Why is the Rent So Darn High? The Role of Growing Demand to Live in Housing-Supply-Inelastic Cities *

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Abstract

Real rents measured in the United States CPI increased 17.4 log-points from 2000-2018. We present a spatial equilibrium framework to decompose the increase into several channels, including demand to live in housing-supply-inelastic cities. We find location demand contributed significantly: using parameterizations from the literature and a new rent index, we find it is responsible for between 17 and 73 percent of the overall rent increase, and an even larger share in cities where CPI is measured. The wide range is primarily due to a lack of consensus over the population elasticity to rents, so we estimate it by comparing the effects of demand shocks across cities of differing housing supply elasticities. We find that demand changes have similar effects across cities, suggesting a high population elasticity. Therefore, our preferred estimate is that location demand accounts for more than half of the increase. We discuss implications for housing supply policy.

JEL Codes: R31, R23, E31

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The rental price of housing in the United States has risen substantially this century. From 2000 to 2018, the rent component of the consumer price index (CPI) rose 17.4 log-points more than the overall index. Many people's feelings are summarized by the name of a single-issue political party in New York City: "The Rent is Too [Darn] High."

So why is the rent so darn high? Explanations have fallen primarily into two categories. The first explanation is that housing supply was restricted because of increased regulation (e.g., Ganong and Shoag, 2017; Parkhomenko, 2020; Bunten, 2017). The second explanation is a change in the quantity or quality of housing demand, for example demand for houses rather than apartments (e.g. Joint Center for Housing Studies, 2015; Albouy, Ehrlich and Liu, 2016; Gete and Reher, 2018). We propose a third explanation, that the demand for living in housing-supply-inelastic areas has increased.[1] The location demand channel matters because, when a person leaves an elastic city for an inelastic one, the rent in the elastic city falls only a little, but rises more in the inelastic one. So in the aggregate, rents increase. Using a spatial model to decompose the data, we find this location demand channel explains more than half of the national rent increase from 2000 to 2018, and three-quarters of the rent increase in CPI.[2,3]

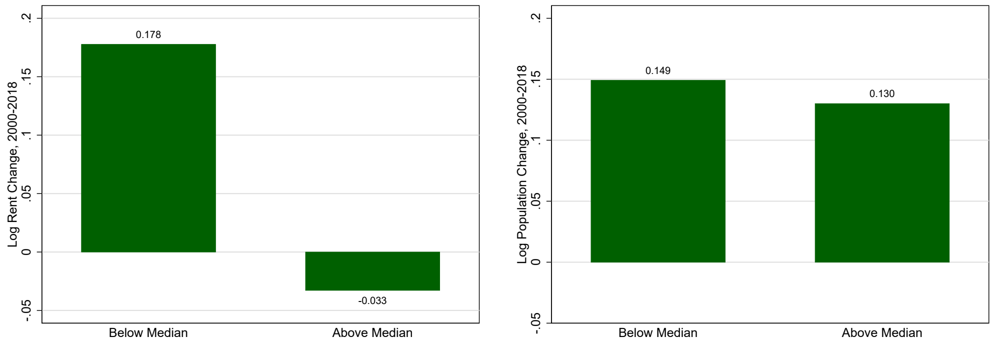
We first want to establish that demand did rise for housing-supply-inelastic cities. The left panel in Figure 1 shows that the rise in rents was greatest in cities with an inelastic housing supply.[4] By itself, the fact that rent increases were concentrated in inelastic cities is consistent with any of the three channels. However, we can bring more data to this question.

[1]The correlation between demand changes and housing supply elasticity has been noted in Davidoff (2016). We are expanding this observation to suggest it can explain a significant increase in the aggregate level of rents.

[2]The CPI measures prices only for certain urban areas, which experienced a relative increase in location demand compared to places not covered by the CPI. We focus on 2000-2018 because real rents increased more quickly then than in previous decades; CPI-rents shows no real rent increase from 1990 to 2000.

[3]As discussed by Molloy (2020), the correlation between local prices and supply restrictions is well-documented. However, our paper considers the causes and implications of such a correlation while taking into account the general equilibrium effects of migration.

[4]To create this graph, we use the definition of Metropolitan Statistical Area (MSA) in Saiz (2010). Using the dataset from his paper, we split all counties into below or above median by the measure of housing supply elasticity that he calculates. We assume that areas outside of MSAs have above-median elasticity. Population data comes from Census estimates. To measure rents, we use the series we create, as described in Appendix B.



(a) Log Rent Change

(b) Log Population Change

Figure 1: The Change in Rent and Population, by Housing Supply Elasticity, 2000-2018

The right panel shows that population also increased more in these cities. This pattern is hard to explain with changing supply restrictions or increases in housing demand, but it is a natural part of our explanation. If people demanded larger houses or if housing became more restricted, we would expect a population decrease in cities where it is harder to build compared to cities where it is easier to build. But the data shows the opposite, which is what we would expect if the demand to live in harder-to-build areas increased.[5]

While Figure 1 is helpful to make the basic point that demand to live in housing-supply-inelastic areas increased, it does not say how much of the rent increase might be explained by this channel. In fact, our channel could be operative even if populations were growing more in the more housing-supply-elastic regions, precisely because low-elasticity regions are hard to build more housing in.

So we turn to a quantitative general equilibrium spatial model. In our model, individuals make both an intensive-margin choice of how much housing to consume as well as an extensive-margin choice for where they want to live. Housing supply varies across cities, and all individuals must choose to live somewhere. For a set of parameters, the model allows us to decompose the observed changes in rents, housing quantity, and population into four types of shocks: location demand (the demand to live in a particular place), intensive-margin

[5]We can also directly measure some things that correspond to this demand increase. In Appendix C, we provide direct evidence that wages and amenities increased more in low-housing-supply-elasticity MSAs.

housing demand (what kinds of home each person wants), housing supply, and a national population increase. Including all these shocks allows us to match the changes in population, rents, and housing quantities exactly, and then calculate the moments in the data which tell us why rents changed nationally.

Our model does not have all the sophistications of some urban models because it focuses exclusively on the housing sector. Its strength is in its tractability: we can perform counterfactuals using easily observed moments in the data, similar to a sufficient statistics approach. Critically, we are able to consider the general equilibrium aspect of location demand, that everyone must live somewhere, and maintain closed-form solutions to counterfactuals.

Using the formulae from the model, we learn that the location demand channel is quantitatively important for explaining the rent increase since 2000. For common parameterizations of the key elasticities, our channel explains somewhere between 17 and 73 percent of the increase in rents, and somewhere between 23 and 85 percent of the increase in rents measured by the CPI. Even at the lower end, this is a substantial proportion of the increase.

However, these intervals are fairly wide, and we wish to be more precise in how responsible the location demand channel is for explaining high rents. We learn from the theory that a critical parameter of our model is the elasticity of population to local rents. This elasticity is defined to be how much, as a percent of the city's initial population, the population changes in response to a one percent increase in rents. Why is this elasticity so important? If it is low, the change in location demand is reflected in populations, so the important moment to quantify the location demand channel is the covariance of population changes and housing supply elasticities, which in the data is small.[6] Under this assumption, an economist would conclude the importance of the location demand channel was at the low end of the range. But if population is highly elastic, location demand changes are reflected in local rents, and the important moment is the covariance of rent increases with housing supply elasticities.[7]

[6]More precisely, Proposition 1 shows the covariance that matters is population growth with the inverse of the housing supply elasticity plus a constant. This is also small.

[7]The intuition is similar to a supply-and-demand graph. If demand is elastic, then changes in demand are reflected in price even for different supply curves. If demand is inelastic, then changes in demand are

Because this covariance is large, an economist would recognize location demand changes as the primary reason rents have increased.[8]

A variety of values for the population elasticity have been used in the literature. Existing parameterizations that we could find range from one-third to infinity,[9] which would lead to very different beliefs on the causes of recent rent increases and the policy implications for ways to lower rents. We also provide estimates of the strength of the location demand channel for the parameters used in these other papers.

Rather than relying on assumptions about the functional form of utility—a widely used approach—we estimate the population elasticity by calculating heterogeneous effects of income changes by housing supply elasticity.[10] This is a strategy similar to Saks (2008) and Diamond (2016), but we study a longer time horizon than Saks (2008) and relax an important assumption in Diamond (2016).[11] If the population elasticity is small, the income change's effect on rent should be larger in a housing supply inelastic area. If the population elasticity is large, there should be no heterogeneity in the rent response. We find a rent increase to income changes that is roughly constant across elasticities. Therefore, our preferred estimate of the eighteen-year population elasticity to rents is infinity, meaning that rents will fully offset any location demand shocks.

Our estimate of this parameter implies that changing location demand is the key reason for the increase in rents since 2000. Overall, we find that more than half of the rent increase is due to this location demand channel, and it was especially important for areas covered by

reflected in quantities.

[8]It is a model result that a statistic sufficient to calculate the location demand channel are covariances of rents or populations with (transformed) housing supply elasticities.

[9]See Table 1 for a list of papers with different parametrizations.

[10]The total effect on rent to the same change should be proportional to the inverse of the sum of three elasticities: housing supply, intensive housing demand, and location demand. The literature has a much smaller range for intensive housing demand, between 0 and 1.

[11]Saks (2008) estimates the effects of Bartik shocks in cities with high and low housing supply elasticities. She finds that employment responds more in housing supply elastic cities and house prices respond less, both in the short-run. While she does investigate longer-term effects using a VAR structure, the results are not statistically distinguishable. Diamond (2016) explicitly assumes that housing supply elasticities are orthogonal to unobserved local demand shocks. This is a stronger assumption than we need, and it rules out the location demand channel that we have in mind, except to the extent that location demand is captured by the observed shocks she considers.

CPI, where it explains three-quarters of the rent increase.

One of the contributions of this theoretical framework is a way to calculate how cross-sectional shocks affect aggregate rents. For example, this method would tell us the contribution of manufacturing to rents via the location demand channel. Typically, economists would start by regressing the local change in rents on some measure of the decline. But to translate that coefficient into a general equilibrium effect requires additional assumptions. In our model, the national population adding-up constraint implies that we also need to know the covariance of the shock with housing supply elasticities.[12]

We also contribute to research on rental prices by developing a new rent index that starts in 2000 and exists for a larger cross-section of cities than is available elsewhere. As noted by Molloy (2020), there is relatively little research on the relationship between housing regulations and rents (as opposed to house prices). We hope that the development of our new index will further the development of this research area.

Our measures are repeat rent indexes we create using multifamily mortgage-backed securities from Trepp. Our series are largely similar to the consumer price index series, but are available for more than 200 cities, rather than the 25 published by the BLS. By measuring rents for a large section of the country, we are able to aggregate local shocks to housing demand and supply in order to estimate their national impact. This would not be possible with more conventional measures. Details of how we construct the series and a comparison to CPI is presented in Appendix B.[13]

While our model was designed to decompose past data, it is also suitable to consider

[12] In the data, it turns out this covariance is significantly positive (Liebersohn, 2017). This means that even though manufacturing might have a negative local effect on rents, it aggregates to a small but positive national effect via the location demand channel. There may also be intensive housing demand changes from manufacturing that this exercise would ignore, but which could still be quantified using our model.

[13] One reason indices similar to the ones we use are not published is that they are subject to measurement error at small levels of geography. And though we do our best to limit it, our indices are also subject to measurement error. One approach we take to limiting the noise is to use empirical Bayes methodology to shrink the estimates based on the uncertainty in the estimation of the rents index. More generally, though, the statistics we consider will be the covariance of rents with housing supply elasticities, and as long as the measurement error is well-behaved, the law of large numbers will mean that our statistics converge. So even if we have insufficient observations to trust our rent index for a specific small city, the measurement error will average out across many cities.

housing-specific counterfactuals. Our estimate of a high population elasticity to rents imply that a local expansion of housing supply is unlikely to have significant long-run effects on rents. Furthermore, expansion of housing supply at the national level has similar effects on rents regardless of where it occurs.[14] Finally, subsidies of housing are more effective at lowering rents when they target housing elastic cities rather than housing inelastic ones.[15]

Our paper is organized as follows: In this next subsection, we review the relevant literature. In Section 1, we present the model that we use to decompose the important forces. In Section 2, we show that the population elasticity to rents is the key parameter to disentangle different causes of the rent increase. In Section 3, we outline our empirical strategy and estimate this elasticity.

Literature Review. The literature has taken a variety of empirical and theoretical approaches towards understanding changes in housing costs. For example, many empirical papers take a cross-sectional approach, seeing how various local shocks, such as regulatory changes or immigration, affect housing prices. More structural papers start with a spatial equilibrium model and estimate the effects of the shock of interest through counterfactual analysis. Our framework focuses on the most critical housing elements of the models, allowing us to make a contribution to both literatures. For the empirical papers, it gives a general equilibrium lens to interpret the coefficients from a cross-sectional regression. For the theoretical papers, it highlights the location preference parameter as central to determining the causes of the rent increase.

Our theoretical contribution builds on the spatial equilibrium framework first developed by Rosen (1979) and Roback (1982). Most closely related to our paper, Van Nieuwerburgh and Weill (2010) develop a spatial equilibrium model showing that wage changes can explain much of the cross-sectional dispersion of house price changes over a long time period. In another related paper, Glaeser, Gyourko, Morales and Nathanson (2014) use a spatial equi-

[14] In this case, the location can still have large effects on other outcomes of interest, such as GDP (see Hsieh and Moretti, 2019).

[15] All of these statements use our estimate of population elasticity to rents. However, our theory does provide formulas for calculating the effects of these policies at any value of this elasticity.

librium model to argue that income volatility largely explains house price volatility at the local level. These papers focus primarily on explaining cross-sectional changes.[16] Our paper emphasizes that these cross-sectional changes also have important aggregate effects.[17]

A related model-based literature uses spatial equilibrium models to estimate how housing restrictions affect cross-sectional and aggregate productivity. Focusing on the cross-section, Ganong and Shoag (2017) argue housing supply regulation can help explain the slow-down in regional convergence. Other papers focus on aggregate productivity or welfare (Hsieh and Moretti, 2019; Herkenhoff, Ohanian and Prescott, 2018; Bunten, 2017; Jayamaha, 2019). All four argue that housing restrictions lower aggregate productivity.[18] Like us, they are interested in the aggregate consequences of cross-sectional changes. However, the focus of this literature is on productivity and output, while ours is on housing costs.

Turning to the cross-sectional empirical research, it can largely be split into two categories: estimating local effects of supply and estimating local effects of demand. Starting with supply channels, Saks (2008), Glaeser, Gyourko and Saks (2005) and Ihlanfeldt (2007) argue that regulatory changes have made housing production more expensive, raising house prices and causing prices to respond more to housing demand shocks. Diamond, McQuade and Qian (2019) study the effects of rent control on rental prices. Two recent reviews, Gyourko and Molloy (2015) and Glaeser and Gyourko (2018), synthesize the literature on the effects of supply constraints.[19] This is also closely tied to a literature on the relationship between housing supply and housing affordability (Glaeser and Gyourko, 2003; Brueckner,

[16]The model in Van Nieuwerburgh and Weill (2010) also features an endogenous national equilibrium price, but they strongly emphasize the cross-sectional results of their model.

