across communities.

⁸[Baum-Snow and Han \(2024\)](#) provide several housing supply elasticity estimates. We use the elasticity estimates based on their quadratic finite mixture model, which are the authors’ preferred estimates. This model allows parameters governing tract supply elasticities to flexibly differ between metropolitan areas as functions of developable land, regulation, and developed land. We use the elasticity estimates from the 2021 version of this working paper, which produces nearly identical groupings of tracts as the estimates in the published version of the paper.

business district, land availability, topographical features, and land use regulations. These tract-level elasticities are primarily meant for comparison *within* metropolitan areas rather than *across*, and thus we combine these tract-level elasticity measures with the [Saiz \(2010\)](#) measure to produce a characterization of a Census tract’s elasticity that is comparable across metropolitan areas. To do so, we take the simple average of MSA-level ([Saiz, 2010](#)) and tract-level ([Baum-Snow and Han, 2024](#)) supply estimates. 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 $\text{PM}_{2.5}$ concentration was $13\mu\text{g}/\text{m}^3$ in 2000, and the average change over the 2000–2010 decade was a decline of $3\mu\text{g}/\text{m}^3$. 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 8 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 $\text{PM}_{2.5}$ 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 housing markets over the 2000–2010 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 $\text{PM}_{2.5}$ concentrations.

Table 1: Summary statistics for primary outcome & independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PM _{2.5} conc. (2000)	Med. home value (2000)	ΔPM _{2.5} 2000–10	2010 HPI (2000=100)	Δln(pop) 2000-10	Metro-level elasticity	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 inelastic)	15.0 (4.9)	161,813 (87,929)	-4.4 (2.5)	155.8 (25.6)	4.8 (19.0)	0.6 (0.0)	0.4 (0.1)
2	12.7 (2.5)	147,508 (80,922)	-2.9 (1.3)	138.4 (24.4)	7.4 (24.3)	0.8 (0.0)	0.5 (0.1)
3	13.1 (4.5)	97,863 (41,315)	-3.6 (2.3)	126.8 (20.4)	12.3 (28.0)	1.0 (0.1)	0.6 (0.1)
4	12.2 (2.7)	105,208 (47,300)	-2.8 (1.6)	121.7 (34.8)	7.9 (24.6)	1.3 (0.1)	0.8 (0.1)
5	12.7 (2.6)	113,858 (54,065)	-3.5 (1.1)	148.1 (31.5)	9.8 (27.5)	1.6 (0.0)	0.9 (0.1)
6	12.2 (3.4)	90,808 (40,335)	-2.5 (1.7)	129.9 (21.1)	15.0 (33.5)	2.0 (0.2)	1.2 (0.1)
7	14.0 (2.4)	92,350 (43,426)	-2.6 (1.4)	117.3 (20.7)	14.1 (29.0)	2.5 (0.1)	1.4 (0.1)
8 (most elastic)	12.2 (2.2)	83,502 (35,861)	-1.6 (1.2)	120.0 (16.1)	17.9 (33.2)	3.4 (0.6)	1.9 (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 Social Explorer, 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 \(2024\)](#).

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 approach follows [Chay and Greenstone \(2005\)](#), [Sager and Singer \(2022\)](#), and others who instrument for mid-period CAA nonattainment status to estimate the effect of air quality improvements on subsequent outcomes. Here, we use this framework to separately identify both price *and* quantity effects, and we estimate how this relationship differs based on the elasticity of local housing supply. This allows us to elucidate the extent to which housing supply constraints mediate the price capitalization of air quality improvements.

Consider the following long-difference equation:

$$\Delta y_j = \beta_0 + \beta_1 \Delta PM_{2.5_j} + \mathbb{X}'_j \gamma + \delta_d + \varepsilon_j \quad (1)$$

Where Δy_j is the dependent variable in tract j (the change in housing prices and the change in population counts), $\Delta PM_{2.5_j}$ is the long-difference change in average $PM_{2.5}$ concentrations in tract j , \mathbb{X}'_j reflects tract-level covariates, and δ_d represents Census division fixed effects. We focus on two primary 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., Census 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 vacant, 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. Again, our point estimates are relatively stable across specifications (e.g., omitting controls). We cluster standard errors at the county level. Estimating equation 1 using Ordinary Least Squares, β_1 measures the association between a one-unit change in average tract-level $PM_{2.5}$ concentrations and the change in the tract's price or population between 2000 and 2010 after controlling for observable covariates.

In order to determine whether the relationship between air quality improvements and associated price and quantity changes differs depending on the elasticity of local housing supply,

we estimate a slightly modified version of equation 1, where we interact the primary explanatory variable ($\Delta PM_{2.5j}$) with a binned value of the Saiz (2010) elasticity assigned to the tract’s MSA, e_j . We allow for eight, equal-sized bins of this value and estimate the following:

$$\Delta y_j = \sum_{q=1}^8 \beta_q (\Delta PM_{2.5j} \times \mathbf{1}[e_j = q]) + \mathbb{X}'_j \gamma + \delta_d + \varepsilon_j \quad (2)$$

Tracts in the lowest quantile ($e_j = 1$) are in the most inelastic metro areas 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 used for the primary analysis. 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 their metro-level elasticity and the tract-level elasticity 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 $PM_{2.5}$ 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, we focus on two outcome variables Δy_j : The 2010 HPI, indexed to 2000 levels, and the 2000–2010 change in the natural log of the population. We can then compare the point estimate across bins to understand how the ‘price’ and ‘quantity’ effect of air quality improvements differs across regions with varying housing supply constraints.

