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The Push of Big City Prices and the Pull of Small Town Amenities

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Abstract

As house prices rise in large, supply-constrained cities, what are the implications for other places that have room to grow? We explore how location amenities have differentially driven population and price dynamics in big cities versus other areas. We provide theory and evidence that demand for high-amenity locations has increased. High-amenity counties in large metropolitan areas have experienced price increases, while high-amenity counties in small metros and rural areas have absorbed increased demand through population growth. High-income and college-educated workers sort into large and high-amenity places, while retirees and other households detached from local productivity gravitate to high-amenity small towns.

Keywords: housing supply, amenities, population dynamics, domestic migration
JEL classification: R11, R31, R23

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1 Introduction

Housing costs in large cities have been rising rapidly for decades, driven in part by limited supply in the face of high demand. This phenomenon has generated substantial discourse in both the economics literature and the public sphere. Despite high demand for housing, large metros have seen sluggish population growth: from 1980 to 2019, counties in the 10 largest U.S. metros grew 37%, compared to 45% nationwide. Mid-size metros, by contrast, have grown over 60%. At the same time, another kind of location has seen massive increases in housing demand: 5% of rural counties doubled in population over the same time period, without major increases in price and despite overall low population growth in rural areas of 25%. What drives these differences in growth?

In this paper, we provide a unified explanation for both the big-city housing crunch and the small towns that have bucked the trend of rural stagnation: as real incomes have risen across the country over the last 40 years, demand has increased for location amenities, driving housing demand to high-amenity places. We show that in large metros, high-amenity counties experienced large growth in prices, while in rural areas, high-amenity counties saw large growth in population. These outcomes suggest that high housing demand is accommodated differently in different locations.[1]

We explain these diverging trends with the price elasticity of housing supply, which varies greatly across locations. Gyourko and Molloy (2015) and Been et al. (2019) provide extensive reviews of the literature on housing supply and affordability. Schuetz (2021) provides a comprehensive assessment of affordable housing policies. We contribute to this literature by demonstrating that supply constraints in some locations can affect long-term outcomes throughout the country. In particular, if high-amenity locations outside of the largest metros can accommodate large population increases without the same price changes, then these smaller geographies may alleviate housing pressure in the largest cities.

Supply elasticities can be affected by geography (Baum-Snow and Han 2024; Lutz and Sand 2023; Saiz 2010) and regulation (Glaeser et al. 2005; Gyourko and Molloy 2015). Importantly, the price elasticity of housing supply also decreases with city size. This relationship has been both predicted by theory (Capozza and Helsley 1989; Mayer and Somerville 2000) and measured empirically (Glaeser et al. 2005; Oikarinen et al. 2015; Paciorek 2013). The intuition behind the relationship between city size and price elasticity is that as cities grow, there is a decline in the quantity and quality of land that is still available for development. This increases the marginal cost of additional housing. Housing supply is constrained in the very largest cities, but most other locations have room to grow. Therefore, increased demand for housing generates price run-ups in large metros and explosive population growth in "superstar towns." Glaeser and Tobio (2008) make a similar argument about the huge population increases observed in the Sun Belt.

[1] Rappaport (2018) argues that both the benefits and costs of size have increased since 2000, which would redound to the benefit of small locations that have desirable features.

To the extent that this housing demand is driven by local amenities, those amenities act as a "pull" factor driving population growth in some small towns. Of course, housing demand is driven by more than amenities alone. Since 1980, the cross-sectional wage premium for working in a large metro has increased among college-educated workers (Baum-Snow and Pavan 2013). This change increases housing demand in large metros for college-educated workers. The resulting upward price pressure generates a countervailing "push" of demand to smaller areas, particularly by those whose income is not tied to their location of residence, such as retirees. Indeed, we show that domestic out-migration from large metros follows changes in housing costs. As college-educated workers sort into large metros to take advantage of high wages, they also demand amenities, so the high-amenity parts of the largest metros experience increases in price.[2]

A broad literature argues that consumption amenities are a key factor in understanding location decisions, including Glaeser et al. (2001), Rappaport (2009), Diamond (2016), Carlino and Saiz (2019), Couture and Handbury (2020), and Hausman et al. (2025). We contribute to this literature by showing that consumption amenities drive growth throughout the distribution of city size, including in rural areas outside of any metropolitan area. The small metros and rural areas that we highlight collectively account for half the U.S. population, and we show that these locations are affected by the same forces documented in the literature on mid-sized and large metros. However, they accommodate this amenity demand very differently than more-populous areas. We also build on the work by Gyourko et al. (2013) who document and explain the increasing concentration of high-income workers and rising prices in "superstar cities." In contrast, we explicitly examine the role of increased demand for amenities and document the heterogeneity of population and price growth on this dimension across the spectrum of location sizes, including in small towns and rural areas.

In this paper, we explore how productivity, amenities, and housing supply combine to influence population and price growth, and how such influence varies throughout the city size distribution. We pay particular attention to the tails of the distribution: the 10 largest metro areas, and counties outside of any metro area (along with some single-county metros). The mechanisms we describe rest on five key facts, which come from both the literature and our own analysis: first, amenities are a key aspect of location choice. Second, high-amenity locations can be found throughout the size distribution. Third, housing supply elasticities tend to fall with city size. Fourth, productivity increases since 1990 have been concentrated at the top end of the size distribution, especially for college-educated workers. Fifth, not all individuals are equally dependent on local productivity for wages. The first three facts generate the basic population and price relationship we find throughout the paper: amenities predict price growth in large locations and population growth in small locations. The final two facts induce changes in sorting of residents across locations. For college-educated workers, rising productivity in relatively-inelastic large metros generates very high

[2]Howard and Liebersohn (2021) provide evidence that demand has increased in supply-inelastic locations.

price growth (especially in high-amenity areas), along with increased sorting of college workers to these locations. Other groups have not seen the same wage increases in large metros, so they may be "pushed" out by increasingly unaffordable housing costs. For example, retiree incomes are independent of local productivity. We observe strong sorting of retirees into high-amenity small towns in particular, a pattern which did not exist in 1990. Non-college workers, while benefiting somewhat from rising productivity in large metros, experienced wage growth that lagged behind college workers (Autor 2019), and we see their increased sorting into mid-sized and small metros and rural areas as well.

We begin by developing a spatial equilibrium model that formalizes how amenities, wages, and housing supply interact to determine population and price growth across locations. We use a discrete location-choice model in the style of Diamond (2016). The model features heterogeneous households who choose locations based on local wages, housing costs, and amenity levels, with preferences that may vary across household types. A key insight from the model is that increased demand for amenities generates different outcomes depending on local housing supply elasticity: in high-elasticity locations, demand translates into population growth, while in low-elasticity locations, it translates into price growth. The model also predicts that households will sort based on the degree to which their income is tied to local productivity, with "location-detached" households such as retirees gravitating toward affordable high-amenity places while workers with location-dependent wages concentrate in productive cities despite high costs.

We then document basic patterns of population and price growth across the U.S. between 1990 and 2019. We use counties as our main unit of analysis, since they are the smallest geographic unit in rural areas with consistent boundaries. We group counties based on the size of their containing metro area, taking non-metro counties as singletons, then show the differences that have emerged between these groups in the last 30 years. Rent growth is strongly associated with initial size group, with large metros growing in rent more than smaller metros, which in turn grow more than small towns and rural areas. Population growth is concentrated in mid-sized metros, with both large metros and small towns lagging behind. We use the methods similar to Baum-Snow and Han (2024) to estimate housing supply elasticities for all counties, and show that housing supply is negatively correlated with size.

Next, we estimate implied amenities for U.S. counties in 1990. We use an established method, similar to Roback (1982), Chen and Rosenthal (2008), Albouy (2016), and Albouy and Stuart (2020), among others, to calculate amenities using local rents and wages. The underlying idea of this method is that in equilibrium, geographically-mobile households must be compensated for differences in location-specific amenities through changes in consumption. We adjust income and rents to account for observable differences in population and housing stock. We confirm that high-amenity locations exist throughout the size distribution. As a check on our estimates, we show that they are positively correlated with good weather, universities, mountainous terrains, and coastlines.

We find evidence that high amenity value is predictive of price growth in large metro areas, but not in small towns or rural areas. On the other hand, high amenity value is predictive of population growth in small towns and rural areas, but not in large metros. In our preferred specification, we find that a one-standard-deviation increase in amenity is associated with 6 log points of additional population growth in small towns, but -7 log points in large metros. The same increase in amenity is associated with -3 log points of rent growth in small towns, but 9 log points of rent growth in large metros.

We next turn to domestic migration and sorting patterns to find evidence of the mechanisms described above. We decompose county population change into the core components of natural increase (births and deaths), international immigration, and net domestic migration. Domestic migration drives the observed patterns: high-amenity counties in large metros have negative net domestic migration, while high-amenity small towns and rural areas have positive net domestic migration. Domestic migration out of large metros accelerates during the house price run-ups of 2000-2007 and 2012-2019, but slows in 2007-2012. We show that in large metros, counties with greater rent growth saw more domestic outflow, while in small towns, counties with greater rent growth saw more domestic *inflow*.

We observe sorting across locations that reflects our proposed mechanisms: college workers go to big cities and high-amenity areas, and retired workers gravitate toward high-amenity small towns. We thus corroborate results from Duncombe et al. (2001) and Lu (2020) that retirees seek amenities in their location choice. However, this sorting cannot be due entirely to life-cycle preferences, since the pattern has emerged since 1990 and because we see similar patterns by remote workers, who (like retirees) earn the same income regardless of their residential location. We show that other factors, such as good weather or low density alone, cannot explain observed sorting as well as our measured amenities. We view this sorting as two ways of satisfying demand for amenities (the "pull"): high wages mean that locating in a high-amenity part of a big city is worthwhile for college workers, despite high housing cost, but not worthwhile for retirees (the "push"). We also provide some long-run context to the recent literature on how remote work affects across-metro migration and show that our 1990 amenity estimates predict COVID-era population growth.[3]

Finally, using the model, we assess the relative importance of changes to amenities, productivity, and housing supply in explaining population and price growth. We model several types of workers, including a type with entirely nonlocal income. We fit the model to 1990 and to 2019 and evaluate a series of counterfactuals that hold fixed amenity valuations, productivities, and housing supply. The calibration reveals that amenity preferences have increased substantially over time, particularly for retirees and non-college workers. In 1990, college workers exhibited the strongest preference for high-amenity locations, while retirees actually sorted away from them. By 2019, all household types

[3] A number of papers have studied how the shock to remote work arising from COVID-19 affects the geography of households including Althoff et al. (2022), Davis et al. (2023), Haslag and Weagley (2022), and Mondragon and Wieland (2022).

show positive amenity preferences, with retirees experiencing the largest change, consistent with their increased sorting into high-amenity small towns.

We find that changes in amenity valuations are quantitatively important in explaining the observed population patterns. In the data, high-amenity small towns experienced 10 percent more population growth than low-amenity small towns, while high-amenity large metros experienced only 0.5 percent more population growth than low-amenity large metros. When amenity valuations are held fixed at their 1990 levels, the population advantage of high-amenity small towns disappears and even reverses slightly, with high-amenity small towns experiencing 1.4 percent less population growth than low-amenity small towns. The reversal is much larger in large metros: high-amenity large metros experience 8.6 percent less population growth than low-amenity large metros. The corresponding counterfactual results for rents show similar reversals in the relationship between amenities and rent growth. In contrast, holding wages at their 1990 levels has little effect on the population growth difference between high- and low-amenity small towns, while wage growth plays a somewhat larger role in explaining the population differences across high- and low-amenity large metros. Changes in housing supply productivity also contribute to the observed differences in growth, particularly in large metros, consistent with the conclusions Hsieh and Moretti (2019) and others.

Overall, our results suggest that less-populated geographies may provide a release valve for housing demand pressure in the form of out-migration from housing-constrained large cities. Mid-sized and small metros prove appealing to workers who remain attached to local productivity, while rural areas provide low-cost amenities to retirees and other "detached" households. In addition, if households continue to increase their valuation of location amenities, high-amenity rural places will grow relatively faster than low-amenity rural places. The welfare implications of these trends are unclear. Large cities continue to provide significant production advantages, which suggests that easing housing supply constraints may still be an important public policy concern.[4] Finally, as the nature of in-person work and residential location choices change in the wake of the COVID-19 pandemic, these results may help guide predictions about future growth patterns in different locations.

The rest of the paper proceeds as follows. Section 2 lays out the model and discusses its predictions for growth in population and rent. Section 3 documents the basic patterns present in the raw data, as well as our data sources, and outlines our supply elasticity estimation and amenity estimation. Section 4 presents regression results on population and price dynamics, and evaluates domestic migration and sorting as a mechanism. Section 5 outlines the model estimation. Section 6 discusses counterfactuals that evaluate the relative importance of amenities and wage growth for understanding population and price changes over time. Section 7 concludes.

[4]Hsieh and Moretti (2019) and Duranton and Puga (2023) find large productivity and growth losses from misallocation of population across cities. Therefore, even if small towns absorb housing demand from larger metros, there may be remaining concerns surrounding the low supply elasticity in those large metros.

2 Model

2.1 Setup

Housing demand. The economy is made up of a discrete set of locations $j \in \mathcal{J}$. Each location is endowed with a fixed exogenous consumption amenity B_j.[5] Households are heterogeneous with type $i \in \mathcal{I}$, receive an income w_{ijt}, and have increasing preferences over traded consumption goods c, local goods l, and amenities. Utility for agent n of type i in location j at time t is given by:

$$\ln U_{nijt} = \rho_{it} \ln B_j + (1 - \beta) \ln c + \beta \ln l + \nu_{njt}, \tag{1}$$

where β is the consumption share of local goods, and ρ_{it} is a key parameter that determines the relative importance of the amenity in utility. Note that ρ_{it} may vary both across groups and over time.[6] The term ν_{njt} is an agent's idiosyncratic preference for a given location, which is drawn from a Type I Extreme Value distribution with a scale parameter σ. In each location, households maximize utility subject to $w_{ijt} = c - r_{jt} l$, where r_{jt} is the price of local goods including housing and the price of c is normalized to 1 in each period. Solving the agent's maximization problem and omitting constants, indirect utility for type i in location j in time t is:

$$\ln V_{nijt} = \rho_{it} \ln B_j + \ln w_{ijt} - \beta \ln r_{jt} + \nu_{njt}. \tag{2}$$

Given the Type I Extreme Value distribution of idiosyncratic preferences, we can solve for the probability that an agent of type i chooses to live in location j in time t. We combine the standard choice probability equation with the size of each group N_{it} to find the population demand N^D_{ijt}:

$$N^D_{ijt} = N_{it} \frac{\exp\left(\frac{1}{\sigma}\left(\rho_{it} \ln B_j + \ln w_{ijt} - \beta \ln r_{jt} + \delta_j\right)\right)}{\sum_j \exp\left(\frac{1}{\sigma}\left(\rho_{it} \ln B_j + \ln w_{ijt} - \beta \ln r_{jt} + \delta_j\right)\right)} + \epsilon_{ijt}. \tag{3}$$

The term δ_j represents a location fixed effect that captures long-run cross-sectional persistence in population unrelated to our model fundamentals, allowing us to analyze how changes in preferences, wages, and rents lead to changes in population, as in a standard linear panel analysis.[7] Finally, ϵ_{ijt} is a mean-zero error term, which we minimize in our estimation of the model parameters.

[5] For simplicity, we assume that the amenity is fixed and does not change endogenously with population growth or changes in population composition.

[6] In our calibration, we expect to find higher ρ_{it} for groups and time periods with higher incomes, which would reflect non-homothetic demand for amenities. We also expect to see ρ_{it} grow more over time for groups with higher income growth, such as college-educated workers.

[7] A richer model would be required to capture both population responses to shocks as well as the cross-sectional distribution of city sizes, as these are governed by different processes (see, e.g., Duranton and Puga (2023)). For example, Diamond (2016) in persistent cross-sectional differences by estimating a home preference using micro data. Our interest is in changes over our sample period, so in our calibration we take B_j from our empirical exercise and use δ_j to fit the empirical size distribution.

Local income. Each city has many homogenous firms, indexed by d. Each firm uses a single type of labor L_{dijt}. Type i firms use type i labor and capital K_{djt} to produce output Y_{dijt} according to the production function:

$$Y_{dijt} = A_{ijt} L_{dijt}^{\alpha} K_{djt}^{1-\alpha}. \tag{4}$$

For simplicity, we abstract away from the local skill complementarity in Diamond (2016) and treat the wages of each type as separately determined in unconnected labor markets. We also assume that capital is perfectly mobile across locations, with returns determined in global markets, so that local wages are determined by local productivity rather than local labor supply. Because firms are identical and face constant returns to scale production functions, we can define the marginal productivity of labor for type i workers, denoted a_{ijt}, as:

$$a_{ijt} = \frac{\partial Y_{dijt}}{\partial L_{dijt}} = \alpha A_{ijt} L_{dijt}^{\alpha-1} K_{djt}^{1-\alpha}. \tag{5}$$

Because there are many homogenous firms and no barriers to entry, wages equal the marginal product of labor. Thus, each type earns a_{ijt} for working in location j in time t. Some households also earn income irrespective of location, which we denote $\overline{w}_{it}$. Retirees and remote workers are two classes of such households. For retirees, $\overline{w}_{it}$ represents pension income, Social Security, or retirement account withdrawals. For remote workers, $\overline{w}_{it}$ represents labor income, but labor income that can be earned regardless of the residential location j. We expect these households to be more sensitive to the rising housing costs of large cities, since they lack the counterbalancing force of higher wages. The wage equation for type i living in location j in time t becomes:

$$w_{ijt} = \overline{w}_{it} + a_{ijt}. \tag{6}$$

Housing Supply. The total population for which housing is supplied, N_{jt}^{S}, increases with local prices and is given by:

$$\ln N_{jt}^{S} = \eta_j \ln r_{jt} + C_{jt}, \tag{7}$$

where η_j is the price elasticity of housing supply, which can vary by location, and C_{jt} is a shifter that represents productivity in housing production. The housing productivity term is used in Albouy and Stuart (2020) to pin down equilibrium city size. This is often ignored in the quality-of-life literature, which generally focuses on prices. For our application, this formulation is useful to rationalize the variation in prices and city size in the data, which clearly does not show a one-to-one relationship between population size and housing costs. C_{jt} could reflect differences in supply constraints like geography or regulation, or could represent differences in general local

productivity.[8] Note that here we are modeling the total population for which housing is supplied, conditional on prices. Thus, the elasticity parameter effectively subsumes the intensive margin of housing demand. This is consistent with our estimation method where we use population and prices to estimate elasticities as opposed to a measure of housing services.

The distinction between the housing supply elasticity and the housing supply shifter is important for our quantitative analysis. We estimate η_j separately for each location and treat it as time-invariant in the model. Thus, η_j determines how strongly housing supply responds to changes in rents, but does not itself generate changes in housing supply over time. In contrast, C_{jt} is allowed to vary over time and shifts the overall level of housing supply. Changes in C_{jt} can capture changes in construction costs, regulation, and other factors affecting the productivity of housing supply. We therefore use changes in housing supply productivity in our counterfactual exercises rather than changes in housing supply elasticities. This allows us to examine the role of changes in housing supply productivity in explaining the observed evolution of population and rents while holding the estimated responsiveness of housing supply fixed.

Equilibrium. Equilibrium is defined as the set of rents for each location r_{jt} such that the population for which housing is supplied equals the sum of population demand across household types, for each location. That is, an equilibrium in t is the set of r_{jt} such that Equation 7 equals Equation 3 in all j:

$$N_{jt}^S = \sum_{i \in \mathcal{I}} N_{ijt}^D \quad \forall\ j \in \mathcal{J}. \tag{8}$$

Because rents are simultaneously determined in a nonlinear manner across locations, the equilibrium must be solved computationally. In Sections 5 and 6, we find the equilibrium via a contraction mapping.

Discussion. The model formalizes the intuition for several empirical regularities discussed in Section 1. First, given an increase in the demand for amenities (increasing ρ), higher-amenity places will experience greater increases in demand. Conditional on amenities, more elastic places will experience greater increases in demand. To see this relationship, assume for notational convenience that $\rho_{it} = \rho$ for all i and t and observe that in equilibrium:

$$\ln N_{jt} = \ln\left(\sum_i N_{it} \frac{\exp(\frac{1}{\sigma}(\rho \ln B_j + \ln w_{ijt} - \beta \ln r_{jt} + \delta_j))}{\sum_{j'} \exp(\frac{1}{\sigma}(\rho \ln B_{j'} + \ln w_{ij't} - \beta \ln r_{j't} + \delta_{j'})}\right). \tag{9}$$

The partial derivative $\partial \ln N_{jt}/\partial \rho$ is both greater than 0 and is increasing in B_j. The same is true of ρ_{it} for each i. Of course, the change in equilibrium population depends also on the change in rents. While the level of rent in j appears in both the numerator and the denominator of Equation

[8] For example, Albouy and Stuart (2020) find a strong correlation between housing productivity and goods productivity as reflected in local wages.

9, the denominator will be nearly constant after a change in r_{jt}, and the relationship will be nearly linear. From Equation 7:

$$\ln r_{jt} = \frac{\ln N_{jt}}{\eta_j} - \frac{C_{jt}}{\eta_j}. \tag{10}$$

Then $\partial \ln r_{jt}/\partial \rho = (1/\eta_j)\partial \ln N_{jt}/\partial \rho$ which is both positive as long as $\eta_j > 0$ and decreasing in η_j. If supply elasticity is negatively correlated with initial size, then smaller locations will experience more population growth and less rent growth than larger locations with the same level of initial amenities. In Section 4 we will test for this pattern, by examining rates of population and price growth in both high- and low-amenity locations of different initial sizes.