[17]Another related literature has focused on explaining what causes the income divergence that we have seen over the last forty or so years, mostly arguing that technology is the primary driver with an important role for the sorting of high-skilled workers (Giannone, 2017; Eeckhout, Pinheiro and Schmidheiny, 2014). So far, this literature has not focused on the implications for housing costs. Aladangady, Albouy and Zabek (2020) document an increase in housing inequality over the past fifty years and a lesser increase in rent inequality, but include both inter- and intra-regional inequality.

[18]Bryan and Morten (2019) shows that lowering migration costs can increase aggregate productivity in a developing market context.

[19]More papers studying the cross-sectional price implications of variation in housing supply elasticity include Glaeser and Gyourko (2003), Zabel and Dalton (2011), Glaeser, Gottlieb and Tobio (2012), Guerrieri, Hartley and Hurst (2013), Gyourko, Mayer and Sinai (2013), Hilber and Vermeulen (2016), and Albouy and Ehrlich (2018).

2009), which is reviewed by Quigley and Rosenthal (2005) and Molloy (2020).

On the demand side, Gete and Reher (2018) argue that mortgage availability can decrease rents, and Reher (2018) shows that it can raise house prices by increasing the quality of housing. Saiz (2007) shows that immigration shocks can increase rents, and Gorback and Keys (2020) and Li, Shen and Zhang (2021) show that capital inflows raise prices on local housing. Davidoff (2013) and Davidoff (2016) show that many demand-side factors are highly correlated with housing supply elasticities. He focuses on the fact that this ought to rule out using these elasticities as instruments, whereas we are focused on showing that such a correlation has important aggregate effects.

Our theory is flexible enough to accommodate many of the mechanisms studied in these empirical papers, as we would model them as an increase in the demand for housing quantity or a shock to housing supply. In fact, for the supply side, we give an explicit formula for calculating the aggregate effects.

Finally, our paper is related to a large literature on internal migration in the United States. This literature includes both reduced-form and structural research, and studies links between labor markets and migration patterns. Glaeser (2011) gives an overview of the many advantages of moving to cities. In a recent influential lecture, Autor (2019) documents changes in the labor market for college-educated and non-college-educated workers over time. In Appendix C, we show that the location demand shocks we document correlate to observed changes in wages and amenities, consistent with the literature on the determinants of migration (Kennan and Walker, 2011; Molloy, Smith and Wozniak, 2011).[20]

[20] A subset of this literature has emphasized the heterogeneity within migration patterns. For example, younger and more-educated workers are more likely to move (Chen and Rosenthal, 2008; Molloy et al., 2011). Diamond (2016) shows that different skill groups value amenities differently, Berry and Glaeser (2005) shows that network effects can lead to clustering of high-skilled workers, and Kaplan and Schulhofer-Wohl (2017) discusses location demand for particular skills and occupations. We address concerns regarding heterogeneity in Appendix E.

There is a big literature focused on the reasons for moving. Most related to ours are papers that document that housing costs play a large role in explaining migration patterns (Zabel, 2012; Plantinga, Détang-Dessendre, Hunt and Piguet, 2013). Ferreira, Gyourko and Tracy (2011) argues that declines in house prices can lock people into their homes. Halket and Vasudev (2014) and Bilal and Rossi-Hansberg (2021) emphasize the life-cycle and investment returns to location. Consistent with that, Nakamura, Sigurdsson and Steinsson (2021) shows that young people have much larger gains to moving than older people. Monte, Redding and

1 Model of Housing Markets

For our analysis, we use a static general equilibrium spatial model, typical of the spatial economics literature. However, our model abstracts from many features of spatial models, focusing exclusively on the housing sector. The purpose of the model is to be able to decompose the data into several types of shocks, as is commonly done in the business cycle literature to determine the causes of recessions. We can also do counterfactuals by imagining the shocks had been otherwise. One of the contributions that comes from focusing only on the housing sector is that the model is tractable enough so that the counterfactuals can be solved analytically, leading to sufficient statistics for the contribution of location demand.

People in our model, denoted by j, choose a location i in which to live, supply one unit of labor, and consume housing and tradable goods. The price of tradable goods is normalized to 1. Locations differ in their supply curve for housing, their amenity value, and their productivity. In Appendix E, we extend the model to have multiple types of people or multiple types of housing.[21] The utility of an agent is given by

$$U_{ij} = \log u(c_i, b_i h_i, a_i) + \epsilon_{ij}$$

subject to the budget constraint $w_i = c_i + r_i h_i$. The consumption of non-housing goods is c_i,[22] h_i is the consumption of housing, b_i is a city-specific housing demand shifter, a_i is the general amenity level of city i, ϵ_{ij} is a match-specific amenity term, w_i is the productivity of city i, and r_i is the rent in city i. Denote L_i as the number of people that choose to live in city i. We assume ϵ_{ij} is an i.i.d. Gumbel.

Rossi-Hansberg (2018) argues that commuting openness is an important determinant in the elasticity of employment to a demand shock.

[21] Other features, such as taxes, can be added as part of productivity or the housing production function.

[22] Here, non-housing goods are all tradable. You could add in non-tradable goods whose equilibrium price depends on w_i or r_i. You would still end up with equations (1) and (2).

This generates a per-capita housing demand function

$$h_i = h_i(w_i, r_i, b_i) \tag{1}$$

which is decreasing in r_i, and an indirect utility function

$$v_i = v_i(w_i, r_i, a_i, b_i) \tag{2}$$

where $U_{ij} = \log v_i + \epsilon_{ij}$. v_i is also decreasing in r_i.

We assume housing is supplied competitively using local land, which is available in a fixed quantity, and the consumption good. Assume the production function is $H_i = Z_i^{\frac{1}{\sigma_i+1}} X_i^{\frac{\sigma_i}{\sigma_i+1}}$, where Z is local land and X is intermediate inputs of the consumption good whose price is already normalized to one. Then from the construction profit first-order condition, the supply curve is

$$\log H_i = \sigma_i \log r_i + \text{constant}_i \tag{3}$$

Note that the housing supply elasticity differs by city.

Local housing markets have to clear, and everyone must live somewhere

$$H_i = L_i h_i \tag{4}$$

$$L = \sum_i L_i \tag{5}$$

Given the Gumbel distribution, the allocation of population to cities is given by:

$$L_i = \frac{(v_i)^\mu}{\sum_j (v_j)^\mu}$$

where $1/\mu$ is the scale parameter of the Gumbel distribution. So

$$\log L_i = \mu \log v_i - \tilde{u} \tag{6}$$

where $\tilde{u}$ is the log of the denominator, which is common across all cities.

Equations (1)-(6) define the equilibrium. Given the exogenous wages, i.e. a lack of agglomeration, the equilibrium exists and is unique (Allen, Arkolakis and Takahashi, 2020).

We take a log-linearized approximation of the indirect utility around the steady-state:

$$\log v_i = \gamma_1 \log w_i - \gamma_2 \log r_i + \gamma_3 \log b_i + \gamma_4 \log a_i + \text{constant}_i,$$

where γs are constants, and its corresponding policy function,

$$\log h_i = c_1 \log w_i - \lambda \log r_i + c_3 \log b_i + \text{constant}_i.$$

where cs are also constants.

These need not be approximations if utility is Cobb-Douglass, in which case $\lambda = \gamma_1 = c_1 = 1$ and γ_2 is the Cobb-Douglass parameter. However, empirical estimates suggest λ closer to two-thirds measured across cities, and the size of a house is subject to large adjustment costs, so imposing Cobb-Douglass may introduce a counterfactually high housing demand elasticity (Albouy et al., 2016).[23] The utility function allows for a normalization, so we normalize $v_2 \equiv 1$.

We are interested in changes in equilibrium, so we express these equations in differences:

$$d \log h_i = -\lambda d \log r_i + \epsilon_i \tag{7}$$

$$d \log H_i = \sigma_i d \log r_i + \xi_i \tag{8}$$

$$d \log L_i = -\mu d \log r_i + \eta_i - d\tilde{u} \tag{9}$$

$$d \log H_i = d \log L_i + d \log h_i \tag{10}$$

$$d \log L = \sum_i L_i d \log L_i = \mathbb{E} d \log L_i \tag{11}$$

[23] Albouy et al. (2016) is estimated across cities. Even in the medium-run, changing the amount of housing consumed in a city requires large adjustment costs, so it may be an overestimate. We also present results for $\lambda = 0$ throughout.

where the expectation is initial-population-weighted. These are the five key equations of our model: a housing demand per capita equation, a housing supply equation, a location demand equation, a housing market clearing condition, and a population adding-up constraint. The adding-up constraint is a log-linear approximation.[24,25]

Given data on h_i, L_i, and r_i, there is a unique set of ϵ_i, ξ_i, and $\eta_i - d\tilde{u}$ that can match the data. There are four "shocks" here: η_i is a shock in location demand and is of primary interest. It includes amenity or wage changes. ϵ_i is a shock to housing demand, and includes wage changes and changes in the utility from housing. ξ_i is a local shock to housing supply and includes shocks to available land. The last shock is the change in total population.[26]

These shocks are not the fundamental shocks of the model, but are central to distinguishing the competing hypotheses for why the rent is so darn high. For example, at this point in the paper, we are not interested in whether productivity changes were the fundamental change that caused a rise in rents.[27] We are, however, interested in whether it was a shift in the housing (per capita) demand curves, the housing supply curves, or in location demand that cause the increase in rents. This decomposition will let us attribute the rise in rents to the four channels and allow us to do counterfactual policy analysis.

Our model has abstracted from many features of urban models, including agglomeration, sorting, and housing types. Some of these are easy to map onto our shocks. The model will interpret wage gains from agglomeration as positive location demand and housing demand shocks. A recent literature has also emphasized the endogenous nature of supply (Parkhomenko, 2020). If a location became more desirable which endogenously led

[24]The error induced by the log-linear approximation is approximately half of the variance of population changes, and empirically, it is quite small. In the data, the variance of population growth is a bit over 1 log-point. In all of our counterfactuals, we are considering possibilities in which the variance of population growth is smaller. So given that the average housing supply elasticity is about 2, the overall impact of the approximation error on aggregate rent is at most two-tenths of a log point.

[25]In Appendix E, we consider two extensions to the model and discuss how they would affect our results. In the first, we consider heterogeneity by location elasticity, by including a group of agents that do not move. In the second, we consider a segmented housing market, where some housing is rented and some is owned.

[26]In particular, $\epsilon_i = c_1 d\log w_i + c_3 d\log b_i$; $\xi_i = d\log Z_i$; and $\eta_i = \mu d\log a_i + \mu v_1 d\log w_i + \mu v_3 d\log b_i$.

[27]In the last part of the paper we will return to this question and provide evidence on the factors that correlated with changes in location demand.

to tighter housing supply, the model would interpret that response as a housing supply shock even though the fundamental shock is about location demand. In addition, sorting (e.g., gaining a larger share of college graduates) will be interpreted as a housing demand shock if a city increases its share of people that consumer larger houses. We further discuss sorting in Appendix E. There, we also show how our model accommodates multiple types of housing.

Importantly, the theory allows cities to vary by their housing supply elasticities. This is the key heterogeneity on which we focus. Combining that with the population adding-up constraint will give us our interesting results.

1.1 Model Results

Given shocks to η_i, ϵ_i, and ξ_i, we can calculate the effects on rent. Using equations (7)-(10), the change in rents in city i is

$$d \log r_i = \frac{\eta_i + \epsilon_i - \xi_i - d\tilde{u}}{\sigma_i + \mu + \lambda} \tag{12}$$

This formula is going to help us identify μ, the population elasticity to rents. If μ is large, the effects of various shocks on rents will be similar across elasticities, but if μ is small, the effects of a shock will be larger in areas with smaller elasticities.[28] Intuitively, if people are highly willing to move, changes in demand lead to population movement in or out of a city until rent changes offset the wage changes, regardless of the elasticity of housing supply. In the extreme case where $\mu \to \infty$, as in the Rosen (1979)-Roback (1982) model, a change in wages should lead to an offsetting change in rents regardless of the housing supply elasticity.[29]

Our primary question is: to what extent is the change in average rent due to shifts in η_i, the location demand channel? To answer this, we invert the model to find the relative η_i's, and consider what the change in rents would have been had all the η_i's been zero.[30] We

[28] A high μ does not mean the effects of any shock on rents are small because η_i and $d\tilde{u}$ can scale with μ.

[29] Note that the model-implied η_i's are also changing when μ changes so that the right-hand side of equation (12) does not go to zero.

[30] Zero is an unimportant normalization because if all the η_i's increased by 1, then $d\tilde{u}$ would increase by

define the *location demand channel* to be the difference in aggregate rents between the real data and this counterfactual.

To do this with population and rents data, we calculate the η's from the model: $\eta_i = d\log L_i + \mu d\log r_i + d\tilde{u}$. We then change these η's to zero and recompute the equilibrium, in order to quantify the importance of location demand.

We start with two extreme scenarios that simplify the algebra significantly: $\mu = 0$ and $\mu \to \infty$. These correspond to inelastic mobility and perfectly elastic mobility. The formulas for these give us intuition for the important moments in our data. We then generalize our formulas to intermediate values of μ. Proofs are collected in Appendix D.

1.1.1 Population inelastic to rent

Proposition 1: If $\mu = 0$, then the contribution of location demand is

$$\text{Location Demand Channel} = Cov\left(d\log L_i, \frac{1}{\sigma_i + \lambda}\right)$$

where the covariance is initial population-weighted.

Here, the effect of location demand is to raise populations more in some regions than others. The increase in population will have a smaller effect on rent in elastic regions as in (12). So if there are bigger population increases in inelastic regions, then location demand will have had a positive effect on average rents.

When $\mu = 0$, most of the interaction between cities is eliminated. η_i determines the population increase directly, because agents are inelastic to the endogenous change in rents. Without the interactions between cities, the model boils down to independent supply and demand curves across cities: equations (7), (8), and (10). Given the excess population, the effect on rents is given by the size of the shock divided by the sum of the demand and supply elasticities: $\frac{1}{\sigma_i+\lambda}(d\log L_i - d\log L)$. Taking the expectation leads to the formula in the proposition.

1 and completely offset it.

1.1.2 Population perfectly elastic to rent

Proposition 2: If $\mu \to \infty$, then the contribution of location demand is

$$\text{Location Demand Channel} = -\frac{Cov(d\log r_i, \sigma_i)}{\bar{\sigma} + \lambda}$$

where the covariance is initial-population-weighted, and $\bar{\sigma} \equiv \mathbb{E}\sigma_i$ which is also initial-population weighted.

In this case, the key covariance for quantifying the location demand channel is the change in local rents and housing supply elasticity. If rents rise comparatively more in housing inelastic areas, then aggregate rents must rise to make sure enough housing is produced for everyone to have a place to live. This is reflected in the intuition given in the introduction—if one person moves from an elastic to an inelastic place, then rents must rise on average.