4.1 Causal inference: Clean Air Act

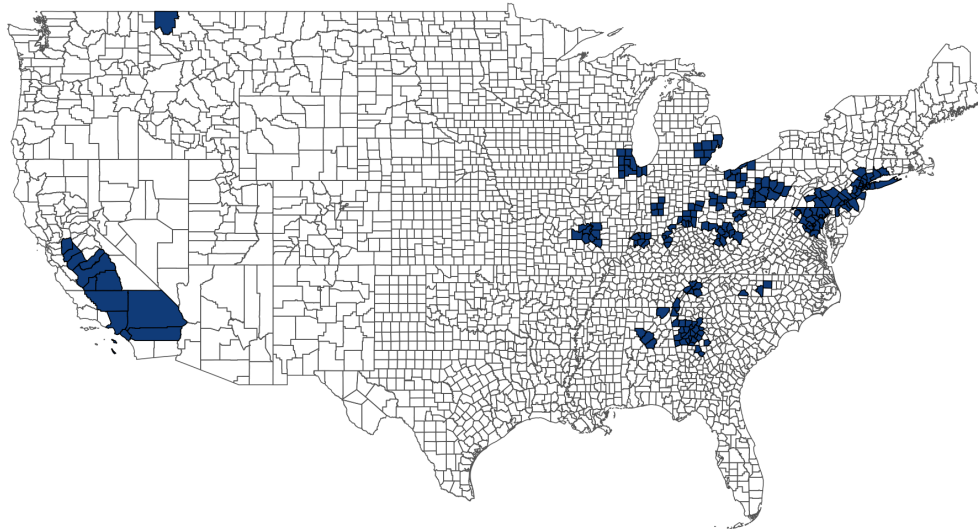
Many unobserved characteristics covary with both air pollution and the central outcomes of interest, introducing bias in the estimation of the pollution-price or pollution-population gradient. The issue of misspecification in the traditional hedonic price model is well-known, and researchers have used a wide variety of quasi-experimental solutions to address it.⁹ 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.¹⁰ 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

⁹See, for example, Chay and Greenstone (2005); Bayer et al. (2009); Lee and Taylor (2019); Banzhaf (2021).

¹⁰The regulation also imposed a daily standard of $65 \mu g/m^3$.

period. These areas are displayed in blue in Figure 2. Following this designation, states with nonattainment areas were required to submit to the EPA state implementation plans (SIPs) identifying how nonattainment areas would meet $PM_{2.5}$ standards, and meet these standards by 2010. The observed decline in $PM_{2.5}$ concentrations between 2000 and 2010 is shown in Figure 3.

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

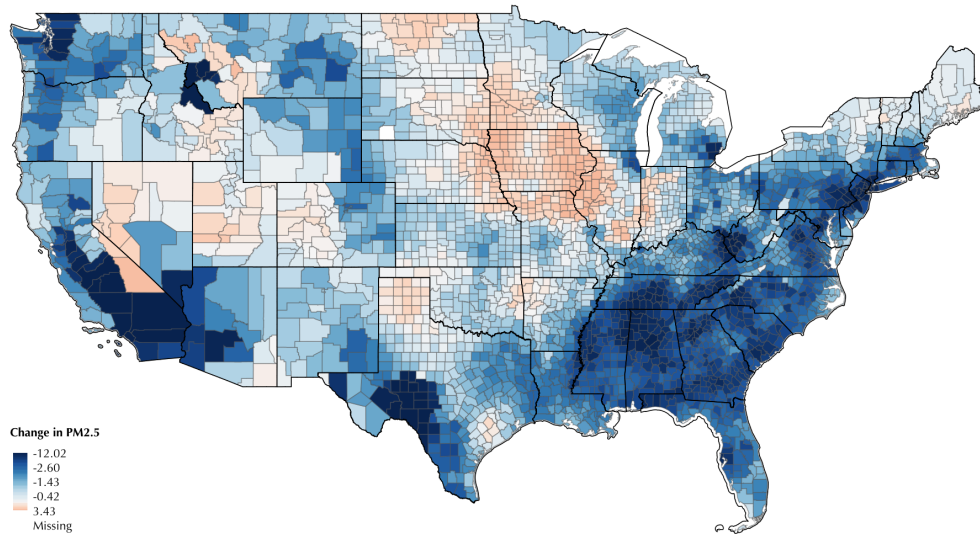


Notes: Areas classified as nonattainment under the 1997 NAAQS (as announced in December 2004) are indicated in blue. Source: U.S. Environmental Protection Agency (EPA).

A comparison of Figures 2 and 3 suggests that while much of the country experienced air quality improvements over the 2000-2010 period, many of the areas with the greatest improvements (e.g., Southern California, Northern Georgia, and the Central Atlantic region) were those that were in nonattainment in 2005. Currie et al. (2020) document that the 1997 NAAQS greatly improved air quality in newly regulated areas, indicating that the standards were relevant to the differential reduction in $PM_{2.5}$ seen in Figure 3. We provide additional evidence of instrument relevance below.

