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Can more housing supply solve the affordability crisis? Evidence from a neighborhood choice model[☆]

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ABSTRACT

We estimate a neighborhood choice model using 2014 American Community Survey data to investigate the degree to which new housing supply can improve housing affordability. In the model, equilibrium rental rates are determined so that the number of households choosing each neighborhood is equal to the number of housing units in each neighborhood. We use the estimated model to simulate how rental rates would respond to an exogenous increase in the number of housing units in a neighborhood. We find that the rent elasticity is low, and thus marginal reductions in supply constraints alone are unlikely to meaningfully reduce rent burdens. The reason for this result appears to be that rental rates are more closely determined by the level of amenities in a neighborhood—as in a Rosen-Roback spatial equilibrium framework—than by the supply of housing.

1. Introduction

Housing rents have appreciated significantly in recent years. Rising rents and stagnant incomes across much of the income distribution have contributed to what has been called an “affordability crisis”, where the share of households spending greater than 30 percent of their income on housing is near an all-time high.[1] The increasing expenditure share on housing does not appear to be driven by households consuming housing units of higher physical quality, or by rising construction costs. Rather, quality-adjusted prices are increasing even as the cost of producing a home has stayed more or less the same. These facts have prompted many to suggest that constraints on the supply of housing, such as land use regulations or labor shortages, are at the heart of the affordability crisis. Relaxing such constraints is widely proposed as a solution to the affordability crisis.[2]

However, the effect of relaxing supply constraints on affordability will, of course, depend on the elasticity of rent with respect to new housing supply. If the rent elasticity is low, for potential reasons that we will discuss later, then relaxing supply constraints may spur construction but still do little to improve affordability. Ideally, we could estimate the rent elasticity directly from data. But identification is a challenge because there are few sources of exogenous variation in the housing supply. Indeed, we are not aware of any direct estimates of the rent elasticity with respect to new housing supply in the literature.

In this paper, we present simulation-based evidence that the elasticity of rent with respect to small changes in housing supply within metropolitan areas (henceforth, “cities”) is low. The implication of this finding is that even if a city were able to ease some supply constraints to achieve a marginal increase in its housing stock, the city will not experience a meaningful reduction in rental burdens.[3] Following Bayer et al. (2007), we first estimate an equilibrium model of neighborhood choice,

☆ The analysis and conclusions set forth are those of the authors and do not indicate concurrence by other members of the research staff or the Board of Governors of the Federal Reserve System.

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[1] Housing expenditures for owners have also been increasing in recent years, but the fraction of cost burdened households is much higher among renters than owners.

[2] Examples of proposed solutions for relaxing constraints include more accommodative monetary policy, construction worker retraining, and the transfer of local housing regulation authority to state or federal levels where the externalities associated with restrictive housing supply could be internalized more effectively.

[3] As an example of such city action, the Los Angeles mayor recently outlined a plan to improve affordability by increasing the housing stock in LA by 100,000 units by 2021 through subsidies and cutting of red tape that drive up costs for builders. Source: http://www.latimes.com/business/realestate/la-fi-garcetti-build-100k-new-units-20141029-story.html.

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in which equilibrium rents are determined so that the number of households choosing each neighborhood in a city is equal to the number of housing units in that neighborhood.[4] We estimate the model using data on household neighborhood choice from the 2014 American Community Survey (ACS) for 10 major cities. We define neighborhoods within cities as public use microdata areas (PUMAs), which are contiguous geographic areas of at least 100,000 people.[5] Using the estimated model, we then simulate the effect on rents of exogenously adding housing stock to the most expensive neighborhoods in each city. We find that increasing the housing stock in the most expensive neighborhoods by 5% would only reduce equilibrium rents in those neighborhoods by less than 0.5%. The implied rent elasticity is therefore quite low.

An important reason for the low rent elasticity in the model is that we estimate a relatively low amount of preference heterogeneity across households. In other words, there tends to be more agreement than disagreement across households on which neighborhoods in the city have the most attractive amenities. This finding implies that the willingness to pay to live in a particular neighborhood for a household that is on the margin between living in that neighborhood and elsewhere will be similar before and after a change in housing supply. As prices are set by the willingness to pay of the marginal household in our model, the price elasticity with respect to new supply is small. In our estimated model, rental rates are more closely determined by the level of amenities in a neighborhood—as in a Rosen-Roback (Rosen et al. (1979); Roback (1982)) spatial equilibrium framework—than by the supply of housing.

We close the paper by considering an alternative approach for reducing rents, which is to improve amenities in substitute neighborhoods. For example, improving access to and the quality of public transportation in neighborhoods far from the city core could make these neighborhoods more competitive with more expensive, downtown neighborhoods and so could relieve some price pressure in downtown neighborhoods through a substitution effect. To explore this idea, we conduct a counterfactual simulation in which we assume that the resources used to construct a given number of new homes in high-priced neighborhoods are instead used to increase the amenity quality in low-priced neighborhoods. We find that, even when using conservative estimates of the construction cost of building more units, improving amenities in low-priced neighborhoods has a larger effect on rents in high-priced neighborhoods than directly adding new housing supply in those neighborhoods.

One potentially important assumption behind our analysis throughout this paper is that our model treats each city as a closed economy. Although households can choose from among many different types of neighborhoods within the city, they cannot choose to live outside the city, and households from outside the city cannot choose to move to the city. Therefore, in our counterfactuals where we expand the housing supply, we must assume that the new entrants to the city arrive exogenously, and we must make an assumption about the distribution of preferences among the new entrants. Our counterfactuals are concerned with small changes to the housing stock, so it turns out that our results are not too sensitive to this assumption. However, for larger changes to the housing stock of the city, the number and particular preference distribution of new entrants may become important for the main results. Moreover, our model ignores any potential congestive or agglomerative effects associated with increasing housing supply in a city, which may be appropriate for small changes but is less realistic for large changes. Thus, we caution against extrapolating our model's elasticities to very large changes to the housing stock.