This is the case of Rosen (1979) and Roback (1982), with perfect mobility. Any changes in desirability of a place will be reflected in local rents. The housing supply elasticity, along with the local housing demand elasticity, will then determine how much the population will change in response to those rents.

In this situation, which will be our preferred specification later on, the theory provides a key link between cross-sectional relationships and aggregate effects. When $\mu \to \infty$, $d\log r_i$ is the same as $\frac{\eta_i}{\mu}$. So the equation in Proposition 2 provides a framework to consider the effects of a cross-sectional effect on the aggregate. This micro-to-macro approach rests on the national population-adding-up condition, which is the basis for proving the proposition.

1.1.3 Intermediate elasticities

Proposition 3: For intermediate values of μ, the contribution of location demand is

$$\text{Location Demand Channel} = \frac{Cov\left(d\log L_i, \frac{1}{\sigma_i+\mu+\lambda}\right) - Cov\left(d\log r_i, \frac{\sigma_i+\lambda}{\sigma_i+\mu+\lambda}\right)}{\mathbb{E}\frac{\sigma_i+\lambda}{\sigma_i+\mu+\lambda}}$$

The limits for this as μ goes to 0 or ∞ correspond to our previous formulas. The formula here is a bit more opaque and in general depends on both the covariance of populations with elasticity as well as the covariance of rents. In the next section, we examine what values the location demand channel takes in the data for various μ's and λ's based on this formula.

1.2 Policy Implications

We can use our model to understand the equilibrium effects of counterfactuals. The most policy-relevant questions surround housing supply. In the case of housing supply, the first-order welfare effects for the agents are proportional to the change in average rents, since the effects on the location of workers has only second-order effects by a standard envelope argument. So it suffices to concentrate on the effects on rent. There are also going to be effects on the welfare of landowners, but they will depend on the nature of the housing supply changes, which is outside our model.

A common policy suggestion to make housing more affordable is to expand housing supply. In our model, this corresponds to an increase in ξ_i.[31] Changing ξ_i in one small city has the effect:

$$d \log r_i = -\frac{\xi_i}{\sigma_i + \mu + \lambda}$$

assuming the city is too small to have an effect on $d\tilde{u}$. These effects are decreasing in housing supply elasticity (σ_i), population elasticity (μ) and housing demand elasticity (λ).

We also want to consider a shock to several ξ_i that has an effect on the general equilibrium. In this case, the effect is given by

$$\mathbb{E} d \log r_i = -\frac{\mathbb{E}\frac{\xi_i}{\sigma_i+\lambda+\mu}}{\mathbb{E}\frac{\sigma_i+\lambda}{\sigma_i+\lambda+\mu}}$$

[31] A common result in the urban literature is that changes in regulation actually affect the housing supply elasticity, but are not a shock to the housing supply. If housing supply elasticity changes from σ_i to σ_i', our model will interpret $(\sigma_i' - \sigma_i) d \log r_i$ as a housing supply shock, ξ_i. The propositions hold under this alternate interpretation. However, we will miss second-order effects: for example, a location demand shock combined with a change in the housing supply elasticity.

For a finite population elasticity, expanding housing has a larger general equilibrium effect if it expands in low-housing-supply-elasticity places. If population elasticity is very large (i.e. $\mu \to \infty$), this formula reduces to $d\log r = -\frac{\mathbb{E}\xi_i}{\bar{\sigma}+\lambda}$.[32] In that case, the location of the housing supply increase is irrelevant for average rents. That does not mean the equilibrium is unchanged; people will locate in different cities. However, the rent change will be uniform across space and will not depend on where the additional housing is built.[33]

A second policy suggestion we consider is the subsidizing of rents. For example, the "Rent Relief Act" (S.3250) introduced by Senator Kamala Harris would subsidize the rents of low-income households above 30% of their incomes. We consider what would happen if rents in some areas are subsidized, financed by lump-sum taxation of the landowners. In this case, the equilibrium change in rents is

$$\mathbb{E}d\log r_i = -\frac{\mathbb{E}\frac{\tau_i\sigma_i}{\sigma_i+\lambda+\mu}}{\mathbb{E}\frac{\sigma_i+\lambda}{\sigma_i+\lambda+\mu}}$$

where τ_i is the percentage subsidy in city i. In this case, the subsidy times the local elasticity has the identical role to a housing supply increase. Again, if the population elasticity is large, the effect reduces to $-\frac{\mathbb{E}\tau_i\sigma_i}{\bar{\sigma}+\lambda}$. In that case, subsidizing rents in inelastic areas will have

[32] Note that this formula implies that if one city is perfectly housing-supply-elastic and agents are perfectly location-elastic, then housing supply does not affect the average rent.

[33] One exercise we will do later is to empirically evaluate the effects of observed housing supply changes over this time period. If we have data on the intensive margin of housing supply, we back out the shocks:

$$\xi_i = d\log H_i - \sigma_i d\log r_i = d\log h_i + d\log L_i - \sigma_i d\log r_i$$

Hence

$$\begin{aligned}\text{Housing Supply Channel} = -\frac{1}{\mathbb{E}\frac{\sigma_i+\lambda}{\sigma_i+\lambda+\mu}}\Bigg(&\mathbb{E}\left[\frac{1}{\sigma_i+\lambda+\mu}\right](\mathbb{E}d\log L + \mathbb{E}d\log h) \\ &+ Cov\left(\frac{1}{\sigma_i+\lambda+\mu}, d\log L_i\right) + Cov\left(\frac{1}{\sigma_i+\lambda+\mu}, d\log h_i\right) \\ &- \mathbb{E}\frac{\sigma_i}{\sigma_i+\lambda+\mu}\mathbb{E}d\log r_i - Cov\left(\frac{\sigma_i}{\sigma_i+\lambda+\mu}, d\log r_i\right)\Bigg)\end{aligned} \tag{13}$$

We measure almost all these things in the data. We see $d\log L_i$ in the Census, $d\log r_i$ from our rent series, and $\mathbb{E}d\log h$ from the AHS. We do not have high-quality data on $d\log h_i$. However, we can proxy for it with 2001-2013 changes. As $\mu \to \infty$, the empirically relevant case, the individual $d\log h_i$'s, which we measure poorly, do not matter. In that case all that matters is $\mathbb{E}d\log h_i$ which we measure reasonably well.

a smaller effect on average rents than subsidizing rents in elastic areas. In fact, regardless of the population elasticity, subsidizing rents in elastic areas will be more effective at lowering rents than in places that are inelastic. The reason is that subsidies will lead to more new construction in elastic areas than in inelastic areas, which lowers rents for everyone.

2 The Importance of Population Elasticity

To quantify the location demand channel's contribution to the rent increase of 2000-2018, we apply the formula derived in Proposition 3 to the data. The main takeaway from this section is that the size of the location demand channel will vary greatly depending on the calibration of the population elasticity μ.

2.1 Data

First, we collect data on population growth ($d \log L_i$), housing supply elasticities (σ_i), and rents ($d \log r_i$). We use this to quantify the location demand channel under a variety of assumptions about μ and λ which we take from the literature. Throughout, we use the MSA as our unit of analysis, primarily because the housing supply elasticities at this aggregation have already been estimated by Saiz (2010). Section 3 will show how we estimate μ in the data, which will be the basis of our preferred estimates. Appendix B describes the data sources in greater detail.

We create a new rent index based on the net operating incomes of commercial residential properties. The value-added of our series is that it is available for 217 MSAs, a much greater number than the 25 that the CPI collects.[34] This allows us to calculate how rents covary with elasticity for nearly the entire country, as required by our formulas. The source for this data is CMBS records provided by Trepp. We use an adapted repeat-sales methodology

[34]There are not many data sources for rents that cover more than a handful of MSAs back to 2000. The Census reports rents, but it is not quality-adjusted and there are relatively few variables with which to build a hedonic index. Importantly, if we cannot adjust for the quantity of housing as well as the quality, we are likely to measure $r_i \cdot h_i$, the rent times the amount of housing consumed. The repeat rent index avoids that.

in which we run a regression of log operating incomes on property and year fixed effects in each city, and use the year fixed effects as our city-specific index. In Appendix B, we describe the methodology in greater detail and show that it closely approximates the CPI rents in both the cross section and the time series. Throughout the paper, we present two versions of the rent index. First, we use our unadjusted rent numbers are based solely on the Trepp data. In addition, we improve power in some of our regressions by using an empirical Bayes methodology to shrink them using house price indices. For the majority of cities, this shrinkage makes very little difference, but it does matter for a few outliers that we know are noisily measured.[35] This also allows us to infer rents for the cities where NOI data is not available, so that we can use data from all 269 MSAs where elasticity is available. All of the results are consistent with either set of rent data. If not otherwise specified, statistics in the paper are based on the shrunken rent index. See Appendix B for details.

Housing supply elasticity comes from Saiz (2010). We take these elasticities as given and note that they are estimated using a time sample prior to the one in this paper.[36] Because these elasticities are available by 2000 MSA/Metropolitan Division, this is the basic unit of geography for the empirical estimates. We have to assign non-MSA regions an elasticity because our formulas rely on market-clearing conditions that would not apply if some regions of the country were dropped. We assign them a value of 5.35, which is equal to the 99th percentile of places with a measured elasticity because these regions are primarily small MSAs and non-MSAs with much lower population densities than areas covered by Saiz (2010).[37]

Our results on the importance of location demand do not depend on measuring housing quantity ($d \log h_i$). But for the contribution of housing supply, we need to measure this quantity. We use square footage per person, which we believe is a good proxy for h_i. The

[35]The median weight on the Trepp index we create is 87 percent, and the mean is 84 percent, so for most cities, the shrinkage is minimal.

[36]Other housing supply elasticity estimates are available in Quigley and Raphael (2005), Green, Malpezzi and Mayo (2005), Cosman, Davidoff and Williams (2018), Gorback and Keys (2020) and Baum-Snow and Han (2021). The Saiz (2010) are by far the most ubiquitous in the literature. We check the robustness of our key estimation using the elasticities from Gorback and Keys (2020).

[37]The estimates change very little when varying the value assigned to unmeasured places, for example by assigning them the 90th percentile of MSAs with a measured elasticity.

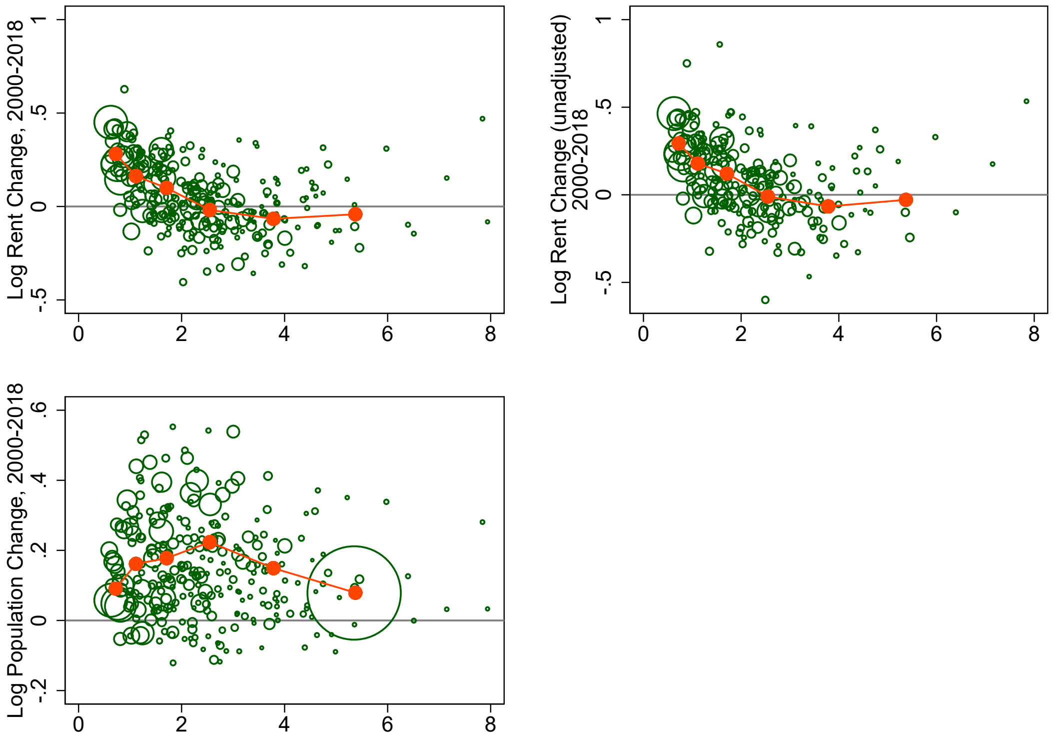


Figure 2: The relation of rent and population changes (y-axis) with housing supply elasticity from Saiz (2010) (x-axis). The size of the circle represents the MSA's 2000 population. The large circle in the bottom left panel represents all areas outside of MSAs. Averages across sextiles in orange.

important moments for $d \log h_i$ in equation (13) are the average national change in square footage per person and the covariance of this quantity with the (transformed) housing supply elasticity by MSA. We measure the former using published tables from the American Housing Survey (AHS) showing median square feet per person, 2001-2017. We calculate the latter ourselves from AHS micro data from 2001-2013. Post-2013 AHS public data does not include locations for most housing units, but we believe the 2001-2013 calculations are a good proxy given that the covariance term is close to zero. Appendix B describes the data in detail.

Given the previous theoretical results, the key moments in the data for quantifying the location demand channel will be how rent and population changes relate to housing supply elasticity. To get a sense of the data we plot these relationships in Figure 2. We show our constructed rent index in the top right, as well as the empirical-Bayes-adjusted rent index in the top left. The patterns are very similar, but there are fewer outliers in the shrunken version of our index. To non-parametrically show the trends, we plot the average change of six quantiles of elasticity.

The increase in rents is concentrated among the least elastic cities. For the least elastic sextile, rents increase by more than 29 log-points. But for each of the three most elastic sextiles, rent actually decreases slightly. For population, the change is hump-shaped, increasing most in areas with elasticity around 2 or 3. The patterns shown in these graphs mean that there is a high covariance between elasticity and rents or prices, but a lower covariance between elasticity and population. This difference will mean that the size of the location demand channel will depend on which covariance is more important for quantifying its effect.[38] A natural question is to what degree does the aggregate population changes hide heterogeneity. In Figure A.1 of Appendix A, we show that the same non-linear pattern holds for a number of subgroups of individuals: immigrants and non-immigrants, college educated and non-college educated, and renters and owners.