We have formulated the model treating amenities as exogenous and fixed, and we consider the effects of changes in ρ, the weight of amenities in utility. One would expect ρ to increase over time if demand for amenities shows non-homotheticity: as real incomes have grown over the last 40 years, demand for amenities increases. This interpretation aligns with work such as Couture and Handbury (2020). However, our empirical strategy for estimating amenities finds the combined value $\rho \ln B_j$ for each location. An alternative mechanism to explain the empirical patterns we observe involves endogenizing B_j as in Diamond (2016): if high-amenity places are endogenously becoming even more high-amenity over time, our estimates do not capture pure changes to underlying preferences. Available data makes disentangling changes in amenities over our time period difficult, especially outside of major metros. The model's predictions and counterfactuals serve to assess the overall importance of amenities for understanding growth patterns nationwide, rather than to estimate structural preference parameters.

The second major set of predictions from the model concerns sorting among worker types. Consider an increase in type-location-specific worker productivity, A_{ijt}, and the effects on housing demand for that type:

$$\frac{\partial \ln N^D_{jt}}{\partial A_{jt}} = \frac{1}{\sigma}\frac{\partial \ln w_{ijt}}{\partial A_{ijt}} - \frac{1}{\sigma}\frac{\partial \ln r_{jt}}{\partial A_{ijt}}. \tag{11}$$

The increase in productivity increases housing demand by increasing wages, but the effect is dampened through general equilibrium effects on local rents. As a result, for workers whose income is less sensitive to local productivity, the main effect of local productivity growth will be through increases in r_{jt}. For example, for retirees, $\partial w_{ijt}/\partial A_{ijt}$ is close to 0, since the majority of retirement income accrues from non-wage sources such as Social Security. Since 1990, productivity growth has been concentrated in large metros and among college educated workers, with increases in both the share of college workers and their skill premium (see Baum-Snow and Pavan (2013)). As a result, the model predicts that college workers will gravitate toward higher-productivity locations for which wage growth compensates for rent growth. Such compensation could occur because wage

growth is large (as in large metros) or because rent growth is small (as in smaller towns). At the same time, households with "productivity detachment" will gravitate towards smaller towns.

3 Data and Descriptive Facts

In this section, we detail our data sources and our estimation of local amenities. Then, we verify as empirical correlations in the data several of the key predictions of the model described above: in particular, that in small places, high amenities are correlated with population growth, while in large places, high amenities are correlated with price growth.

In our analysis, we are interested in local effects of amenities on population and prices, and how these effects vary for different city sizes. A key difficulty in our analysis is obtaining data on rural areas. Census tracts, urbanized areas, and Census designated places all change boundaries over time in ways that are likely endogenous to growth, and unlike in heavily populated metros, there is little granular data available to produce geographically harmonized versions of these geographies. Therefore, we use counties as our main unit of analysis. Counties partition the entire United States, and have stable boundaries. For some analysis, we will use sub-county data, so we begin our main analysis in 1990 when the U.S. was fully tracted. We occasionally present descriptive facts or robustness tests using data starting in 1980. To summarize aggregate patterns, we obtain data from the U.S. Census on housing costs and population at the county level between 1980 and 2019. For 1980, 1990, and 2000, we use the Decennial Census of Population and Housing, and for 2010 and 2019 we rely on the American Community Survey.[9] Here, we depart from the literature on cross-metro differences, which often groups rural areas into state-level observations ("non-metro California," "non-metro Pennsylvania," etc.). By preserving rural counties as distinct observations, and by separating the counties within large metros, we can explore heterogeneity both within and across the size distribution.

While our county-level analysis provides new insight on rural areas, it requires us to account for the influence of other counties in a given metro. Metros are, by definition, characterized by large commuting flows, so they are reasonably treated as part of a larger housing market. Therefore, to study the size distribution, we group counties by the size of their associated MSAs. This strategy allows the metro context to affect otherwise-similar counties: there is no reason to expect two counties with the same initial population and amenity level to grow the same way if one is on the outskirts of a major metro. Our estimates allow variation on this dimension.

For ease of exposition, we construct our groups so that each group contains one-quarter of the total initial population, or 55 million people per group. The first group includes only counties in the 10 largest metropolitan areas. The smallest metro in this group is Dallas-Fort Worth-Arlington, TX, with a population of 3 million. The next group includes metros with size ranks 11 through

[9]The data were obtained from IPUMS National Historical Geographic Information System (Manson et al. 2021).

45. The smallest metro in this group is Bridgeport-Stamford-Norwalk, CT, with a population of 800,000. The third group is metros ranked 46 through 210. The smallest included metro is Barnstable Town, MA, with a population of 150,000. The final group is all remaining metro areas, as well as all non-metro counties. We refer to these groups as "large metros," "mid-sized metros," "small metros," and "small towns," respectively. In the small town group, 82 percent of counties are either single-county metros or non-metro counties.

In order to estimate the relationship between amenities, size, and population and price growth, we first need to measure amenities. To do so, we employ standard methods from the quality-of-life literature following Roback (1982). The method is based on residualizing housing costs net of labor costs: if workers are mobile, locations with higher-than-predicted housing costs must be more appealing, or else demand would decrease until housing and labor costs were brought into alignment. The housing market thus serves to capitalize non-market goods like pleasant weather. The full model estimated in Section 5 can solve for residualized amenities. However, here we estimate amenities using a simple setup with one type of worker and no idiosyncratic preferences, which allows for visualization and discussion of amenities, as well as our reduced-form exercises, without solving the full model.[10]

This method is agnostic to the source of amenities, which can be observable or unobservable and endogenous or exogenous. It also includes the value of accessibility to amenities in neighboring areas, such as coastlines, to the extent that such accessibility is capitalized into rents. As our primary measures of local wages and prices, we take median household income and median rent from the U.S. Census at the county level.

One challenge to identifying amenities is that locations vary widely in their housing quality and workforce composition. We want to estimate equivalent prices across locations, so we must control for factors like house size and population education. To do so, we use data on demographics and housing from the U.S. Census to control for differences in housing quality and workforce composition. We follow methods similar to Chen and Rosenthal (2008) and others, making use of data on housing and demographics and hedonic regression methods. We describe these hedonic adjustments in detail in Appendix A. In summary, we estimate regressions predicting median log rents at the Census tract level using data throughout the country, with county fixed effects and observable data on

[10]Formally, workers in location j derive Cobb-Douglas utility from consuming housing services l and a consumption good c, which is the numeraire. Workers spend a fraction β of income on local goods. Workers also enjoy local amenities B_j, which affect utility with weight ρ. Solving the agent's maximization problem and omitting constants, indirect utility in j is:

$$\ln V_j = \rho \ln B_j + \ln w_j - \beta \ln r_j. \tag{12}$$

Normalizing the reservation utility to zero and rearranging, we obtain the standard expression for amenities in a location:

$$\rho \ln B_j = \beta \ln r_j - \ln w_j. \tag{13}$$

characteristics of housing size and quality. Then, we predict log rents in each county using average characteristics of housing within the county, and use that predicted value as an input in our amenity estimation. Similarly, we obtain predicted wages at the county level using characteristics of the workforce.

In our estimation, we calibrate the local consumption parameter β to 0.65, which captures the share of total expenditures on local goods. This value is an effective expenditure share suggested by Albouy (2016). It includes housing and other local goods, but also should account for differences in tax burden due to progressive federal taxes and the fact that a significant share of income comes from non-local sources.[11] We standardize the amenity values by subtracting the mean and dividing by the standard deviation.

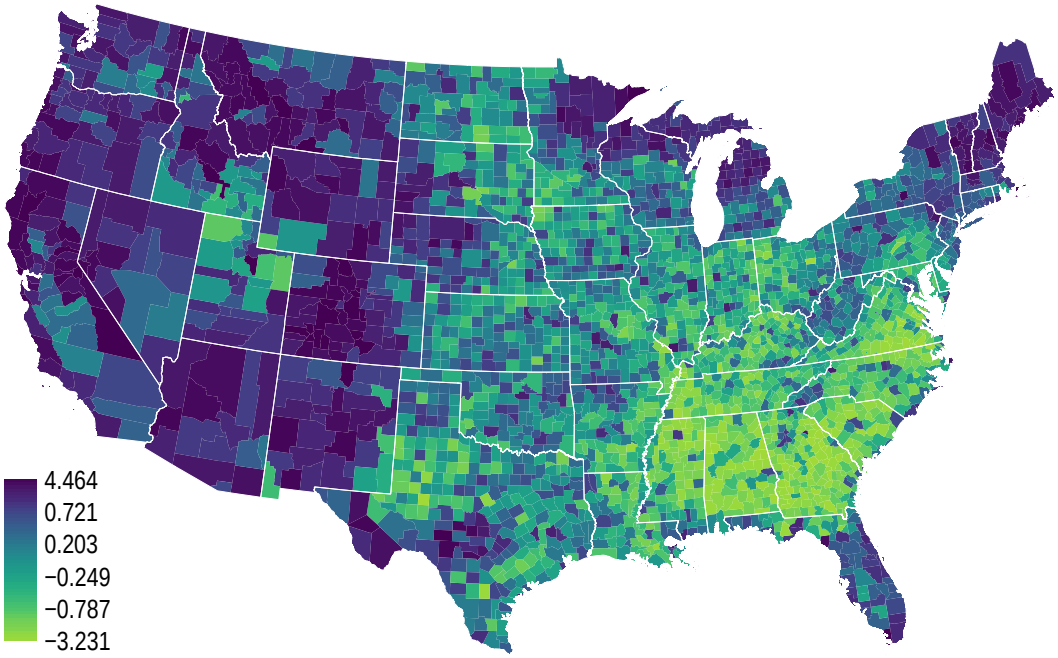
We visualize the resulting amenity estimates using 1990 adjusted prices in Figure 1. The highest- and lowest-ranked counties in each size category are shown in Tables A3 and A4.

Because we construct our estimates from observed wages and rents, there are a few unexpected values, particularly for counties with small populations. This could occur for several reasons. In particular, there may be differences in construction costs, particularly in mountainous small towns or the few high-amenity small towns that are very supply-inelastic (such as Martha's Vineyard). High housing costs in these areas would increase our amenity estimates. Therefore, one may worry that our estimates pick up not amenities, but the level of impediment to construction. However, we would not expect high construction costs to predict large population growth. We also show in Appendix Figure A1 that our amenities are correlated with the USDA Natural Amenities Scale.

To aid in assessing the reasonableness of our estimates, we perform a purely correlational descriptive regression of our estimated amenities on a variety of observable factors, shown in Table 1. To measure geographic features, we use data from the Census Bureau and the U.S. Geological Survey's National Elevation Dataset to construct an indicator for coastline counties and to calculate the average slope (in degrees) of each county. We also capture broad geographic features using indicators for the four Census regions (West, South, Midwest, and Northeast). To measure weather, we use the National Oceanic and Atmospheric Administration's National Centers for Environmental Information to measure 1980 values of maximum July temperature, minimum January temperature (both in degrees Fahrenheit), and precipitation totals (in inches) for both months. To measure durable institutional features, we use the 1994 vintage of the Carnegie Classification of Institutions of Higher Education to construct indicators for 1) the presence of at least one institution classified as a baccalaureate, master's, or doctoral university or college; and 2) an indicator for at least one research university. Only 125 institutions receive this highest classification. We also measure the percent of the population currently enrolled in college in 1990, as another measure of college towns. Finally, we include the Census Bureau measure of the population density, an endogenous character-

[11] Diamond (2016) uses a similar value of 0.62 estimated from the Consumer Expenditure Survey. Because other studies have used smaller values, we perform a robustness exercise which sets $\beta = 0.35$. We show those results in Column (3) of Table A10 and Column (3) of Table A11.

Figure 1: 1990 amenity estimates



This map shows amenity estimates using 1990 adjusted prices for each county. The values shown are for standardized amenities, representing the number of standard deviations above or below the mean.

istic that may be correlated with amenities such as public goods or increased consumption variety or may directly confer either amenities or disamenities.

The first column shows the results for all counties in the U.S., while Columns (2) through (5) stratify the sample into different size categories. Many of the results are intuitive. Counties near coasts and with good weather have higher measured amenities. For example, for the entire sample, coastal counties have an average amenity value that is 0.821 standard deviations above the overall average. More mountainous counties (that is, counties with a higher average slope) have higher average amenities. In addition, counties that have colleges or research universities also have higher average amenities. Counties in the West, which is the omitted regional category, have the highest average amenity. In terms of endogenous characteristics, a higher share of college graduates is associated with a higher amenity level, while population density is associated with a lower amenity

Table 1: Predicting amenities with observable characteristics

	Dependent variable:				
	Adjusted Amenity 1990				
	Country	Top 10	Top 45	Top 210	Remaining
	(1)	(2)	(3)	(4)	(5)
Coastline	0.820^{***}	-0.007	0.458^{***}	1.031^{***}	0.874^{***}
	(0.059)	(0.147)	(0.140)	(0.116)	(0.091)
Slope	3.908^{***}	3.880	3.153^{**}	3.019^{***}	4.356^{***}
	(0.328)	(3.265)	(1.479)	(0.777)	(0.375)
Northeast	-0.578^{***}	0.011	-1.134^{***}	-0.921^{***}	-0.242^{**}
	(0.078)	(0.670)	(0.250)	(0.173)	(0.102)
Midwest	-0.667^{***}	-0.215	-1.135^{***}	-1.034^{***}	-0.454^{***}
	(0.066)	(0.787)	(0.250)	(0.181)	(0.077)
South	-1.062^{***}	-0.171	-1.452^{***}	-1.240^{***}	-0.927^{***}
	(0.063)	(0.666)	(0.216)	(0.149)	(0.076)
Precipitation Jan	-0.087^{***}	-0.193^{***}	-0.084^{***}	-0.116^{***}	-0.080^{***}
	(0.009)	(0.061)	(0.026)	(0.021)	(0.012)
Precipitation Jul	-0.054^{***}	-0.075	-0.062^{**}	0.016	-0.062^{***}
	(0.009)	(0.063)	(0.027)	(0.019)	(0.011)
Max Temp Jul	-0.014^{***}	-0.044	-0.010	0.017^{*}	-0.017^{***}
	(0.004)	(0.027)	(0.012)	(0.010)	(0.005)
Min Temp Jan	-0.0004	0.050^{***}	0.006	-0.011	0.001
	(0.003)	(0.014)	(0.007)	(0.007)	(0.003)
College Present	0.141^{***}	-0.179	0.064	-0.046	0.164^{***}
	(0.041)	(0.132)	(0.114)	(0.079)	(0.057)
Research University	0.324^{***}	-0.025	0.076	-0.186	0.588^{***}
	(0.086)	(0.171)	(0.168)	(0.145)	(0.208)
Pct Pop College	3.688^{***}	5.456^{***}	3.419^{**}	8.364^{***}	3.221^{***}
	(0.410)	(1.892)	(1.459)	(1.215)	(0.564)
Log Pop Density (1980)	-0.036^{***}	0.156^{***}	0.122^{***}	0.110^{***}	-0.115^{***}
	(0.012)	(0.042)	(0.042)	(0.031)	(0.018)
Constant	1.967^{***}	2.498	1.355	-1.062	2.264^{***}
	(0.342)	(2.326)	(1.070)	(0.869)	(0.409)
Observations	3,102	110	282	490	2,220
R^2	0.445	0.480	0.519	0.515	0.465
Adjusted R^2	0.443	0.409	0.496	0.502	0.462

This table shows the results of a descriptive regression of estimated amenities on various location characteristics. The first column contains the results using all U.S. counties. Columns 2 through 5 include only counties within each metro size category: top 10, 11 to 45, 46 to 210, and remaining counties. *p<0.1; **p<0.05; ***p<0.01

level.[12]

[12]We also performed this exercise by using each independent variable separately for each population category, and results were qualitatively similar.

While the results are fairly consistent across size categories, there are some notable differences. The correlation between natural features and amenities is generally stronger for counties in rural areas and small metros. Both coastlines and average slope are uncorrelated with amenities in large metros but have large significant positive coefficients for small metros and rural areas. The presence of colleges is also more important for the amenity value of small towns compared to that of the largest metros. This is true even after controlling for local income and education, which suggests that universities may provide some quality-of-life spillovers beyond peer and job effects. Finally, we include the correlation between amenities and population density, since high population may itself be an indication that a place is attractive to many people. Population density is a positive predictor for big cities but not for small towns. This result may suggest that the relationship between density and amenities is not monotonic.[13]

The map in Figure 1 makes clear that high-amenity locations can be found throughout the country, although they are more common in Western states. What is less clear from the map of amenities is that high-amenity locations can be found throughout the size distribution. Figure 2 plots the density of estimated amenity values for all counties by size group. Metro areas of all sizes have a slightly higher mean amenity than rural areas, but the distributions all overlap considerably, and rural areas in particular have a wide standard deviation of amenities,[14] with many locations two standard deviations or more above the national average. If demand for amenities has increased since 1990, we would thus expect to see increases in population and/or price in at least some locations throughout the size distribution. Figure 3 shows the distribution of growth in both population and rent for each size category. Panel (a) shows percent growth in population. Mid-sized metros showed the highest average population growth, with both small towns and top 10 metros lagging behind. However, all size categories show long right tails, particularly the smallest category, indicating surging demand in some areas in all categories. Panel (b) shows percent growth in nominal median rent.[15] Unlike population growth, average growth rates in rent were monotonically associated with metro size: nominal rents in the 10 largest metros grew the most, while rents in the smallest metros and rural counties grew the least. High rent growth in large metros despite low population growth also indicates high demand for housing.

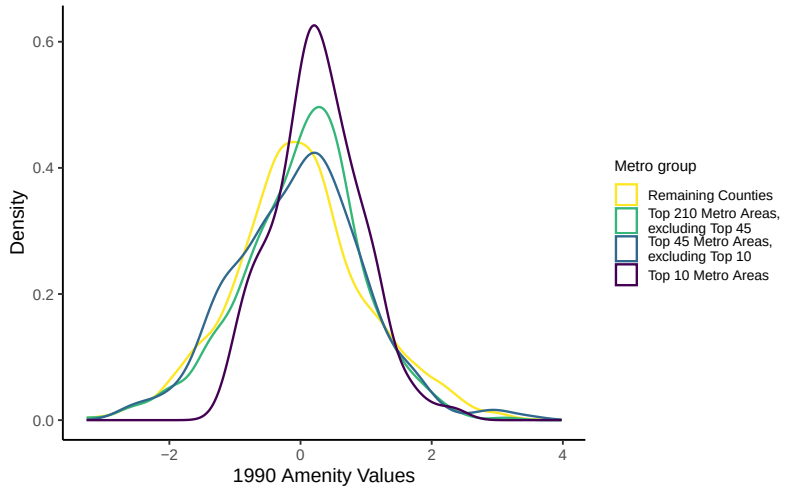
We relate the patterns in Figure 3 to two key concepts: amenities and housing supply elasticities. In Figure 4, we display scatter plots of our amenities against growth in population and rent for each size category. Panel (a) shows that amenities predict population growth in small towns, with the slope decreasing in magnitude as metro size increases. Indeed, amenities do not predict population

[13] This table of descriptive correlations does not provide evidence on mechanism for any of the observed relationships. Speculatively, increased density may signal increased consumption variety in large cities, but a pure congestion effect in small towns.

[14] Amenity values are demeaned and given a standard deviation of 1 nationally, but each subgroup may have different standard deviations, as shown.

[15] Given that we do not use microdata, median rent is constructed as a population weighted average of the median rent for each county. For this exercise, we do not adjust rents based on housing quality or characteristics.

Figure 2: Amenity Density By Size Group



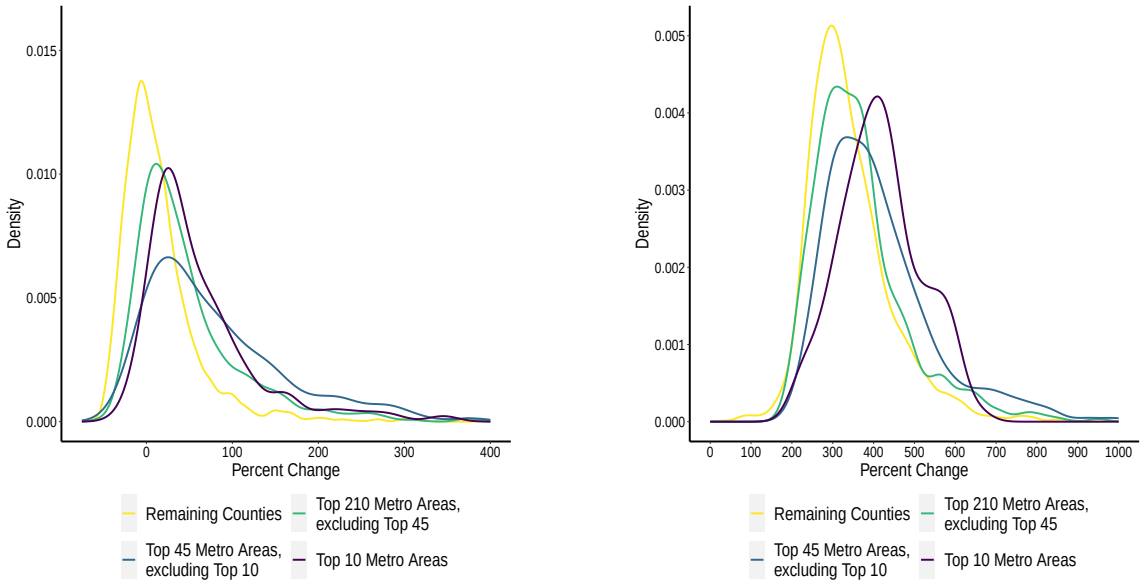
This figure shows the distribution of the estimated amenities for U.S. counties by size group. The counties are grouped by the size of the containing Metropolitan Statistical Area. Amenities are standardized to have mean 0 and standard deviation of 1 nationally.

growth in top 10 metros. However, Panel (b) shows that amenities predict large rent increases in large metros, with the slope decreasing in magnitude as metro size decreases.[16] Together, Figures 3 and 4 suggest amenities as a key factor in explaining rising housing demand, a hypothesis we test more formally in Section 4.