We are not aware of any studies that directly estimate the rent elasticity with respect to new housing supply. However, a number of papers estimate the effect of regulation on the price and quantity of housing.[6] Gyourko and Molloy (2014) review this literature and conclude that regulation tends to have sizable positive effects on prices and negative effects on construction, though there are a range of estimates in the literature and many of the estimates should be interpreted with caution because variation in regulation is deeply endogenous.[7] Interestingly, Glaeser and Ward (2009), who study the effects of local regulation on relative house prices between towns within the Boston metro area, find small effects of regulation on price, consistent with our findings. They attribute the small effects to the high substitutability of towns within Boston, which is consistent with the mechanism highlighted in our model of low preference heterogeneity resulting in a low elasticity of rent with respect to new supply. The papers that find large effects of regulation on house prices are not necessarily at odds with our findings in this paper, because regulations can have very large effects on the housing stock. For example, Jackson (2016) finds that an additional regulation reduces residential permits by 4–8 percent per year. Glaeser and Ward (2009) estimate even larger effects on supply. These effects on construction can accumulate into very large changes to the housing stock, especially when these regulations are in place for many years, as is often the case. Thus, regulation may be associated with changes to the size of the housing stock that are outside the scope of our model for the reasons mentioned above. Like our paper, most of the papers in the literature focus on prices and do not consider welfare implications of changing the housing supply. For discussions of welfare, see Hsieh and Moretti (2017), Turner et al. (2014), Herkenhoff et al. (2017), Engle et al. (1992), and Helsley and Strange (1995).

The intuition for our results is closely related to the theoretical model of Helsley and Strange (1995). Helsley and Strange (1995) consider the effect of growth controls (i.e. supply constraints) in a system of neighborhoods with homogeneous households. In the equilibrium of their model, price differences across neighborhoods reflect the amenity value of growth controls (i.e. through reduced congestion) rather than differences in the elasticity of housing supply created by the growth controls. So absent any direct effects of growth controls on neighborhood amenities, relative rents between neighborhoods are unaffected by growth controls. The total effect on rents depends on the housing supply elasticity in neighborhoods without growth controls. If housing supply is elastic in such neighborhoods, then the total effect on rents will also be small. This is comparable to the case emphasized in Engle et al. (1992), whose basic model is similar to Helsley and Strange (1995) but explicitly has rent in the neighborhood without growth control as being insensitive to population. Our model also bears many similarities to the model in Aura and Davidoff (2008), who show that in a model of housing demand with heterogeneous households, the effect of increasing land supply in a particular area on house prices in that area can be very small.

2. Motivating facts

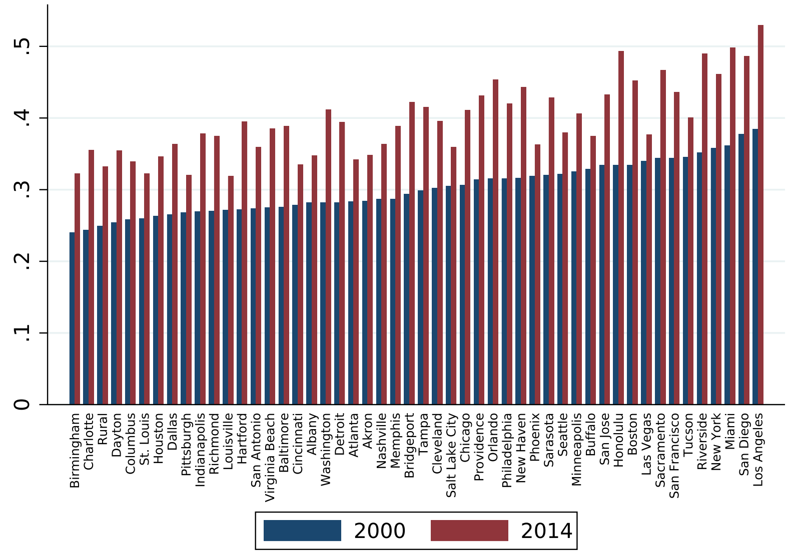
We begin with some basic facts on the geographic distribution of rental housing affordability that we compute using 2000 Census and

[4] The model and estimation strategy are based on McFadden (1978) and Berry et al. (1995), respectively. Bayer et al. (2004, 2007) were the first to introduce this empirical approach into urban economics, and the approach has become a foundation for structural estimation of neighborhood choice models in urban economics (Holmes et al. (2015)).

[5] PUMAs are constructed by the Census Bureau based on census tracts and counties. It is the smallest geographic unit used by the Census for disseminating individual level data from survey respondents.

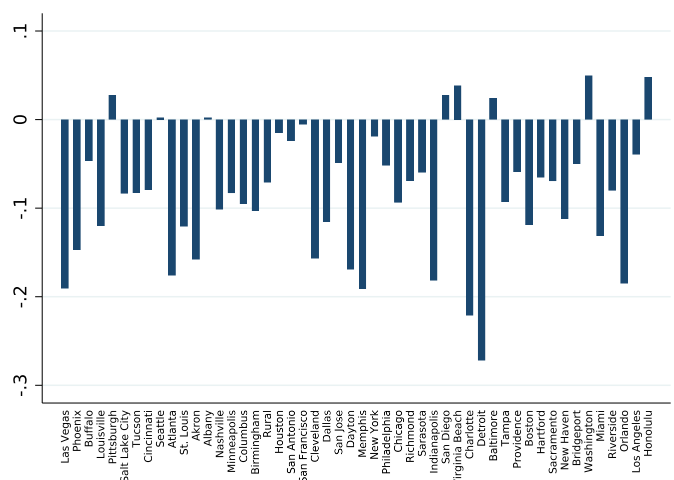
[6] We focus on the price elasticity with respect to new housing supply because regulations are difficult to measure and vary quite a bit across location and time periods, making it difficult to extrapolate the elasticities to actual policies under consideration. Furthermore, supply constraints can be relaxed to increase housing supply through policies other than land use regulation.

[7] Some examples in this literature include Katz and Rosen (1987); Pollakowski and Wachter (1990); Quigley and Raphael (2005); Malpezzi (1996); Mayer and Somerville (2000); Segal and Srinivasan (1985); Black and Hoben (1985).



Shows share of households in each CBSA that spend at least 30 percent of their income on rent. Plot is for fifty most populous CBSAs as of 2000. Source: Census data.

Fig. 1. Share of households cost burdened, 2000–2014.



Plot is for fifty most populous CBSAs as of 2000 sorted by the largest change in the cost burdened share between 2000-2014. Source: Census data.

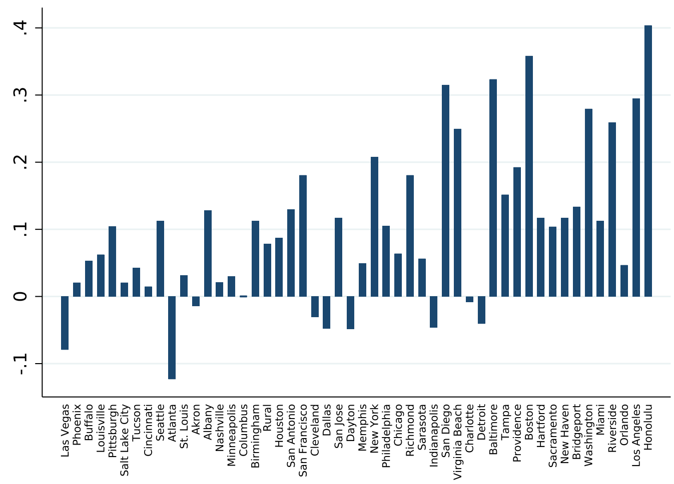
Fig. 2. Change in log median real household income, 2000–2014.