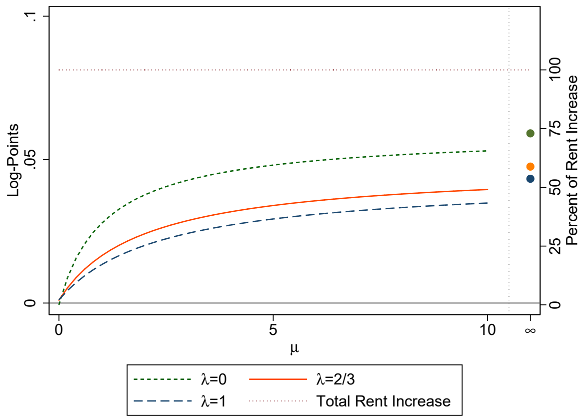
One key unmeasured data point is how much rent changes in areas that are outside of MSAs. Given that MSA rent changes are close to zero in the three most elastic quantiles, we will use a rent change of zero for the non-MSA areas as well.[39]

2.2 Estimates

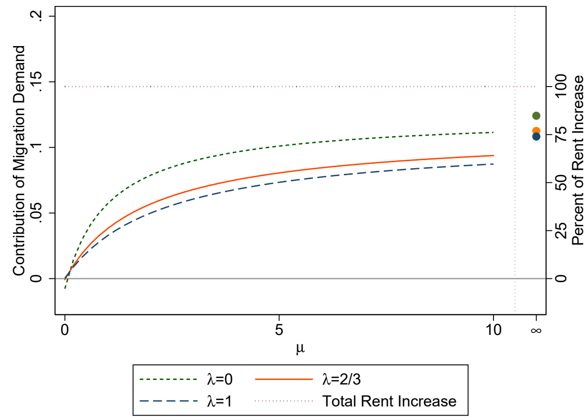
We plug the data into the formula given by Proposition 3 for a variety of values of μ and λ to show how the parameters change the strength of the location demand channel. The results are in Figure 3a. The dashed horizontal line at the top of the figure shows the realized total rent increase, and the solid lines show the total rent increase due to the location demand channel as implied by our formulas. We see that the effect is increasing in μ. The dots on the far-right side of the diagram show the rent increase predicted by $\mu = \infty$. Because μ

[38]For the interested reader, there is a statistically significant negative correlation between population changes and housing supply elasticity, consistent with what we showed in Figure 1. However, the relationship is clearly non-linear, and we think the best way to understand it is with the help of the model.

[39]When we look at house price changes in these areas, they are also close to zero.



(a) Overall Rents



(b) CPI-measured Rents

Figure 3: The contribution of location demand to the rise in rents

is important for determining the strength of the location demand channel, we provide new estimates for its value in the next section.

λ is the intensive-margin elasticity of housing demand with respect to rents. Albouy et al. (2016) estimates $\lambda = \frac{2}{3}$, which we adopt as our preferred estimate of λ. We also show results for $\lambda = 0$ which would suggest housing per capita is unaffected by rents, and $\lambda = 1$, which corresponds to Cobb-Douglass utility and is common in the literature. As shown in this figure, our results are not that sensitive to the intensive-margin housing demand elasticity. There is little economic difference between our baseline, $\lambda = \frac{2}{3}$, and the largest value used in the literature, $\lambda = 1$. $\lambda = 0$ gives a mildly larger role for location demand.

Given the prominence of rent changes measured in the consumer price index, we also focus on cities in which CPI-rents are measured, in Figure 3b.[40] The overall rise in rents is higher in these cities, but so is the percentage due to location demand, for most values of μ and λ. These cities, which are larger and denser than the average city in the U.S., in particular saw some of the biggest increases in location demand.

[40]We do not include urban Hawaii and urban Alaska because we do not measure rents in those places.

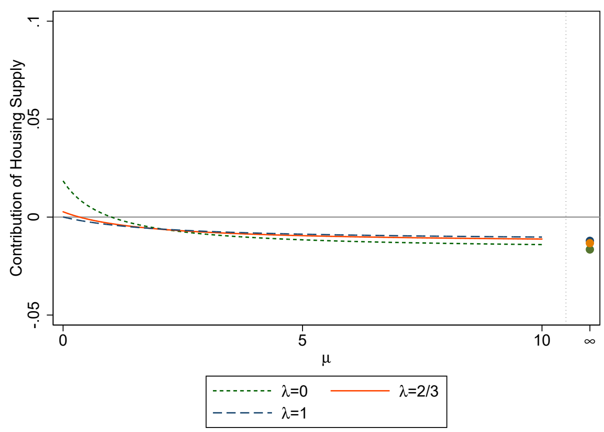


Figure 4: The contribution of housing supply shifts to the rise in rents

2.3 The Role of Housing Supply Changes

Given our estimates of the location demand channel, the rest of the the rent increase can be decomposed into housing supply, intensive-margin housing demand, and population increase. There is particular interest in the literature on housing supply, so we show here how its contribution depends on μ.

The housing supply shocks are close to mean-zero and have a positive correlation with elasticity.[41,42] We apply the formula from (13) to calculate the contribution of these shocks, presented in Figure 4. As we hinted above, these housing supply restrictions—which are concentrated in *ex ante* inelastic regions—have a larger effect on rents when neither mobility nor construction react very much. When people are fully mobile, the effect is close to zero and actually slightly negative. Overall, however, housing supply shocks play very little role in explaining housing prices. The reason for this is that changes in total housing quantities (that is, population changes times changes in square feet per person) are close to what one would expect given the changes in rents and the housing supply elasticities calculated using

[41] This finding confirms the finding in Ganong and Shoag (2017) that *ex ante* land use regulation correlates with increases in regulation over the course of the 20th century.

[42] When measuring this channel, changes in population are more important than changes in housing quantity per person. The latter are small and overall slightly negative from the years 2001-2017 (median square footage per person decreased from 720 to 700 according to published AHS tables). The covariance between changes in quantity per person and elasticity is close to zero.

historical data (Saiz, 2010).

3 Estimating the Population Elasticity to Rents

From the model, we know that the population elasticity is the key parameter for determining the importance of migration for the rise in rents. There are a large variety of estimates used in existing research, ranging from one-third to infinity. We collect a range of parameters used in the literature in Table 1 to illustrate.[43] For all of these parameters, the location demand channel is quantitatively important. Even using the Hsieh and Moretti (2019) parameters, for which we find the lowest effect of any papers' preferred parameters, the channel accounts for about 20 percent of the rent increase. Nonetheless, there is still a wide range, and we next estimate the parameter ourselves to improve the precision of our estimate.

The ideal way to estimate the parameter would be to identify exogenous shocks to housing supply, and use that as an instrument for rent changes. Typically, however, there are not large shocks in the data for which the identifying assumptions are plausible.[44] This approach *has* been successfully used to estimate the local, within-city effects of changes to housing supply (Mast, 2019; Asquith, Mast and Reed, 2021; Tricaud, 2021).[45] However, city-wide supply shocks which identify the aggregate population elasticity are harder to identify, which gives rise to alternative approaches used in the literature.

A typical way to calibrate this parameter is to estimate the effects of wage changes on population, and to multiply that number by the share of income spent on housing. The reasoning would be that if rents go up by one dollar, that should have the same marginal effect as if wages went up by one dollar by the envelope theorem. However, this strategy

[43] A related but distinct literature structurally estimates the mobility response to labor market shocks. Alongside Kennan and Walker (2011), recent research includes Oswald (2019) and Koşar, Ransom and Van der Klaauw (2021).

[44] We pursued this strategy using local votes to conserve land. While the results were suggestive of a large elasticity, the data was not conclusive.

[45] Anenberg and Kung (2018) also estimate a high μ within a city, using a more structural methodology. In their setting, a strong preference by particular agents to be in neighborhoods with specific characteristics – including potentially being around neighbors with particular demographics – would imply a low average elasticity of mobility with respect to rents.

Table 1: Effect of location demand for Various Parameter Combinations

Paper	μ	λ	Percent Explained Average	CPI
Suárez Serrato and Zidar (2016), lowest[a]	.34	1	8	9
Hsieh and Moretti (2019)[b]	1.07	1	17	23
Diamond (2016), College[c]	1.31	1	20	26
Diamond (2016), Non-College[c]	2.50	1	28	38
Suárez Serrato and Zidar (2016), highest[a]	5.1	1	36	50
Caliendo, Parro, Rossi-Hansberg and Sarte (2017)	∞	1	53	74
Albouy, Ehrlich and Liu (2016)[d]	∞	$2/3$	58	77
Van Nieuwerburgh and Weill (2010)	∞	$1/2$	61	79
Glaeser, Gyourko, Morales and Nathanson (2014)[e]	∞	0	73	85

[a] Suárez Serrato and Zidar (2016) provide a large range of estimates in Table 6 of their paper. To calculate the migration elasticity to rent, we take the inverse of their preference dispersion parameter and multiply by the housing share. We report the lowest and highest values from this procedure, corresponding to columns C(5) and B(2), respectively

[b] Hsieh and Moretti (2019) report the migration elasticity to wages as 1/0.3 and the share of housing at 0.32. We calculate their λ as the product of these two. Parkhomenko (2020) also uses this parameterization in his analysis.

[c] Diamond (2016) estimates separate elasticities for college and non-college graduates. We put them both here. These are from Column 3 of Table 4. These estimates impose a housing share of consumption, making them more similar to the strategy in Hsieh and Moretti (2019). Without imposing that, the elasticities estimated are slightly larger, closer to 3.

[d] Albouy et al. (2016) estimates λ using the assumption of free mobility, i.e. $\mu = \infty$.

[e] Glaeser et al. (2014) uses a congestion amenity which plays the same role as μ. They set it to infinity but acknowledge that they are not sure if people like or dislike more population.

could underestimate the population elasticity to rents because frictions to changing jobs and frictions to changing houses are likely different. For example, a positive shock in one industry may affect demand primarily for the small group of people in that industry, whereas a change in rents likely affects everyone that consumes housing.[46] In practice, approaches which require assumptions about the form of the utility function require both precise measurement of rents and knowledge about all the inputs to utility.

We take a less-restrictive approach, and use equation (12) to identify the elasticity. We look for heterogeneous effects of housing demand shocks on rents, by housing supply elas-

[46] A separate concern may be that the housing share of consumption may be hard to measure because it ought to include the effects of housing or other land prices as an intermediate for other consumption. This is one of the reasons there are many estimates in the literature.

ticity. This is a strategy similar to the one pursued by Saks (2008) and Diamond (2016). Equation (12) states that the effect of a local shock on local rents should be proportional to the inverse of the sum of the elasticity of housing supply, the elasticity of housing demand, and the population elasticity. The heterogeneous effects of a wage shock on rents across housing supply elasticities will give us an estimate of the population elasticity. To put it simply, if a wage shock has the same effect on rents in an elastic and an inelastic city, then the population elasticity must be high. If the wage shock has higher effects on rents in the inelastic city, then the population elasticity must be low. We can derive our regression specification by combining Equation (12) with the expression in Footnote 26.

Our approach departs somewhat from Saks (2008) and Diamond (2016). We consider a longer time horizon than Saks (2008). We relax the assumption in Diamond (2016) that unobserved labor demand shocks are uncorrelated with housing elasticity.[47] Our assumption is weaker: we require only that changes in unobserved demand shocks are not correlated to the interaction of housing supply elasticity and observed demand shocks. In practice this will mean controlling non-parametrically for housing elasticity in our estimates.

Why not structurally estimate the model instead? Using our approach, we are not using information that we have on housing quantities or population, which could be helpful. There are two reasons not to use housing quantities: first, conditional on the other variables, quantities help us distinguish between local housing demand and supply, but have no information about location demand; and second, we think they are particularly noisily measured (see Appendix B). We will use population, but to do model validation, rather than using it in estimation.[48]

[47] Diamond (2016) explains that "the exclusion restriction assumes that the level of land-unavailability and land use regulation are uncorrelated with unobserved local productivity changes." Later, she also explains the identifying assumption that "housing supply elasticity characteristics are independent of changes in local exogenous amenities."

[48] Housing supply elasticities from Saiz (2010) are likely noisily measured, and may have shrunk compared to the past (Ganong and Shoag, 2017). Checking the population predictions of the model post-estimation will give us a sense of how large these concerns should be.

To get a sense of our identifying variation, we run the following regression:

$$d \log r_i = \beta_0 d \log w_i + \beta_1 d \log w_i (\sigma_i - \bar{\sigma}) + f(\sigma_i) + \nu_i \tag{14}$$

where $d \log w_i$ is a measure of the 2000-2017 change in local wages, conditional on observables, from the American Community Survey,[49] and $f(\cdot)$ is a flexible function so that shocks correlated with elasticity are not influencing the regression. In practice, we control for ten equal-sized bins of elasticity and a linear control.[50] We demean the σ_i on β_1 in order to make β_0 interpretable as the effect of a wage change in an average-elasticity city.

The estimate for how much a wage shock affects the rent is given by $\beta_0 + \beta_1(\sigma_i - \bar{\sigma})$. A negative β_1 would indicate that wage shocks have less effect on rent in elastic areas, indicative that there is a small migration elasticity. A β_1 near zero would indicate that the elasticity is high because the effects are similar in both elastic and inelastic areas.

We present our estimates in Figure 5. The blue line graphs $\beta_0 + \beta_1(\sigma_i - \bar{\sigma})$, along with 90 percent confidence intervals. Using either unadjusted rents (right) or using empirical Bayesian shrinkage (left), the main result from the regression is that the blue line is flat; wage changes have similar effects on rents regardless of housing supply elasticity. This would suggest that the migration elasticity is close to infinite. The orange lines present the results from a different specification, in which we split our data into ten evenly-sized bins of elasticity, and within each bin, run a regression of rent changes on income changes. The orange dots show the estimated coefficient, and the lines are 90 percent confidence intervals.

[49] See details in Appendix B.

[50] One possible violation of our exclusion restriction would be the effect of agglomeration or congestion, but this effect is likely to be small. In places with higher housing supply elasticity, more people will end up moving in in response to an income shock (see Figure 6). That could generate a correlation between unmeasured shocks to rent (e.g. congestion or agglomeration) and the interaction of the income shock and the elasticity. The reason this would be small is that the amount cities grow in response to a 1 percent income shock differs only by about 1 percent between the most and least elastic cities, so the agglomeration or congestion change in response to a 1 percent change in the population would have to be quite large to significantly bias our results. For example, if all the wage-density relationship is the causal effect of agglomeration economies, that would suggest an increase of 1 percent in population would raise wages by 0.01 percent (Glaeser, 2010), an order of magnitude smaller than our measurement error. While measures for amenities are harder to pin down, we find it unlikely that a 1 percent change in population has effects large enough to worry us for these regressions.

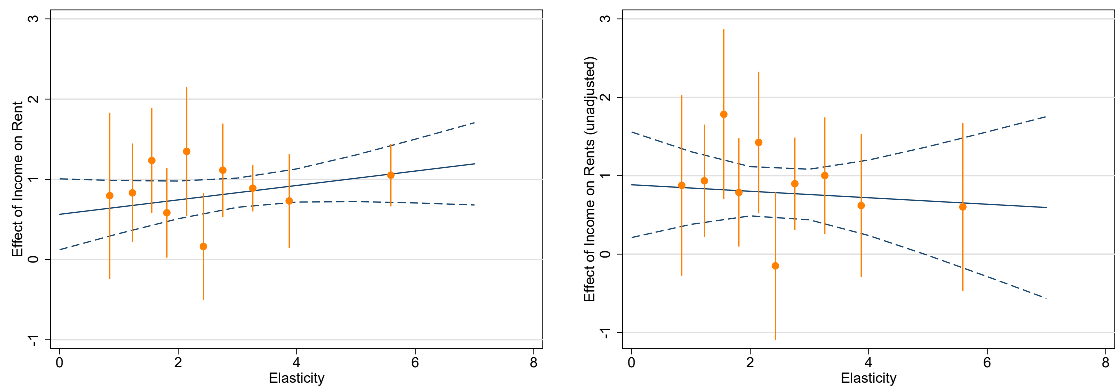


Figure 5: The effect of wage changes on rent, for different elasticities, with 90 percent confidence intervals

These results confirm the previous regression: the effects of income changes seem roughly constant across elasticities.