Following Chay and Greenstone (2005), who instrumented for changes in county-level TSP concentrations from 1970-1980 with mid-decade nonattainment status, several papers leverage differential nonattainment status designation across place to identify the effect of relevant air quality improvements on outcomes of interest (e.g., Bento et al. (2015); Sager and Singer (2022); Currie et al. (2020)). Here, we instrument for tract-level changes in average $PM_{2.5}$ concentrations with a

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. \(2019\)](#).

dummy variable indicating whether the tract was in a nonattainment status area in 2005.¹¹ The central identifying assumption is that conditional on observable characteristics, nonattainment status is exogenous to expected outcomes. In this setting, this would be violated if places 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 pollution reductions (e.g., employment effects).¹² We observe in Appendix section A that nonattainment tracts were growing more slowly – in terms of both population changes and housing price changes – prior to the period of analysis. For this reason, we believe that our instrumental variable strategy likely yields a lower bound estimate on the change in prices and quantities attributable to regulation-induced declines in PM_{2.5} concentrations. In robustness checks, we match attainment and nonattainment tracts according to these population and price pre-trends, and weight observations using the weights generated in this matching process. This produces quantitatively similar estimates as our primary specification, as detailed in Appendix section A.¹³

¹¹We cluster standard errors on county, as nonattainment “areas” tended to align with county boundaries.

¹²[Sager and Singer \(2022\)](#) similarly instrument for changes in tract-level PM_{2.5} concentrations with mid-decade nonattainment status.

¹³A 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. This relies

Table 2: First stage and reduced form: Nonattainment status

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ PM _{2.5} , 2000-10		2010 HPI (2000=100)		Δ ln(pop), 2000-10	
Nonattainment	-1.685*** (0.209)	-1.574*** (0.187)	10.289** (4.831)	9.196** (4.367)	-0.506 (1.742)	0.081 (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 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. Nonattainment status refers to the 1997 NAAQS standards, which went into effect in 2005.

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

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 $1.7\text{-}\mu\text{g}/\text{m}^3$ decline in PM_{2.5} concentrations over the 2000-2010 period, relative to an average PM_{2.5} concentration of $13.0\ \mu\text{g}/\text{m}^3$ in 2000 across the entire sample (Table 1). Table 2 also displays the reduced-form relationship between nonattainment status and the central outcome variables of interest, indicating that nonattainment status is associated with a 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.¹⁴

on the slightly weaker assumption that the relationship between nonattainment status and expected price changes is the same across inelastic and elastic areas.

¹⁴This 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. Alternatively, if individuals are willing to pay more for air quality improvements at higher initial levels of pollution, inelastic tracts should experience larger price effects. However, the evidence on taste-based sorting suggests that the opposite is likely the case. Chay and Greenstone (2005) provide "modest evidence" that MWTP for pollution reductions is *lower* in communities with relatively high pollution levels, consistent with preference-based sorting, whereby individuals living in places with initially *low* levels of air quality have higher MWTP for incremental pollution reductions. We do not take a stand on which of these effects (if either) dominates, but if preference-based sorting is at play, this would bias our estimates toward finding a *larger* price effect in elastic markets, with lower initial PM_{2.5} concentrations.

While our strategy addresses endogeneity concerns around air quality, it does not address potential selection across elastic and non-elastic places. Conditional on observable characteristics, individuals may still sort into elastic or inelastic housing markets based on their underlying preferences for air quality. If sorting into elastic vs. inelastic locations arises due to unobservable taste dispersion, then the underlying MWTP for pollution reductions are expected to differ across housing markets.¹⁵ 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 variations in the price response to pollution reductions. While this is a limitation in comparing the point estimates β_q across elasticity bins, it does not obstruct the broader conceptual point that market constraints influence the capitalization of amenity improvements.

As discussed in [Bishop et al. \(2020\)](#), a central challenge to interpreting the estimates produced by this instrumental variable approach, which is an application of a more general class of difference-in-differences hedonic valuation techniques, is that price functions may change over time. [Kuminoff and Pope \(2014\)](#), [Banzhaf \(2021\)](#), and others show that the MWTP estimate produced in the typical difference-in-differences framework combines information on two hedonic price functions (pre- and post-treatment) and thus may be biased. Our setting overlaps with the Great Recession and the associated housing crisis, which fundamentally altered the price functions in housing markets across the United States. While this would complicate the MWTP estimate produced from price capitalization in the canonical setting for the reasons discussed by [Kuminoff and Pope \(2014\)](#) and [Banzhaf \(2021\)](#), the central goal of our reduced-form exercise is not to produce unbiased estimates of MWTP based on price capitalization. Rather, it is to elucidate another, distinct source of bias in the canonical framework: the assumption of fixed quantities. Our empirical approach demonstrates how price capitalization differs depending on the elasticity of the local housing market, or its capacity to absorb increased demand. We present a theoretical strategy to recover MWTP in the presence of both price and quantity margins in [Section 6](#).

¹⁵Note that this is different from the issue of endogenous or taste-based sorting often discussed in the canonical hedonic setting (which remains an issue here). Individuals with higher MWTP might choose to live in places with initially low levels of pollution reduction. [Banzhaf and Walsh \(2008\)](#) show that individuals with greater MWTP might endogenously sort *in response to* air quality improvements, such that individuals living in newly clean areas have different MWTP than those elsewhere.

5 Results: Price and quantity effects of air quality improvements

This section presents the central quasi-experimental evidence on the price and quantity effects of air quality improvements across metropolitan Census tracts. Section 5.1 offers our primary empirical results for the effect of these improvements across metro-area Census tracts over the 2000 to 2010 period.¹⁶ In Appendix A, we show that these results are largely robust to alternative weighting schemes that explicitly address any potential pre-trends in the central outcome variables. In Section 5.2, we demonstrate how price and quantity effects of air quality improvements differ depending on the elasticity of local housing supply. We find consistent evidence that housing prices capitalize improvements in air quality across U.S. Census tracts over the 2000-2010 period, with this price effect mediated by the elasticity of local housing supply. More inelastic-supply places experience much larger price capitalization of air quality improvements, while more elastic-supply places experience larger quantity changes. This suggests that housing supply constraints are relevant when estimating the MWTP for amenity improvements, and motivates 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.