2014 American Community Survey download from IPUMS-USA (Ruggles et al. (1997)), and other sources. In 2014, 38.7 percent of U.S. households that rent spent more than 30 percent of their household income on rent, up from 29.2 percent of renters in 2000. Housing expenditures for owners have also been increasing in recent years, but the fraction of cost burdened households is much higher among renters than owners (see also Molloy (2017)). The renter share of US households has been increasing in recent years and stands near a 50-year high of around 37 percent (Fernald (2017)).[8] Motivated by the higher cost burdened share among renters and the increase in rental demand in recent years, in this paper we focus on renter households. Fig. 1 shows that cost burdened renter households are not predominantly located in certain areas of the country. In most large metropolitan areas (more specifically, core-based statistical areas (CBSAs)), a significant share of households are cost burdened.

Figs. 2–3 show that both declining incomes and increasing rents have contributed to the rising share of renters that are cost burdened. The increases in rents likely reflect increases in demand combined with some inelasticity of the housing supply due to a variety of factors, some of which we will discuss below. The declines in real median income are due to a variety of factors that are largely outside the scope of the housing market, and so there is probably little that housing policy—including the specific counterfactuals that we consider in our model below—can do to improve affordability through the income channel. Nonetheless, we motivate our model with a discussion of affordability to show that high rents are in fact burdening the budgets of many households.

The magnitude of the cost burdened share differs somewhat across metro areas. For example, in high-priced cities like Los Angeles and San

[8] For example, Gete and Reher (2018) provides evidence that the contraction in mortgage supply after the great recession contributed to the increased rental demand in recent years.



Plot is for fifty most populous CBSAs as of 2000 sorted by the largest change in the cost burdened share between 2000-2014. Source: Census data.

Fig. 3. Change in log median real rent, 2000–2014.

Cost burdened share is computed from the Census data. Rents are adjusted for unit quality and are from from Zillow.

Fig. 4. Correlation between quality-adjusted rent/sqft and share cost burdened across census PUMAs in 2014.

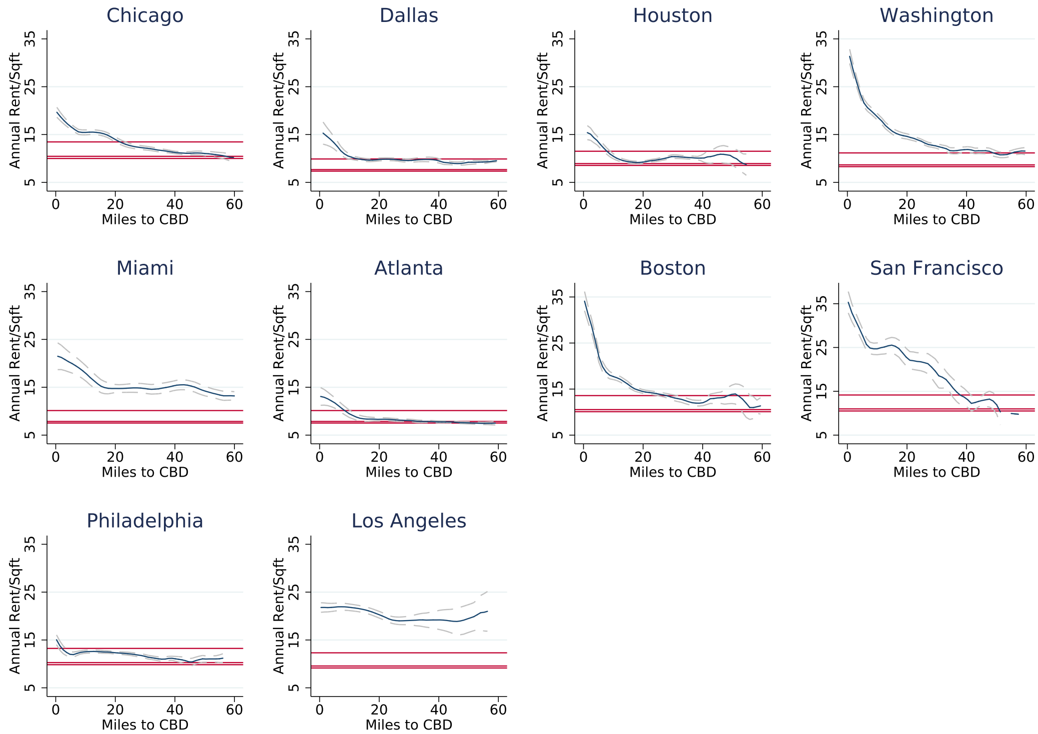
Diego, the cost burdened share is about 15 percentage points higher than in lower-priced cities such as Houston and Charlotte. The positive correlation between rent and cost burden share holds across PUMAs as well, and also when rents are adjusted for differences in housing unit quality across PUMAs. Since house and neighborhood characteristics are limited in the ACS data, we obtain quality adjusted rents from Zillow. The Zillow rent index estimates the median rent that would be offered for all properties within a geographic unit (regardless of which units are actually for rent at any given time). Zillow provides rent data at the zipcode level, which we then aggregate to PUMAs using a crosswalk provided by the Missouri Census Data Center. Fig. 4 shows that, across PUMAs, a one dollar increase in quality-adjusted monthly rent per square foot is a associated with a 9.5 percentage point increase in the cost burdened share.[9]

To further investigate differences in rents across neighborhoods, Fig. 5 plots average quality-adjusted rent per square foot by distance-to-CBD for the ten largest metro areas.[10] Rents are from Zillow and are measured at the zipcode level. In most metro areas, including the ones shown in the figure, rents are highest in zipcodes closest to the city center.[11] In neighborhoods further from the CBD, Fig. 5 shows that rents tend to flatten out around a rough estimate of annualized construction cost per sqft for each metro area, as estimated by the Company (2015). These construction cost estimates exclude land and regulatory costs. In areas of the city where rents are closer to construction costs, housing supply is likely to be more elastic due to more available land and fewer or less binding regulations in such areas

[9] See https://www.zillow.com/research/zillow-rent-index-methodology-2393/for more information on Zillow's methodology.