Given the flat line, a linear approximation to equation (12) is reasonable:

$$d\log r_i = \frac{\text{shock}_i}{\lambda+\mu+\sigma_i} \approx \frac{\text{shock}_i}{\lambda+\mu+\bar{\sigma}} - \frac{\text{shock}_i}{(\lambda+\mu+\bar{\sigma})^2}(\sigma_i-\bar{\sigma}) \equiv \beta_0 + \beta_1(\sigma_i-\bar{\sigma})$$

We can then estimate $\mu+\lambda+\bar{\sigma} = -\frac{\beta_0}{\beta_1}$.[51] For a non-negative β_1, our point estimate would be infinity.

Table 2 shows estimates of β_0 and β_1. We check the robustness using two plausibly-exogenous variables that affect local incomes. The decline in manufacturing was a widespread shock that decreased incomes in many regions, and so in columns (2) and (5) we use the manufacturing share as a proxy for the extent of this shock.[52] Columns (3) and (6) use a shift-share (or "Bartik", following Bartik (1991)) shock that predicts local job growth using the interaction of local labor shares and industry-specific wage growth in other regions. The

[51]Note that the scale of the "shock" depends on μ, so if $\mu \to \infty$, β_0 and β_1 do not converge to zero.

[52]The manufacturing shock provides two benefits relative to using the Bartik shock alone. First, the reasons for manufacturing decline are well-studied in the labor economics literature so this shock is more transparent than the Bartik shock. Reasons for the decline in manufacturing employment, which led to lower labor participation in high-manufacturing areas, include import competition with China (Autor, Dorn and Hanson, 2013) and greater use or robots (Acemoglu and Restrepo, 2020). Second, timing of manufacturing job losses coincided generally with the timing of the 2000s housing boom. The degree to which these two phenomena are interrelated is independently interesting.

Table 2: The Heterogeneous Effects of Income Changes on Housing Costs, by Elasticity

	(1) Rent	(2) Rent	(3) Rent	(4) Raw Rent	(5) Raw Rent	(6) Raw Rent
Income Change	0.792***			0.780***		
	(0.121)			(0.179)		
Income Change by Elasticity	0.0898			-0.0414		
	(0.0767)			(0.150)		
Manufacturing Share		-0.734***			-0.821***	
		(0.158)			(0.232)	
Manufacturing Share by Elasticity		-0.109			-0.229	
		(0.107)			(0.151)	
Bartik Shock			3.440***			4.033***
			(0.624)			(0.989)
Bartik by Elast.			0.742			0.680
			(0.466)			(0.717)
Observations	269	269	269	217	217	217
Controls	X	X	X	X	X	X

Standard errors in parentheses

Robust standard errors. Specifications include controls for deciles of elasticity and a linear control.

* $p < .1$, ** $p < .05$, *** $p < .01$

shift-share purges shocks that might affect income and housing costs contemporaneously. Using these variables, we show that rent decreased in manufacturing-exposed areas, and rents increased in areas exposed to growing industries, but that these effects were also not that heterogeneous by elasticity.

Table 3 shows the implied μ's from the regression in Table 2, in the corresponding columns. They are constructed by dividing β_0 by β_1 and subtracting off our preferred value for λ, two-thirds, and the mean elasticity in our data, 2.31.[53] For those on which the sign of β_0 and β_1 is the same, the point-estimate of μ is infinity. In addition, we construct the tenth percentile of estimates via a bootstrap.[54] Drawing samples of our data, we run the same regression and get a distribution of estimated μ's.

Across all six specifications, our point-estimate of μ is infinity or extremely high, suggesting agents are highly mobile in response to changes in rent. Even at the tenth percentile,

[53]To adjust the estimates in Table 3 for a different λ, simply subtract the preferred λ and add two-thirds.

[54]We use 1000 bootstrap samples. The bootstrap is known to be conservative when parameters are at their boundaries.

Table 3: Implied μ's from Heterogeneous Effects Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Implied μ	∞	∞	∞	15.6	∞	∞
10th Percentile of $\hat{\mu}$	62	20	84	0	21	0.75

the estimates of μ are on the higher end of the literature, suggesting highly mobile agents. The exceptions are the results from Columns (4) and (6), where the regression is noisily estimated because we use the non-shrunk rents series. Given these results, our preferred estimate of μ is infinity, meaning that location demand plays a large role in explaining the rise in rents since 2000.

To ensure that the estimates in Table 2 are robustly estimated, Table A.1 in Appendix A shows estimates using more controls and independent variables. Columns 1-2 and 4-5 repeat the estimates in Table 2, adding controls for bins of unavailable land as well as elasticity.[55] Columns 3 and 6 of this table use alternative proxies for income growth, instead of the overall income shock and the manufacturing share. Specifically, we measure income by aggregating a broader range of income-related variables into a single measure using principal components analysis (PCA). Appendix C will use the PCA measure to study the causes of changing locational demand and describes which variables are used to create it. The values of μ implied by these specifications, shown in Table A.2 of Appendix A, are uniformly large. In Columns 7-8, we use the elasticity measure from Gorback and Keys (2020).[56]

Finally, in Columns 9-10 we exploit two components of the Saiz housing supply elasticity—the Wharton Regulatory Land Use Index (WRLURI) and the amount of land unavailable for development—to help deal with measurement error in elasticity. We consider these two variables as noisily-measured proxies for the true elasticity and use one as an instrument for the other to help deal with measurement error.[57]

[55] The unavailable land measure is from Saiz (2010).

[56] This elasticity has few large, negative values, which we set to zero prior to estimation. This measure is available for a much smaller sample of MSAs than the Saiz measure, so we prefer the Saiz measure for our main specifications.

[57] We first scale the WRLURI by projecting the Saiz elasticity onto it. We interact this with income changes in each area to create a version of the elasticity-income shock interaction. Our specification instru-

A major contrast to the previous literature, especially Diamond (2016), is our choice of control variables. Specifically, we flexibly control for housing supply elasticity, whereas such controls are absent from her model. Davidoff (2016) argues that housing supply elasticity is correlated with regional productivity, which could have a direct effect on housing demand. In fact, any channel along these lines is exactly the sort of causal mechanism we are considering in this paper. Therefore, our preferred estimates control flexibly for this elasticity. Appendix Table A.3 estimates μ using specifications that do not have elasticity controls. The estimated μ from these specifications is smaller and more in line with findings from previous papers such as Diamond (2016).

With the previous theoretical results, and our preferred estimate of $\mu = \infty$, we conclude that the location demand channel is responsible for the majority of the increase in rents from 2000-2018. For the full set of cities in the sample, we calculate that the location demand channel causes a rent increase of 4.8 log points, which is 58% of the overall rent increase. For the cities where CPI is defined, we find that the location demand channel causes a 10.8% rent increase or 77% of the overall increase in CPI-rents.

The significant role of location demand is robust to the uncertainty from our regression and over the calibration of the housing demand. Recall from Table 1 that if $\lambda = 0$ and $\mu = \infty$, the channel is 6 log points, and if $\lambda = 1$ and $\mu = \infty$, the channel is 4 log points, which are of similar magnitude to our baseline. We can also directly bootstrap the location demand channel to account for uncertainty in μ: At the tenth percentile of the bootstrap distribution, where $\mu = 62$, the geography channel is 4.6 log points, nearly as large as the median. For cities where CPI-rents are defined, the geography channel is 4.6 log points at the 10th percentile (74%, close to the median value). Even at the 5th percentile, where $\mu = 17$, the geography channel is 4.2 log points, which explains 52% of the rise in rents overall. Using the raw rent measure, which is not shrunk towards house price changes, leads to more uncertainty, but the point-estimate is consistent with our baseline finding. As Figures 3a

ments for this interaction uses the interaction of the amount of unavailable land times the Bartik shock.

and 3b show, these estimates are not affected much by varying the choice of λ. We conclude that regardless of prior beliefs on λ and statistical uncertainty of μ, the location demand channel is explaining a significant chunk of the increase in rents.

3.1 Model Validation

Given our estimate of high mobility, our model predicts that population should be more responsive to a location demand shock in more housing-supply-elastic areas. From the model,

$$d \log L_i = (\sigma_i + \lambda) d \log r_i + \xi_i - \epsilon_i$$

We showed that the effect of our shocks on rents was positive and uniform across elasticities. And our identification assumption was that the correlation of our shocks with ξ_i and ϵ_i was the same across elasticities.[58] So the effect of our shocks should be increasing in the housing supply elasticity. We can show this using the same regression as (14). This is shown in Figure 6. Indeed, we find that the effect of the income shock on population is increasing in housing supply elasticity. While the results qualitatively support our model, the slope of the line in Figure 6, 0.2, is smaller than our theory predicts, about 0.8. This is primarily driven by the most housing-supply-elastic places; over the least elastic seventy-five percent of cities, the strength of the relationship is consistent with our theoretical prediction. We think there are two possible reasons we see a smaller slope. One is that housing supply might be noisily measured, leading to attenuation bias. Another is that housing supply has become less elastic, a la Ganong and Shoag (2017). We find both of these explanations plausible.

Neither of these possibilities would substantially affect our previous estimation of μ. Comparing the model-implied and empirical slopes provides an estimate of how large either of these concerns should be. The two concerns together lower the slope by about three-

[58] Almost certainly, the correlation with ϵ_i, the housing demand shock, is positive, but as long as the correlation is the same for different housing supply elasticities, it should not be a problem. This does mean that we can make predictions on the slope of the relationship, but not the level.

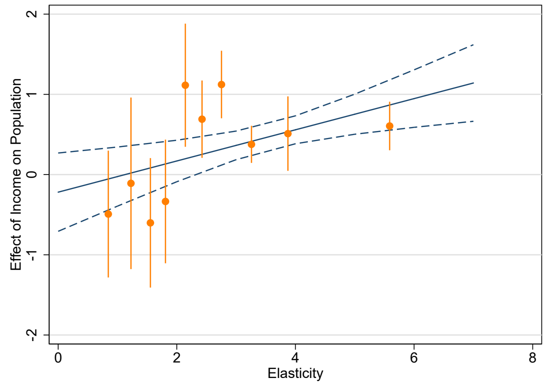


Figure 6: The effect of wage changes on population, for different elasticities

quarters. Attenuation in the x-variable of a regression proportionally lowers the regression coefficient. Quadrupling β_1, which is a fairly precise zero, is still zero. Similarly, if the true housing supply elasticity is about a fourth of the real ones, the correct adjustment would be to quadruple β_1, and we would still get a fairly precise zero. Quadrupling would not change our point-estimate for μ at all. The tenth percentile would be closer to 10, which still leads to a very high location demand channel contribution.[59]

In addition to this argument, we also investigate the role of measurement error in biasing our estimate by instrumenting one component of the Saiz (2010) elasticity, the unavailable land, with another, the amount of regulation. This strategy can be found in Appendix Table A.1 and still leads to a high estimate of μ.

Another way of validating the model is to ask whether observable drivers of demand changes match up with the demand shifts implied by the results. In Appendix C, we show that proxies for labor market conditions and amenity growth strongly covary with housing supply elasticity. Then, using the formulas from our model, we quantify the fraction of the location demand channel explained by these factors. We show that a combination of labor-market and amenities changes can explain most of the location demand channel.

[59]Similarly, measurement error or smaller housing supply elasticities will not greatly affect our estimate of the importance of the location demand channel. Our formula involves the covariance of supply elasticities and rents, so measurement error will add noise, but not bias. We also have housing supply elasticities in the numerator and the denominator, so it is approximately scale invariant.

Our estimate of μ, while not outside of values used in the literature, is at the upper-extreme and may be surprising to some readers. Importantly, our estimates do not show that everyone has infinite elasticity, only that there is some group that does. As long as such a group exists, the change in location demand will be reflected in rents regardless of elasticity. In Appendix E, we propose an extension of our model in which there are two groups of people, one of which never moves between cities. Nonetheless, when the other group is infinitely elastic, it acts to equalize utility between the cities, and the formula for calculating the location demand channel is exactly the same.[60] Previous literature has emphasized the heterogeneity in moving rates for different groups (Chen and Rosenthal, 2008; Molloy et al., 2011; Diamond, 2016).[61] We can think of μ as estimating the elasticity of the marginal group, which is in equilibrium more elastic than the average person's elasticity.[62]

Because we calculate a high μ, we can plug that into our formulas from before. We conclude that the location demand channel is responsible for more than half of the rent increase, and three-quarters of the rent increase measured by CPI.

4 Conclusions

The past several decades have seen the longest sustained increase in U.S. rents in the post-war period. This paper uses a spatial equilibrium framework of the national housing market to explain why. Our framework allows us to decompose aggregate rent increases into portions explained by changes in housing supply, changes in housing demand, and changes in where people want to live—the location demand channel.

[60]There is a small adjustment if the two groups consume different-sized housing. However, just the fact that one group consumes smaller housing would not be an issue. It would require that they consume smaller housing and are disproportionately represented in elastic regions. Even then the effect is likely small.

[61]In Figure A.1, we show that on various observable characteristics, the patterns of population changes look fairly similar. Nonetheless, there could very well be heterogeneity within demographic groups.

[62]A related concern is that our model abstracts from the rent-own margin. Also in Appendix E, we present a version of the model with both rental and owner-occupied housing. The lesson from that extension is that we might want to average the user cost of housing with the rents. While the use cost of housing is difficult to measure, Figure B.3b shows that house prices and rents are highly correlated, so we do not think this is a concern.

Our key finding is that the location demand channel explains the largest portion of the national increase in rents. Under our preferred parameterization, the location demand channel explains 54 percent of the rent increase in all U.S. cities and 75 percent of the rent increase where the CPI rents data exists. These estimates depend on an important unknown parameter: the elasticity of migration with respect to rents. Over the years 2000-2018, we estimate an elasticity of infinity, which corresponds to the parameters in the Rosen-Roback model. We also show that the location demand shocks correspond to increases in wages and amenities in the data.

Our estimate allows us to speak to the policy implications of changing housing supply. First, local expansions of housing supply will have negligible effects on local rents in the long-run. This is because the population elasticity is high, meaning that as more people move in, the marginal person values the housing just as much.[63] Second, national expansions of housing supply can have effects, but it does not matter for rents where the housing is built. A 10 percent housing supply increase will have the same effect whether it occurs in the most elastic or least elastic regions of the country (of the same population). Finally, subsidizing rent in inelastic cities has small effects on rents paid, whereas subsidies in elastic cities have large effects on rent everywhere. Using the formula from Section 1, a 10 percent subsidy in the 10 percent least elastic cities lower aggregate rents by 0.26 log-points, whereas a 10 percent subsidy in the 10 percent most elastic parts could reduce rents by 1.63 log-points, more than six times as large an effect.