5.1 Price and quantity impacts of air quality improvements

We first examine the price and population response to change in average annual PM_{2.5} concentrations over the 2000–2010 period without differentiating housing markets according to their 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 ($\mu\text{g}/\text{m}^3$) decline in average annual PM_{2.5} concentrations yields a 5.8 percent increase in local 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 Sager and Singer (2022), as well as other hedonic estimates of the benefits of air quality improvements. The IV estimates for the effect of

¹⁶We illustrate how price responses differ across various lengths of time in Appendix B, showing that prices are relatively more responsive under short time horizons.

Table 3: Price and population responses to $\Delta PM_{2.5}$, 2000-2010

	(1)	(2) 2010 HPI (2000=100)		(4)	(5)	(6) $\Delta \ln(\text{population}), 2000-2010$		(7)	(8)
	OLS	IV			OLS	IV			
$\Delta PM_{2.5}, '00-10$	-1.551 (1.438)	-0.984 (1.316)	-6.108** (2.664)	-5.843** (2.750)	1.608*** (0.488)	0.880** (0.418)	0.301 (1.030)	-0.051 (0.818)	
Controls		✓		✓		✓			✓
Division FE	✓	✓	✓	✓	✓	✓	✓		✓
Observations	25,843	25,843	25,843	25,843	25,843	25,843	25,843	25,843	25,843

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. 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.

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

pollution declines on population changes are statistically indistinguishable from zero, while the positive OLS coefficients imply that population *declines* with pollution declines. This is consistent with existing evidence of a strong correlation between pollution and economic activity. When we instrument for declining pollution levels with regulatory designations, this relationship becomes indistinguishable.

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. We note that, in estimating the price and quantity impacts of air quality improvements induced by nonattainment status, one must also consider potential pre-trends in these outcome variables. In Appendix Section [A](#), we show that the price and quantity impacts of regulation-induced pollution declines presented 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.

5.2 Price and quantity impacts by housing supply elasticity

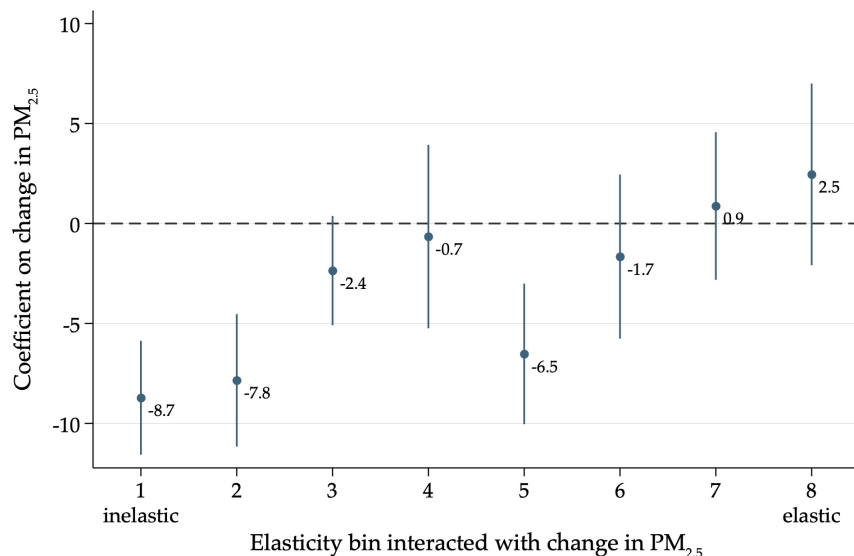
Next, we consider heterogeneity in the effect of air quality improvements across relatively inelastic and elastic housing markets. To do so, we estimate equation 2 for the 25,853 Census tracts, grouping tracts into 8 bins of metro-level elasticity according to the values in Saiz (2010), where bin 1 is the most inelastic and bin 8 is the most elastic. 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. 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 2000–2010 period with nonattainment status. Panel A reports the coefficient estimates for HPI (the ‘price’ effect), and Panel B reports the coefficient estimates for population changes (the ‘quantity’ effect). The estimates in each panel are estimated from a single regression.

The leftmost point estimate in Panel A 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. The figure suggests that housing prices appear to increase the most in response to regulation-induced pollution declines in the most inelastic tracts and that there is a clear relationship between supply elasticities and price capitalization.¹⁷