[10] We exclude New York because of missing rent data for some PUMAs. CBDs are defined as in Holian and Kahn (2015).

[11] The coefficient on distance-to-CBD in a regression of rent/sqft on distance-to-CBD with metro area fixed effects for the 100 largest metro areas is −0.23 and is statistically significant. A similar result holds for house prices.



Rents are measured at the zipcode level. Rents are adjusted for unit quality and are from Zillow. The three horizontal red lines denote an estimate of construction cost per sqft for a 1-3 story (lowest cost), 4-7 story, and 8-20 story (highest cost) apartment building of average quality. The construction cost data come from the RS Means Company and are annualized by multiplying the cost by 0.05. The rent gradient for each CBSA is smoothed using a kernel-weighted local polynomial regression. The 95-percent confidence interval is shown by the dotted grey lines.

Fig. 5. Average rent/sqft by distance to central business district in 2014.

(see Glaeser and Gyourko (2017)). Indeed, using the Census data, Fig. 6 shows that in areas of the country that experienced household growth between 2000 and 2014, rent growth has been highest in areas close to the CBD, and household growth has been highest in areas furthest from the CBD, consistent with such areas having a more elastic housing supply than in areas closer to the CBD.[12] These results suggest that the rent elasticity with respect to new construction may vary significantly within cities, and motivates using a model that potentially allows for such within-city variation in the rent elasticity.

3. Model

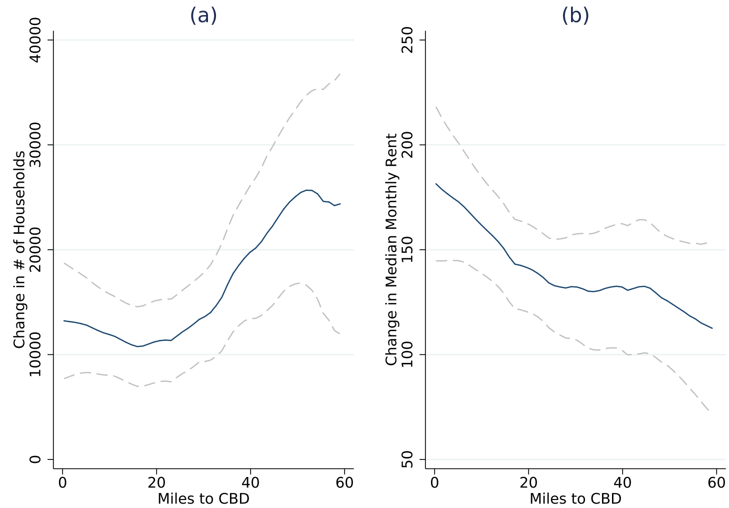
We now present a model of equilibrium rent prices in a closed system of neighborhoods, i.e. a closed city. The model is based on the discrete choice framework of Bayer et al. (2004) and Bayer et al. (2007), in which heterogeneous households choose over a discrete set of housing choices, the supply of which is taken as given. In equilibrium, rental rates are set so that the number of households choosing each type of housing is equal to the supply of that type of housing. The vacancy rate is thus assumed to be zero.

Consider a city with $j = 1, \ldots, J$ locations (neighborhoods), each with observed characteristics $\mathbf{x}_j$ and rental price p_j. Neighborhood j has H_j units of housing, which for simplicity we will assume are identical in physical quality. The city is populated by $i = 1, \ldots, N$ households, with observed characteristics $\mathbf{z}_i$. The utility that household i receives from living in neighborhood j is:

$$V_{ij} = \mathbf{x}_j'\alpha + \mathbf{z}_i'\Theta\mathbf{x}_j + \beta p_j + \mathbf{z}_i'\gamma p_j + \xi_j + \epsilon_{ij} \\ \equiv v_{ij} + \epsilon_{ij} \tag{1}$$

where α, Θ, β, γ are $K_x \times 1$, $K_z \times K_x$, 1×1, and $K_z \times 1$ vectors of parameters, where K_x is the number of observed neighborhood attributes and K_z is the number of observed household attributes. α defines the mean utility that households have over observed neighborhood attributes, and Θ defines how that utility varies by household attribute. β defines the mean utility that households have over rental rate, which should be negative, and γ defines how that utility varies by household attribute. ξ_j is a scalar that captures any unobserved vertical quality differences between neighborhoods, i.e. differences in the mean utility across neighborhoods, and ϵ_{ij} is a scalar that captures any unobserved heterogeneity in tastes for different neighborhoods across households. Following Bayer et al. (2007) and much of the discrete choice literature, we assume that ϵ_{ij} is iid across households and neighborhoods, and that it is distributed according to a type-1 extreme value distribution. No assumptions are made about the distribution of ξ_j.

[12] Couture and Handbury (2016) show a similar result for house price growth using Zillow house price data and household growth using ACS data at the census tract level. See also Bogin et al. (2016) for evidence that house price growth gradient with respect to distance from CBD has been strongly negative in recent years.



The graph summarizes household and rent growth in every 2000-2010 consistent Census PUMA in the US with at least at a 10,000 increase in number of households between 2000 and 2014. Consistent Census PUMAs are larger than PUMAs and are used to compare consistent geographic areas over time in the Census. All data shown uses Census data. Rents are not adjusted for unit quality. The gradient with respect to distance to CBD is smoothed using a kernel-weighted local polynomial regression. The 95-percent confidence interval is shown by the dotted grey lines.

Fig. 6. Change in number of households and median monthly rent, 2000–2014.

Given these assumptions, the probability that a household i chooses neighborhood j is:

$$P_{ij} = \frac{\exp v_{ij}}{\sum_{k=1}^{J} \exp v_{ik}} \tag{2}$$

and the total number of households choosing neighborhood j is simply $\sum_{i=1}^{N} P_{ij}$.[13] In equilibrium, housing markets clear and so the number of households choosing neighborhood j must be equal to the number of housing units in neighborhood j. The equilibrium condition is therefore:

$$\sum_{i=1}^{N} P_{ij} = H_j \tag{3}$$

Bayer et al. (2004) prove that if V_{ij} is a decreasing, linear function of p_j for all households, and if the distribution of ϵ_{ij} is continuous, then there exists a unique vector of rent prices p_j that clears the market (up to an additive constant).[14]

4. Estimation

4.1. Estimation data

In order to estimate the model, we use public-use microdata from the 2014 American Community Survey. We use data from the 10 large metropolitan areas described in Section 2. We define neighborhoods as PUMAs, which is the finest level of geographic disaggregation that is available for public use in the ACS. For our sample of high population cities, we found that PUMAs capture fairly well the different neighborhoods within the city. Appendix Fig. 1 shows a map of PUMAs for each city in our sample. For PUMA characteristics $\mathbf{x}_j$, we choose to include the percent white, percent with bachelor's degree or higher, percent population who do not drive to work,[15] the distance to central business district, the median household income, and the number of restaurants in the PUMA.[16] For household characteristics $\mathbf{z}_i$, we include the household's yearly income, an indicator for whether the household head is white, an indicator for whether the household head has a bachelor's degree or higher, an indicator for whether the household head is married, and an indicator for whether there are children in the household.