Our research highlights the importance of the parameter μ for understanding changes in rents. While we think our estimate is an improvement over the existing literature, we hope to see more direct estimates, ideally capitalizing on natural experiments in housing supply.

[63]Each of these policy implications ignores any congestion and agglomeration effects. The literature is not sure of the net sign of these externalities.

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A Supplemental Figures and Tables

The figure below replicates Panel 3 of Figure 2 for various population subgroups. The figure shows the relation of population changes (y-axis) with housing supply elasticity (x-axis) for foreign-born individuals, US-born individuals, home-owners, renters, college-education individuals (with an associates degree or higher), and non-college-educated. The source for all subfigures is the 2000 decennial census and 2015-2019 5-year ACS (Ruggles, Flood, Goeken, Grover, Meyer, Pacas and Sobek, 2019).

The estimates in Table A.1 extend the specifications used to create Table 2. Columns (1), (2), (4) and (5) add control for deciles of land availability constructed in Saiz (2010), in addition to housing supply elasticity. In Columns (3) and (6) we use the first principal component of various labor market variables as the independent variable which we interact with elasticity. See Appendix C for details on the construction of this measure. In Columns (7) and (8) we use the elasticity measure created in Gorback and Keys (2020) and control for deciles of this measure as well as deciles of the Saiz elasticity.

In Columns (9) and (10) we use an instrumental variables strategy to control for measurement error in the Saiz elasticity. The Saiz elasticity is created by combining several variables, including the Wharton Regulatory Land Use Restriction Index and the fraction of unavailable land in each city. These two variables are correlated with the overall housing supply elasticity and with each other. In the specifications shown here, we consider them both as distinct but noisy measures of elasticity, with independent measurement errors. This means that we can use unavailable land × income growth as an instrument for WRLURI × income growth, after scaling WRLURI to be in the same units as elasticity.[64] These estimates are shown in Columns (9) and (10). The first stage F statistic is above 12 for both specifications.

Table A.2 shows the implied μ and 10th percentile lower bound from these specifications.

[64] We do this by regressing WRLURI on elasticity and taking the fitted values.

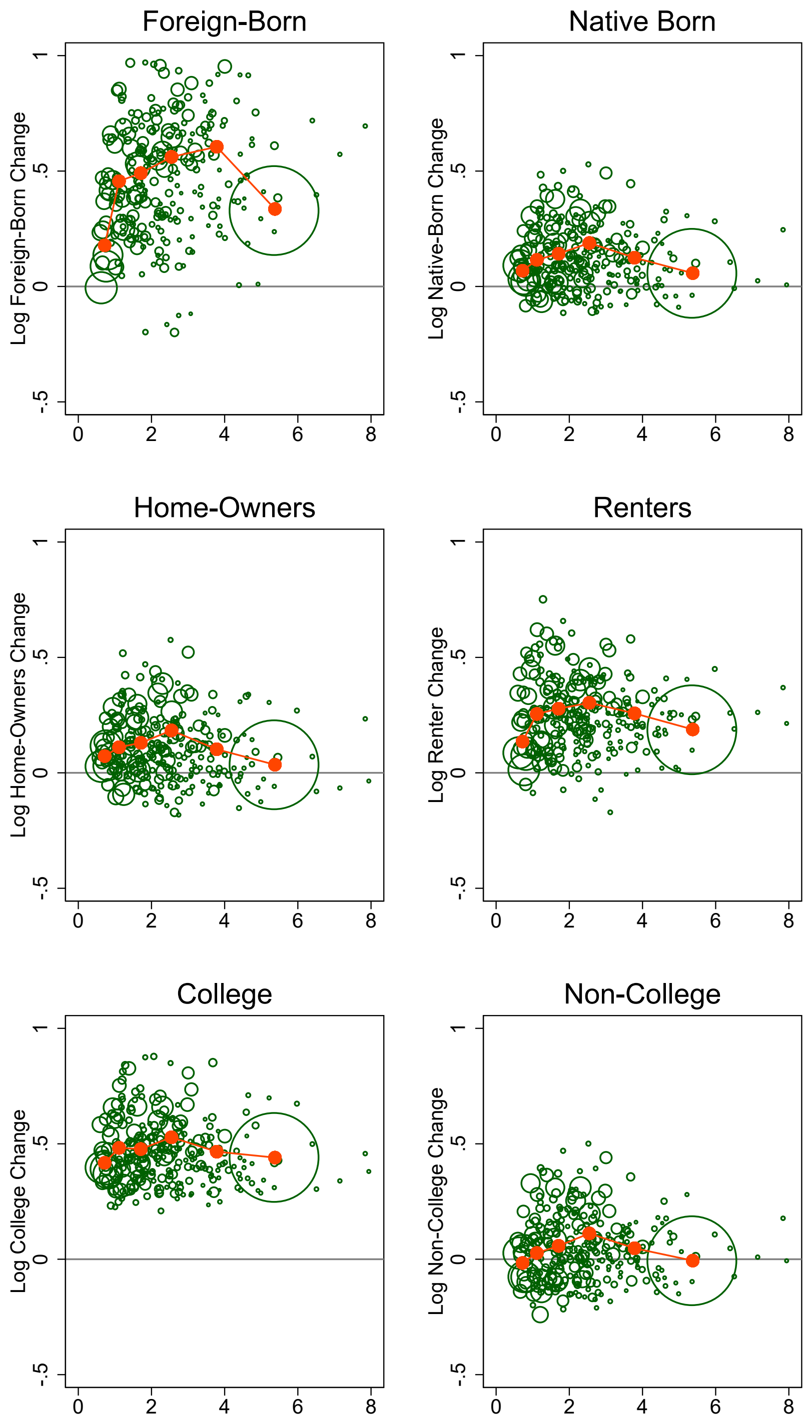


Figure A.1: The relation of rent and population changes (y-axis) with housing supply elasticity from Saiz (2010) (x-axis). The size of the circle represents the MSA's 2000 population. The large circle in the bottom left panel represents all areas outside of MSAs. Averages across sextiles in orange.

Table A.1: The Heterogeneous Effects of Income Changes on Housing Costs, by Elasticity (Alternative Measures)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Rent	Rent	Rent	Rent (undadjusted)	Rent (undadjusted)	Rent (undadjusted)	Rent	Rent (undadjusted)	Rent (IV)	Rent (unadjusted, IV)
Income Change	0.862***			0.875***			0.592**	0.606*	0.840***	0.833***
	(0.124)			(0.183)			(0.281)	(0.308)	(0.128)	(0.211)
Income Chg. by Elast.	0.0607			-0.0646						
	(0.0861)			(0.142)						
Manufacturing Share		-0.762***			-0.835***					
		(0.142)			(0.216)					
Mnf. Share by Elast.		-0.108			-0.252					
		(0.0924)			(0.166)					
PCA Employment			0.0192***			0.0151**				
			(0.00287)			(0.00635)				
PCA Emp by Elasticity			0.00458**			0.00572				
			(0.00201)			(0.00437)				
Gorback-Keys Elasticity							-0.0376	-0.0560		
							(0.0826)	(0.0906)		
Income Chg by Gorback-Keys Elast.							0.284	0.366		
							(0.435)	(0.477)		
Income Chg by Regulation									0.489**	0.454*
									(0.227)	(0.254)
Observations	269	269	267	217	217	216	103	103	269	217
Elast. Deciles	X	X	X	X	X	X	X	X	X	X
Unavail. Deciles	X	X		X	X				X	X
Gorback-Keys Elast.							X	X		

Standard errors in parentheses
Robust standard errors.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table A.2: Implied μ's from Heterogenous Effects Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Implied μ	∞	∞	∞	10	∞	∞	∞	∞	∞	∞
10th Percentile of $\hat{\mu}$	15	20	∞	0	149	22	0	0	∞	∞

Table A.3: The Heterogeneous Effects of Income Changes on Housing Costs (No Elasticity Control)

	(1) Rent (raw)	(2) Rent (raw)	(3) Rent (raw)	(4) Rent	(5) Rent	(6) Rent
Income Change	1.479***			1.410***		
	(0.266)			(0.172)		
Income Change by Elasticity	-0.223**			-0.180***		
	(0.0762)			(0.0477)		
Manufacturing Share		-0.216			-0.608*	
		(0.368)			(0.243)	
Manufacturing Share by Elasticity		-0.302***			-0.116*	
		(0.0882)			(0.0522)	
Bartik Shock			10.46***			9.466***
			(1.954)			(1.298)
Bartik by Elast.			-1.544			-1.353*
			(0.794)			(0.554)
Constant	-0.0980**	0.204***	-0.0627	-0.122***	0.183***	-0.0684**
	(0.0361)	(0.0328)	(0.0353)	(0.0237)	(0.0241)	(0.0229)
Observations	217	217	217	269	269	269

Standard errors in parentheses
Robust standard errors.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

B Data Sources

Our basic unit of observation is year-2000 MSAs and Metropolitan Divisions. This is because the Saiz (2010) elasticities are made available at this unit of geography. We either use data that is directly available at this level of geography or available by county. For county-level data, we correct for changes in FIPS codes that occur over time and use a correspondence file from the Missouri Census Data Center to transform this into MSA-level data.

Several data sources are not available for every MSA. These cases are noted below.

Table A.4: Implied μ's from Heterogenous Effects Regressions (No Elasticity Control)

	(1)	(2)	(3)	(4)	(5)	(6)
Implied μ	3.42	∞	1.46	4.6	∞	1.69
10th Percentile of $\hat{\mu}$	1.78	0	0	3.0	∞	0

B.1 Rents Index

B.1.1 Trepp NOI Rents Index Construction

To quantify the magnitude of the location demand channel, we require a rent index that is available for a large number of MSAs for the years 2000 and 2017. Existing rent indexes do not make this possible. The CPI-rents series (Consumer Price Index for All Urban Consumers–Rent of Primary Residence) is only available for a small number of MSAs, although we use it as a basis of comparison and a validation of the series we create. Other series, like the Fair Market Rents series from HUD and the rent index made available by Zillow, are either not available for many MSAs in the years we study or do not match the patterns we observe in the CPI-rents index.

When creating a rent index, our key concern is to measure rents by region in a way that controls for changing characteristics of the housing stock and changes in the sample over time. We create a repeat-observation index based on changes in rental incomes of multifamily residential property *within* property over time. This allows us to control for changes in the fixed characteristics of property over time. Furthermore, as we will show, it closely matches the CPI-rents series for the set of cities where both series are available.

Because our estimates are based on data from commercial properties, and because we observe within-building changes over time, our methodology is closest to the one in Ambrose, Coulson and Yoshida (2015). Indeed, our estimates are similar to the ones that they create, but we cannot use the series created by Ambrose et al. (2015) because it is available for very few cities in the year 2000.

Our rents index is based on data from commercial mortgage backed securities, provided by Trepp. We use the complete history of CMBS records collected by Trepp as of February

2019. These records include comprehensive information about commercial properties with a securitized mortgage. We limit the sample to multifamily properties used in single-property MBS loans. Following common practice for housing market indexes, we filter the data, limiting to observations with: Within-property growth in any year of less than 0.4 log points and above -0.3 log points; Property value at least $500,000; with at least 10 units.

We then assign properties to MSAs using the zip code-MSA correspondence file from the Missouri Census Data Center (geocorr). To create the MSA-level price indexes, we estimate the following regression specification using each city's sample of properties:

$$\log(NOI_{it}) = \sum_{\{t\}} \beta_t^m 1(Year = t) + \gamma Occupancy_{it} + \sum_{\{i\}} \delta_i 1(Property = i)$$

where i indexes properties, t indexes years, β_t^m is the fixed effect corresponding to MSA m in city t, and the δ_i coefficients are fixed effects estimates for each property. The omitted year is 2000 so all estimates are relative to their year-2000 values. NOI is the net operating income of each property, Occupancy is the occupancy rate. We estimate this specification separately for each MSA. The β_t^m terms are collected to create a repeat-rent index for each MSA. This procedure yields a NOI-based rent index for 217 of the MSAs/Metropolitan Divisions where we have housing supply elasticity data available.

This index is constructed slightly differently from a repeat-sales index, as it is estimated using a property fixed effect rather than in long-differences. In a setting with only two observations per property (which is typically true for much of the sample in repeat-sales estimates), the fixed effects and long-differences estimates are equivalent. However, we typically observe each property many times – we typically have one observation per year for each property – so we estimate a fixed effects regression instead.

To validate our index, we match the MSAs to CPI-rents data from the BEA for the MSAs where this is available. Figure B.1 is a scatterplot showing price growth in the BEA index by MSA against price growth in our index.

Because our index is created using a fixed effects regression, relative price changes across

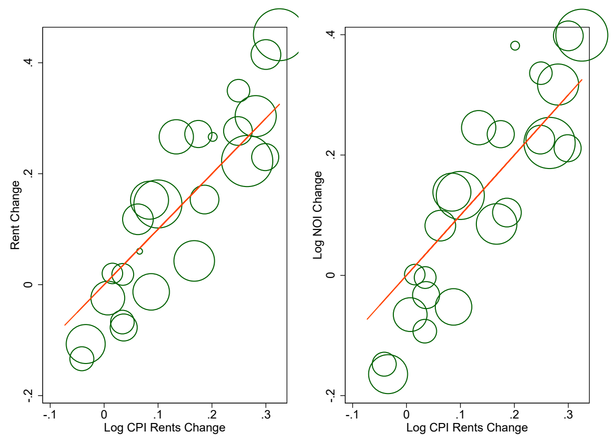


Figure B.1: Repeat-rent index change and CPI-rents change by MSA, 2000-2017. Left panel shows the unadjusted (raw) rents and the right panel shows rents after doing the Empirical Bayes adjustment. Circle sizes correspond to city populations.

MSAs are identified but, as always with repeat-sales indexes, average aggregate price changes are not identified and require a measure of depreciation. Therefore we adjust the aggregate price change from 2000-2017 to match the aggregate change in the CPI-rents over the entire time period 2000-2017. This matches the average value but does not have an effect on the relative values across cities.

After adjusting the overall growth rates to be the same in these series, we validate this approach by showing how the year-by-year fluctuations in our rent series match those in the BEA series for the same set of series. This is shown in figure B.2. The two measures correspond closely. The dip during the Great Recession is also a prominent feature of Ambrose et al. (2015).[65]

Due to sampling variance, there is probably some measurement error in the city-by-year rent index, as there would be with any price index. However, this measurement error should not affect our results due to the law of large numbers. The next subsection also describes an Empirical Bayes procedure which we use to reduce measurement error.