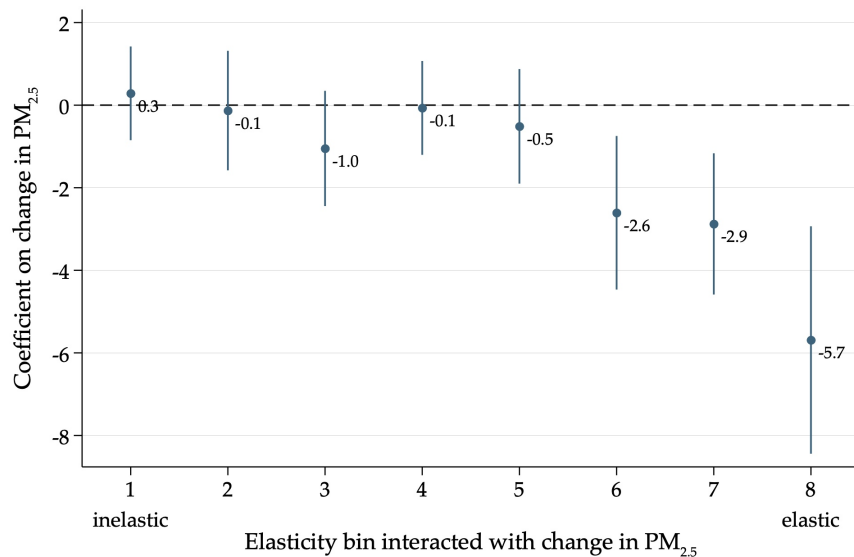
At the same time, Panel B — showing the quantity effect — displays a somewhat striking mirror-image version of Panel A. Regulation-induced pollution declines yield the largest population increases in the most *elastic* Census tracts. The rightmost point estimate in Panel B implies that a 1-unit decline in annual PM_{2.5} concentrations produces about a 5.7 percent increase in population in the most elastic tracts. Moving rightward from the leftmost estimate, there is a clear downward trend in the point estimate, with a 0.3 percent decline in population in the most inelastic census tracts. Population responses to pollution declines grow as places are more elastic.

¹⁷The most inelastic bin of tracts began the period with higher levels of annual PM_{2.5} emissions than other bins (15 $\mu\text{g}/\text{m}^3$ in the most inelastic tracts versus 13 $\mu\text{g}/\text{m}^3$ 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. The implied elasticity of housing prices with respect to pollution is thus about -1.3 in the most inelastic tracts, compared to -0.75 across all metro-area Census tracts in the sample. The implied elasticity reported in Sager and Singer (2022) is -1.1. Chay and Greenstone (2005) estimate that the implied elasticity of housing prices with respect to TSP concentrations is between -0.2 and -0.35.

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



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



(b) Outcome: $\Delta \ln(\text{population})$, 2000-10

Notes: Figure shows the point estimates and 95 percent confidence intervals of the regression coefficient β_k on change in tract-level $PM_{2.5}$ concentrations over the 2000–2010 in parentheses 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 on 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.

We note that the grouping of Census tracts into 8 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 4 quantiles or 10 quantiles). We also note that there exists heterogeneity in supply constraints *within* metropolitan areas. In Figure 5, we replicate the analysis above but incorporate tract-level elasticity estimates from [Baum-Snow and Han \(2024\)](#). Specifically, we group tracts into 8 bins based on the average of their tract- and metro-level elasticity estimates from [Baum-Snow and Han \(2024\)](#) and [Saiz \(2010\)](#). This produces extremely similar patterns as 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.¹⁸

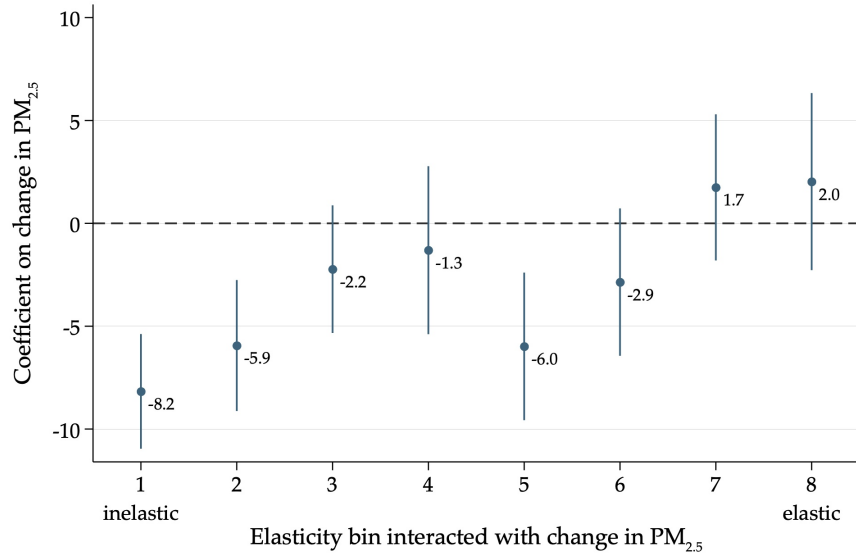
The relationships described in this section are consistent with economic theory, as we expect housing market constraints to play a role in determining the price and quantity effects of demand shifts. What is less clear is what this implies for estimating the marginal benefits of pollution reductions. If price capitalization were there sufficient statistic necessary for estimating MWTP, the results in Panel A of Figure 5 suggest that MWTP is simply larger in inelastic-supply places. However, the quantity effects in Panel B imply that other margins of adjustment may attenuate the price capitalization in elastic-supply places. In the section that follows, we present a simple spatial equilibrium model that allows us to interpret the reduced-form price and quantity effects 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