To estimate the rental rate in each PUMA, we use Zillow's zipcode-level Zillow Rent Index, which is an estimate of the median monthly rental rate offer for properties in that zipcode as described in Section 2.

4.2. Estimation methodology

Our estimation methodology follows Bayer et al. (2007). Consider for now data from only a single city. The ACS data allows us to see the neighborhood choices of individual households in that city, and thus allows us to form the log-likelihood of the data for estimation. For each household i observed in the data, let $d_{ij} = 1$ if that household lives in PUMA j, and 0 otherwise. Let w_i be the sampling weight associated

[13] We assume that N is large so that the number of households choosing neighborhood j approaches the expected number of households choosing neighborhood j.

[14] An equilibrium rent vector can only be found up to an additive constant because in a closed city where all households are required to choose one neighborhood, a level shift in the rents for all neighborhoods would not affect the share of households choosing each neighborhood. We discuss how we choose the normalization constant in counterfactual simulations in Section 5.

[15] Ideally, we would like to know a household's place of work and compute for each household the commuting time between place of work and place of residence. However, in the public-use microdata, the place of work measure is only available at very high geographic aggregation (place-of-work PUMA, which is much larger than a standard PUMA), and so is not very useful for accurately estimating commuting time. We found that the best proxy for the degree to which a neighborhood is close to a typical resident's workplace is the percentage of the working population in that neighborhood that does not drive to work. This would include walking, biking, and taking public transportation (mostly bus, subway, or light rail).

[16] We found that the number of restaurants is an important variable which probably captures the level of consumption amenities in the location.

Table 1
Estimation results.

	Pct. White	Pct. College	Pct. No Drive	Dist. to CBD	log Med. HH Inc.	# Restaurants	log Rent
Mean	0.435***	2.005***	0.2289	−0.6857***	0.8393***	0.2277**	−3.542***
	(0.1319)	(0.6051)	(0.1453)	(0.2226)	(0.3022)	(0.1013)	(1.048)
log HH Income	−0.03276***	−0.04454***	0.01663***	−0.001831***	0.1663***	−0.0051***	0.02733***
	(0.0002836)	(0.0004919)	(0.0002833)	(0.0002607)	(0.0004207)	(0.0002254)	(0.0003653)
White	0.4364***	−0.03558***	−0.006715***	0.01703***	−0.018***	−0.007669***	0.01945***
	(0.0002562)	(0.0004938)	(0.0002824)	(0.000278)	(0.0004288)	(0.0002358)	(0.0003688)
B.A. or higher	−0.01821***	0.3804***	0.003513***	−0.002896***	−0.03911***	0.006576***	−0.01141***
	(0.0003029)	(0.0005294)	(0.0003032)	(0.000281)	(0.0004568)	(0.0002421)	(0.0003925)
Married	0.03636***	−0.05255***	−0.04733***	0.03752***	0.1235***	−0.04145***	−0.01049***
	(0.000309)	(0.0005615)	(0.0003193)	(0.0002826)	(0.0004854)	(0.0002655)	(0.0004183)
Children in HH	−0.003192***	−0.1178***	−0.03988***	−0.04194***	0.08393***	−0.06094***	0.01269***
	(0.0002951)	(0.0005476)	(0.0003116)	(0.0002708)	(0.0004705)	(0.0002736)	(0.0004106)

Standard errors in parentheses, $^{***}P < 0.01, ^{**}P < 0.05, ^{*}P < 0.1$.
Note: This table reports maximum likelihood estimation results as described in Section 4. The coefficients in the row labeled “Constant” correspond to the estimates for α and β. The other coefficients correspond to Θ and γ. Each cell reports the increase in utils associated with a one standard deviation change to the neighborhood or household characteristic.

with that household (w_i represents the number of households that the surveyed unit represents). The log likelihood of the data is therefore[17]:

$$LL = \sum_{i=1}^{N} w_i \left(\sum_{j=1}^{J} d_{ij} \log P_{ij} \right) \tag{4}$$

One complication of estimating the model by maximum likelihood is that besides the parameters α, Θ, β, γ, there are also J unknowns, ξ_j, that affect the choice probabilities but that we have made no assumptions about. However, we note that V_{ij} can be written as:

$$V_{ij} = \lambda_{ij} + \delta_j + \epsilon_{ij} \tag{5}$$

where

$$\lambda_{ij} = \mathbf{z}_i'\Theta\mathbf{x}_j + \mathbf{z}_i'\gamma p_j \tag{6}$$

and

$$\delta_j = \mathbf{x}_j'\alpha + \beta p_j + \xi_j \tag{7}$$

λ_{ij} is the observable component of utility that varies across households and neighborhoods, and δ_j is the component of utility that is constant within neighborhoods. δ_j can be thought of the mean utility of the neighborhood j and λ_{ij} can be thought of how the utility shifts according to household characteristics.

As described in Bayer et al. (2004) and Bayer et al. (2007), estimation can proceed in two steps. In the first step, the paramters Θ, γ, and the full vector of δ_j's will be estimated by maximum likelihood. In the second step, the estimated δ_j's will be regressed on $\mathbf{x}_j$ and p_j, as in equation (7), to estimate α and β.

To implement the first step, we note that the equation:

$$\delta_j' = \delta_j + \log H_j - \log \left(\sum_{i=1}^{N} w_i P_{ij} \right) \tag{8}$$

is a contraction mapping in δ_j.[18] So, given an initial guess of Θ and γ, which allows us to compute λ_{ij}, repeated iteration of equation (8) will yield the unique vector of δ_j's such that the equilibrium condition $\sum_{i=1}^{N} w_i P_{ij} = H_j$ is satisfied. Intuitively, if the predicted number of households choosing neighborhood j is higher than the number of housing units, then the mean utility of that neighborhood, δ_j, will be reduced in the next iteration, and vice versa, until the equilibrium condition is satisfied for every j. Thus, we can estimate Θ and γ by the following algorithm:

1. For any guess of Θ and γ:
    (a) Start with an initial guess of the δ_j's
    (b) Repeatedly iterate on equation (8) until the δ_j's converge
    (c) Calculate the log likelihood at this vector of δ_j's
2. Search over Θ and γ to maximize the log likelihood.