[65]While we are not sure about the reasons for the 2004-2008 disparity with CPI, it seems likely that rents on housing in our sample are more volatile than rents on housing overall. One reason might be that our properties are higher-turnover and so the rents are less sticky. Another possibility is that our properties were more hit by the financial crisis than others. Either of those explanations seems unlikely to bias our results which only use the estimated difference across 2000-2018.

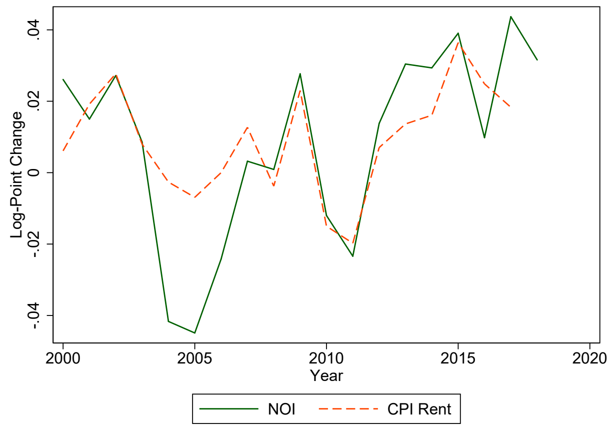


Figure B.2: The time series of net operating income and CPI rents

B.1.2 Empirical Bayes Shrinkage

While the NOI index in many of the cities is based on a large number of properties, some smaller MSAs have few properties available in the data. For these cities, the smaller number of properties implies that the rent index is measured with less certainty. To reduce the sampling variance of our estimates, we shrink the rent changes implied by the Trepp data towards a value implied by their house price changes. As we will show, this reduces mismeasurement of the rents index mostly by shrinking rents changes in places with few properties where there is high measurement error in our index.

The Empirical Bayes procedure we use follows the strategy in Chandra, Finkelstein, Sacarny and Syverson (2016). The methodology follows from two assumptions. First, the growth in the NOI index from 2000-2018 is an unbiased measure of the true rent growth but is measured with noise:

$$\Delta \log NOI_i = \Delta \log Rent_i + \varepsilon_i$$

where $\Delta \log Rent_i$ is the true, unobserved rent growth over the years 2000-2018, and where ε_i is mean-zero, independent of true rent growth, and $var(\varepsilon_i) = \sigma^2_{\varepsilon,i}$.

Second, rent growth in each city is a multiple of house price growth plus noise:

$$\Delta \log Rent_i = \beta \Delta \log HPI_i + \upsilon_i \tag{15}$$

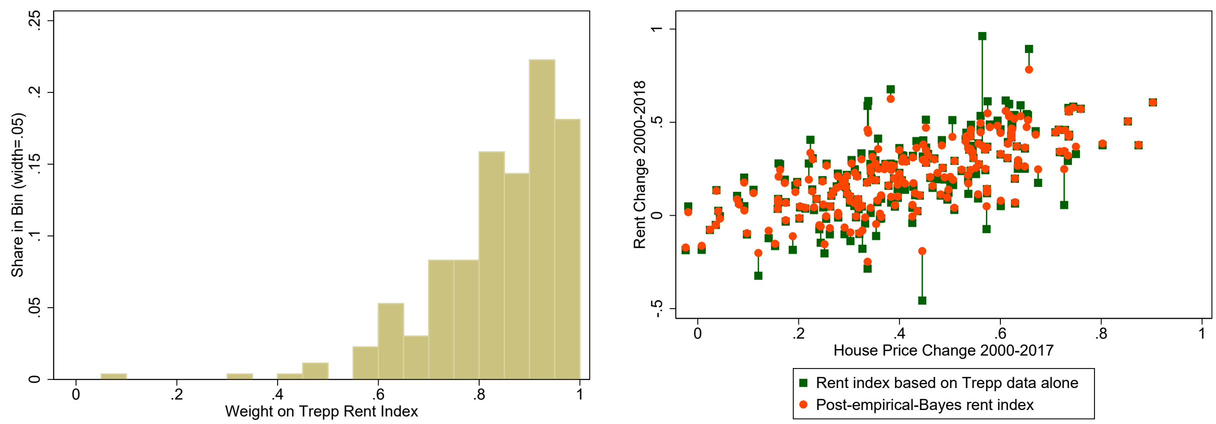
where υ_i is mean-zero, independent of true rent growth, $var(\upsilon_i) = \sigma_\upsilon^2$ and υ_i is independent of ε_i. These two assumptions imply that the minimum-MSE measure of $\Delta \log Rent_i$ is a weighted average of $\log NOI_i$ and $\Delta \log HPI_i$ divided by a constant, where the weights depend on the variance of the noise. The formula for our shrunken rent index is given by

$$\Delta \widehat{\log Rent}_i = \frac{\frac{\Delta \log NOI_i}{\sigma_{\varepsilon,i}^2} + \frac{\beta \Delta \log HPI_i}{\sigma_\upsilon^2}}{\frac{1}{\sigma_{\varepsilon,i}^2} + \frac{1}{\sigma_\upsilon^2}}$$

If we knew β, $\sigma_{\varepsilon,i}^2$ and σ_υ^2, we could plug them into this formula to arrive at the minimum-MSE estimate $\widehat{\Delta Rent}_i$. Instead, we estimate these from the data and plug in our estimates, which yields an estimate of the minimum-MSE rent index that is asymptotically the same as the optimal estimator. From our NOI index estimation procedure, we already have standard errors of the NOI index, and we use these for our estimate of $\sigma_{\varepsilon,i}^2$. To estimate β, we regress $\Delta \log NOI_i$ on $\Delta \log HPI_i$. The variance of the residuals from these estimates, minus the mean of $\sigma_{\varepsilon,i}^2$, is our estimate for σ_υ^2. We use $\beta \Delta \log HPI_i$ as an estimate of the rent for cities where NOI data is not available.

A potential concern with using the shrunken estimates is that they mostly use information from house prices. In practice, though, for most cities, there is not much shrinkage – the degree of shrinkage is only significant for the handful of cities where there are few properties. Figure B.3a is a histogram showing the weights on the Trepp NOI index by city. The mean weight on the NOI index is 0.84 and the median is 0.87, so most of the information is coming from NOI changes rather than house prices.

Figure B.3b shows the degree of shrinkage by city. Again, we can see that there are some cities that have extremely large or small values of the NOI index, where the shrinkage reduces measurement error. But for most cities, there is little shrinkage from the NOI index.



(a) Histogram of Weights on Trepp Rent Index (b) Shrinkage of Trepp Rent Index

Figure B.3: Trepp Rent Index Bayes Shrinkage

B.2 Housing Quantity Data

We measure the quantity of housing per person by MSA using data from the American Housing Survey. The total quantity of housing in each MSA is measured as the median square footage per person by MSA in the years 2001 and 2017. By multiplying this by the number of people per MSA, we calculate the total housing supply. Our formula also requires us to know the covariance between changes in housing supply per person and housing supply elasticity. We calculate this using AHS microdata from the years 2001-2013, since MSA identifiers are not available for most housing units after 2013.

To calculate the covariance between housing supply elasticity and changes in housing quantities, we measure median square feet per person by MSA using AHS microdata from the years 2001 and 2013. Calculations using the microdata follow the AHS methodology for calculating the published tables. We drop non-occupied units, units with no reported square footage, and units with no reported population. Then we calculate square footage per capita at the unit level, and take the weighted median square footage per capita by MSA. We do this in the same way for both the years 2001 and 2013.

We use the national median square footage per capita from 2001 and 2017 which we take from published tables.[66]

B.3 Other Data Sources

We use the development all-transactions county-level house price index produced by the FHFA. We convert the county-level index to an MSA-level index by calculating the average log change at the county level, and merging this with a correspondence file from the Missouri Census Data Center. County growth rates are weighted by county population.

Population data comes from the 2000 Decennial Census and the 2017 Post-Censal estimates. We collect county-level data and correct changes in FIPS codes over time. We use a correpondence file from the Missouri Census Data Center to calculate populations for 2000 MSAs/Metropolitan Divisions.

Manufacturing shares are measured as of 2000 in the QCEW.

EPOP (employment to population ratio) is measured as the ratio of total employment (from the BLS Local Area Unemployment Statistics) to population (from census data, as described above).

C Measuring Locational Demand Changes

This Appendix decomposes the causes of aggregate rent changes using observable variables. Because labor market conditions and amenities are closely related and endogenously determined, we are not trying to make causal claims about which particular factors caused specific regions to become more desirable. Rather, we provide descriptive evidence that observable wage and amenity changes are consistent with the shocks we found to be important in the model. We then consider whether the magnitudes of the location demand channel are consistent with the size of these changes.

[66] These are available at: `https://www.census.gov/content/dam/Census/programs-surveys/ahs/data/2001/h150-01.pdf` and `https://www.census.gov/programs-surveys/ahs/data/interactive/ahstablecreator.html?s_areas=00000&s_year=2017&s_tablename=TABLE2&s_bygroup1=1&s_bygroup2=1&s_filtergroup1=1&s_filtergroup2=1` .

We first show that the relationship between elasticity and both amenities and labor market changes is qualitatively similar to the relationship of rents and elasticity. We begin our analysis by studying an index of amenities changes and an index of the labor market. We create these by taking the first principal component of a large set of labor market or amenity variables that we pull from various data sources.

We create an index of amenities changes at the MSA level that extends the index in Diamond (2016) to when the most recent data is available. The index uses several components of urban amenities, including education, environmental quality, crime, labor market conditions, retail establishments and public transit provision. In addition, we include January temperature.[67] We then take the first principal component of these variables. This follows the methodology in Diamond (2016).[68]

Similarly, we take a large set of labor market changes, such as wage changes at different parts of the distribution and employment-to-population ratio changes, and take the first principal component.[69]

Figure C.1 is a binned scatter plot showing the relationship between the two indices and housing supply elasticity between 2000 and 2018. Throughout this section, we consider only MSAs for which we have a measure of rent changes. Both indices are highly correlated with elasticity, and both indices have an especially sharp increase for the very lowest elasticities. This pattern recalls the relationship between rents and elasticity shown non-parametrically

[67] People's preferences for January temperature have changed over time (Rappaport, 2009).

[68] See Appendix B for details. Diamond (2016) includes a categories of amenities called "jobs." Moving this category into the labor market category of variables does not change much.

To create the amenities index, we update the measure from Diamond (2016). We follow the methodology described in Diamond (2016) by first creating city-level indexes of school quality, retail establishments, public transit, parks, jobs, and crime. Each of these indexes is created by taking the first principal component of changes in relevant local variables over the years 2000-2018 (or whenever data is available). The overall index is created by taking the first principal component of the subindexes. The main difference between our methodology and the one in Diamond (2016) is that we do not have updated data on traffic and public transit provision. Instead, we use public transit spending per capita and employment in public transit.

[69] This is the full list of variables considered: demographically-adjusted log changes in wages for college-educated workers from the ACS, demographically-adjusted changes in wages for all workers from the ACS in logs and levels, changes in annual income in logs and levels from the IRS Statistics of Income database, changes in the employment-population ratio, mean hourly and annual income growth from the Occupational and Employment Statistics, and the 10th, 25th, 50th, 75th 90th percentiles of income from Occupational and Employment Statistics.

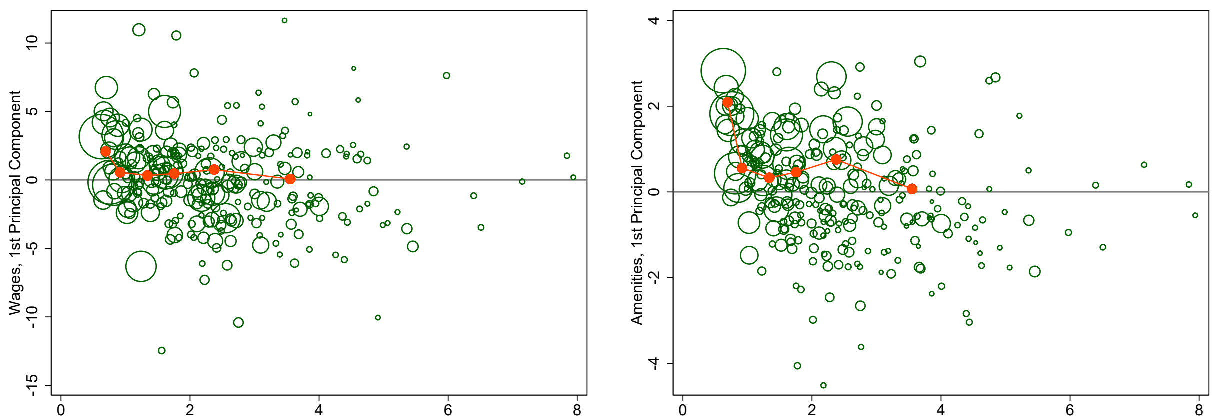


Figure C.1: The first principle component of amenity changes and wage changes. The size of the circles represents the MSA's 2000 population. Also included are the mean of points in sextiles by elasticity (orange).

in Figure 2.

The graphical evidence seems suggestive that the location demand shocks are consistent with labor market and/or amenity changes. We then turn to the structure of our model to make a quantitative assessment. For each index, we run a cross-sectional regression to project relative changes in rents onto the index in question. We take the fitted values from this regression, and we calculate the covariance of the fitted values with elasticity. This covariance, as a fraction of rent growth's covariance with elasticity, shows what fraction of the location demand channel is explained by that particular index. As the covariance approaches the covariance of rent growth, the index in question explain a greater part of the location demand channel.

As the figures above suggest, both the labor market index and the amenities index are negatively correlated with elasticity, so when rents are projected onto these variables, they will explain a substantial portion of the location demand channel. We do not just use these indices, though. By including more of the labor market or amenities measures in the first-stage regression at the same time, we can quantify the joint contribution of these variables. Given that wage changes and amenities are closely linked, any particular amenity or employment variable probably captures part of both effects. Therefore, we are more interested

Table C.1: Fraction Explained by Select Amenities and Labor Market Measures

Variables	Method	(1) Number of Regressors	(2) R^2 of rent changes	(3) Percent of Location Channel Explained
	Principal Component	1	0.21	0.28
Amenities	LASSO	6	0.32	0.40
	OLS	7	0.32	0.40
	Principal Component	1	0.33	0.30
Wages	LASSO	11	0.54	0.72
	OLS	18	0.55	0.72
	Principal Component	1	0.35	0.32
Both	LASSO	18	0.61	0.79
	OLS	25	0.62	0.79

in how much of the contribution we can explain with these variables than in disentangling the two effects. We are also more interested in assessing their overall contribution than measuring the effect of any particular wage or amenity-related variable.

For each group of variables, we take three approaches: First, we use the index shown in the previous figures, which is the first principal component; Second, we use LASSO to select a subset of the variables which we then use in a regression; Third, we use all the variables in a simple regression.[70] The R^2 column shows what percent of the variation in rents is explained by those variables, and the Percent of the Location Demand Channel Explained column shows what percent of the covariance of rents and elasticity is explained by these variables.[71]

The results of this exercise are shown in Table C.1. Alone, amenities can explain a non-trivial amount of the location demand channel. Using a principal component can explain

[70] There are 212 MSAs for which we have rents, so even in our most-saturated regression, there are still 187 degrees of freedom for the model. So while we show LASSO for robustness, we do not think that OLS is likely to overfit the rent changes.