Housing supply elasticities help explain the flat relationship between amenities and population growth in Figure 4. As discussed in Section 1, housing supply tends to decrease with city size. Indeed, in Appendix Figure A5, we show that metropolitan housing supply estimates by both Saiz (2010) and Baum-Snow and Han (2024) decrease with metro size. However, one major difficulty of studying rural America is that there are no existing estimates for housing supply elasticity. To obtain estimates of housing supply elasticities for rural areas, we employ methods similar to Baum-Snow and Han (2024). We use Bartik (1991)-style shocks for labor demand and measure the resulting changes in population and rent. To discipline estimates, particularly for counties with negative population growth, we allow elasticity to vary with the fraction of land already developed in 1990. We describe our methods in detail in Appendix B. The left panel of Figure 5 shows a scatter plot of elasticity estimates against metro population in 1990, confirming the negative relationship. The fact that larger metros have lower housing supply elasticities on average strengthens the basis for our prediction that housing demand in large metros will be capitalized into rents, while in small metros populations will actually grow. The right panel shows that, except in the very largest metros,

[16] To reduce visual noise, Figure A2 presents this relationship as a binned scatter plot.

Figure 3: Population and Rent Growth by Size Group



(a) Distribution of Population Growth

(b) Distribution of Rent Growth

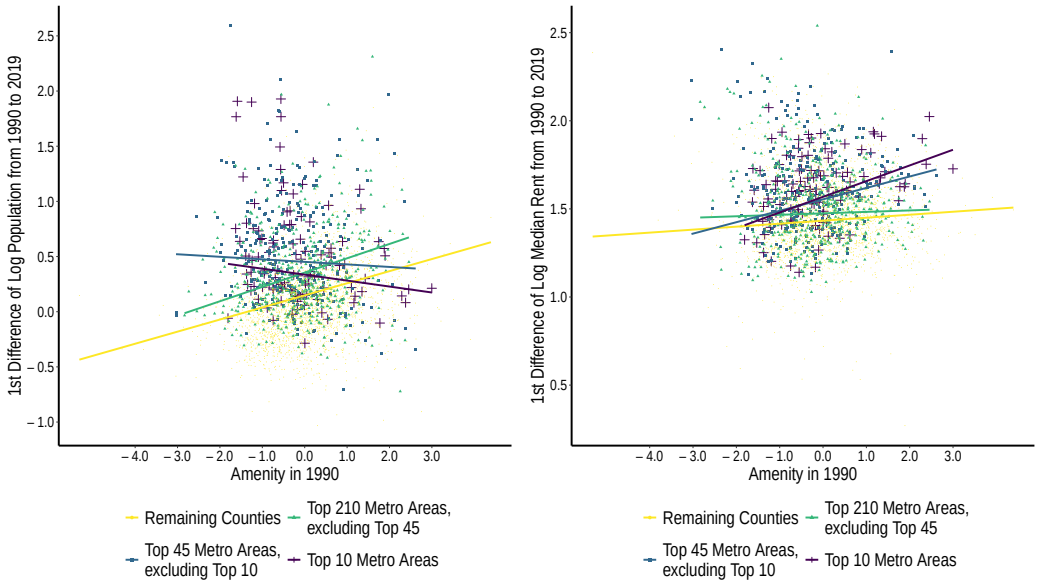
This figure shows the distribution of the percent change in population (Panel (a)) and median rents (Panel (b)) for U.S. counties between 1980 and 2019. The counties are grouped by the size of the containing Metropolitan Statistical Area. Population-weighted average population growth was 34.4% for top 10 metros, 62.7% for top 45 metros (excluding top 10), 53.2% for top 210 metros (excluding top 45), and 24.6% for remaining counties. Population-weighted average nominal rent growth was 422.0% for top 10 metros, 373.6% for top 45 metros (excluding top 10), 340.2% for top 210 metros (excluding top 45), and 328.3% for remaining counties.

elasticity is not strongly correlated with amenities, which provides reassurance that population and price growth related to amenities can be separated from growth related to supply constraints.

Of course, housing supply varies within metro areas. Even if large metros are, on average, relatively inelastic in housing supply, some areas might nevertheless be quite elastic. If this were the case, it would be improper for our analysis to simply group counties by metro size. However, in Appendix Figure A4, we plot the empirical CDFs of tract-level housing supply elasticities from Baum-Snow and Han (2024), separately for our size classes. We show that housing supply elasticities in top 10 metros very nearly exhibit first-order stochastic dominance over the smallest size category. While the sample contains few small towns, we are reassured that large metros are relatively inelastic even deep into their suburbs.

In addition to diverging in population and price growth, cities of different sizes also diverged in their composition. As documented in Diamond (2016), larger cities have attracted a greater share of college-educated workers, drawn in part by amenities. Large and small cities have also seen a

Figure 4: Changes in log population and log rent versus initial amenity level



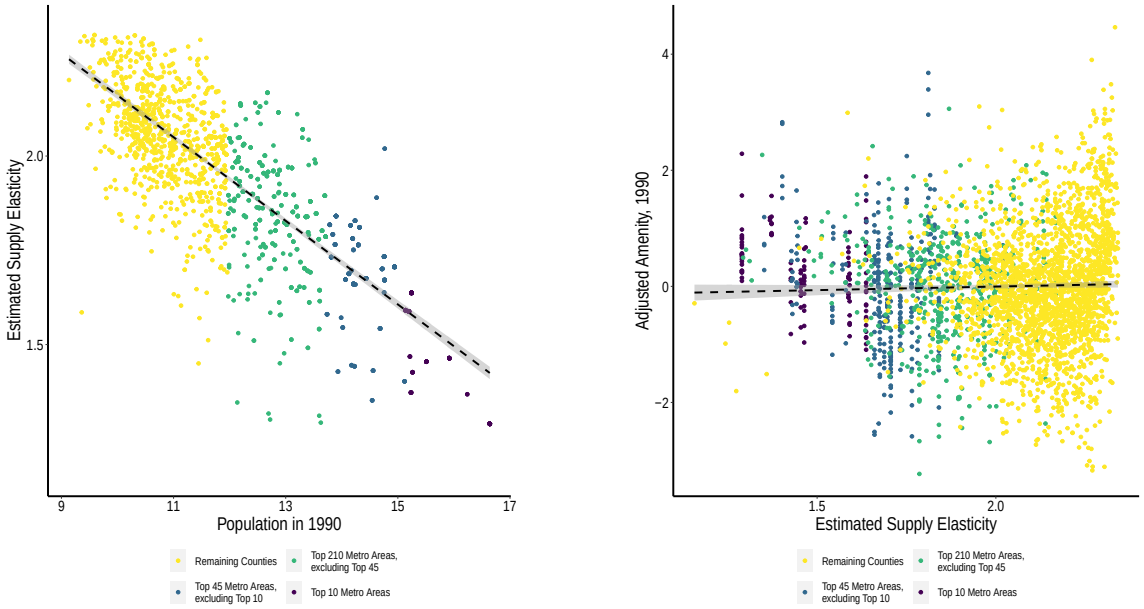
(a) Change in log population

(b) Change in log prices

This figure shows the change in the natural log of population (Panel (a)) and median rents (Panel (b)) between 1980 and 2019 for U.S. counties plotted against amenity level in 1980. Different colors and symbols are used to group counties based on the size of their containing metro areas. Lines and equations represent best linear fit for each group. The amenities shown here have not been adjusted for characteristics of the population or housing stock. A binned scatter plot version of this figure is presented as Figure A2.

divergence in the growth of nominal household income. Particularly in urban areas, the loss of skilled non-college jobs has eroded the wage benefits of living in a large city for non-college workers (Autor 2019). In Appendix Figure A6, we trace income growth and college-educated sorting (as well as total population and rent growth) for all size categories. We replicate the patterns established in the literature: top 10 metros have high initial college-educated shares, which only increase over time, as they also experience higher-than-average income growth. Baum-Snow and Pavan (2013) show that over time, the wage returns to locating in a large metro have increased, and more so for college-educated workers. In Section 4, we show that a sorting pattern similar to that shown by Diamond (2016) has occurred within the set of small towns: college educated workers and higher-income people are increasingly found in high-amenity rather than low-amenity small towns.

Figure 5: Estimated Supply Elasticities Versus Metro Population and Amenities



(a) Elasticity versus Size

(b) Elasticity versus Amenities

This figure shows the relation between estimated long-run housing supply elasticities and metro population in 1990 (Panel (a)) and estimated amenities in 1990 (Panel (b)). For non-metro counties, "metro population" is county population. Employing the methods of Baum-Snow and Han (2024), we use Bartik (1991)-style shocks for labor demand as an instrument, and estimate elasticity from the resulting changes to rents and population. Elasticity is allowed to vary with the fraction of land already developed in 1990.

4 Reduced-Form Evidence

4.1 Population and Price

In this section, we test whether amenities are predictive of population and price growth for areas throughout the city size distribution. If amenities are increasingly important to understanding population growth, we would expect housing demand to increase in high-amenity areas of all sizes. Given the established relationship between size and supply elasticities, we should expect amenities to be predictive of price increases in large metros and of population increases in small metros and rural areas. Through the lens of the model, we test here the predictions of Equations 9 and 10: amenities predict both population and rent growth, with high-elasticity places growing more in population and low-elasticity places growing more in rent.

We begin by formally testing the relationship suggested by Figure 4. We regress changes in the natural logarithm of rent and population on the level of initial amenity, interacted with indicator

variables for our population size categories. Let B_j represent the standardized level of amenity in county j, and let D_j be a vector of indicator variables for the population size categories, with rural areas as the omitted category. The estimating equations are:

$$\Delta \ln N_j = \beta_0 + \beta_1 B_j + \beta_2 D_j + \beta_3 B_j * D_j + \epsilon_j \tag{14}$$

$$\Delta \ln r_j = \beta_0 + \beta_1 B_j + \beta_2 D_j + \beta_3 B_j * D_j + \epsilon_j. \tag{15}$$

Table 2 shows the results of this exercise. Since amenities are transformed to have a mean of zero and a standard deviation of one, coefficients can be interpreted as the change in log population or rent associated with a one-standard-deviation difference in amenity. The first column shows changes in (log) population from 1990 to 2019 using adjusted amenities. The first row contains the coefficient on amenity for the omitted category, small towns and rural areas: a one-standard-deviation difference in amenities is associated with a 5.8 percent increase in population growth. Rows 2 through 4 are the interaction terms for the other size categories, so these should be added to the first row to get the total effect in each category. For the 10 largest metro areas, the total effect is $-.074$, implying an association of 7.4 percent less population growth with each standard deviation increase in amenities. This is consistent with housing supply constraints in the largest metros preventing substantial population growth. The second column shows estimates for rents, again for 1990-2019. In the first row, the coefficient of $-.027$ indicates that in the smallest population category, a one standard deviation difference in the amenity value is associated with slightly slower rent growth by 2.7 percent over the 40-year period. For counties in the top 10 metro areas, a one standard deviation difference in amenity value is associated with a 9.3 percent increase in rents over the period.

We can benchmark the size of these effects by comparison with overall growth. Small towns on average grew 25% in population since 1980, so that an additional 5.8% growth is quite substantial. Similarly, given concerns around housing affordability in major metros, additional rent growth of 9.3% per standard deviation difference in amenities is noteworthy.[17]

We next reinforce our findings against a number of potential concerns. First, both amenity values and population and rent growth are correlated across nearby counties. To ward against concerns about unobservable correlation in regression residuals, Table A5 clusters standard errors by both containing metro area and by size category, and Table A6 uses Conley spatial standard errors that allow arbitrary correlation between counties within 100 kilometers of each other.[18] Next, one might be concerned about 1990 as a starting point, or about the adjustment of amenities for

[17] In Section 6, we perform a series of counterfactuals to evaluate the relative contribution of amenities to price and population growth.

[18] In these specifications, not all adjacent size categories have coefficients that are statistically distinguishable from each other, but the overall relationship across the distribution remains: amenities predict different growth patterns in small towns and large metros, in ways that align with the predictions of the model.

Table 2: Relationship between amenities and price and population growth

	Dependent variable: Change in log...	
	Population	Rent
	(1)	(2)
Amenity	0.058^{***}	-0.027^{***}
	(0.010)	(0.005)
Amenity*Top 210 Metro Areas, excluding Top 45	-0.025	0.006
	(0.016)	(0.008)
Amenity*Top 45 Metro Areas, excluding Top 10	-0.074^{***}	0.091^{***}
	(0.015)	(0.008)
Amenity*Top 10 Metro Areas	-0.132^{***}	0.120^{***}
	(0.019)	(0.010)
Top 210 Metro Areas, excluding Top 45	0.126^{***}	-0.031^{***}
	(0.014)	(0.007)
Top 45 Metro Areas, excluding Top 10	0.171^{***}	-0.032^{***}
	(0.015)	(0.008)
Top 10 Metro Areas	0.123^{***}	-0.063^{***}
	(0.016)	(0.008)
Constant	0.134^{***}	0.900^{***}
	(0.009)	(0.005)
Observations	3,102	3,102
R^2	0.074	0.096
Adjusted R^2	0.072	0.094

*p<0.1; **p<0.05; ***p<0.01

This table shows the results of a regression of the change in the natural log of population or rents on estimated amenities in 1990. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Delta method tests show that the Top 10 metro size group has a different amenity interaction coefficient than the Top 45 group, with p-values of 0.006 for population and 0.000 for rent; and that the Top 45 group has different amenity interaction coefficient than the Top 210 group, with p-values of 0.005 for population and 0.007 for rent. *p<0.1; **p<0.05; ***p<0.01

observable characteristics. Table A7 shows that our results are robust to starting in 1980 (although we lose about 45% of counties due to the incomplete availability of subcounty data) or to using amenities that are not adjusted for differences in the housing stock.

Another possible concern is that of sensitivity to our choice of amenity measurement. Because many amenities are unobserved by the researcher, we treat our implied amenities as a baseline. However, in Table A8, we perform the same exercise using (1) a measure of natural amenities provided by the USDA Economic Research Service, which is based entirely on observable, exogenous characteristics, like summer temperatures and average slope, and (2) a "predicted amenity" version of our own estimated amenities. To make this prediction, we regress our amenities on the observable characteristics present in Table 1, and use the fitted value in our regression specification. This prediction smooths out unobservables that affect wages or rents. We find that the USDA amenities explain population and rent growth in small towns, but struggle to predict the outcomes of large

metros. This may be unsurprising—while Los Angeles has good weather and beaches, these features are probably not the primary drivers of its extremely high price growth. The predicted amenities qualitatively match our estimated amenities, and if anything suggest greater divergence between large and small geographies than in our baseline specification.

Another possible concern about our specification comes from the fact that metro areas are, by definition, interconnected sets of counties. One might be concerned that housing demand spillovers within metros contaminate our estimation. A related concern is that metros, while connected, are not impermeable, such that people do commute from neighboring non-metro areas. Additionally, one might worry that our "small towns and rural areas" are really exurbs that are not officially part of major metros, but nonetheless experience spillover housing demand from their expensive urban neighbors. We address these concerns in Table A9. We first collapse observations to the metro level (treating non-metro counties as singleton "metros") and find similar results. Next, we include as a control the log distance to a metro area with a population of at least 150,000 people in 1990. We find that counties further from these major metros experience less population growth, but the estimated effects on amenities are not substantially altered. Finally, we subset our analysis only to our small town size group, and interact amenities with our measure of distance to a major metro. We find that the positive population growth associated with amenities is *stronger* for counties further from major metros, suggesting that exurbs are not driving our results.

To further reinforce our results, we perform a variety of additional robustness exercises. We summarize the population results of these exercises in Table A10 and the rent results in Table A11. Column (1) of each table adds population density as a control. This addresses the concern that density is correlated with amenities and that initial density differences (within size groups) may drive growth. Column (2) subtracts commuting costs from local wages, to account for the possibility that commuting differences affect amenity estimates. Column (3) tests for the sensitivity of our calibration of local expenditure share, by lowering our value of $\beta = 0.65$ to $\beta = 0.35$. Column (4) addresses the concern that rents may not appropriately measure housing costs, by using median house value instead of median rent. This last check generates the only discrepancy in our results: population results are consistent, but we lose the monotonic relationship between amenities and metro size for price changes. One explanation for this is that house values are partially driven by expectations of future growth. Because rents are a better measure for *contemporary* housing costs, we believe they are better suited to the patterns we document.

Finally, in Tables A12 and A13 we include results that show the estimates by individual decades. In all four decades between 1980 and 2019, the same patterns persist and are statistically significant. The correlation of amenities and population growth is higher for small towns, while the correlation of amenities and rents is higher for large cities, as in the baseline results. The relationships weaken slightly over time; the strongest relationships are found in the 1980s and 1990s. Note that the estimates for 2010 to 2019 do not capture an entire decade as the 2019 value is based on a 5-year

lagged average, and therefore we would expect smaller coefficients relative to other decades.

The results in this section are consistent with increasing preferences for amenities. In large cities, high-amenity counties have increased relatively more in price, while in high-amenity small towns populations have grown. In the next section, we consider how to account for these trends by investigating the predictions on sorting from Equation 11.

4.2 Migration and Sorting

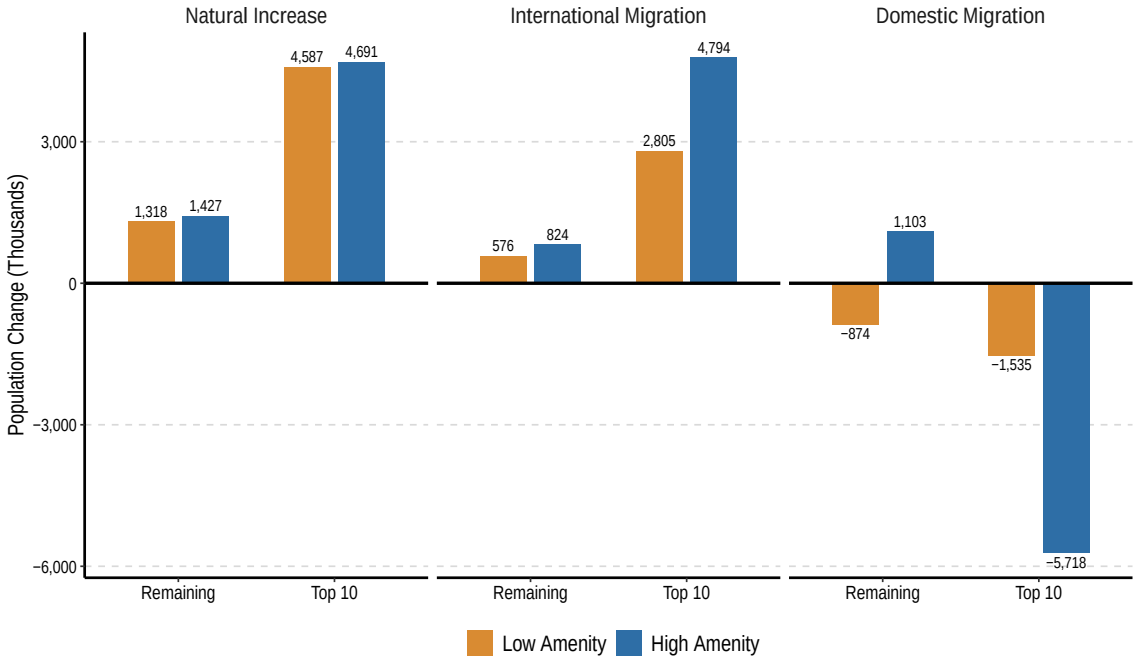
The location choice model described in Section 2 implicitly treats domestic migration as the key driver of population changes, rather than international immigration or differences in birth or death rates. In particular, the model predicts that workers will sort toward locations where their type-specific income growth outpaces rent growth. In Figure 6, we verify that domestic migration drives the divergent population growth observed between size groups and between high- and low-amenity areas. We focus for clarity on the largest and smallest size categories, and split each category into two equally-populated categories of "High" and "Low" amenities. The figure uses data from the U.S. Census Population Estimates Program, which decomposes net population growth into natural increase (net births), domestic migration (net moves within the U.S.) and international migration (net moves outside the U.S.). Natural increase is unsurprisingly much larger in large metros, but with only small differences between high- and low-amenity areas. International immigration is also higher in large metros, with a skew toward high-amenity areas of both types. Domestic migration displays the key divergence: in small towns, high-amenity areas experience net inflow and low-amenity areas exhibit net outflow. In large metros, *both* high- and low-amenity areas exhibit net outflow. In fact, net outmigration rates are over three times larger for the high-amenity areas.[19]

We formalize the relationship in Figure 6 by embedding it in our regression framework. Table 3 relates each component of population growth to amenities. The dependent variable is the change in log population from 2000 to 2019 that is attributable to each category. Column (1) confirms that births are not higher in high-amenity areas in any size category. Column (2) shows that high-amenity small towns experience more population growth from domestic migration, while high-amenity counties in large metros experience substantially *negative* growth from domestic migration. International migration in Column (3) is higher in high-amenity areas of all sizes, with stronger effects in large metros, as discussed above.

The tables above show that although top 10 metros grew on net from 2000 to 2019, they experienced domestic outflow not seen in most locations. As this net population loss is higher in high-amenity counties, it suggests a "pushing" force. In Figure 7, we see evidence of the source of this "push." The left panel plots an annual time series of the population decomposition for the largest metros. Net migration is negative in all years. It becomes more negative from 2000 to

[19]Table A15 displays these components of population change, as well as residual changes calculated by the Population Estimates Program, for all four size categories.

Figure 6: Decomposing changes in population



This figure shows a decomposition of population changes for U.S. counties between 2000 and 2019 by size and amenity categories. All numbers are in thousands of people. Amenity categories use 1990 amenity estimates adjusted for housing and worker characteristics. Each size group is split into high- and low-amenity counties, such that population is as even as possible between groups. Size groups are exclusive: for example, "Top 210" is the largest 210 metros excluding the largest 45. Residual population changes are excluded from the figure but presented in Table A15.