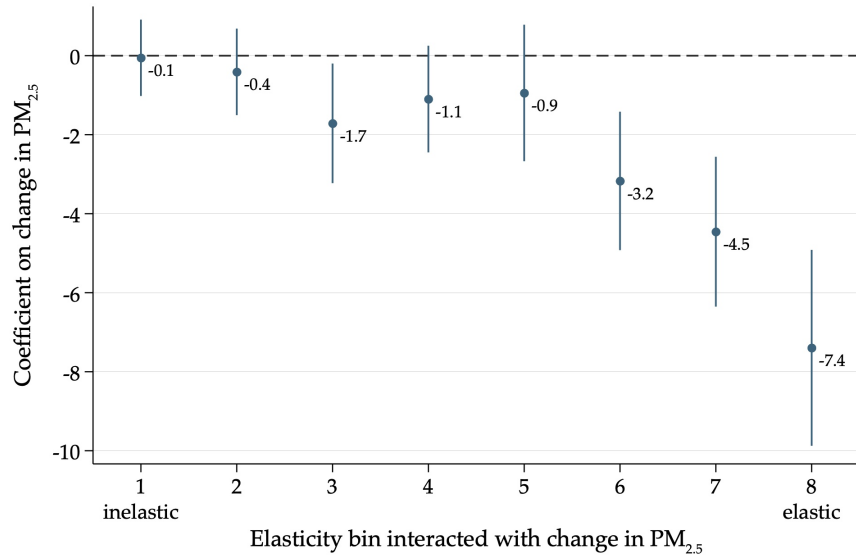
Our empirical evidence shows that pollution declines yield larger price increases in places characterized by relatively inelastic housing markets, and larger quantity (population) in places characterized by relatively elastic housing markets. Intuitively, in markets in which housing supply is not perfectly inelastic, a quantity adjustment may attenuate the price capitalization of demand

¹⁸Housing 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 Appendix Section B, 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: $\Delta \ln(\text{population}), 2000-10$

Notes: Figure shows the point estimates and 95 percent confidence intervals of the regression coefficient β_k on change in tract-level PM_{2.5} concentrations over 2000–2010 in parentheses 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 on 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.

shifts. This suggests that when supply is not perfectly inelastic, incorporating both price and quantity effects will be necessary for generating credible estimates of MWTP.

To make progress towards incorporating this quantity margin when estimating MWTP for amenity changes, we develop a simple spatial equilibrium model for air-quality improvements that provides expressions for local population and housing prices as a function of local amenities. This model builds on the long line of research that extends the logic of [Rosen \(1979\)](#) and [Roback \(1982\)](#) to estimate the benefits of amenity improvements.¹⁹ We show that when housing supply is perfectly inelastic, price capitalization from an amenity improvement is indeed a sufficient statistic for estimating the MWTP. When housing is elastically supplied, the traditional hedonic price capitalization approach must incorporate a measure of housing supply elasticity in order to back out MWTP.

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 (and hence face the same wage, W_j).²⁰ 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:

$$V_{ij} = W_j + S_j - \ln R_j + \varepsilon_{ij} \quad (3)$$

where ε_{ij} reflects worker i 's idiosyncratic 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:

$$\ln R_j = \bar{R} + \rho_j \ln N_j \quad (4)$$

¹⁹Our 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.

²⁰We 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.

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

Assume that ε_{ij} follows a Type 1 Extreme Value distribution. In equilibrium, the marginal worker is indifferent between place j and all other places $-j$. The number of workers living in place j can be written in terms of the probability that worker i chooses to live in place j , scaled by the number of workers (N_{total}):²¹

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

Write log population ($\ln N_j$) and housing prices (R_j) as functions of amenity value S_j :

$$\ln N_j = \frac{1}{1 + \rho_j} (W_j + S_j - \bar{R}) + C_1 \quad (6)$$

$$\ln R_j = \frac{\rho_j}{1 + \rho_j} (W_j + S_j) + \frac{1}{1 + \rho_j} \bar{R} + C_2 \quad (7)$$

where C_1 and C_2 are constants.

Taking the long difference in each variable over time:²²

$$\Delta \ln N_j = \frac{1}{1 + \rho_j} (\Delta W_j + \Delta S_j + \Delta \bar{R}) \quad (8)$$

$$\Delta \ln R_j = \frac{\rho_j}{1 + \rho_j} (\Delta W_j + \Delta S_j) + \frac{1}{1 + \rho_j} \Delta \bar{R} \quad (9)$$

²¹This is based on the conditional logit setup from McFadden (1973), used in a variety of settings in urban economics (see, for example, Diamond (2016)).

²²For 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. The derivations of these expressions can be found in Appendix C.1.

Now, let amenity value S_j be a linear function of local pollution concentrations X_j . The long difference over time (ΔS_j) is given by:

$$\Delta S_j = \gamma_1 \Delta X_j + \tilde{\nu}_j \quad (10)$$

where $\tilde{\nu}_j$ is an unobservable determinant of ΔS_j .²³

We assume that wages are orthogonal to local pollution concentrations X_j . In the Appendix, we extend the model to allow for local pollution concentrations to influence local productivity. The broad conclusions are insensitive to this extension. Empirically, we find little evidence that wages respond to local pollution concentrations.

Plugging equation 10 into the long difference expressions for population (equation 8) and housing prices (equation 9), we can write the central parameters as functions of ΔX_j :

$$\Delta \ln N_j = \frac{1}{1 + \rho_j} (\Delta \bar{R} + \Delta W_j) + \frac{\gamma_1}{1 + \rho_j} \Delta X_j + \xi_j^n \quad (11)$$

$$\Delta \ln R_j = \frac{\rho_j}{1 + \rho_j} \Delta W_j + \frac{1}{1 + \rho_j} \Delta \bar{R} + \frac{\rho_j \gamma_1}{1 + \rho_j} \Delta X_j + \xi_j^r \quad (12)$$

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 11 and 12 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 .

Thus ρ_j , combined with the coefficient from a regression of the change in housing prices on the change in pollution concentrations, together offer sufficient statistics for MWTP, γ_1 .

6.2 Marginal WTP 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 ($\Delta \ln N_j$).²⁴ The model presented above indicates that $\hat{\beta}_R$ — the housing price capitalization of air quality improvements

²³ $\tilde{\nu}_j$ is not orthogonal to air quality improvements ΔX_j , as unobserved characteristics may covary with both air quality and amenity improvements.