Once this procedure is complete, we have an estimate of the equilibrium values of the δ_j's. If ξ_j is uncorrelated with $\mathbf{x}_j$ and p_j, then we can recover α and β by regressing δ_j on $\mathbf{x}_j$ and p_j. Of course, ξ_j will *not* generally be uncorrelated with p_j since unobserved quality of the neighborhood is expected to have a direct effect on the rental rate. We therefore need to construct an instrument for p_j in estimating equation (7). We follow the strategy of Bayer et al. (2004), which is to guess a reasonable value of α and β, and then compute the vector of market clearing prices $\hat{p}_j$ that would prevail if $\xi_j = 0$. We note that because the estimates of δ_j are not used for this computation, $\hat{p}_j$ is a function only of the $\mathbf{x}_j$'s, which we assume to be exogenous to ξ_j. We then use $\hat{p}_j$ as the instrument for p_j. To choose initial values for α and β, we simply assume that $\beta = -1$ and then regress p_j on $\mathbf{x}_j$ to recover our initial guess of α.

4.3. Estimation results

Table 1 reports our estimation results for the parameters α, β, Θ, γ as described above. The row labeled “Mean” corresponds to estimates for α and β, while the other rows correpond to Θ and γ. We note that before estimating, we standardized each variable so that it has mean zero and standard deviation 1 within each city. We also pool the data from all the cities together, and assume that the preferences over the standardized units of amenities are the same across cities.[19] Thus, the interpretation of the coefficient on row “Mean” and column “Log Rent” is that the average household's utility is decreased by 3.542 utils when their log rental payment is increased by 1 standard deviation. In Table 2, we convert the parameter estimates to marginal willingness-to-pay, in units of log monthly rent, for a one standard deviation increase for each attribute. [20] The estimates on the row labeled “Mean” show the marginal willingness-to-pay for the average household in each city. The estimates on the rows labeled “log HH Income”,

[17] Note that with sampling weights, the equilibrium condition becomes $\sum_{i=1}^{N} w_i P_{ij} = H_j$. We omitted sampling weights from the discussion in the previous section for expositional clarity.
[18] See Berry et al. (1995) for further discussion and proof.

[19] We do this because there are only about 40 PUMAs per city, so estimating equation (7) separately for each city results in very imprecise estimates.
[20] We define marginal willingness-to-pay as the increase in monthly rent associated with a 1 s.d. increase in a neighborhood attribute that would leave a household living in the average neighborhood indifferent to the change. Since the average neighborhood is different in each city, the estimates we report are averaged across cities.

Table 2
Willingness to Pay in Log Rent for +1 s.d. in Neighborhood Amenities.

	Pct. White	Pct. College	Pct. No Drive	Dist. to CBD	log Med. HH Inc.	# Restaurants
Mean	0.0306	0.1410	0.0161	−0.0482	0.0590	0.0160
log HH Income	−0.0013	−0.0013	0.0008	−0.0003	0.0078	−0.0002
White	0.0709	−0.0040	−0.0009	0.0021	−0.0022	−0.0010
B.A. or higher	−0.0028	0.0535	0.0004	−0.0001	−0.0060	0.0008
Married	0.0049	−0.0082	−0.0067	0.0055	0.0169	−0.0059
Children in HH	−0.0002	−0.0159	−0.0056	−0.0064	0.0125	−0.0087
S.D. of attribute	0.1964	0.1627	0.1003	33.29	0.3289	129.6

Note: This table reports willingness to pay for one standard deviation increase in neighborhood amenities. The willingness to pay is defined as the change in log-rent associated with an increase to the neighborhood amenity that would leave the household living in the average neighborhood indifferent to the change. Because the average neighborhood is different for each city, the willingness-to-pay estimates are averaged across cities.

Table 3
Simulation results - increasing housing stock to single neighborhoods.

City	Rent response to adding + X% housing stock			
	+1%	+5%	+10%	+20%
Atlanta	−0.06%	−0.31%	−0.61%	−1.18%
Boston	−0.05%	−0.25%	−0.49%	−0.93%
Chicago	−0.07%	−0.34%	−0.66%	−1.27%
Dallas	−0.07%	−0.36%	−0.71%	−1.35%
Houston	−0.06%	−0.30%	−0.58%	−1.11%
Los Angeles	−0.07%	−0.36%	−0.71%	−1.36%
Miami	−0.06%	−0.30%	−0.59%	−1.13%
Philadelphia	−0.07%	−0.34%	−0.66%	−1.27%
San Francisco	−0.10%	−0.49%	−0.95%	−1.82%
Washington DC	−0.07%	−0.34%	−0.67%	−1.29%

Note: For each city, 4 J simulations are conducted (4 for each PUMA), in which the housing stock in a single target PUMA is increased by 1%, 5%, 10%, or 20%. (The housing stock in each other PUMA remains the same.) This table reports the average simulated rental price response in target PUMAs, averaged within cities.

Table 4
The role of preference heterogeneity in the rent response.

City	Rent response to adding +5% housing stock		
	$\sigma = 1$	$\sigma = 2$	$\sigma = 3$
Atlanta	−0.31%	−0.62%	−0.94%
Boston	−0.25%	−0.49%	−0.74%
Chicago	−0.34%	−0.67%	−1.01%
Dallas	−0.36%	−0.72%	−1.07%
Houston	−0.30%	−0.59%	−0.88%
Los Angeles	−0.36%	−0.73%	−1.09%
Miami	−0.30%	−0.60%	−0.90%
Philadelphia	−0.34%	−0.67%	−1.01%
San Francisco	−0.49%	−0.97%	−1.45%
Washington DC	−0.34%	−0.68%	−1.02%

Note: For each city, a counterfactual rent vector is first simulated, assuming that the standard deviation of the idiosyncratic preference shock ϵ_{ij} is increased by a factor of 2 or 3 ($\sigma = 1$ is the baseline). For each counterfactual value of σ, J simulations are then conducted per city, one for each PUMA, in which the housing stock of a single target PUMA is increased by 5%. This table reports the average simulated rental price response in the target PUMAs, for counterfactual values of σ, averaged within cities.