2007 and from 2012 to 2019, as house prices in large metros climbed. From 2007 to 2012, domestic outflow slowed as house prices fell.[20] We see the opposite pattern on the right panel, which provides a time series of population decomposition for our smallest size category. When house prices climb, from 2000-2007 and 2012-2019, population inflow increases in small towns.

To connect domestic migration flows more strongly to price growth, we next regress population growth attributable to domestic and international migration on log rent growth from 2000 to 2019, with results shown in Table 4. Column (1) shows domestic migration and Column (2) shows international migration. In small towns, higher rent growth is associated with more domestic migration, which clearly suggests increased demand. However, higher rent growth is not related to international immigration in small towns. In large metros, higher rent growth is associated with

[20] Murphy (2024) documents similar cyclical patterns in price growth and population composition in gentrifying city neighborhoods.

Table 3: Relationship between amenities and components of population growth.

	Dependent variable: Change in log population due to...			
	Natural	Domestic	International	Residual
	(1)	(2)	(3)	(4)
Amenity	0.004	0.032^{***}	0.005^{***}	0.001
	(0.003)	(0.006)	(0.001)	(0.001)
Amenity∗Top 210 Metro Areas, excluding Top 45	0.004	-0.034^{***}	0.007^{***}	-0.001
	(0.004)	(0.010)	(0.002)	(0.001)
Amenity∗Top 45 Metro Areas, excluding Top 10	0.011^{**}	-0.092^{***}	0.028^{***}	0.002^{**}
	(0.004)	(0.009)	(0.002)	(0.001)
Amenity∗Top 10 Metro Areas	0.004	-0.166^{***}	0.042^{***}	0.005^{***}
	(0.005)	(0.011)	(0.003)	(0.001)
Top 210 Metro Areas, excluding Top 45	0.044^{***}	0.051^{***}	0.016^{***}	0.003^{***}
	(0.004)	(0.008)	(0.002)	(0.001)
Top 45 Metro Areas, excluding Top 10	0.057^{***}	0.087^{***}	0.021^{***}	0.003^{***}
	(0.004)	(0.009)	(0.002)	(0.001)
Top 10 Metro Areas	0.074^{***}	-0.026^{***}	0.046^{***}	0.011^{***}
	(0.005)	(0.010)	(0.002)	(0.001)
Constant	0.036^{***}	-0.021^{***}	0.020^{***}	-0.004^{***}
	(0.003)	(0.006)	(0.001)	(0.001)
Observations	2,999	2,999	2,999	2,999
R^2	0.167	0.235	0.477	0.111
Adjusted R^2	0.165	0.233	0.476	0.109
Note:	*p<0.1; **p<0.05; ***p<0.01			

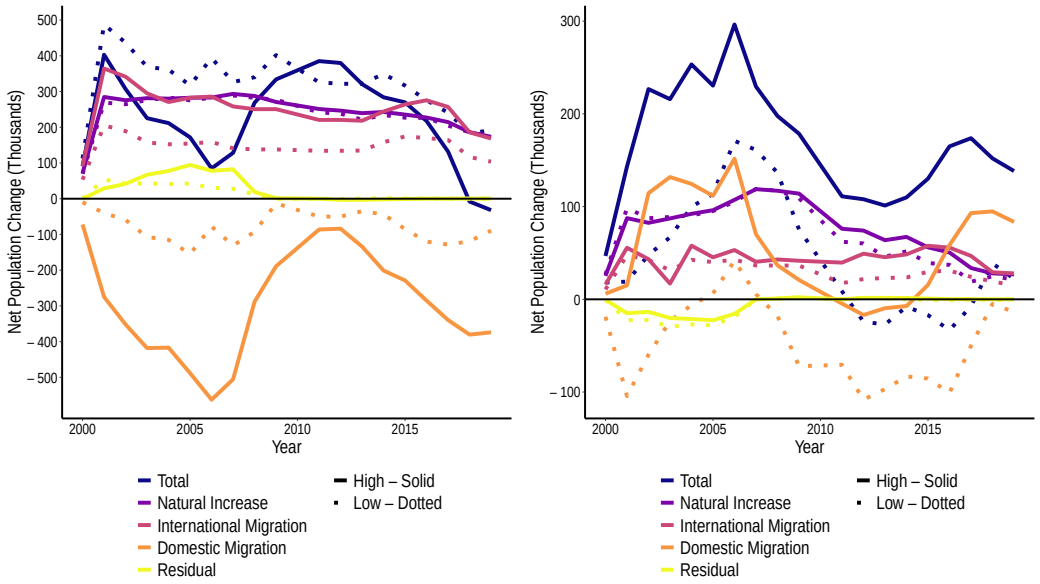
This table shows the results of a regression of the log population change from 2000 to 2019 that can be attributed to each component of population change on estimated amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Column (1) shows natural increase (net births). Column (2) shows net domestic migration. Column (3) shows international immigration. Column (4) shows residual population growth unaccounted for by the Census Bureau. *p<0.1; **p<0.05; ***p<0.01

both more domestic *outflow* and more international *inflow*. The international immigration despite high price growth suggests high housing demand, supporting the idea that domestic outflow is at least in part driven by high prices themselves.

Having established that domestic migration drives net population changes and appears related to house prices and amenity values, a natural next step is to look directly at migration flows across space. In the U.S. Census County-to-County Migration Flows, we found that new arrivals to high-amenity small towns are not disproportionately from large metros, and departures from large metros do not move disproportionately to small towns.[21] However, net changes in population do not necessarily reflect any particular move or set of moves. For example, our net population results could be the cumulative result of many "laddering down" moves, in which some people move from large metros to mid-sized metros and others leave mid-sized metros for small towns or rural areas,

[21] Schubert (2021) presents evidence on persistent migration links and their effect on correlated house-price dynamics.

Figure 7: Net population change decomposition over time



(a) Change in largest metro areas

(b) Change in small towns and rural areas

This figure shows the decomposition of population growth for U.S. counties for each year between 2000 and 2019. Different colors represent different components of population growth. Solid lines are high-amenity locations, while dotted lines represent low-amenity locations. Amenity categories use 1990 amenity estimates adjusted for housing and worker characteristics. Note that the y-axis scale is different for the two plots to improve clarity. The 2010 points are an interpolation using the trend between 2009 and 2011; in the data, the 2010 points are estimates for a 3-month period and are dropped.

and "laddering up" moves, in which still others leave low-amenity small towns to seek their fortune in big cities. Therefore, as we document the net effects of many cascading moves over 40 years, we cannot characterize the moves that generate our results. Instead, we probe our narrative by examining changes in the demographic composition of different locations.

The type of sorting that has received the most attention in the economic literature is that of college-educated workers. Column (1) of Table 5 shows that college workers are indeed increasingly sorting into high-amenity areas. However, this sorting is not different between large metros and small towns. As a whole, college workers increasingly sort into large metros, but the demand for amenities and the demand for large size appear approximately separable. We next turn to other forms of sorting.

Our primary hypothesis to explain increased amenity demand is that amenity demand is broadly non-homothetic and that real incomes have increased on average over the last 30 years. This generates the testable prediction of high-income individuals sorting into high-amenity locations. We

Table 4: Relationship between rent growth and migration.

	Dependent variable:	
	Domestic 2000-2019	Inter 2000-2019
	(1)	(2)
Log Rent Growth	0.112**	0.018
	(0.049)	(0.012)
Log Rent Growth∗Top 210 Metro Areas, excluding Top 45	0.123	0.024
	(0.079)	(0.019)
Log Rent Growth∗Top 45 Metro Areas, excluding Top 10	0.009	0.102***
	(0.067)	(0.016)
Log Rent Growth∗Top 10 Metro Areas	−0.504***	0.220***
	(0.070)	(0.017)
Top 210 Metro Areas, excluding Top 45	−0.018	0.008
	(0.042)	(0.010)
Top 45 Metro Areas, excluding Top 10	0.032	−0.017*
	(0.037)	(0.009)
Top 10 Metro Areas	0.182***	−0.062***
	(0.040)	(0.010)
Constant	−0.075***	0.011*
	(0.026)	(0.006)
Observations	2,995	2,995
R^2	0.187	0.438
Adjusted R^2	0.185	0.437
Note:	*p<0.1; **p<0.05; ***p<0.01	

This table shows the results of a regression of the log population change from 2000 to 2019 that can be attributed to domestic and international migration on log rent growth from 2000 to 2019. The omitted category is counties outside the top 210 metro areas by population. *p<0.1; **p<0.05; ***p<0.01

consider a particular kind of income sorting: in our framework, only one's absolute income determines demand for amenities, with relative income only affecting demand through the equilibrium force of changing prices. Therefore, we define "high-income" with a fixed, absolute threshold, such that the share of high-income households increases nationwide from 1990 to 2019. In particular, we deflate 2019 incomes to 1990 prices, and fix our income threshold at the 80th percentile of the 1990 wage distribution. Column (2) of Table 5 shows income sorting on amenities. The results suggest that a one standard deviation increase in amenity is associated with an increase in the share of high-income households of around 1 to 2 percent. Again, sorting towards amenities is not obviously different by size category.

In Column (3), we instead measure the change in the share of the population that is over 65 years old. We find that in small towns, amenities are associated with increased growth in the retiree share. In large metros, high amenities are associated with *decreased* growth in the retiree share. Given that retirees make up an increasing share of the U.S. population, and given the prominence

Table 5: Relationship between amenities and group sorting

	Dependent variable: Change in share of population that is...		
	College-Educated	High-Income	Over 65
	(1)	(2)	(3)
Amenity	0.007^{***}	0.010^{***}	0.007^{***}
	(0.001)	(0.002)	(0.001)
Amenity∗Top 210 Metro Areas, excluding Top 45	-0.007^{***}	-0.003	-0.005^{***}
	(0.002)	(0.003)	(0.002)
Amenity∗Top 45 Metro Areas, excluding Top 10	-0.001	0.017^{***}	-0.011^{***}
	(0.002)	(0.003)	(0.001)
Amenity∗Top 10 Metro Areas	-0.002	-0.001	-0.012^{***}
	(0.002)	(0.003)	(0.002)
Top 210 Metro Areas, excluding Top 45	0.010^{***}	0.0005	-0.004^{**}
	(0.002)	(0.002)	(0.001)
Top 45 Metro Areas, excluding Top 10	0.027^{***}	0.006^{**}	-0.008^{***}
	(0.002)	(0.003)	(0.001)
Top 10 Metro Areas	0.018^{***}	-0.012^{***}	-0.008^{***}
	(0.002)	(0.003)	(0.002)
Constant	0.088^{***}	0.084^{***}	0.039^{***}
	(0.001)	(0.002)	(0.001)
Observations	3,102	3,102	3,102
R^2	0.138	0.132	0.065
Adjusted R^2	0.136	0.130	0.063

This table relates changes in population composition to our amenity values and size categories. Each dependent variable is the 1990-2019 change in the fraction of the population meeting the criteria for a particular indicator variable. "College-educated" refers to holding an Associate's degree or higher. "High-income" is true when household income, measured in 1990 dollars, exceeds the 80th percentile of the 1990 wage distribution. "Over 65" refers to being 65 years of age or older. Amenities are based on 1990 rents and wages and are adjusted for observable characteristics of the 1990 population and housing stock. The omitted category is counties outside the top 210 metro areas by population. *p<0.1; **p<0.05; ***p<0.01

of "retirement towns" in public consciousness, the results in Column (3) merit further discussion. First, retiree sorting to high-amenity areas is a new phenomenon: Figure A8 shows that in 1990, there was no cross-sectional relationship between retiree share and amenities. Second, the rising share of retirees in high-amenity small towns is not the mechanical product of population aging: Figure A9 shows the relationship between amenities and the share of the population who will age into retirement in the next 5, 10, 20, and 30 years. In small towns, there is no relationship, and in large metros, one would actually expect amenities to be associated with *greater* increases in retiree share, not smaller increases. Third, the sorting of retirees on amenities is robust and not well-explained by other factors, as shown in Table A14. Column (1) excludes Florida, the top retiree destination, from our analysis, with results almost unchanged. Columns (2) through (4) try to predict retiree growth on other factors that one may hypothesize are enjoyable to retirees, with mixed success. Initial density and warm summer weather both struggle to explain observed patterns. USDA natural amenities have greater success.

Taking these findings together, we view the sorting of retirees as the product not simply of aging, but of other economic forces. In particular, in this section we highlight the importance of a novel form of sorting: local income detachment. Retiree income is not dependent on local productivity—both Social Security payments and draws from individual retirement accounts are unaffected by a person's area of residence. When a worker decides whether to move from a large metro to a small town, she must balance the lower house prices against the lower wages. The retiree does not face such a tradeoff, and thus has a higher real income outside of expensive major metros. Figure A10 confirms that, cross-sectionally, average incomes of retirees increase only slightly with city size, particularly when compared to working individuals.

We reinforce the idea of income-detachment sorting in Table 6. First, we confirm that over-65 households do have portable, non-local income. We use the Bureau of Economic Analysis Panel of Personal Current Transfer Receipts, and use it to calculate the change in county-level Social Security transfers. Column (1) shows that Social Security transfers increase substantially more in small towns and rural areas than in other geographies, the same places that over-65 households increasingly locate. In large metros, Social Security spending increases less in higher-amenity counties, which complements our finding of over-65 households leaving high-amenity parts of major cities. Column (2) shows the growth of another group of individuals whose income is not determined by local productivity: remote workers. In the period 1980-2019, remote workers make up less than 5% of the workforce, so they are not numerous enough to drive the bulk of our findings. However, they exhibit similar sorting patterns as retirees. In large metros, the decreased growth in high-amenity counties is smaller than for retirees, which may suggest an incomplete detachment. Finally, we show that our 1990 amenity estimates are predictive of population growth during the COVID pandemic, when many households were unexpectedly able to decouple their place of residence and place of employment. Column (2) shows the change in log population between the 2015-2019 5-year ACS and the 2017-2021 5-year ACS. The overall population patterns for this time period match the long-run patterns of detached households, with amenities predicting greater population growth in small towns and less population growth in large metros. While point estimates are much smaller than for the long-run population results in Table 2, these changes cover a 2-year span rather than a 40-year span.

5 Model Calibration

The reduced-form evidence in Section 4 establishes that amenities strongly predict population and price growth, with effects varying systematically across the city size distribution. However, our empirical analysis alone cannot quantify the relative importance of amenities compared to other drivers of spatial reallocation—changing local productivities, demographic shifts, and housing supply constraints. To address this, we use the spatial equilibrium model from Section 2 to conduct

Table 6: Relationship between amenities and income detachment

	Dependent variable:		
	Social Security	WFH	COVID Pop Growth
	(1)	(2)	(3)
Amenity	0.014	0.006^{***}	0.008^{***}
	(0.011)	(0.001)	(0.001)
Amenity∗Top 210	-0.061^{***}	-0.001	-0.006^{***}
	(0.019)	(0.001)	(0.002)
Amenity∗Top 45	-0.153^{***}	-0.001	-0.013^{***}
	(0.018)	(0.001)	(0.001)
Amenity∗Top 10	-0.220^{***}	-0.005^{***}	-0.019^{***}
	(0.022)	(0.001)	(0.002)
Top 210	-0.081^{***}	0.017^{***}	0.016^{***}
	(0.016)	(0.001)	(0.001)
Top 45	-0.160^{***}	0.024^{***}	0.019^{***}
	(0.017)	(0.001)	(0.001)
Top 10	-0.231^{***}	0.025^{***}	0.025^{***}
	(0.019)	(0.001)	(0.002)
Constant	0.894^{***}	0.001	-0.0003
	(0.011)	(0.001)	(0.001)
Observations	3,051	3,051	3,051
R^2	0.241	0.275	0.121
Adjusted R^2	0.239	0.274	0.119
Note:	*p<0.1; **p<0.05; ***p<0.01		

This table shows the results of a regression of the 1990-2019 changes on size categories and estimated amenities. "Social Security" is per-capita Social Security transfers to the county. "WFH" means working remotely most of the time. "COVID Pop Growth" measures the change in log population from the 2015-2019 5-year ACS to the 2017-2021 5-year ACS. Amenities are based on 1990 rents and wages and are adjusted for observable characteristics of the 1990 population and housing stock. The omitted category is counties outside the top 210 metro areas by population. *p<0.1; **p<0.05; ***p<0.01

counterfactual exercises that decompose observed dynamics into components attributable to each channel. By isolating these forces, we can assess which most powerfully shape growth patterns in large metros versus small towns.

To implement these counterfactuals, we must first calibrate the model to match observed data in both 1990 and 2019. We calibrate the model using data on observed rents, populations, and incomes throughout the country, as well as our amenity estimates. In our reduced-form exercises, we treated counties as individual locations, to allow for variation in demand both within and across metro areas. In the model, we seek to decompose the relative importance of amenities, productivities, demographics, and housing supply. As a result, we must consider work location choices in addition to residential location choices. Metropolitan areas are, by definition, composed of counties that experience substantial commuting flows, and the model framework established in

Section 2 does not accommodate the joint choice of home and work location. As a result, for this quantitative exercise, we treat each metropolitan area as a single location. Non-metro counties are still treated as individual locations.[22]

We split the population into three mutually exclusive types: college-educated workers, non-college-educated workers, and retirees. We calibrate the consumption share of local goods, β, to be 0.65 based on the literature as discussed in Section 3. The remaining parameters to estimate are the amenity demand for each type and time, ρ_{it}, and the scale of idiosyncratic shocks σ.[23] We also estimate population persistence fixed effects for each location δ_j; and local housing productivity for each location C_{jt}. We estimate these parameters by minimizing the squared errors ϵ_{ijt} in the demand equation (Equation 3), as well as matching the relationship between rent and population in the supply equation (Equation 7).

For amenities B_j, we use the 1990 amenity estimates from Section 3. Rents r_{jt} are the observed median household rent adjusted for housing characteristics in 1990 and 2019. Populations are total populations in 1990 and 2019. To calculate wages, we first partition the population into: people under 25, people 25-64 with at least a Bachelor's degree ("college workers"), people 25-64 without a Bachelor's degree ("non-college workers"), and people over 65 ("retirees").[24] Each group must be assigned a local wage w_{ijt}. Given that income by age and education is not available at the county level, we use the IPUMS USA microdata to impute wages by type for each county (Ruggles et al. 2025). In 1990, these data are available aggregated to groups of counties with a combined population of at least 100,000. We treat incomes as constant within these groups.[25]

In 2019, the data are available in Public Use Microdata Areas of at least 100,000 people, which are not coterminous with counties. In this case, we use an area-weighted crosswalk to assign incomes by type for each county. In each area, we calculate "college income" as the mean total income (across all sources) among individuals who are working, have a college degree, and had nonzero income.[26] We calculate "non-college income" as the mean total income among individuals who are working, do not have a college degree, and had nonzero income. We calculate "retiree income" as mean total income across all individuals who had either nonzero Social Security income or nonzero other retirement income.

The demand parameters in Equation 3 to be estimated are ρ_{it}, the amenity preferences by type; δ_j, the location fixed effects; and σ, the extreme-value scale parameter. The parameters are estimated by minimizing the squares of the residuals ϵ_{ijt} in both time periods, analogous to estimation of an ordinary least square linear panel model. As a normalization, we set the amenity

[22] Columns (1) and (4) of Table A9 show that our empirical results hold for this definition of location.

[23] We do not estimate the Cobb-Douglas production parameter α, because we work directly with observed wages.

[24] We do not model the behavior of people under 25. Instead, we inflate the populations of the 25-and-older groups to match the total population, while keeping constant the shares of each group among the 25-and-older population.

[25] In practice, urban counties are singleton "groups" with observable wages, while rural areas combine multiple counties together.

[26] Because incomes are top coded in these data, the mean income is not unduly skewed by high earners.

preference parameter for non-college workers to zero in 1990, which allows us to identify the relative values of all other parameters. This normalization allows for easy interpretation of how preferences differ across groups and over time.[27] Given the non-linearity of the model, it is solved using a computational search algorithm that finds parameter values that minimize sum of squared residuals.

It is useful to provide some intuition for how parameters are structurally identified from variation in the data. The fixed effects δ_j are identified by the cross-sectional population of locations. The amenity preference parameters ρ_{it} are identified by the correlation of amenities B_j and the share of different household types in each location and time N_{ijt}. Finally, the scale parameter σ is identified by the correlation of wage growth and population growth between the two periods, where less sensitivity to wage growth indicates a larger role for idiosyncratic preferences.

The supply parameters to be estimated are the location housing supply elasticities η_j as well as the supply shifters for each time period C_{jt}. For the elasticities, we use the estimated elasticities described in Appendix B. With the supply elasticities in hand, the supply shifters C_{jt} are set to exactly match the population and rent in each location and time period. The supply shifters account for aggregate price growth between periods as well as relative price changes not explained by the estimated elasticities. As we will discuss further below, our estimates of C_{jt} will suggest that growing supply restrictions over the sample period were positively correlated with amenities.

The model therefore matches population and rents exactly in each location and time period, while the amenity preference parameters and σ are estimated to minimize the residuals in population shares across household types and locations. The fit of the model can consequently be assessed by comparing the observed and predicted population shares that are not targeted directly by the calibration. Figure A13 in the appendix plots the observed and predicted population shares by household type and location.

Parameter Estimates. Table 7 presents the key parameters from our model calibration. The top panel shows the estimated amenity valuation parameters (ρ_{it}) for each household type in 1990 and 2019, with standard errors in parentheses.[28] The bottom panel displays other key parameters: the housing expenditure share (β), which we calibrate following Albouy and Stuart (2020), and the taste dispersion parameter (σ), which we estimate from the data by fitting.

It is worth highlighting the interpretation of some of these parameter estimates. The estimate of the extreme-value scale parameter σ provides information about the responsiveness of location choices to economic fundamentals. A rough interpretation of this estimate is that a 1 percent change in wages over time results in a 0.83 ($1/\sigma$) percent change in population.

The estimates of preference parameters ρ_{it} are informative of how preferences for amenities vary across types and how preferences have changed over time. We normalize the 1990 preference parameter for non-college workers to zero. The preference parameter estimates for college workers and

[27] An alternative would be to normalize the fixed effect for one location.