²⁴We proxy for the change in log housing prices with the percent change in housing prices, based on the HPI.

— reflects the MWTP scaled by the expression $\frac{\rho_j}{1+\rho_j}$:

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

Recall that ρ_j is the inverse housing supply elasticity, i.e. $\frac{d \ln R_j}{d \ln N_j}$. When housing supply is perfectly inelastic (i.e. as $\rho_j \rightarrow \infty$), the coefficient from a typical hedonic price regression thus offers a sufficient statistic for MWTP, γ_1 , because $\lim_{\rho_j \rightarrow \infty} \frac{\rho_j}{1+\rho_j} = 1$. 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. To account for the housing supply elasticity, one can estimate the regression coefficient on the amenity change ΔX_j interacted with the term $\frac{\rho_j}{1+\rho_j}$.

Thus, if ρ_j is known, it may be combined with the reduced-form hedonic price coefficient to back out MWTP. If 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 $\hat{\beta}_N$ then provide 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 housing supply elasticity. Do note that ρ_j may vary across place j . If the empirical setting includes many locations with heterogeneous supply elasticities, the ρ_j that is produced by the ratio of $\hat{\beta}_R$ and $\hat{\beta}_N$ will reflect a weighted average across place. Thus, this strategy is most appropriately used in settings in which housing supply constraints do not vary substantially across observations.²⁵

In summary, $\hat{\beta}_R$ is a sufficient statistic for ρ_j 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 housing 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 then used to back out the MWTP

²⁵Note that, in our empirical setting, housing supply constraints do vary substantially across Census tracts.

parameter, γ_1 .²⁶

6.3 MWTP estimates that incorporate elastic housing supply

Informed by the model expressions derived above, this section presents estimates of MWTP which account for housing supply elasticities. We first provide estimates of MWTP based on values of inverse elasticity ρ_j taken from the literature. Following equation 12, we regress the change in log housing prices on the change in $PM_{2.5}$ multiplied by $\frac{\rho_j}{1+\rho_j}$:

$$\Delta y_j = \beta_0 + \beta_{MWTP} \cdot \frac{\rho_j}{1 + \rho_j} \Delta PM_{2.5j} + \mathbb{X}'_j \gamma + \delta_d + \varepsilon_j \quad (13)$$

where estimates of inverse elasticities ρ_j from the literature. 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. As before, we instrument for the change in $PM_{2.5}$ between 2000 and 2010, with NAAQS nonattainment status. Here, β_{MWTP} can be interpreted as the reduced-form estimates of average MWTP for an additional unit decline in $PM_{2.5}$ across all Census tracts, accounting for the housing supply elasticities in each tract.

In Table 4, we present the IV coefficient estimates of β_{MWTP} from equation 13 using these three different methods of characterizing ρ_j , as well as the standard hedonic approach. Column 1 reproduces estimates 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-unit decline in $PM_{2.5}$ 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.

In contrast, columns 2–4 of Table 4 present estimates of MWTP that account for local housing

²⁶In other words, 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.

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

	(1)	(2)	(3)	(4)
		2010 HPI		
$\Delta PM_{2.5}$, 2000-10	-5.843** (2.750)			
$\frac{\rho_j}{1+\rho_j} \times \Delta PM_{2.5}$, 2000-10		-12.69** (4.952)	-6.498** (3.033)	-9.722** (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 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. In columns 2–4, we interact $\Delta PM_{2.5}$ 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 ($\Delta PM_{2.5}$ between 2000 and 2010, or that scaled by ρ_j) with NAAQS nonattainment status, as described in text.

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

supply elasticities, and the attenuation effect that elastic supply will have on the hedonic price coefficient. The primary independent variable in these specifications is the change in $PM_{2.5}$ concentrations over the 10-year period times $\frac{\rho_j}{1+\rho_j}$. We again instrument for this with mid-decade NAAQS nonattainment status. 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 model predictions, these estimates of MWTP are larger — on the order of about 12 to 117 percent larger — than the estimates based on the standard hedonic estimates. Thus, the classic hedonic approach produces MWTP estimates that are substantially lower than those produced after accounting for market constraints.

7 Conclusion and discussion

Many applications of the hedonic approach exploit price capitalization in the housing market to estimate the benefits of local amenities. Implicit in these applications is the assumption that

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

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

Motivated by this empirical evidence, we develop a spatial equilibrium model of local housing markets and population, which allows for improvements in environmental amenities to generate both price *and* quantity effects. The model provides expressions for housing prices and population counts as functions of local amenities, with these relationships mediated by the elasticity of local housing supply. 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 regulation-induced improvements in air quality, as well as measures of local housing supply elasticities from the literature. We find that the resulting MWTP for air quality is 12 to 117 percent larger than the estimate produced based on price capitalization alone. This indicates that the canonical hedonic price coefficient will tend to underestimate the value of environmental im-

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

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

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Appendix

A Pre-trends and alternative weighting schemes

While we do not observe significant differences in 2000-level covariates between tracts in nonattainment and attainment areas, there are differences in population and price pre-trends between the two groups of tracts. These characteristics are presented in Columns 1-3 of Table A1. We consider the 1990-2000 change in log population and the 1995 HPI (where 2000=100) as the primary indicators of possible pre-trends.²⁷ Because the HPI is indexed to 2000-level prices, a higher value in 1995 reflects *less* price appreciation between 1995 and 2000. Thus, Table A1 indicates that nonattainment tracts were growing more slowly – both in terms of population and prices – prior to the period of analysis. For this reason, we believe that our primary instrumental variable strategy likely yields a lower bound estimate on the change in prices and quantities attributable to regulation-induced declines in PM_{2.5} concentrations.