"White", "B.A. or higher", "Married", and "Children in HH" show how the willingness-to-pay estimate changes with a one unit increase to each demographic characteristic. Finally, the numbers on the row labeled "S.D. of attribute" show the standard deviation (averaged across cities) of each neighborhood attribute.

On average, we find that households are willing to pay 3% more in rent for a 1 s.d. increase in the white-share of a neighborhood, 14% for a 1 s.d. increase in the college share, 1.6% more for a 1 s.d. increase in commutability, 4.8% more for a 1 s.d. *decrease* in the distance to CBD, 5.9% more for a 1 s.d. increase in neighborhood income, and 1.6% more for a 1 s.d. increase in the number of restaurants. Compared to the mean willingness-to-pay, the effect of household demographic characteristics is comparatively small. Consistent with the results of Bayer et al. (2004), we find that the strongest effects are in the self-sorting preferences, i.e. whites prefer white neighborhoods, college educated prefer college educated neighborhoods, etc.

5. Can more supply improve affordability?

5.1. Marginal effects of increasing supply

We now use our model to simulate the effects of increasing housing supply. For our baseline experiment, we increase the housing stock in one target neighborhood by a small amount, and solve for the effects on equilibrium rental rates. We can solve for rental rates using equation (3) and replacing H_j for each j with the new, counterfactual size of the housing stock in each neighborhood. Aside from rental rates, the other variables and parameters in equation (1) are assumed to be invariant to the counterfactual change in housing supply.

To conduct this exercise, two further assumptions need to be made. First, because our model assumes a zero vacancy rate, increasing the number of housing units will increase the population in the city, in equilibrium, and so we need to assume the population characteristics of the new residents.[21] For our baseline counterfactual, we will assume that the distribution of characteristics in the new households is the same as in the existing population.[22]

Second, we need to choose a normalization constant for the counterfactual rent vector because equilibrium rents are only unique up to an additive scalar, as mentioned above. To choose the normalization constant, we define a set of PUMAs for each city as "outskirts", based on distance to CBD, and in the simulation we normalize the counterfactual

[21] We do not consider the possibility that existing residents will increase their consumption of housing space. This is unlikely to happen in the short-run when the experiment is to add new, separate housing units. However, it could happen in the long run if existing units get converted into larger units, or if the size and quality of newly constructed units changes. Our experiment is therefore best understood as the short-run effects of an exogenous increase in new housing units of equal quality to existing neighborhood units.

[22] In results available on request, we show that the main results are robust to different assumptions on the incoming population. For example, if we assume that all new entrants are college-educated, white, married, with no children, and high income, then the average effects are not much changed, but there are some slight differences in effects across neighborhoods (rental rates are reduced more if construction takes place in low SES neighborhods than if it took place in high SES neighborhoods).

Table 5
Increasing Housing Stock vs. Improving Amenities.

City	Rent response in top decile most expensive PUMAs to:						
	adding +5% housing stock	improving amenities in the bottom 9 decile PUMAs (construction cost = base cost + X%)					
		X = 0%	X = 10%	X = 20%	X = 30%	X = 40%	X = 50%
Atlanta	−0.32%	−0.44%	−0.48%	−0.52%	−0.57%	−0.61%	−0.65%
Boston	−0.27%	−0.35%	−0.38%	−0.42%	−0.45%	−0.48%	−0.52%
Chicago	−0.36%	−0.44%	−0.48%	−0.53%	−0.57%	−0.62%	−0.66%
Dallas	−0.35%	−0.30%	−0.33%	−0.36%	−0.39%	−0.42%	−0.45%
Houston	−0.29%	−0.43%	−0.48%	−0.52%	−0.57%	−0.61%	−0.65%
Los Angeles	−0.33%	−0.30%	−0.33%	−0.35%	−0.38%	−0.41%	−0.44%
Miami	−0.30%	−0.25%	−0.27%	−0.30%	−0.32%	−0.35%	−0.37%
Philadelphia	−0.36%	−0.40%	−0.44%	−0.48%	−0.52%	−0.56%	−0.60%
San Francisco	−0.48%	−0.30%	−0.33%	−0.36%	−0.39%	−0.42%	−0.45%
Washington DC	−0.37%	−0.27%	−0.30%	−0.32%	−0.35%	−0.38%	−0.41%

Note: For each city, we first simulate the equilibrium rent vector when the housing stock of the top decile most expensive PUMAs is increased by 5%. The first column of the table reports the average rent response in those top decile PUMAs. We then simulate the equilibrium rent vector when the housing stock remains at baseline, but the construction cost associated with the first simulation is instead spent on improving amenities in the bottom 9 decile PUMAs (Section 5.2 describes the exercise in more detail). Columns 2–7 of the Table reports the rent response in the *top decile* PUMAs in response to the increase in amenities to the *bottom* 9 decile PUMAs. Each column in columns 2–7 makes a different assumption about construction cost (+X% of the RS Means estimate of an economy apartment unit).

rent vector so that average rents in the outskirts do not change.[23] This decision is motivated by the evidence in Section 2 showing that in some areas of each city, housing supply appears fairly elastic and rents/house prices appear to be mainly determined by construction costs. Therefore, it is reasonable to assume that the prices in such areas will not change in our counterfactual.[24]

Table 3 reports the results of the baseline simulations. For each city, we conduct 4 J simulations—four for each PUMA—of increasing the housing supply in that PUMA by 1%, 5%, 10%, and 20%. The table reports the average effect on rental rates in the target PUMA, averaged across PUMAs for each city. We only reported averages because the variance in the response across PUMAs for each city was very small. There are also equilibrium effects on the rental rates of non-targeted PUMAs, but they are very small and we do not report them. The results show that within PUMAs, the elasticity of rental rate with respect to an exogenous increase to housing supply is fairly low, less than 0.1 in all cases. It follows that the affordability or share cost burdened elasticity is also fairly low.

As we discussed in the introduction, demand for neighborhoods can be very elastic with respect to price (and thus price is inelastic with respect to new supply) if there is relatively little preference heterogeneity. We find that this is indeed the case based on our model estimates. We find that the variance of V_{ij} across PUMAs within households is between 14 and 15.4 for each city. The variance across households within PUMAs is an order of magnitude smaller—between 1.38 and 1.44—for each city. This suggests that neighborhoods are much more vertically differentiated than they are horizontally differentiated. As a result, the willingness to pay to live in a particular neighborhood for a household who is on the margin between living in that neighborhood and elsewhere will not be too different before and after a change in housing supply. As prices are set by the willingness to pay of the marginal household in our model, the price elasticity with respect to new supply is small.