[28] Standard errors are calculated using standard nonlinear least squares methodology with numerical approximation of the Jacobian matrix. The objective function minimizes squared residuals of population shares by type and location.

Table 7: Key parameters

Amenity Values			Source: Estimation
ρ_{it}	*Retiree*	*Non-College*	*College*
1990	-0.09 (0.010)	0.00 (0.004)	0.53 (0.013)
2019	0.07 (0.008)	0.12 (0.008)	0.48 (0.013)
Other Parameters	Interpretation	Value	Source
β	Housing share	0.65	Albouy and Stuart (2020)
σ	Taste dispersion	1.20	Calibration

This table presents key parameters from the model calibration. The top panel shows estimated amenity valuation parameters (ρ_{it}) for three household types (retirees, non-college workers, and college workers) in 1990 and 2019. Standard errors are shown in parentheses. The bottom panel displays other structural parameters used in the model: β is the expenditure share on local goods including housing, and σ is the scale parameter governing the dispersion of idiosyncratic location preferences.

retirees in 1990 are 0.53 and -0.09, respectively. These estimates, divided by σ, can be interpreted as the difference in population of a type for a one-standard-deviation difference of amenities in the cross-section relative to the non-college workers in 1990. For example, a one-standard-deviation difference in amenities is associated with a 4.3 percent ($0.53/\sigma$) increase in college-educated workers relative to workers without a college education. College graduates exhibited the highest demand for amenities, while retirees were less likely to locate in high-amenity places than other groups. This suggests that demographic change alone cannot account for higher population growth of retirees in high-amenity locations. In 2019, the preference parameter estimates ρ_{it} had risen to 0.07 for retirees and 0.12 for non-college workers, while college workers fell slightly to 0.48. This decline could reflect increased sorting on wages and productivity as well as growth in college attendance. The biggest change was the preferences of retirees, which helps explain the increased sorting of this group into high-amenity locations in 2019.

6 Counterfactuals

Section 4 established that amenities are a powerful factor in explaining the population and price growth of small towns and large metros. However, our reduced-form exercise alone cannot explain the quantitative importance of amenities compared to other factors, such as changing local productivities, demographics, and housing supply restrictions.

This section presents results of counterfactual simulations that decompose the importance of changes in amenity preferences, wages, supply restrictions, and demographic composition for population and price dynamics. To conduct the analysis, we fix selected components of the economy (amenity valuation ρ_{it}, wages w_{ijt}, demographic composition N_{it}, and housing productivity C_{jt}) at

1990 values and solve the model to obtain counterfactual rents and populations in each location. Because the model has no spillovers or endogenous amenities, the counterfactual equilibrium is unique and can be found computationally via contraction mapping.

To present the results, we separate locations into four categories: high-amenity large, low-amenity large, high-amenity small, and low-amenity small. "Large" locations collapse our two large categories from the empirical analysis, and thus include all of the top 45 metro areas. "Small" locations collapse our two smaller categories, and thus include all other metros and non-metro counties. Thus each group has approximately half the U.S. population in 1990. "High-amenity" locations are above-mean in estimated amenities, and "low-amenity" locations are below mean. Because wages, amenities, demographics, and housing supply are often covarying, the effects of each counterfactual do not necessarily sum to the total effect. This is true even after accounting for residuals, ϵ_{ijt}, which we allow to vary in the counterfactuals. Each counterfactual reflects the partial effect of changes in each component on differences in population and price changes for each location category, holding other components fixed. In all counterfactuals, aggregate population growth is held fixed, and households are reallocated across locations subject to this adding-up constraint.

These counterfactuals should be interpreted as partial decompositions within the model rather than as a complete decomposition of all forces underlying spatial growth. The model abstracts from agglomeration effects and other endogenous labor-market interactions, so changes in the spatial distribution of workers do not generate additional productivity effects through these channels. Similarly, we treat amenities as exogenous, so the counterfactuals do not allow changes in population or household composition to affect the underlying amenities of a location. These assumptions allow us to isolate the contribution of changes in amenity preferences, wages, housing supply, and demographics while holding the other components of the model fixed.

The key object of interest is the additional growth in population or rent experienced by high-amenity versus low-amenity locations. Figure 8 displays this object for the data and for our key counterfactuals, with the top panel displaying population results and the bottom panel rent results. First, we re-establish as a point of comparison the data: high-amenity large metros experienced only 0.5% more population growth than low-amenity large metros, compared to 10% for small towns. In terms of rent, high-amenity large metros saw 3.5% more rent growth than low-amenity large metros, while high-amenity small towns saw 8.5% *less* rent growth than low-amenity small towns.

These aggregate patterns are more muted than a simple story of rising amenity demand might predict, particularly the modest population advantage in large metros and the negative rent growth difference in small towns. However, as we show below, the counterfactual exercises reveal that amenity demand growth plays a substantial role in shaping these outcomes, with the patterns becoming much clearer when we isolate the contribution of amenities from other confounding factors.

In the first counterfactual, we set ρ_{it} to its 1990 values for all groups, shutting down the growth in amenity demand over the data window. We find that in small towns, the relationship between

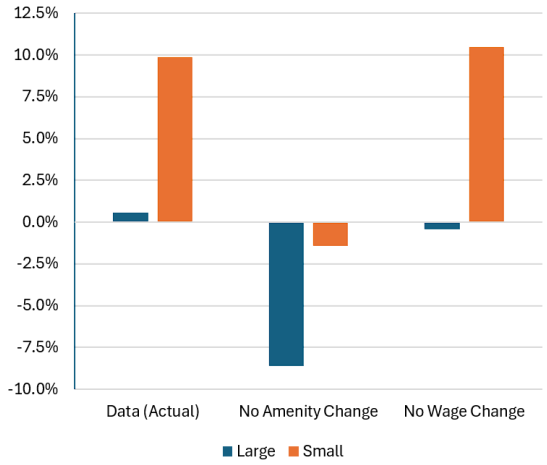
amenities and population growth disappears and slightly reverses, with high-amenity small towns growing 1.4% less than low-amenity small towns. In large metros, the relationship reverses more dramatically: high-amenity metros grow 8.6% *less* than low-amenity metros. The effects on rents help explain this finding: when amenity preferences are fixed, high-amenity small towns grow 15% *less* in rent than low-amenity small towns.[29] Similarly, high-amenity large metros also grow 2.9% *less* in rent than low-amenity large metros when amenity preferences are fixed, representing a reversal from the 3.5% advantage observed in the data. Amenity demand is thus a key channel driving the population patterns of both large and small locations.

In our second counterfactual, we fix wages for each group w_{ijt} to their 1990 levels. The difference in growth between high- and low-amenity small towns is not substantially affected by this change: population growth differences remain at 10.5%, nearly identical to the 10% observed in the data, and rent differences shift only slightly from -8.5% to -8.0%. This finding suggests that wage growth plays a minimal role in explaining the divergent growth paths of high- versus low-amenity small towns. In large metros, shutting down wage growth has a more noticeable effect, with the population growth difference between high- and low-amenity locations shifting from 0.5% to -0.4%. This modest reversal suggests that wage growth in high-amenity large metros helps explain their slight population advantage over low-amenity large metros. In terms of rents, when wages are fixed, high-amenity large metros grow 2.7% more than low-amenity large metros, somewhat less than the 3.5% observed in the data. Wage growth thus plays a more important role in driving population patterns in large metros than in small metros, though the magnitudes are modest.

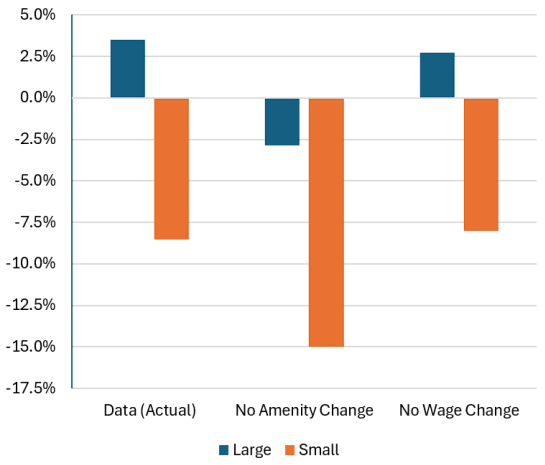
We perform two other counterfactual exercises that assess the importance of demographic changes and housing supply changes to growth patterns, shown in Figure A11. We find that fixing the demographic composition of the country to 1990 values, thus shutting down the relative growth of both college and retiree populations, has little impact on the patterns we observe. Fixing supply shifters does have some impact: high-amenity large metros have become less productive in construction over time compared to low-amenity large metros, so this counterfactual approximately doubles population growth in high-amenity large metros relative to low-amenity large metros and decreases their rent growth by about half. For small towns, housing productivity in high-amenity areas has relatively *increased* compared to low-amenity areas, so that shutting down changes in housing supply shifters actually makes high-amenity small towns grow less in population and much more in price compared to low-amenity small towns. Housing supply is therefore a channel that reinforces the patterns we document in this paper. To illustrate the way that housing supply elasticities interact with the channels described here, we perform the same counterfactual exercises, but

[29] In our model calibration, high-amenity small towns have higher supply shifters C_{jt} on average than do low-amenity small towns. Supply shifters can be thought of as a measure of construction productivity, so their very low values in low-amenity small towns may reflect the expense and difficulty of constructing new housing in rural areas facing overall population decline. In Figure A11, we find that fixing supply shifters over time increases the price growth of high-amenity small towns compared to low-amenity small towns, for the same reason.

Figure 8: Counterfactual Growth Fixing Amenities and Wages



(a) Counterfactual Population Growth



(b) Counterfactual Rent Growth

This figure shows actual and counterfactual differences between population and rent growth for high-amenity locations and low-amenity locations, split by size. Positive values indicate that high-amenity locations grew more, while negative values indicate that low-amenity locations grew more. "Data" shows actual growth. "Fix Amenity Demand" holds amenity valuations for each group at 1990 values. "Fix Wages" holds incomes for each group at 1990 values.

split locations on the median supply elasticity η rather than by size, and show the results in Figure A12.

Taken together, these counterfactual results demonstrate that changing amenity valuations are central to understanding spatial reallocation patterns, even though the raw 1990-2019 correlations appear modest. When amenity preferences are held fixed, the population advantages of high-amenity locations disappear or reverse dramatically in both large and small geographies. This suggests that the aggregate patterns reflect a combination of forces—rising amenity demand, wage growth, and evolving supply constraints—that partially offset one another in the raw data. The decade-by-decade analysis in Tables A12 and A13 reinforces this interpretation, showing consistent positive relationships between amenities and growth across all four decades between 1980 and 2019, with particularly strong effects in earlier periods. Moreover, in large metros where population effects appear small, the fact that high-amenity areas maintain population parity despite substantial rent premiums indicates strong underlying demand. In small towns, the counterfactual results clarify that amenity demand drives substantial population inflows, even as supply conditions and other factors complicate the rent dynamics.

7 Conclusion

In this paper, we provide a cohesive framework to understand several important economic changes of the last 40 years. We relate the runaway housing costs of large American cities, the increased sorting of college workers into large cities, and the existence of a few breakaway "superstar towns" that buck the broader trend of rural decline. We show that American consumers' demand for local amenities has increased, driving housing demand in high-amenity locations. In the largest cities, supply constraints mean that this demand drives massive price growth, which in turn encourages net population loss to other, less-expensive locations. On the other hand, in supply-elastic areas with high amenities, increased demand is realized through population growth. Furthermore, we document the importance of sorting on "productivity detachment:" while college workers are the driving force behind big-city housing cost, households with nonlocal income decide the fate of small towns.

Our work shows that initial amenities are predictive of large differences in long-term outcomes. In our preferred specification, a one-standard-deviation increase in amenities is associated with a 6 percent increase in rent growth and a 3 percent decrease in population growth in large metros, compared with a 2 percent decrease in rent growth and 6 percent increase in population growth in rural areas. These differences are substantial: a one-standard-deviation increase in amenities predicts price growth divergence of approximately 9 percentage points between a county in a large metro versus rural area. Our quantitative model reinforces these findings, showing that changes in amenity preferences account for nearly all of the population growth advantage of high-amenity small towns, while productivity growth and housing supply conditions play a larger role in explaining growth in large metros.

Supply constraints in America's largest cities affect more than just local rents. Population dynamics throughout the country are altered by their combination of low supply, high amenities, and high wages. The welfare implications of these long-run changes are ambiguous; as large metros continue to experience domestic out-migration, their agglomerative forces may become weaker. Our work thus shows that solutions to the housing crunch in big cities must consider the entire American metropolitan network.

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A Appendix: Amenity Measurement

In Section 3, we estimate implied local amenities at the county level. However, counties vary greatly in their housing and workforce characteristics. If a county has high housing costs because it has large or high-quality housing rather than because of capitalization of local amenities, we could overestimate the amenity value of the location. This section details our procedure for adjusting our amenity estimates to account for such compositional differences. Because individual-level data is not available at the county level, we use Census tract-level data to provide sub-county variation in our estimates.

To calculate adjusted rents, we first estimate the following regression equation to estimate the relationship between the (log) rent and the housing stock in a tract:

$$\ln r_{kj} = \theta_0^R + \theta_1^R Z_{kj}^R + d_j^R + \epsilon_{kj}^R, \tag{16}$$

where r_{kj} are the median housing rents in tract k and county j, and Z_{kj}^R is a vector of flexible controls for the distribution of housing characteristics, including number of units in buildings and year built. The term d_j^R represents a county-level fixed effect.

Next, we calculate adjusted county-level rents, $\ln \hat{r}_j$, as the predicted value of rent for the county-level average characteristics, $\overline{Z}_j^R$;

$$\ln \hat{r}_j = \hat{\theta}_0^R + \hat{\theta}_1^R \overline{Z}^R + \hat{d}_j^R. \tag{17}$$

Similarly, we predict tract-level (log) median household income, $\ln w_{kj}$, from a set of flexible controls for the distribution of age and education, Z_{kj}^W, and a county-level fixed effect d_j^W. We predict adjusted county-level wages, $\ln \hat{w}_j$, from the county-level average characteristics as above, $\overline{Z}^W$:

$$\ln w_{kj} = \theta_0^W + \theta_1^W Z_{kj}^W + d_j^W + \epsilon_{kj}^W, \tag{18}$$

$$\ln \hat{w}_j = \hat{\theta}_0^W + \hat{\theta}_1^W \overline{Z}^W + \hat{d}_j^W. \tag{19}$$

We estimate amenities for both 1980 and 1990 by substituting these adjusted rents and wages into Equation 13 for both 1980 and 1990. We use both years because of data limitations. While we believe the key trends we document begin around 1980, at that time the country was not yet partitioned into Census tracts, with rural areas much less likely to be covered. As a result, we use 1990 as the primary starting point for our regression analysis, so that we can include all counties, rather than selectively losing rural areas. In robustness checks, we use 1980 as a starting point, which contains only about half the sample.

B Appendix: Supply Elasticity Measurement

To estimate our model in Section 5, we require an estimate of housing supply elasticity for every location in the United States. We define a "location" for this purpose as either a metropolitan area or as a non-metro county. Our sample contains 2,195 locations, including 918 metros and 1,277 non-metro counties. Existing estimates in the literature, such as those from Saiz (2010) and Baum-Snow and Han (2024) (hereafter BSH), do not cover the entire United States, and in particular do not cover rural areas. Therefore, we adapt the techniques in BSH to estimate county-level supply elasticity from 1990 to 2019. (Log) housing supply in location j at time t, denoted $\ln Q^S_{jt}$, is a function of log prices $\ln P_{jt}$ and individual housing supply elasticity η_j, plus unobserved shifters u_{jt}.

$$\ln Q^S_{jt} = \eta_j \ln P_{jt} + u_{jt} \tag{20}$$

The purpose of the exercise is to estimate η_j. To do so, we follow BSH in allowing η_j to vary based on observed characteristics of the location. In particular, for simplicity, η_j is a function of the (log of one plus the) fraction of land in the location that is already developed in 1992, the earliest year for which land coverage data are available.[30] That is, we impose the structure $\eta_j = \eta Z_j$, where Z_j includes a constant and the fraction developed, $Z_j = [1, \ln FracDev1992]$. With this structure, the goal is to estimate the coefficients η, from which we can recover η_j using Z_j. We do so using the time-differenced analog of Equation 20:

$$\Delta \ln Q^S_j = \eta_j \Delta \ln P_j + \Delta u_j. \tag{21}$$

To produce an estimable equation, we substitute in our parametrization of η_j. We also include other controls in a vector X_j, including the log population in 1990 and the log median income in 1990:

$$\Delta \ln Q^S_j = (Z_j \times \Delta \ln P_j)\eta + X_j\beta + \Delta u_j. \tag{22}$$

A key difficulty in estimating Equation 22 is that growth in prices may be correlated with growth in unobserved factors affecting housing. If $Cov(\Delta \ln P_j, \Delta u_j) \neq 0$, our estimate of η will be biased. Therefore, to account for the endogeneity of prices, we turn to an instrumental variables approach. The first stage regression uses Bartik (1991)-style shocks to predict changes in prices. Since price growth is interacted with Z_j, we also interact the instrument with Z_j in our first stage regression. In the second stage, we estimate η using the predicted values for $(Z_j \times \Delta \ln P_j)$.

In some counties, the observed data reflect either falling population or falling prices over our

[30] We use logs because the median location has 0.9% of land developed and only 10% of locations have more than 3.7% of land developed. The most-developed location has 51.5% of land developed.

time period. Because housing is durable, η_j may be different for positive versus negative growth (Glaeser and Gyourko 2005). Therefore, we perform our estimation only on locations with positive growth in both rent and population. Approximately one-third of locations are removed from the estimation, so that we estimate the relationship between housing supply and fraction developed on 736 metros and 648 non-metro counties.

We start with the 1992 version of the National Land Cover Database, which spans the continental U.S. at a resolution of 30-meter-by-30-meter pixels. We map each pixel to a county, then group metropolitan counties together to form our sample of locations. In each location, we count the number of pixels that is categorized as "developed land," including use codes "low intensity residential," "high intensity residential," and "commercial/industrial/transportation." We divide that number by the number of all land pixels (total pixels minus "open water" and "perennial ice/snow"). We are left with the fraction of land developed in each location. The least-developed in-sample location (Shannon County, SD) has just 0.6% of land developed, while the most-developed location (Lexington City, VA) has 51.5% of land developed. [31] Because the distribution exhibits substantial rightward skew, we take the log of the fraction developed, plus one so all quantities are positive.

Next, we calculate our instrument. We use data from IPUMS USA to calculate the share of workers in each location that works in each of 17 industries, using household weights for representativeness. The included industries are: "Agriculture, forestry, and fisheries;" "Mining;" "Construction;" "Manufacturing, nondurable goods;" "Manufacturing, durable goods;" "Transportation;" "Communications and other public utilities;" "Wholesale trade;" "Retail trade;" "Finance, insurance, and real estate;" "Business and repair services;" "Personal services;" "Entertainment and recreation services;" "Professional and related services: Health services;" "Professional and related services: Educational services;" "Professional and related services: Other professional and related services;" and "Public administration." We also calculate the percent growth in each industry from 1990 to 2019 to produce our instrument.

The first-stage regression takes the form:

$$\Delta \ln P_j = \gamma(Z_j \times Bartik_j) + X_j\beta + \Delta\epsilon_j. \tag{23}$$

We estimate Equation 22 using Equation 23 as a first stage. First-stage F statistics are all above 20. The results of the two first-stage regressions (for $\Delta \ln P_j$ and for $Z_j \times \Delta \ln P_j$) are shown in columns (1)-(2) of Table A1. The results of the 2SLS regression are shown in column (3). Recall that $\eta_j = \eta Z_j$. Let $\eta = [\eta^0, \eta^1]$. Then η^0 is the constant in calculating η_j (since the first term of Z_j is the constant 1), and η^1 is the change in η_j based on the fraction developed. That is, we calculate:

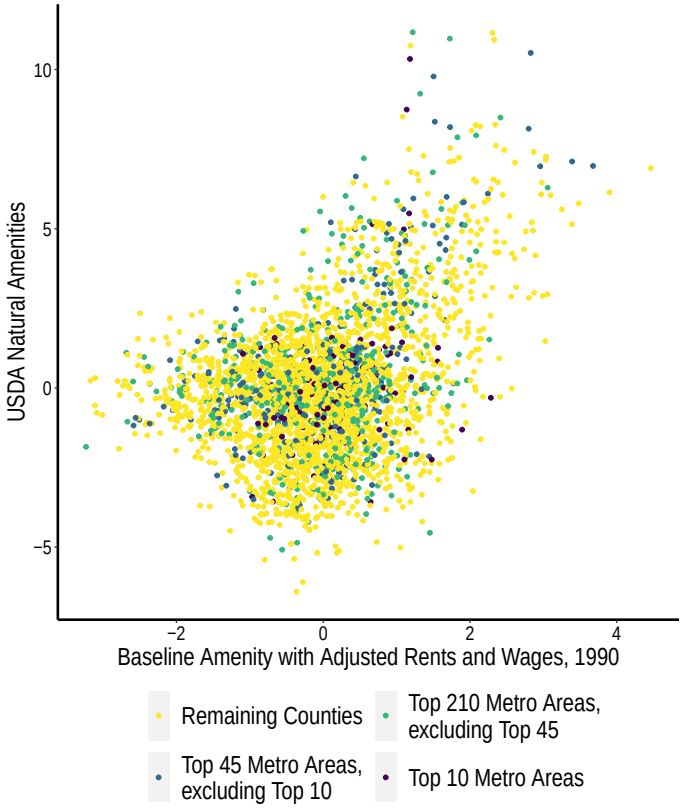
[31] The most-developed metro, New York-Newark-Jersey City, NY-NJ-PA, has 32.7% of land developed.

$$\eta_j = \eta^0 + \eta^1 \ln FracDev1992_j. \tag{24}$$

We calculate η for all locations, including those that were removed from the estimation for having either negative rent growth or population growth. The average estimated elasticity is $\eta_j = 2.11$. Summary statistics of estimated amenities are shown in Table A2. This estimate is higher than that found in BSH, but on par with estimates in Saiz (2010). The lowest elasticity is 1.16 and the highest is 2.34, with a median value of 2.16. As shown in Figure 5, elasticities fall with location size, but are largely uncorrelated with amenities.