Our primary specification exploiting CAA nonattainment status to understand tract-level price capitalization and population responses to amenity improvements does not explicitly address these differential pre-trends. In this section, we show that our central estimates are largely robust to alternative weighting schemes in which we explicitly match attainment and nonattainment tracts based on these pre-trends in 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.²⁸ 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 (at-

²⁷We 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).

²⁸The 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.

Table A1: 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 (0.015)	10.895 (0.027)	-0.028	10.866 (0.012)	10.905 (0.028)	-0.039
adult college share	31.323 (0.712)	30.276 (1.397)	1.047	31.332 (0.695)	30.654 (1.455)	0.678
non-Hispanic white share	75.507 (1.705)	70.572 (5.165)	4.935	78.302 (1.523)	70.738 (5.302)	7.563
renter-occupied housing rate	27.666 (0.646)	27.691 (1.942)	-0.024	26.575 (0.510)	27.466 (1.969)	-0.891
vacancy rate	5.330 (0.215)	4.502 (0.269)	0.829**	5.208 (0.185)	4.379 (0.262)	0.829**
Other characteristics						
1995 HPI	78.215 (0.980)	81.425 (0.752)	-3.210***	81.541 (0.732)	81.425 (0.752)	0.116
Δ ln(population), '90-2000	30.746 (2.801)	18.303 (2.084)	12.442***	18.884 (1.148)	18.077 (2.083)	0.806
PM _{2.5} concentration, 2000	11.051 (0.171)	15.434 (0.558)	-4.383***	11.075 (0.181)	15.455 (0.575)	-4.381***
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 on 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

tainment) 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 A1.

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 treat-

ment 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.

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.²⁹

Table [A2](#) 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 2000–2010 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 [A2](#), we weight by the weights produced in PSM, described

²⁹[Sager and Singer \(2022\)](#) are primarily interested in the effect of nonattainment status on subsequent changes in $PM_{2.5}$ concentrations, and thus match on pre-treatment levels of $PM_{2.5}$. They show how this yields a smaller estimated effect of nonattainment status on subsequent pollution, but a larger estimated effect of nonattainment on housing prices. Given that we are primarily interested in changes in housing prices and population densities as outcomes, the matching strategy we outline here better addresses the concerns related to differential counterfactual trends between nonattainment and attainment tracts.

Table A2: Price and population responses to $\Delta PM_{2.5}$, 2000-2010 (alternative weighting schemes)

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

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

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 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.

Table B3: Price capitalization of air quality improvements over time

	(1)	(2)	(3)	(4)
	X=2007	HPI in year X (2000=100) 2010	2013	2016
$\Delta PM_{2.5}, 2000-X$	-14.596*** (4.709)	-5.843** (2.750)	-3.964** (1.688)	-2.657 (2.454)
Controls	✓	✓	✓	✓
Division FE	✓	✓	✓	✓
Observations	25,749	25,843	25,669	24,855

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 $PM_{2.5}$ between 2000 and the year indicated (X) with NAAQS nonattainment status, as described in text.

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

B 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 the short run (2000-2007) and smaller in the longer run (2000-2013 and 2000-2016).

Table B3 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 2007, 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. 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 pollution reduction becomes increasingly attenuated over time. Consistent with basic economic theory, in very short-run settings, prices appear more responsive to demand shifts. A $1\text{-}\mu\text{g}/\text{m}^3$ decline in average annual $\text{PM}_{2.5}$ concentrations yields nearly a 15 percent increase in housing prices between 2000 and 2007, 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.³⁰

C Model estimation details

C.1 Model derivation

The total number of workers in place j is given by (equation 5):

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

Taking the log of this equation:

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

Let $C_1 = \ln \left(\frac{N_{total}}{\sum_k \exp(W_k + S_k - \ln R_k)} \right)$:

$$\ln N_j = (W_j + S_j - \bar{R}) - \rho_j \ln N_j + C_1$$

→

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

³⁰Depending 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 $\text{PM}_{2.5}$ 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.

→

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

Plugging this expression for $\ln N_j$ into the equation $\ln R_j = \bar{R} + \rho_j \ln N_j$:

$$\ln R_j = \bar{R} + \rho_j \left(\frac{1}{1 + \rho_j} (W_j + S_j - \bar{R} + C_1) \right)$$

→

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

where $C_2 = \frac{\rho_j}{1 + \rho_j} C_1$.

Thus, log population and housing prices as functions of amenity value S_j are given by:

- Population (equation 6):

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

- Housing prices (equation 7):

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

where C_1 and C_2 are constants.

Taking the long difference of equations 6 and 7 over time and plugging in the expression for amenity values as a function of local pollution concentrations:³¹

- Population:

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

- Housing prices:

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

Finally, we let productivity amenity value S_j be a linear function of local pollution concen-

³¹We assume that C and C_2 are time-invariant. We have omitted time subscripts in these expressions for brevity, but we assume that only W_j , N_j , S_j , R_j , and \bar{R} may vary across time. All parameters with a Δ should have a time subscript.

trations X_j :

$$S_j = \gamma_0 + \gamma_1 X_j + \nu_j$$

Taking the long difference of the above equation over time, letting γ_0 be time-invariant:

$$\Delta S_j = \gamma_1 \Delta X_j + \tilde{\nu}_j$$

Plugging this equation into the long difference expressions for population and housing prices, above, we arrive at equations 11 and 12.