To make this point more directly, we simulate how the price response would change if preference heterogeneity were greater. To do this, we first simulate the equilibrium rent vector that would result (under the baseline vector of housing stock) if the standard deviation of the idiosyncratic preference term ϵ_{ij} were increased to two or three times its baseline level. We then simulate the equilibrium rent response to a 5% increase in housing supply to single PUMAs, under the counterfactual distributions of ϵ_{ij}. Table 4 reports the results. Consistent with our hypothesis that low preference heterogeneity explains a low rental rate response, we find that increasing the standard deviation of ϵ_{ij} does increase the rental rate response, and quite significantly. However, even in the scenario where the standard deviation of ϵ_{ij} is three times as large as in our baseline estimates, the rental elasticity is still small at about 0.2. The effect on rents in the non-targeted neighborhoods is also more responsive when there is more preference heterogeneity. However, because the share of households that must be reallocated from each of the non-targeted neighborhoods is very small in our simulations, the marginal person in each non-targeted neighborhood will barely change and the rent effects are still very small in the non-targeted neighborhoods even when there is more preference heterogeneity.

5.2. Increasing supply vs. improving amenities

We now use our model to compare the price effects of building new housing supply versus improving amenities. In this experiment, we first simulate the equilibrium rent response in high priced areas in each of our 10 cities to increasing the housing stock in those areas by +5%. We define high priced areas as the top decile of PUMAs in terms of monthly rents. We then compare this to the equilibrium rent response in high priced areas to improving amenities in the non-high-priced areas (i.e. the bottom 9 deciles of PUMAs). Improving amenities in lower priced neighborhoods will make these neighborhoods more attractive relative to high priced neighborhoods, and could put downward price pressure on the high priced neighborhoods through a substitution effect. We will only compare the two policies on their effect on rents and so we will not make any statements about the total welfare effect of the policies.

In order for the two policies to have a consistent cost basis, we need to make two assumptions. First, we need to assume the total cost of adding 5% to the housing stock in high priced areas. Second, we need to assume the rate at which those construction costs could instead be turned into amenities in the non-high-priced areas. For the total cost, we use the RS Means estimate of the cost of building a 1500 square foot

[23] We defined the distance to CBD threshold for outskirts separately by city. The threshold for each city was determined by visual inspection of Fig. 5. The distance thresholds for each city are reported in Appendix Table 1.

[24] As discussed in the introduction, this assumption may be less realistic if changes to the housing supply are large enough to cause significant population loss and vacancies in the outskirts areas. Then, the total effect on rents will depend on the rent elasticity to population loss in the outskirts. Nevertheless, the effect on *relative* rents will remain the same (absent any changes to amenity levels).

economy apartment unit as a baseline. This is likely an underestimate of the true cost of building in higher priced areas because these areas are already quite dense and are often naturally supply constrained by steep slopes and proximity to water. Therefore the building costs and externalities (e.g. from congestion) associated with adding housing stock to these areas is likely quite high.

To convert the construction cost to amenities, we simply assume a conversation rate of dollars to amenities based on our estimates of the parameters that multiply the rental rate in Table 1. These parameters tell us households' marginal utility of price and thus describes their indifference condition between utils and dollars. The assumption is then that this indifference condition also describes the rate at which utility over amenities (e.g. ξ_j) can be produced from dollars.[25] This particular experiment admittedly has little connection to any real policy (such as investment in public transportation), but without cost/benefit estimates for a specific policy proposal, we believe this is a reasonable benchmark to consider.[26]

Table 5 reports the results of this experiment, for various assumptions on the construction cost. Even for our baseline assumption on construction costs—which is almost surely an underestimate of the cost of building in high-priced neighborhoods—improving amenities in low-priced neighborhoods can have a larger impact on rents in high-priced neighborhoods than new housing supply. As we assume higher construction costs, the comparison favors improving amenities even more. The only city for which improving amenities is still not favored, even when we assume construction costs for high-priced neighborhoods of +50% of an economy apartment, is San Francisco.

For each neighborhood in the bottom 9 deciles of the rent distribution that receives the direct improvement to amenities, we find in unreported results that the effect on rents and affordability is very small. Even for the case of construction costs equal to +50% of an economy apartment, the effect on rents is less than 0.1% in such neighborhoods.

6. Conclusion

The effect of new construction on rents is a highly relevant elasticity for evaluating solutions to the affordability crisis, but direct evidence on the magnitude of the elasticity is scarce. Motivated by a lack of reduced-form evidence, in this paper, we estimate a structural model of neighborhood choice that allows us to simulate this elasticity. Our results suggest that the rent elasticity is likely to be low, and thus marginal reductions in supply constraints alone are unlikely to meaningfully reduce rental burdens. An important reason for the low rent elasticity in the model is that we estimate a relatively low amount of preference heterogeneity across households. We also present evidence to suggest that improving amenities in low-priced neighborhoods is a more cost effective way to reduce prices in high-priced neighborhoods, via a substitution effect, than directly building additional housing units in high-priced areas.

In future research, we would like to more directly estimate the rental price elasticity to new construction, without having to rely on restrictive modeling assumptions. This is a challenging task, because construction of new housing supply is a highly endogenous process influenced by myriad economic and political factors, most of which are not observed. On the modeling side, opening up our framework to allow for migration across metro areas seems like a natural extension to pursue.

Appendix.

Table A.1
Mileage Threshold for Outskirt Neighborhoods by City.

City	Mileage Threshold
Atlanta	16
Boston	38
Chicago	42
Dallas	12
Houston	17
Los Angeles	25
Miami	18
Philadelphia	38
San Francisco	43
Washington DC	40

Census PUMAs beyond the mileage threshold are classified as outskirts. In the counterfactual simulations discussed in Section 5, the counterfactual rent vector is normalized so that average rents in the outskirts do not change.

[25] We assume that the dollars are spread evenly among all housing units in the non-high-priced areas.This implicitly assumes that the expenditures are not on public goods.

[26] An alternative experiment would be to convert the construction cost to direct income subsidies to residents of the non-targeted PUMAs. In results available on request, we show that the effects of the income subsidy are similar in magnitude to and even larger than the conversion to amenities that we consider in Table 5, which further strengthens our argument that improving the attractiveness of low-priced neighborhoods could be a more effective means of improving affordability in high-priced neighborhoods than new construction.

The CBSA is shaded in white. The black lines denote PUMA boundaries. The very light grey areas are water. PUMAs closer to the city core tend to have smaller areas because population density tends to be higher in such areas.

Fig. A.1 Map of Census PUMAs by City.

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