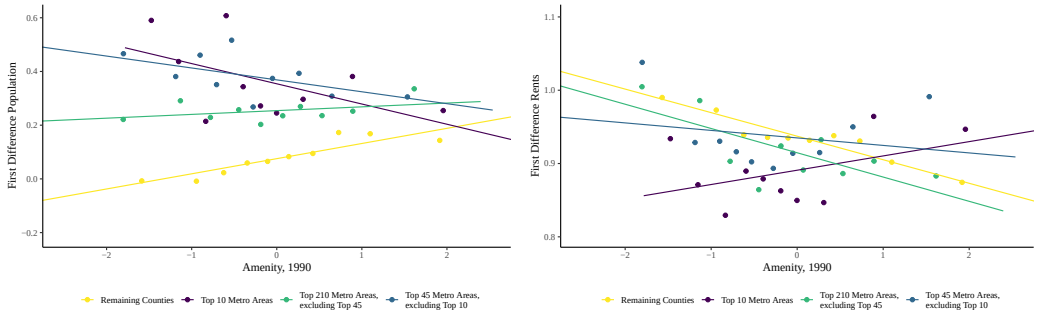
C Appendix: Additional Tables and Figures

Figure A1: Scatter Plot of USDA Amenities vs Estimated Amenities



This figure shows the relationship between the amenities estimated in Appendix A and the USDA Economic Research Service's measurement of natural amenities. Both amenities are standardized to have mean of zero and standard deviation of one.

Figure A2: Binned scatter plot of population and price growth vs initial amenity level

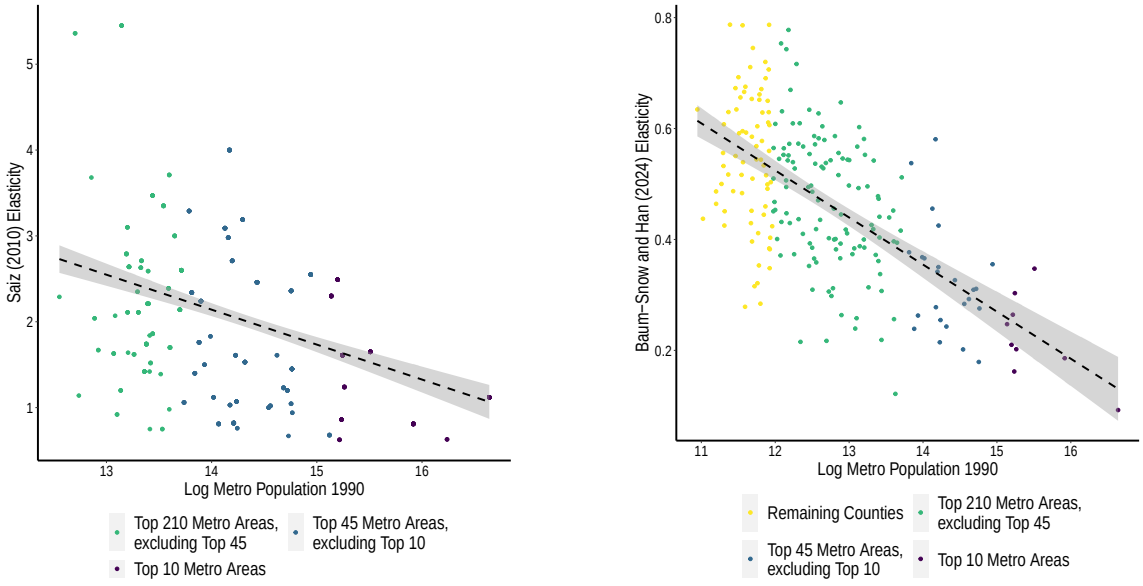


(a) Change in log population

(b) Change in log prices

This figure shows a binned scatter plot version of Figure 4. Bins are constructed to have equal size, and a linear line of best fit is fitted through each set of bins.

Figure A3: Metro population versus housing supply elasticity

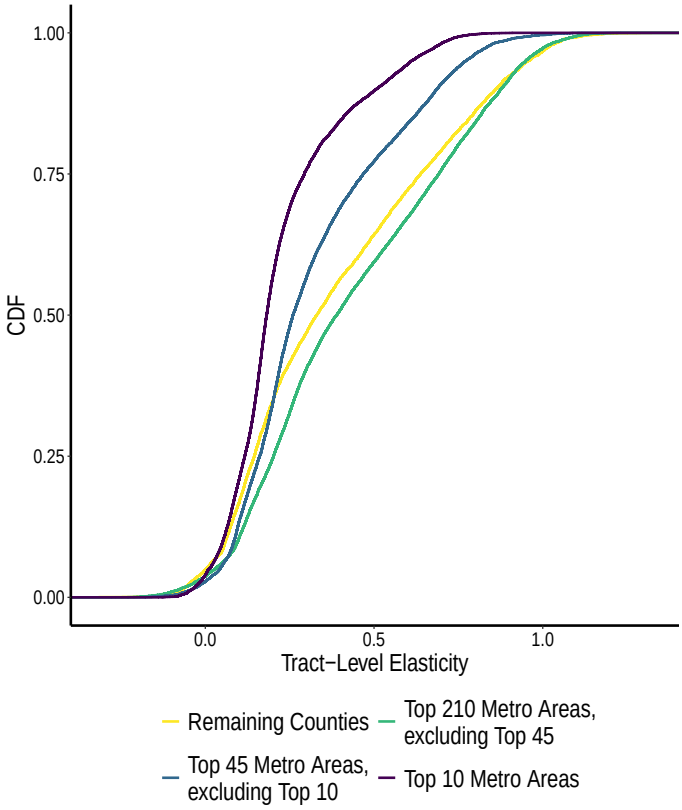


(a) Housing Supply in Saiz (2010) vs Metro Size

(b) Housing Supply in Baum-Snow and Han (2024) vs Metro Size

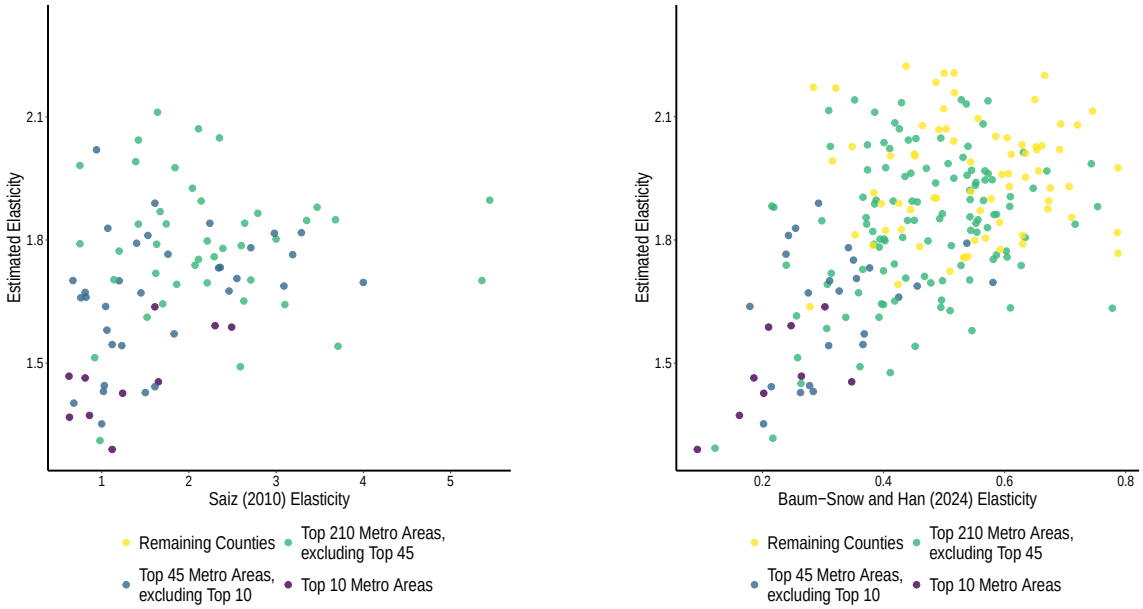
This figure shows the relationship between metro population in 1990 and estimated housing supply elasticities in Saiz (2010) and Baum-Snow and Han (2024). Metros are manually mapped from each paper to the closest existing CBSA in 2010 Census geography. Dashed line is a linear best-fit line.

Figure A4: CDFs of Housing Supply by Metro Size



This figure shows empirical CDFs of tract-level estimated housing supply in Baum-Snow and Han (2024), by the size of the tract's containing metro. Metros are manually mapped to the closest existing CBSA in 2010 Census geography.

Figure A5: Estimated Elasticities Versus Literature

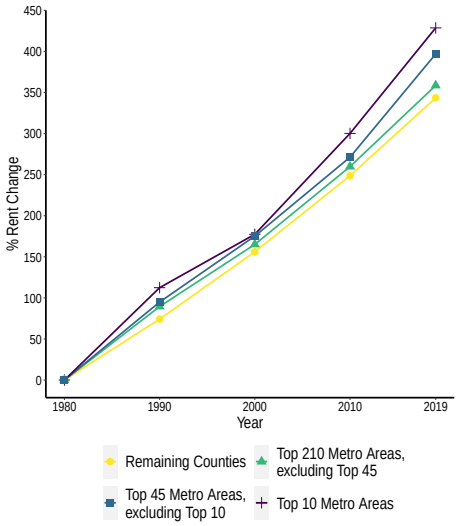


(a) Estimated elasticities vs elasticities from Saiz (2010)

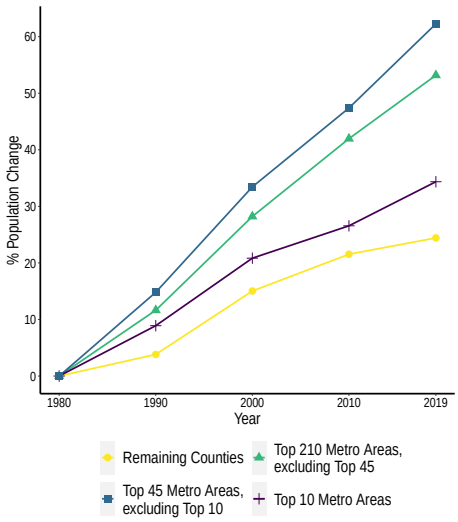
(b) Estimated elasticities vs elasticities from Baum-Snow and Han (2024)

This figure shows the relationship the housing supply elasticities estimated in Appendix B and estimated housing supply elasticities in Saiz (2010) and Baum-Snow and Han (2024). Metros are manually mapped from each paper to the closest existing CBSA in 2010 Census geography.

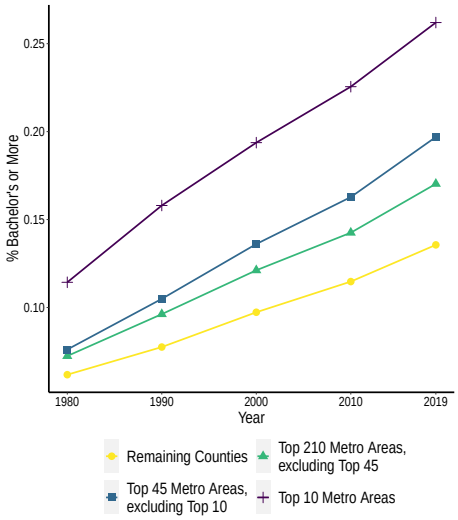
Figure A6: Changes in key variables by initial population categories



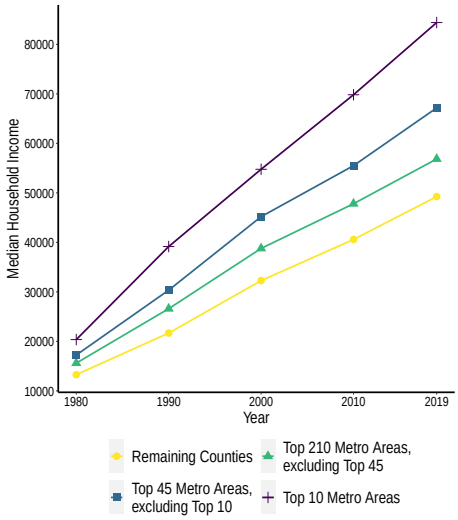
(a) Percent Change Rent



(b) Percent Change Population



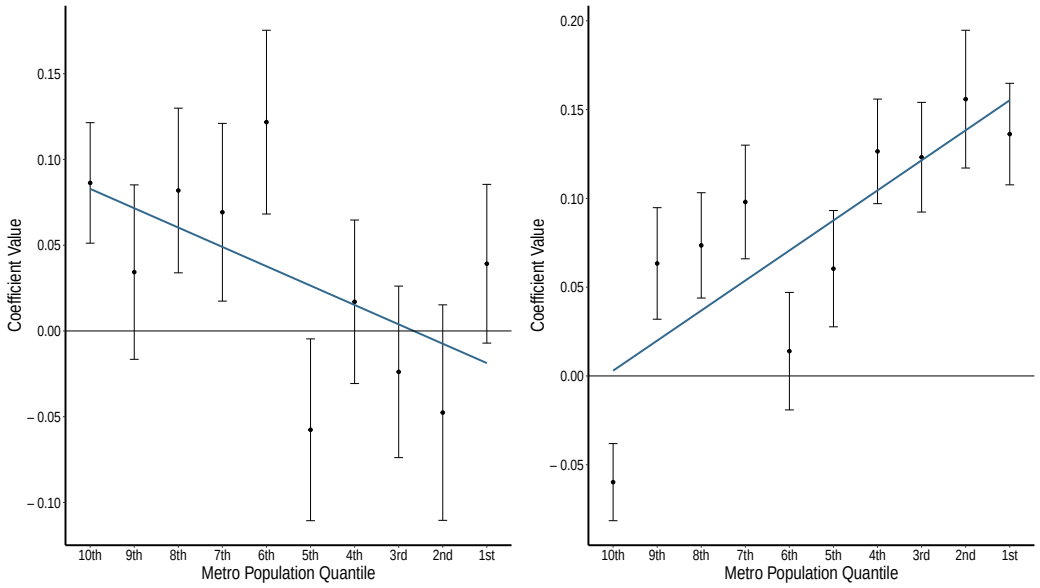
(c) Share College-Educated



(d) Median Household Income

This figure shows the percent change in median rents (Panel (a)) and the percent change in total population (Panel (b)), relative to 1980, as well as the share college-educated (Panel (c)), and the median household income (Panel (d)), for counties grouped by the population of their containing metropolitan area. Median rent is a population-weighted average of county median rent for each category.

Figure A7: The effects of amenities on population and rents by fine metro size categories

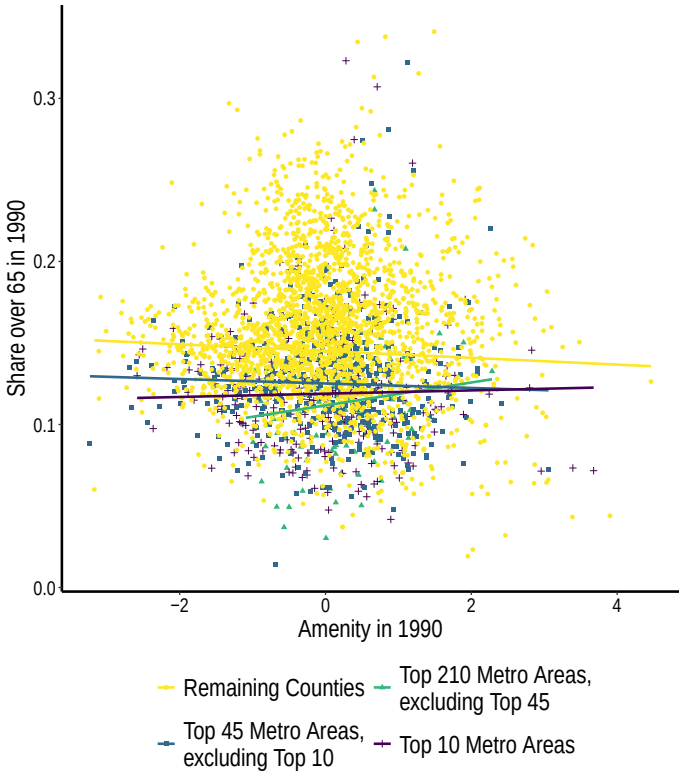


(a) Amenities and population

(b) Amenities and rents

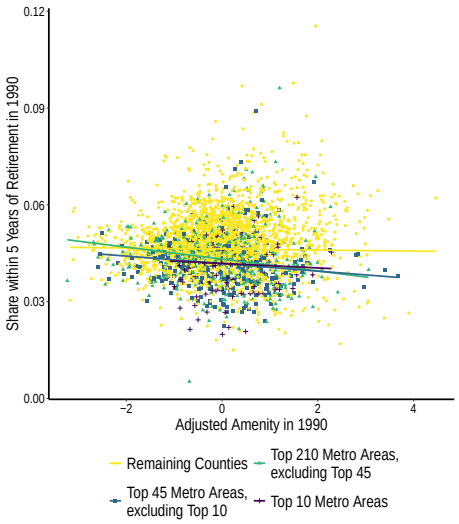
This figure shows estimates of the coefficient on the interaction term between amenities and population category indicators for each quantile. Counties are separated into 10 categories based on the size of their containing metro. Each category has roughly equal population. The left panel shows the coefficients using changes in population as the dependent variables, while the right panel uses rents. Points represent coefficient estimates on the interaction term for each quantile, and lines through the points represent 95 percent confidence intervals. The blue line is a linear fit through the coefficient estimates. Note that this specification uses 1980 amenity levels, not adjusted for observable characteristics of the population and housing stock.

Figure A8: Retiree Sorting in Cross-Section, 1990

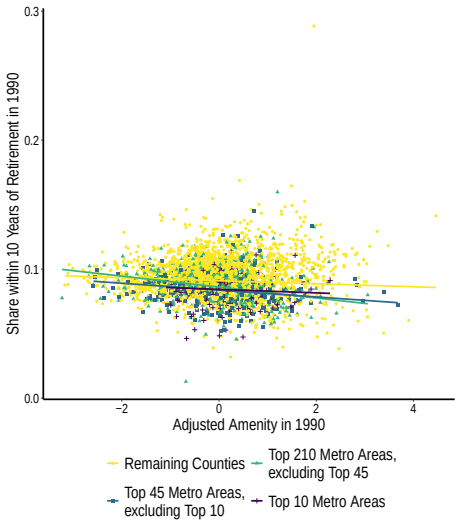


This figure shows the relationship between estimated amenities and the share of the population that is over 65, cross-sectionally in 1990.

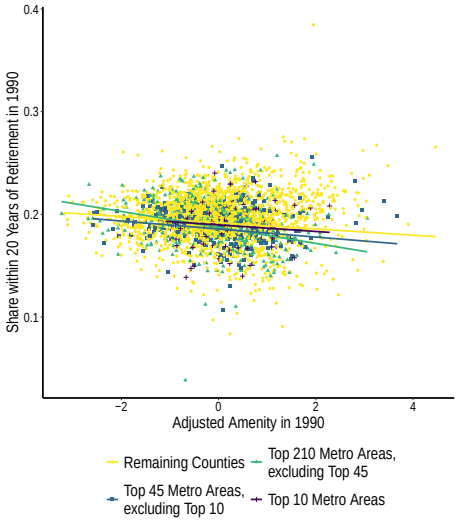
Figure A9: Amenities versus Age Structure in 1990



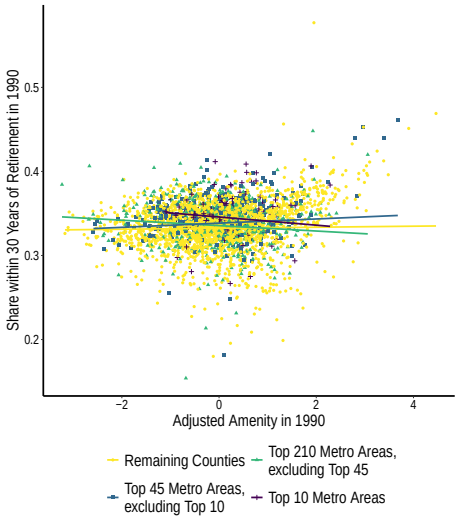
(a) Retirement within 5 Years



(b) Retirement within 10 Years



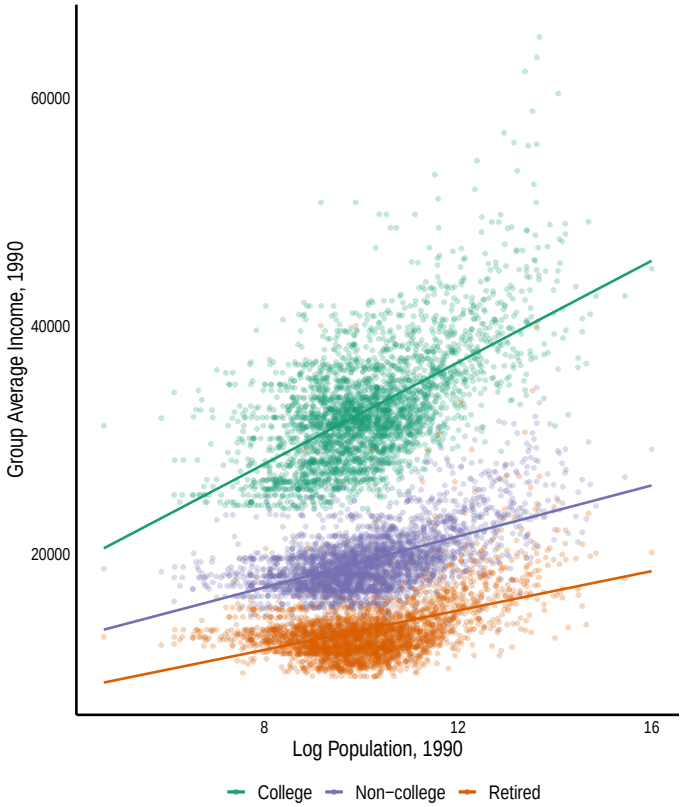
(c) Retirement within 20 Years



(d) Retirement within 30 Years

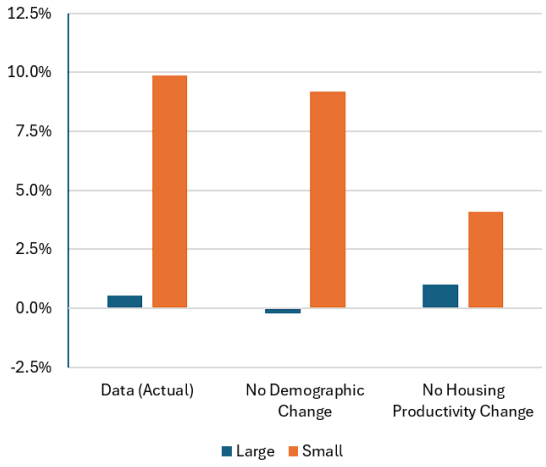
This figure shows the relationship between county-level estimated amenities and the age structure of the population. Panel (a) shows the share of the population within 5 years of retirement (ages 59-64). Panel (b) shows the share of the population within 10 years of retirement (ages 54-64). Panel (c) shows the share of the population within 20 years of retirement (ages 44-64). Panel (d) shows the share of the population within 30 years of retirement, or the approximate end of our sample period (ages 34-64).

Figure A10: Metro Population versus Income by Group, 1990

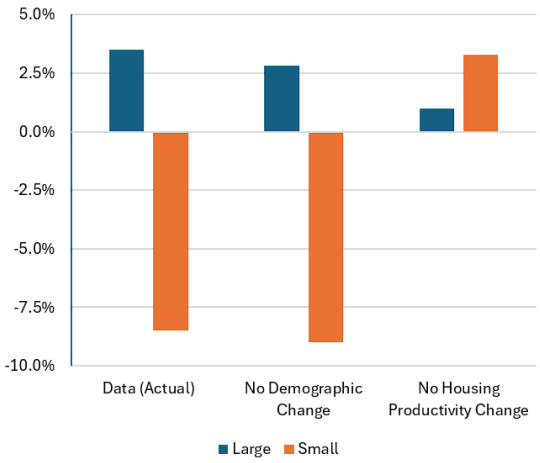


This figure shows a scatter plot relating log metro population in 1990 (with non-metro counties treated as singletons) and average income by three groups: college-educated workers, non-college workers, and retirees. Calculations for group incomes are described in Section 5.

Figure A11: Counterfactual Growth Fixing Demographics and Supply Shifters



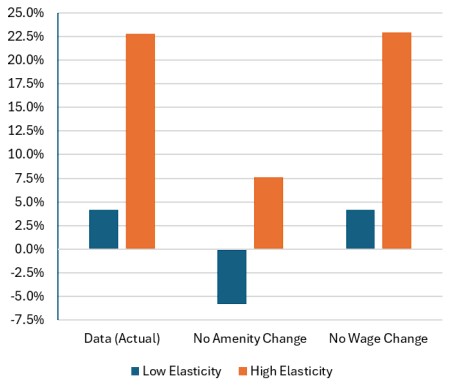
(a) Counterfactual Population Growth



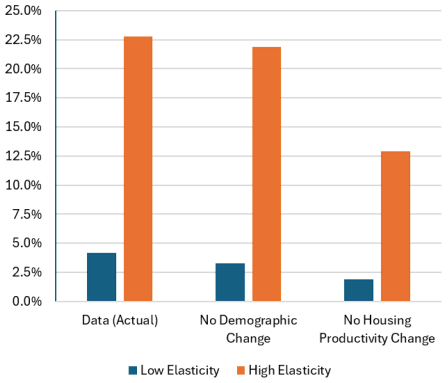
(b) Counterfactual Rent Growth

This figure shows actual and counterfactual differences between population and rent growth for high-amenity locations and low-amenity locations, split by size. Positive values indicate that high-amenity locations grew more, while negative values indicate that low-amenity locations grew more. "Data (Actual)" shows actual growth. "No Demographic Change" holds the total nationwide size of each group (college workers, non-college workers, and retirees) at 1990 values. "No Housing Productivity Change" holds supply shifters at 1990 values.

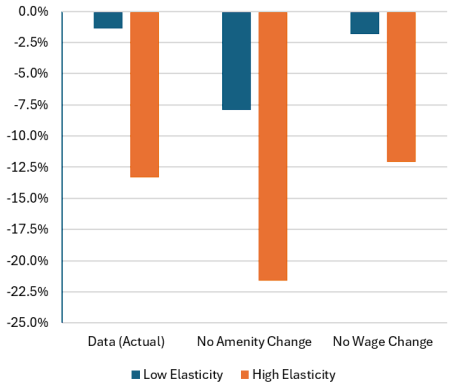
Figure A12: Counterfactual Population and Rent Growth by Housing Supply Elasticity



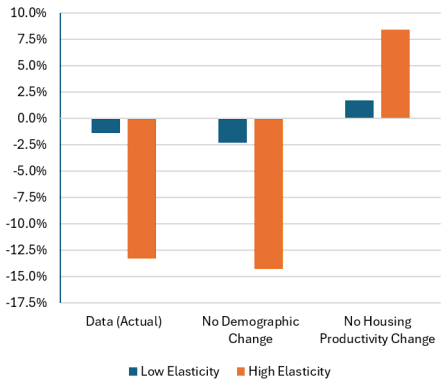
(a) Population, Wages and Amenities



(b) Population, Demographics and Supply



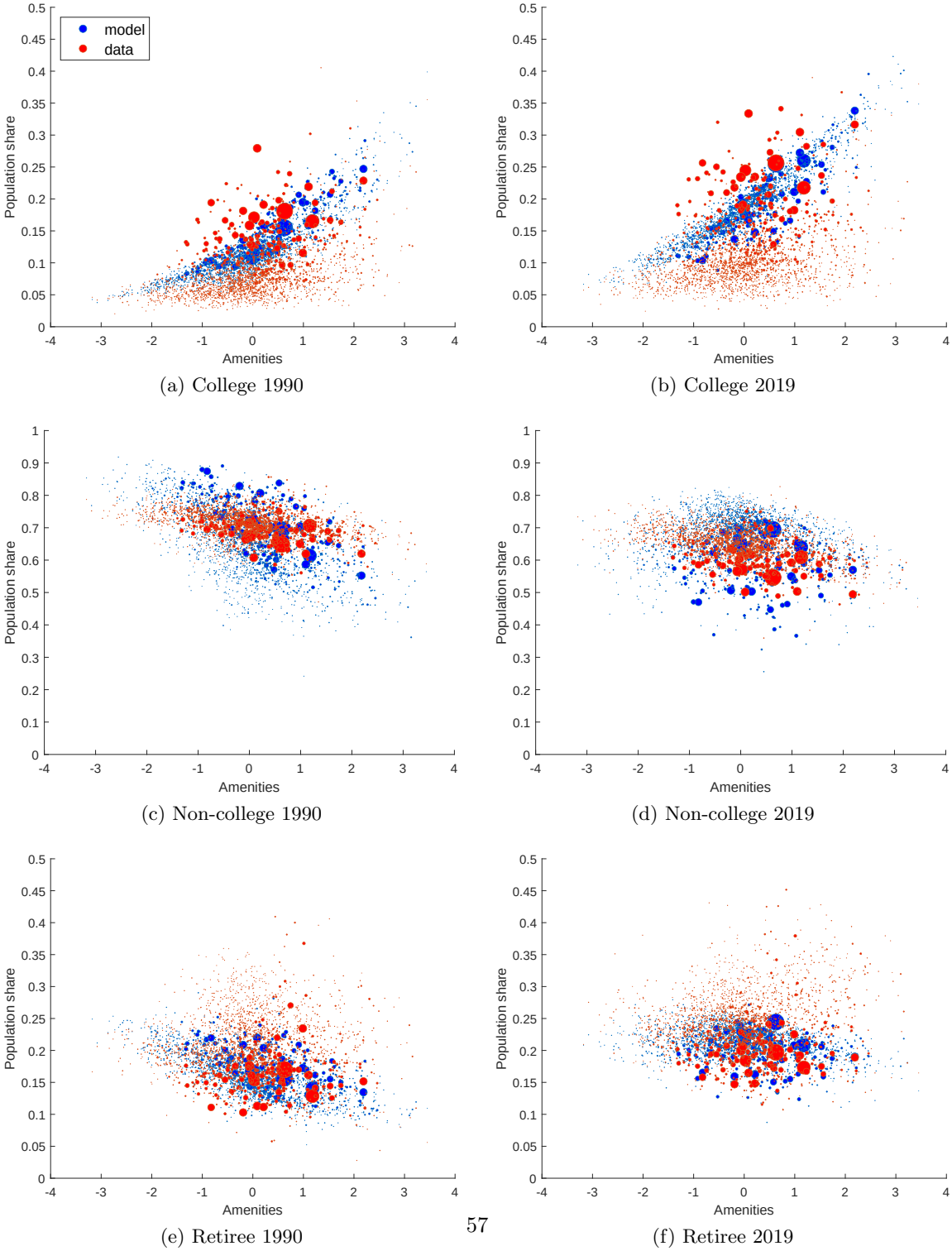
(c) Rent, Wages and Amenities



(d) Rent, Demographics and Supply

This figure shows actual and counterfactual differences between population and rent growth for high-amenity locations and low-amenity locations, split by elasticity. Positive values indicate that high-amenity locations grew more, while negative values indicate that low-amenity locations grew more. "Data" shows actual growth. "Fix Amenity Demand" holds amenity valuations for each group at 1990 values. "Fix Wages" holds incomes for each group at 1990 values. "Fix Demographics" holds the total nationwide size of each group (college workers, non-college workers, and retirees) at 1990 values. "Fix Supply Changes" holds supply shifters at 1990 values.

Figure A13: Model Fit of Demographic Shares



(a) College 1990

(b) College 2019

(c) Non-college 1990

(d) Non-college 2019

(e) Retiree 1990

(f) Retiree 2019

These figures show the share of each population group in the data along with the model equivalent plotted against standardized metro area amenities. The size of the marker is based on total population of the metro area.

Table A1: Elasticity estimation

	Dependent variable: Change in log...		
	Rent	Rent × Dev	Population
	(1)	(2)	(3)
Labor Demand Shock	0.002	-0.009^{***}	
	(0.003)	(0.003)	
× Log Fraction Developed	0.010^{***}	0.024^{***}	
	(0.003)	(0.003)	
Change in Log Rent			2.343^{**}
			(0.944)
× Log Fraction Developed			−0.299
			(0.630)
Log Fraction Developed	-0.304^{***}	0.187^{**}	0.262
	(0.086)	(0.077)	(0.552)
Log Population (1990)	0.002	0.021^{***}	0.032^{**}
	(0.004)	(0.004)	(0.015)
Log Wage (1990)	-0.119^{***}	-0.133^{***}	0.408^{***}
	(0.021)	(0.019)	(0.070)
Constant	2.081^{***}	1.429^{***}	-6.362^{***}
	(0.209)	(0.186)	(1.414)
Specification	First	First	2SLS
Observations	1,384	1,384	1,384
R^2	0.095	0.950	−1.976
Adjusted R^2	0.092	0.950	−1.987

This table shows the results of the 2SLS regression of Bartik (1991)-style demand shocks on rent growth. The sample contains all locations (metro areas and individual non-metro counties) that have both positive population growth and positive rent growth from 1990 to 2019. Column (1) shows the first-stage regression of the shock on rent growth, which has an F statistic of 28.97 with $(5, 1378)$ degrees of freedom. Column (2) shows the first-stage regression of the shock on rent growth interacted with the initial fraction developed in 1990, which has an F statistic of $5,227.86$ with $(5, 1378)$ degrees of freedom. Column (3) shows the 2SLS specification. *p<0.1; **p<0.05; ***p<0.01

Table A2: Summary statistics for η by group

Group	Mean	25th Percentile	Median	75th Percentile	N
Top 10	1.479	1.373	1.464	1.591	111
Top 45	1.694	1.671	1.706	1.765	283
Top 210	1.860	1.786	1.862	1.963	490
Rest of Country	2.138	2.053	2.164	2.246	2223

Table A3: Highest-amenity counties in 1990 by population category

Group	County	Metro Area	Amenity	Median Rent	Median Income	Population
Country	Hinsdale County, Colorado		4.460	275	26,250	467
	Pitkin County, Colorado	Glenwood Springs, CO	3.900	663	39,991	12,661
	Gilpin County, Colorado	Denver-Aurora-Lakewood, CO	3.680	351	31,898	3,070
	Mineral County, Colorado		3.480	231	19,830	558
	Park County, Colorado	Denver-Aurora-Lakewood, CO	3.390	366	32,102	7,174
	San Miguel County, Colorado		3.390	447	30,578	3,653
	Custer County, Colorado		3.250	223	20,000	1,926
	Monroe County, Florida	Key West, FL	3.100	523	29,351	78,024
	Teller County, Colorado	Colorado Springs, CO	3.060	387	32,209	12,468
	Blaine County, Idaho	Hailey, ID	3.060	410	31,199	13,552
Top 10	New York County, New York	New York-Newark-Jersey City, NY-NJ-PA	2.280	478	32,262	1,487,536
	Falls Church City County, Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	1.890	769	51,011	9,578
	Pike County, Pennsylvania	New York-Newark-Jersey City, NY-NJ-PA	1.560	445	30,314	27,966
	Suffolk County, Massachusetts	Boston-Cambridge-Newton, MA-NH	1.560	546	29,399	663,906
	Alexandria City County, Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	1.480	667	41,472	111,183
	Rockingham County, New Hampshire	Boston-Cambridge-Newton, MA-NH	1.200	541	41,881	245,845
	Los Angeles County, California	Los Angeles-Long Beach-Anaheim, CA	1.180	570	34,965	8,863,164
	Miami-Dade County, Florida	Miami-Fort Lauderdale-Pompano Beach, FL	1.170	422	26,909	1,937,094
	Fairfax City County, Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	1.160	729	50,913	19,622
	Orange County, California	Los Angeles-Long Beach-Anaheim, CA	1.140	728	45,922	2,410,556
Top 45	Gilpin County, Colorado	Denver-Aurora-Lakewood, CO	3.680	351	31,898	3,070
	Park County, Colorado	Denver-Aurora-Lakewood, CO	3.390	366	32,102	7,174
	Clear Creek County, Colorado	Denver-Aurora-Lakewood, CO	2.960	335	33,149	7,619
	San Francisco County, California	San Francisco-Oakland-Berkeley, CA	2.830	613	33,414	723,959
	Marin County, California	San Francisco-Oakland-Berkeley, CA	2.800	763	48,544	230,096
	El Dorado County, California	Sacramento-Roseville-Folsom, CA	2.240	478	35,058	125,995
	Bandera County, Texas	San Antonio-New Braunfels, TX	1.920	256	24,671	10,562
	Alameda County, California	San Francisco-Oakland-Berkeley, CA	1.890	570	37,544	1,279,182
	Orleans County, Louisiana	New Orleans-Metairie, LA	1.770	277	18,477	496,938
	San Mateo County, California	San Francisco-Oakland-Berkeley, CA	1.730	711	46,437	649,623
Top 210	Teller County, Colorado	Colorado Springs, CO	3.060	387	32,209	12,468
	Santa Cruz County, California	Santa Cruz-Watsonville, CA	2.420	651	37,112	229,734
	Barnstable County, Massachusetts	Barnstable Town, MA	2.260	547	31,766	186,605
	Lane County, Oregon	Eugene-Springfield, OR	2.090	360	25,268	282,912
	Sonoma County, California	Santa Rosa-Petaluma, CA	2.080	576	36,299	388,222
	Torrance County, New Mexico	Albuquerque, NM	1.990	233	19,619	10,285
	Lake County, Minnesota	Duluth, MN-WI	1.960	217	23,478	10,415
	Storey County, Nevada	Reno, NV	1.930	343	32,457	2,526
	Boulder County, Colorado	Boulder, CO	1.900	449	35,322	225,339
	Cumberland County, Maine	Portland-South Portland, ME	1.850	458	32,286	243,135
Remaining	Hinsdale County, Colorado		4.460	275	26,250	467
	Pitkin County, Colorado	Glenwood Springs, CO	3.900	663	39,991	12,661
	Mineral County, Colorado		3.480	231	19,830	558
	San Miguel County, Colorado		3.390	447	30,578	3,653
	Custer County, Colorado		3.250	223	20,000	1,926
	Monroe County, Florida	Key West, FL	3.100	523	29,351	78,024
	Blaine County, Idaho	Hailey, ID	3.060	410	31,199	13,552
	Nevada County, California	Truckee-Grass Valley, CA	3.040	489	32,200	78,510
	San Juan County, Colorado		3.030	276	26,167	745
	Sutton County, Texas		3.030	209	20,933	4,135

Table A4: Lowest-amenity counties in 1990 by population category

Group	County	Metro Area	Amenity	Median Rent	Median Income	Population
Country	Powhatan County, Virginia	Richmond, VA	-3.230	331	37,394	15,328
	Glasscock County, Texas		-3.170	100	29,306	1,447
	Clinch County, Georgia		-3.110	115	18,098	6,160
	Webster County, Georgia		-3.110	99	19,028	2,263
	Glascock County, Georgia		-3.080	111	21,806	2,357
	Lamar County, Alabama		-3.010	110	20,618	15,715
	Clay County, Alabama		-2.800	116	19,252	13,252
	Jenkins County, Georgia		-2.780	111	16,967	8,247
	Robertson County, Kentucky		-2.780	99	19,756	2,124
	Montgomery County, Georgia	Vidalia, GA	-2.730	121	20,054	7,163
Top 10	Warren County, Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	-1.090	328	31,062	26,142
	Calvert County, Maryland	Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.990	519	47,608	51,372
	Newton County, Indiana	Chicago-Naperville-Elgin, IL-IN-WI	-0.970	207	28,624	13,551
	Jefferson County, West Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.890	294	30,941	35,926
	Charles County, Maryland	Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.880	603	46,415	101,154
	Waller County, Texas	Houston-The Woodlands-Sugar Land, TX	-0.860	237	22,334	23,390
	Lapeer County, Michigan	Detroit-Warren-Dearborn, MI	-0.820	335	35,874	74,768
	Culpeper County, Virginia	Washington-Arlington-Alexandria, DC-VA-MD-WV	-0.780	402	33,523	27,791
	Cecil County, Maryland	Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	-0.710	364	36,019	71,347
	Jasper County, Indiana	Chicago-Naperville-Elgin, IL-IN-WI	-0.680	228	28,546	24,960
Top 45	Fayette County, Tennessee	Memphis, TN-MS-AR	-2.580	137	22,199	25,559
	Southampton County, Virginia	Virginia Beach-Norfolk-Newport News, VA-NC	-2.560	140	26,376	17,550
	Gates County, North Carolina	Virginia Beach-Norfolk-Newport News, VA-NC	-2.510	135	23,408	9,305
	St. James County, Louisiana	New Orleans-Metairie, LA	-2.360	114	23,105	20,879
	Meriwether County, Georgia	Atlanta-Sandy Springs-Alpharetta, GA	-2.170	172	20,212	22,411
	Smith County, Tennessee	Nashville-Davidson–Murfreesboro–Franklin, TN	-2.090	175	23,255	14,143
	Tate County, Mississippi	Memphis, TN-MS-AR	-2.050	185	22,207	21,432
	Heard County, Georgia	Atlanta-Sandy Springs-Alpharetta, GA	-1.890	179	21,513	8,628
	Chester County, South Carolina	Charlotte-Concord-Gastonia, NC-SC	-1.870	169	23,054	32,170
	Marshall County, Mississippi	Memphis, TN-MS-AR	-1.800	145	18,492	30,361
Top 210	Powhatan County, Virginia	Richmond, VA	-3.230	331	37,394	15,328
	Talbot County, Georgia	Columbus, GA-AL	-2.680	99	20,489	6,524
	Goochland County, Virginia	Richmond, VA	-2.670	282	36,239	14,163
	Calhoun County, South Carolina	Columbia, SC	-2.590	127	23,750	12,753
	Crawford County, Georgia	Macon-Bibb County, GA	-2.440	155	25,799	8,991
	Fairfield County, South Carolina	Columbia, SC	-2.390	151	21,484	22,295
	Pickens County, Alabama	Tuscaloosa, AL	-2.360	99	17,879	20,699
	Twiggs County, Georgia	Macon-Bibb County, GA	-2.270	145	19,213	9,806
	Washington County, Alabama	Mobile, AL	-2.070	112	20,082	16,694
	Lowndes County, Alabama	Montgomery, AL	-2.070	99	15,584	12,658
Remaining	Glasscock County, Texas		-3.170	100	29,306	1,447
	Clinch County, Georgia		-3.110	115	18,098	6,160
	Webster County, Georgia		-3.110	99	19,028	2,263
	Glascock County, Georgia		-3.080	111	21,806	2,357
	Lamar County, Alabama		-3.010	110	20,618	15,715
	Clay County, Alabama		-2.800	116	19,252	13,252
	Jenkins County, Georgia		-2.780	111	16,967	8,247
	Robertson County, Kentucky		-2.780	99	19,756	2,124
	Montgomery County, Georgia	Vidalia, GA	-2.730	121	20,054	7,163
	Irwin County, Georgia		-2.700	125	20,169	8,649

Table A5: Robustness of main result to clustering standard errors

	Dependent variable:			
	Pop	Rent	Pop	Rent
	(1)	(2)	(3)	(4)
Amenity	0.058^{***}	-0.027^{***}	0.058^{***}	-0.027^{***}
	(0.007)	(0.004)	(0.000)	(0.000)
Amenity*Top 210 Metro Areas, excluding Top 45	-0.025	0.006	-0.025^{***}	0.006^{***}
	(0.021)	(0.012)	(0.000)	(0.000)
Amenity*Top 45 Metro Areas, excluding Top 10	-0.074^{***}	0.091^{***}	-0.074^{***}	0.091^{***}
	(0.024)	(0.016)	(0.000)	(0.000)
Amenity*Top 10 Metro Areas	-0.132^{***}	0.120^{***}	-0.132^{***}	0.120^{***}
	(0.044)	(0.040)	(0.000)	(0.000)
Top 210 Metro Areas, excluding Top 45	0.126^{***}	-0.031^{***}	0.126^{***}	-0.031^{***}
	(0.019)	(0.010)	(0.000)	(0.000)
Top 45 Metro Areas, excluding Top 10	0.171^{***}	-0.032^{**}	0.171^{***}	-0.032^{***}
	(0.035)	(0.014)	(0.000)	(0.000)
Top 10 Metro Areas	0.123^{**}	-0.063^{***}	0.123^{***}	-0.063^{***}
	(0.052)	(0.023)	(0.000)	(0.000)
Constant	0.134^{***}	0.900^{***}	0.134^{***}	0.900^{***}
	(0.007)	(0.004)	(0.000)	(0.000)
Observations	3,102	3,102	3,102	3,102
R^2	0.074	0.096	0.074	0.096
Adjusted R^2	0.072	0.094	0.072	0.094
Note:	*p<0.1; **p<0.05; ***p<0.01			
	Standard errors clustered by metro code			

This table shows the results of a regression of the change in the natural log of population or rents on estimated amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Columns (1) and (2) cluster standard errors by metro, while Columns (3) and (4) cluster standard errors by size category. Non-metro counties are treated as singleton clusters. *p<0.1; **p<0.05; ***p<0.01

Table A6: Robustness of main result to Conley clustering standard errors

	Dependent variable: Change in log...	
	Population	Rent
	(1)	(2)
Variables		
Amenity	0.058***	-0.027***
	(0.0096)	(0.0065)
Amenity*Top 210 Metro Areas, excluding Top 45	-0.025	0.006
	(0.0217)	(0.0136)
Amenity*Top 45 Metro Areas, excluding Top 10	-0.074**	0.091***
	(0.0331)	(0.0251)
Amenity*Top 10 Metro Areas	-0.133**	0.120**
	(0.0644)	(0.0559)
Top 210 Metro Areas, excluding Top 45	0.126***	-0.031**
	(0.0236)	(0.0146)
Top 45 Metro Areas, excluding Top 10	0.171***	-0.032
	(0.0493)	(0.0221)
Top 10 Metro Areas	0.123	-0.063*
	(0.0774)	(0.0330)
Constant	0.134***	0.900***
	(0.0127)	(0.0078)
Fit statistics		
Observations	3,102	3,102
R^2	0.074	0.096
Adjusted R^2	0.072	0.094

This table shows the results of a regression of the change in the natural log of population or rents on estimated amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The table presents Conley spatial standard errors, allowing arbitrary spatial correlation within 100 kilometers. *p<0.1; **p<0.05; ***p<0.01

Table A7: Robustness of main result to base period and amenity adjustment

	Dependent variable: Change in log...			
	Population		Rent	
	(1)	(2)	(3)	(4)
Amenity	0.079^{***}	0.061^{***}	-0.080^{***}	-0.013^{***}
	(0.022)	(0.010)	(0.010)	(0.005)
Amenity∗Top 210 Metro Areas, excluding Top 45	0.013	0.002	0.044^{***}	0.017^{**}
	(0.033)	(0.014)	(0.016)	(0.008)
Amenity∗Top 45 Metro Areas, excluding Top 10	-0.062^{*}	-0.095^{***}	0.081^{***}	0.052^{***}
	(0.034)	(0.014)	(0.016)	(0.007)
Amenity∗Top 10 Metro Areas	-0.111^{***}	-0.107^{***}	0.298^{***}	0.064^{***}
	(0.033)	(0.012)	(0.016)	(0.007)
Top 210 Metro Areas, excluding Top 45	0.145^{***}	0.131^{***}	0.028^{**}	-0.042^{***}
	(0.027)	(0.013)	(0.013)	(0.007)
Top 45 Metro Areas, excluding Top 10	0.198^{***}	0.181^{***}	0.091^{***}	-0.004
	(0.028)	(0.013)	(0.013)	(0.007)
Top 10 Metro Areas	0.104^{***}	0.106^{***}	-0.005	-0.028^{***}
	(0.033)	(0.013)	(0.016)	(0.007)
Constant	0.179^{***}	0.125^{***}	1.445^{***}	0.900^{***}
	(0.019)	(0.009)	(0.009)	(0.005)
Observations	1,771	3,102	1,771	3,102
R^2	0.057	0.089	0.320	0.077
Adjusted R^2	0.054	0.087	0.317	0.075

This table shows the results of a regression of the change in the natural log of population or rents on estimated amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Columns (1) and (3) show population and rent growth starting in 1980, using adjusted amenities. Columns (2) and (4) show population and rent growth starting in 1990, using *unadjusted* amenities. *p<0.1; **p<0.05; ***p<0.01

Table A8: Robustness of main result to amenity measurement

	Dependent variable: Change in log...			
	Population		Rent	
	(1)	(2)	(3)	(4)
Amenity	0.039^{***}	0.057^{***}	0.007^{***}	-0.019^{***}
	(0.004)	(0.012)	(0.002)	(0.006)
Amenity∗Top 210 Metro Areas, excluding Top 45	-0.008	-0.037^{**}	0.006^{**}	-0.008
	(0.005)	(0.018)	(0.002)	(0.009)
Amenity∗Top 45 Metro Areas, excluding Top 10	-0.018^{***}	-0.061^{***}	0.015^{***}	0.092^{***}
	(0.004)	(0.016)	(0.002)	(0.008)
Amenity∗Top 10 Metro Areas	-0.038^{***}	-0.216^{***}	-0.007^{***}	0.136^{***}
	(0.004)	(0.025)	(0.002)	(0.013)
Top 210 Metro Areas, excluding Top 45	0.101^{***}	0.126^{***}	-0.051^{***}	-0.026^{***}
	(0.013)	(0.014)	(0.007)	(0.007)
Top 45 Metro Areas, excluding Top 10	0.116^{***}	0.158^{***}	-0.031^{***}	-0.038^{***}
	(0.013)	(0.014)	(0.007)	(0.007)
Top 10 Metro Areas	0.070^{***}	0.166^{***}	-0.001	-0.074^{***}
	(0.013)	(0.018)	(0.007)	(0.009)
Constant	0.139^{***}	0.140^{***}	0.896^{***}	0.897^{***}
	(0.009)	(0.009)	(0.005)	(0.005)
Observations	3,102	3,100	3,102	3,100
R^2	0.138	0.077	0.121	0.117
Adjusted R^2	0.136	0.075	0.119	0.115

This table shows the results of a regression of the change in the natural log of population or rents from 1990 to 2019 on amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Columns (1) and (3) show population and rent growth using the USDA Economic Research Service natural amenities scale, measured in standard deviations from the mean. Columns (2) and (4) show population and rent growth using predicted amenities. Amenities are predicted by regressing estimated amenities on the observable characteristics in Table 1, separately for each size category. *p<0.1; **p<0.05; ***p<0.01

Table A9: Robustness of main result to nearby housing demand

	Dependent variable:					
	Pop			Rent		
	(1)	(2)	(3)	(4)	(5)	(6)
Amenity	0.045^{***}	0.068^{***}	0.0002	-0.046^{***}	-0.033^{***}	-0.056^{***}
	(0.010)	(0.010)	(0.026)	(0.005)	(0.005)	(0.015)
Amenity∗Top 210 Metro Areas, excluding Top 45	−0.019	-0.035^{**}		0.001	0.012	
	(0.015)	(0.016)		(0.008)	(0.008)	
Amenity∗Top 45 Metro Areas, excluding Top 10	−0.020	-0.084^{***}		0.084^{***}	0.096^{***}	
	(0.014)	(0.015)		(0.007)	(0.008)	
Amenity∗Top 10 Metro Areas	-0.117^{***}	-0.143^{***}		0.064^{***}	0.125^{***}	
	(0.020)	(0.019)		(0.010)	(0.010)	
Top 210 Metro Areas, excluding Top 45	0.138^{***}	−0.048		−0.007	0.066^{***}	
	(0.013)	(0.045)		(0.007)	(0.023)	
Top 45 Metro Areas, excluding Top 10	0.170^{***}	−0.003		0.007	0.065^{***}	
	(0.013)	(0.045)		(0.007)	(0.023)	
Top 10 Metro Areas	0.125^{***}	−0.051		-0.022^{***}	0.033	
	(0.015)	(0.046)		(0.008)	(0.024)	
Log Dist to Major Metro		-0.043^{***}	-0.049^{***}		0.024^{***}	0.022^{***}
		(0.011)	(0.006)		(0.005)	(0.003)
Amenity∗Log Dist			0.016^{***}			0.006
			(0.006)			(0.004)
Constant	0.132^{***}	0.308^{***}	0.328^{***}	0.925^{***}	0.803^{***}	0.810^{***}
	(0.009)	(0.043)	(0.024)	(0.005)	(0.023)	(0.014)
Observations	2,190	3,102	2,219	2,190	3,102	2,219
R^2	0.112	0.079	0.086	0.104	0.101	0.063
Adjusted R^2	0.109	0.076	0.085	0.101	0.099	0.062
Note:	*p<0.1; **p<0.05; ***p<0.01					

This table shows the results of a regression of the change in the natural log of population or rents from 1990 to 2019 on amenities. Amenities are adjusted for observable characteristics of the population and housing stock. The omitted category is counties outside the top 210 metro areas by population. Columns (1) and (4) show population and rent growth after collapsing each multi-county metro to an individual observation. Columns (2) and (5) show population and rent growth, and include a control for the log distance to the nearest metro with a population of at least 150,000 in 1990. Columns (3) and (6) show population and rent growth only for counties in the smallest size category, and interact amenities with distance to a major metro. *p<0.1; **p<0.05; ***p<0.01

Table A10: Robustness of population results

	Dependent variable: Change in log population			
	Density	Commute	0.35	Value
	(1)	(2)	(3)	(4)
Amenity	0.046^{***}	0.058^{***}	0.020^{**}	0.075^{***}
	(0.009)	(0.010)	(0.010)	(0.010)
Amenity∗Top 210 Metro Areas, excluding Top 45	−0.001	−0.025	−0.006	-0.062^{***}
	(0.015)	(0.016)	(0.017)	(0.014)
Amenity∗Top 45 Metro Areas, excluding Top 10	−0.023	-0.074^{***}	-0.071^{***}	-0.084^{***}
	(0.014)	(0.015)	(0.017)	(0.012)
Amenity∗Top 10 Metro Areas	-0.040^{**}	-0.132^{***}	-0.041^{**}	-0.109^{***}
	(0.019)	(0.019)	(0.021)	(0.012)
Top 210 Metro Areas, excluding Top 45	0.245^{***}	0.126^{***}	0.135^{***}	0.134^{***}
	(0.014)	(0.014)	(0.013)	(0.013)
Top 45 Metro Areas, excluding Top 10	0.347^{***}	0.171^{***}	0.150^{***}	0.166^{***}
	(0.016)	(0.015)	(0.013)	(0.013)
Top 10 Metro Areas	0.369^{***}	0.123^{***}	0.059^{***}	0.108^{***}
	(0.020)	(0.016)	(0.016)	(0.014)
Log Pop Density	-0.078^{***}			
	(0.004)			
Constant	0.369^{***}	0.134^{***}	0.140^{***}	0.135^{***}
	(0.014)	(0.009)	(0.009)	(0.009)
Observations	3,102	3,102	3,102	3,102
R^2	0.181	0.074	0.061	0.080
Adjusted R^2	0.179	0.072	0.058	0.078

This table shows results that demonstrate the robustness of the baseline estimates on population change. Each column shows the results of a regression of the change in the natural log of population on estimated amenities interacted with size categories. The first column shows the results using the natural log of population density as a control. The second column shows the results using commute-adjusted wages. The third column shows the results using a lower value, 0.35, of the local consumption parameter. The fourth column shows the results using median housing value in place of median rents. All columns show the results using adjusted wages and rents (values in the case of column four) for 1990. The time period for the change in the natural log of population is 1990 to 2019. *p<0.1; **p<0.05; ***p<0.01

Table A11: Robustness of rent results

	Dependent variable: Change in log rent			
	Density	Commute	0.35	Value
	(1)	(2)	(3)	(4)
Amenity	-0.030^{***}	-0.027^{***}	-0.007	0.039^{***}
	(0.005)	(0.005)	(0.005)	(0.008)
Amenity∗Top 210 Metro Areas, excluding Top 45	0.010	0.006	0.029^{***}	-0.055^{***}
	(0.008)	(0.008)	(0.009)	(0.012)
Amenity∗Top 45 Metro Areas, excluding Top 10	0.100^{***}	0.091^{***}	0.069^{***}	0.019^{*}
	(0.008)	(0.008)	(0.009)	(0.010)
Amenity∗Top 10 Metro Areas	0.137^{***}	0.120^{***}	0.145^{***}	-0.028^{***}
	(0.010)	(0.010)	(0.011)	(0.010)
Top 210 Metro Areas, excluding Top 45	-0.009	-0.031^{***}	-0.036^{***}	-0.048^{***}
	(0.008)	(0.007)	(0.007)	(0.011)
Top 45 Metro Areas, excluding Top 10	0.0003	-0.032^{***}	0.017^{***}	-0.008
	(0.009)	(0.008)	(0.007)	(0.011)
Top 10 Metro Areas	-0.018^{*}	-0.063^{***}	0.073^{***}	-0.066^{***}
	(0.011)	(0.008)	(0.008)	(0.012)
Log Pop Density	-0.014^{***}			
	(0.002)			
Constant	0.943^{***}	0.900^{***}	0.897^{***}	0.988^{***}
	(0.008)	(0.005)	(0.005)	(0.008)
Observations	3,102	3,102	3,102	3,102
R^2	0.109	0.096	0.111	0.066
Adjusted R^2	0.107	0.094	0.109	0.064

This table shows results that demonstrate the robustness of the baseline estimates on rent change. Each column shows the results of a regression of the change in the natural log of rents on estimated amenities interacted with size categories. The first column shows the results using the natural log of population density as a control. The second column shows the results using commute-adjusted wages. The third column shows the results using a lower value, 0.35, of the local consumption parameter. The fourth column shows the results using median housing value in place of median rents. All columns show the results using adjusted wages and rents (values in the case of column four) for 1990. The time period for the change in the natural log of rents is 1990 to 2019. *p<0.1; **p<0.05; ***p<0.01 *p<0.1; **p<0.05; ***p<0.01

Table A12: Population results by decade

	Dependent variable: Change in log population from...			
	1980-1990	1990-2000	2000-2010	2010-2019
	(1)	(2)	(3)	(4)
Amenity	0.056^{***}	0.028^{***}	0.024^{***}	0.004^{***}
	(0.005)	(0.004)	(0.004)	(0.0005)
Amenity∗Top 210 Metro Areas, excluding Top 45	0.016^{**}	-0.001	-0.006	0.0001
	(0.007)	(0.007)	(0.006)	(0.001)
Amenity∗Top 45 Metro Areas, excluding Top 10	-0.019^{***}	-0.056^{***}	-0.054^{***}	-0.001^{*}
	(0.007)	(0.006)	(0.005)	(0.001)
Amenity∗Top 10 Metro Areas	-0.052^{***}	-0.050^{***}	-0.047^{***}	-0.004^{***}
	(0.006)	(0.006)	(0.005)	(0.001)
Top 210 Metro Areas, excluding Top 45	0.070^{***}	0.039^{***}	0.049^{***}	0.047^{*}
	(0.007)	(0.006)	(0.005)	(0.027)
Top 45 Metro Areas, excluding Top 10	0.101^{***}	0.063^{***}	0.062^{***}	0.119^{***}
	(0.007)	(0.006)	(0.005)	(0.026)
Top 10 Metro Areas	0.072^{***}	0.036^{***}	0.028^{***}	0.234^{***}
	(0.007)	(0.006)	(0.005)	(0.025)
Constant	0.012^{**}	0.083^{***}	0.039^{***}	-0.155^{***}
	(0.005)	(0.004)	(0.004)	(0.019)
Observations	3,100	3,100	3,100	3,100
R^2	0.170	0.068	0.107	0.179
Adjusted R^2	0.168	0.066	0.105	0.177
Note:				*p<0.1; **p<0.05; ***p<0.01

This table shows the results of a regression of the change in the natural log of population on estimated amenities interacted with size categories. The four columns show the results of the change in the natural log of population for 1980-1990, 1990-2000, 2000-2010, and 2010-2019, respectively. The regression uses unadjusted rents and wages. *p<0.1; **p<0.05; ***p<0.01

Table A13: Rent results by decade

	Dependent variable: Change in log rent in...			
	1980-1990	1990-2000	2000-2010	2010-2019
	(1)	(2)	(3)	(4)
Amenity	−0.008	−0.034***	0.012***	−0.0003
	(0.006)	(0.004)	(0.004)	(0.001)
Amenity∗Top 210 Metro Areas, excluding Top 45	−0.0002	0.006	0.012**	−0.0001
	(0.009)	(0.006)	(0.005)	(0.001)
Amenity∗Top 45 Metro Areas, excluding Top 10	0.013	0.002	0.033***	0.002**
	(0.008)	(0.006)	(0.005)	(0.001)
Amenity∗Top 10 Metro Areas	0.037***	0.021***	0.016***	0.004***
	(0.008)	(0.005)	(0.004)	(0.001)
Top 210 Metro Areas, excluding Top 45	0.078***	−0.047***	0.003	0.007
	(0.008)	(0.005)	(0.005)	(0.032)
Top 45 Metro Areas, excluding Top 10	0.122***	−0.046***	0.007	−0.028
	(0.008)	(0.005)	(0.005)	(0.031)
Top 10 Metro Areas	0.160***	−0.108***	0.051***	−0.130***
	(0.008)	(0.005)	(0.005)	(0.030)
Constant	0.536***	0.390***	0.282***	0.240***
	(0.006)	(0.004)	(0.004)	(0.023)
Observations	3,100	3,100	3,100	3,100
R^2	0.171	0.176	0.165	0.081
Adjusted R^2	0.169	0.174	0.163	0.079

This table shows the results of a regression of the change in the natural log of rents on estimated amenities interacted with size categories. The four columns show the results of the change in the natural log of rent for 1980-1990, 1990-2000, 2000-2010, and 2010-2019, respectively. The regression uses unadjusted rents and wages. *p<0.1; **p<0.05; ***p<0.01

Table A14: Robustness of retiree sorting

	Dependent variable: Change in share over 65			
	No Florida	Init. Density	Jul. Temp.	USDA Nat. Amen.
	(1)	(2)	(3)	(4)
Factor	0.007^{***}	-0.00003^{*}	-0.002^{***}	0.003^{***}
	(0.001)	(0.00001)	(0.0001)	(0.0004)
Factor∗Top 210 Metro Areas, excluding Top 45	-0.005^{***}	-0.00001	0.001^{***}	-0.003^{***}
	(0.001)	(0.00002)	(0.0002)	(0.0005)
Factor∗Top 45 Metro Areas, excluding Top 10	-0.010^{***}	0.00002	0.001^{***}	-0.004^{***}
	(0.001)	(0.00001)	(0.0002)	(0.0005)
Factor∗Top 10 Metro Areas	-0.009^{***}	0.00003^{*}	0.001^{***}	-0.003^{***}
	(0.002)	(0.00001)	(0.0002)	(0.0004)
Top 210 Metro Areas, excluding Top 45	-0.003^{**}	0.002	-0.097^{***}	-0.003^{**}
	(0.001)	(0.002)	(0.016)	(0.001)
Top 45 Metro Areas, excluding Top 10	-0.006^{***}	-0.007^{***}	-0.118^{***}	-0.010^{***}
	(0.001)	(0.001)	(0.014)	(0.001)
Top 10 Metro Areas	-0.007^{***}	-0.010^{***}	-0.086^{***}	-0.012^{***}
	(0.002)	(0.001)	(0.018)	(0.001)
Constant	0.039^{***}	0.041^{***}	0.174^{***}	0.040^{***}
	(0.001)	(0.001)	(0.010)	(0.001)
Observations	3,033	3,100	3,100	3,100
R^2	0.051	0.092	0.099	0.066
Adjusted R^2	0.049	0.090	0.097	0.063

This table shows the results of a regression of the change in the share of the population that is over 65 from 1990 to 2019 on a variety of factors. Column (1) uses the estimated adjusted amenities as in Table 2, but excludes Florida from the sample. Column (2) uses initial population density. Column (3) uses maximum July temperature in degrees Fahrenheit. Column (4) uses the USDA Economic Research Service natural amenities scale, measured in standard deviations from the mean. *p<0.1; **p<0.05; ***p<0.01

Table A15: Population growth decomposition across county types

	Remaining		**Top 210**		**Top 45**		**Top 10**	
Amenity	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**
Natural Increase	1,427	1,318	3,202	3,312	3,957	3,899	4,691	4,587
International Migration	824	576	1,662	1,237	2,979	1,487	4,794	2,805
Domestic Migration	1,103	-874	1,932	1,931	1,025	3,138	-5,718	-1,535
Residual	-99	-145	-81	-2	156	-59	481	295
Net Population Change	**3,255**	**875**	**6,715**	**6,478**	**8,117**	**8,466**	**4,249**	**6,152**

This table shows a decomposition of population changes for U.S. counties between 2000 and 2019 by size and amenity categories. All numbers are in thousands of people. Amenity categories use 1990 amenity estimates adjusted for housing and worker characteristics. Each size group is split into high- and low-amenity counties, such that population is as even as possible between groups. Size groups are exclusive: for example, "Top 210" is the largest 210 metros excluding the largest 45.