[71] We calculate column (3) by dividing the covariance of the predicted rents and elasticity by the covariance of rents and elasticity, as described above.

about a quarter, and using LASSO or OLS can explain about a third. Labor market variables do better, explaining about a third with the principal component, or three-quarters with LASSO or OLS. Not surprisingly, taking the kitchen-sink approach does even better, explaining nearly 80 percent of the location demand channel. The fact that throughout, LASSO does about as equally well as OLS suggests that we are not overfitting rents by including all the variables. However, it does appear that there is important variation in the data to explain rents beyond the first principal component of each category.

Interestingly, we did not need to find a high R^2 in the rent measure to explain a large fraction of the location demand channel. This could be due to measurement error in the rents, or other unobserved migration shocks not strongly correlated with elasticity. But what we have shown is that the component of rents correlated with elasticity is fairly well-explained by these amenity and labor market variables.

C.1 Wages

As part of our wage indexes, we use measures of wages that adjust for demographic changes, both for all workers and for college-educated workers. To create these measures we use data on wages is from the 2000 5% Decennial Census sample and the ACS2017 1-year sample, downloaded from IPUMS (Ruggles et al., 2019).

First, we create a demography-adjusted measure of wages by PUMA (Public Use Microdata Area). To do this, we estimate the following regression specification:

$$\log(Wage_i) = \alpha RACE_i + \beta ETHNICITY_i + \gamma PUMA_i + \delta AGE_i$$

where RACE is a race fixed effect, ETHNICITY is a hispanic/non-hispanic fixed effect, AGE is a fixed effect for each possible age, and PUMA is a fixed effect for each PUMA. We do this for 2017 and 2000 using the appropriate PUMA for each census year. Estimates are weighted by household weight. The sample only uses observations for which a wage is available. The

PUMA fixed effects form our measure of regional wage levels.

Second, we use a correspondence file to create a common unit of observation for the wage measure, 2000 PUMAs. To do this we use a correspondence file for 2012 to 2000 PUMAs from the Missouri Census Data Center. Observations are weighted by the product of the household weight and the allocation factor.

Third, we use a correspondence file from the Missouri Census Data Center to create MSA-level wage measures from the 2000 PUMA measures. Again, we weight PUMAs by the product of the total household weight and the allocation factor from the correspondence file. We use the MSA-level measure to calculate 2000 to 2017 wage changes by MSA.

D Proofs

D.1 Proof of Proposition 1

If $\mu = 0$, then one solution for η's is: $\eta_i = d\log L_i$ and $d\tilde{u} = 0$. We wish to consider the counterfactual in which $\eta_i^* = 0$ for all i. In that case, equation (9) implies $d\log L_i^* = d\tilde{u}^*$, for all i. Plugging that into equation (11) implies that $d\log L_i^* = d\tilde{u}^* = d\log L$.

From (12), we see that $d\log r_i - d\log r_i^* = \frac{\eta_i - \eta_i^* - d\tilde{u} + d\tilde{u}^*}{\sigma_i + \lambda}$ which, plugging in values from above is $\frac{d\log L_i - d\log L}{\sigma_i + \lambda}$. Taking the expectation leads to

$$\mathbb{E}d\log r_i - \mathbb{E}d\log r_i^* = \mathbb{E}\left[(d\log L_i - \mathbb{E}d\log L_i)\frac{1}{\sigma_i + \lambda}\right] = Cov\left(d\log L_i, \frac{1}{\sigma_i + \lambda}\right)$$

□

D.2 Proof of Proposition 2

As $\mu \to \infty$, it is helpful to work with $\tilde{\eta}_i = \frac{1}{\mu}\eta_i$ and $d\tilde{\tilde{u}} = \frac{1}{\mu}\tilde{u}$. In this scenario, $\tilde{\eta}_i = d\log r_i + d\tilde{\tilde{u}}$. So $\mathbb{E}d\log r_i = \mathbb{E}\tilde{\eta}_i - d\tilde{\tilde{u}}$. In the counterfactual world, $\tilde{\eta}_i = 0$, so $\mathbb{E}d\log r_i^* = -d\tilde{\tilde{u}}^*$.

The change in population that comes from (7), (8), and (10) is $d\log L_i = (\sigma_i + \lambda)d\log r_i +$

$\xi_i + \epsilon_i$. To clear markets, it must be that $\mathbb{E}[(\sigma_i + \lambda) d \log r_i + \xi_i + \epsilon_i] = d \log L$. Rewriting this,

$$Cov(\sigma_i, d \log r_i) + \mathbb{E}[\sigma_i + \lambda]\mathbb{E} d \log r_i + \mathbb{E}[\xi_i + \epsilon_i] = d \log L$$

In the counterfactual world, there is no dispersion in $d \log r_i^*$, so the covariance term is zero:

$$\mathbb{E}[\sigma_i + \lambda]\mathbb{E} d \log r_i^* + \mathbb{E}[\xi_i + \epsilon_i] = d \log L$$

Simplifying,

$$\mathbb{E} d \log r_i - \mathbb{E} d \log r_i^* = -\frac{Cov(\sigma_i, d \log r_i)}{\mathbb{E}\sigma_i + \lambda}$$

$\square$

D.3 Proof of Proposition 3

From equation (12), and the fact that in the counterfactual, $\eta_i^* = 0$,

$$\mathbb{E} d \log r_i - \mathbb{E} d \log r_i^* = \mathbb{E}\frac{\eta_i - d\tilde{u} + d\tilde{u}^*}{\sigma_i + \mu + \lambda} = \mathbb{E}\left[\frac{1}{\sigma_i + \mu + \lambda}\right]\mathbb{E}[\eta_i - d\tilde{u} + d\tilde{u}^*] + Cov\left(\eta_i, \frac{1}{\sigma_i + \mu + \lambda}\right)$$

Similarly, from (9) and (11),

$$\mathbb{E} d \log r_i - \mathbb{E} d \log r_i^* = \frac{1}{\mu}\mathbb{E}[\eta_i - d\tilde{u} + d\tilde{u}^*]$$

Setting the two equations equal to each other gives us

$$\mathbb{E}[\eta_i - d\tilde{u} + d\tilde{u}^*] = \frac{Cov\left(\eta_i, \frac{1}{\sigma_i + \mu + \lambda}\right)}{\frac{1}{\mu} - \mathbb{E}\left[\frac{1}{\sigma_i + \mu + \lambda}\right]}$$

Multiplying both sides by $\frac{1}{\mu}$,

$$\mathbb{E}d\log r_i - \mathbb{E}d\log r_i^* = \frac{Cov\left(\eta_i, \frac{1}{\sigma_i+\mu+\lambda}\right)}{\mathbb{E}\left[\frac{\sigma_i+\lambda}{\sigma_i+\mu+\lambda}\right]}$$

Plugging in $\eta_i = d\log L_i + \mu d\log r_i + d\tilde{u}$, gives us

$$\mathbb{E}d\log r_i - \mathbb{E}d\log r_i^* = \frac{Cov\left(d\log L_i, \frac{1}{\sigma_i+\mu+\lambda}\right) - Cov\left(d\log r_i, \frac{\sigma_i+\lambda}{\sigma_i+\mu+\lambda}\right)}{\mathbb{E}\frac{\sigma_i+\lambda}{\sigma_i+\mu+\lambda}}$$

□

E Extensions

In these two extensions, we expand the model to include realistic features that were absent from our setup. We discuss how an expanded set of shocks will be interpreted in our model.

E.1 Inelastic Type

Do our results change when there are multiple types of agents or if some of the agents are less elastic than others? In this appendix, we consider an example with two types, one of which is completely unable to move. We find that adding a second type does not affect our results that much. When $\mu \to \infty$, as our empirical results suggest is the right parameterization, the formula is almost exactly the same, with a slight modification if the mobile type has a different-sized house, and when that different size varies with housing supply elasticity.

Assume there are two types of agents. One type of agent is perfectly inelastic in their location choice. The other has elasticity μ. The five main equations become

$$\begin{aligned}
d\log h_i &= -\lambda d\log r_i + \epsilon_i \\
d\log H_i &= \sigma_i d\log r_i + \xi_i \\
d\log L_i &= -\mu d\log r_i + \eta_i - d\tilde{u} \\
d\log H_i &= s_i d\log L_i + d\log h_i \\
d\log L &= \sum_i L_i d\log L_i = \mathbb{E}_w d\log L_i
\end{aligned}$$

where s_i is the housing share of mobile agents, and $1 - s_i$ is the share of perfectly immobile agents. $\mathbb{E}_w$ is the expected value, weighted by the population of mobile-type agents. We proceed the same way as proving Proposition 3:

$$(\sigma_i + \mu s_i + \lambda)d\log r_i = \epsilon_i - \zeta_i + s_i\eta_i - s_i du$$

Taking expectations and subtracting the counterfactual from the the location demand equation and the above equation:

$$\mu(\mathbb{E}_w d\log r_i - \mathbb{E}_w d\log r_i^*) = \mathbb{E}_w[\eta_i - du - du^*]$$

$$\begin{aligned}
\mathbb{E}_w d\log r_i - \mathbb{E}_w d\log r_i^* &= \mathbb{E}_w \frac{s_i\eta_i - s_i du + s_i du^*}{\sigma_i + \mu s_i + \lambda} \\
&= \mathbb{E}_w\left[\frac{s_i}{\sigma_i + \mu s_i + \lambda}\right]\mathbb{E}_w[\eta_i - du + du^*] + Cov_w\left(\eta_i, \frac{s_i}{\sigma_i + s_i\mu + \lambda}\right)
\end{aligned}$$

Combining equations gives us:

$$\mathbb{E}_w d\log r_i - \mathbb{E}_w d\log r_i^* = \frac{Cov_w(d\log L_i, \frac{s_i}{\sigma_i + s_i\mu + \lambda}) - Cov_w(d\log r_i, \frac{\sigma_i + \lambda}{\sigma_i + s_i\mu + \lambda})}{\mathbb{E}_w[\frac{\sigma_i + \lambda}{\sigma_i + s_i\mu + \lambda}]}$$

By a property of weighted covariances, we can rewrite this:[72]

$$\mathbb{E}d\log r_i - \mathbb{E}d\log r_i^* = \frac{\mathbb{E}w_i Cov_w(d\log L_i, \frac{s_i}{\sigma_i+s_i\mu+\lambda}) - Cov(d\log r_i, \frac{\sigma_i+\lambda}{\sigma_i+s_i\mu+\lambda}w_i)}{\mathbb{E}[\frac{\sigma_i+\lambda}{\sigma_i+s_i\mu+\lambda}w_i]}$$

This is the analog to Proposition 3. As $\mu \to \infty$,

$$\mathbb{E}d\log r_i - \mathbb{E}d\log r_i^* = -\frac{Cov(d\log r_i, (\sigma_i+\lambda)\frac{w_i}{s_i})}{\mathbb{E}[(\sigma_i+\lambda)\frac{w_i}{s_i}]}$$

If the population share, w_i is proportional to the housing share, s_i, this reduces to the same formula in the main text. To get a sense of how this adjustment might matter in the more general case, suppose that mobile agents consumed smaller houses. Then w_i/s_i would be large in places where immobile agents were a small percentage of the population, but close to 1 when they are a large percentage. If the mobile agents are more prominent in inelastic regions, we would want to adjust those elasticities down a bit.

Finally, we also are interested if the estimation in Section 3 still makes sense with multiple agents. Note that the effect of a wage shock on rent is now proportional to $\frac{1}{\sigma_i+\lambda+s_i\mu}$. If σ_i and s_i are independent, then having similar effects on elastic and inelastic cities would imply a μ of infinity. In theory, there may be distributions of s_i and σ_i such that the effects of a labor demand shock are equalized for a finite μ, but that would require a strong negative correlation between housing supply elasticity and the share of mobile agents, which we cannot think of any reason to expect.

E.2 Market Segmentation

Do our results change if there are multiple types of housing?

Suppose there is another market for housing, say owner-occupied housing. Denote this

[72]To see this, note that $Cov_w(x,y) = \frac{1}{\mathbb{E}w}Cov(x,yw) + \mathbb{E}_w y(\mathbb{E}x - \mathbb{E}_w x)$, where the w subscript indicates weighting by w.

housing as $\hat{h}_i$ in per capita terms, or $\hat{H}_i$ for the entire city. Call its user cost $\hat{r}_i$. Assume it is substitutable for the household with elasticity κ and substitutable for the producer with elasticity ϕ. Continue to assume that λ governs the elasticity of both types of housing if costs for both increase the same. And continue to assume that if prices of both types of housing increase the same, supply will increase with elasticity σ_i. Then

$$
\begin{aligned}
d\log h_i &= (-s\lambda - (1-s)\kappa) d\log r_i + (-(1-s)\lambda + (1-s)\kappa) d\log \hat{r}_i + \epsilon_i \\
d\log \hat{h}_i &= (-s\lambda + s\kappa) d\log r_i + (-(1-s)\lambda - s\kappa) d\log \hat{r}_i + \hat{\epsilon}_i \\
d\log H_i &= (s\sigma_i + (1-s)\phi) d\log r_i + ((1-s)\sigma_i - (1-s)\phi) d\log \hat{r}_i + \xi_i \\
d\log \hat{H}_i &= (s\sigma_i - s\phi) d\log r_i + ((1-s)\sigma_i + s\phi) d\log \hat{r}_i + \hat{\xi}_i \\
d\log H_i &= d\log h_i + d\log L \\
d\log \hat{H}_i &= d\log \hat{h}_i + d\log L
\end{aligned}
$$

where s is the share of housing expenditures on no-hat housing. This is seven unknowns and six equations, so we can reduce it to:

$$
d\log L = (\sigma_i + \lambda) d\log r + \left((1-s)(\sigma_i + \lambda) \frac{\epsilon_i - \hat{\epsilon}_i - \xi_i + \hat{\xi}_i}{\phi + \kappa} + s(\epsilon_i - \xi_i) + (1-s)(\hat{\epsilon}_i - \hat{\xi}_i) \right)
$$

This corresponds to a combination of (7), (8), and (10). Since we do not observe the different types of housing quality, relabeling the shocks will lead to exactly the same model. If the types of housing are sufficiently substitutable, then a positive shock to either type of housing, i.e. relaxed mortgage standards, will come across as a positive shock for both types of housing. If they are not substitutable, then such a shock could be negative.

Adding in another type of housing also affects the location demand equation:

$$
d\log L_i = -\mu s d\log r - \mu(1-s) d\log \hat{r} + \eta_i
$$

Using our previous equations, we can rewrite that as

$$d \log L_i = -\mu d \log r + \mu(1-s)\frac{\xi_i - \hat{\xi}_i - \epsilon_i + \hat{\epsilon}_i}{\phi + \kappa} + \eta_i$$

In this case, a differential shock across housing types, e.g., a change in lending standards a la Gete and Reher (2018), causes substitution between them. Effectively, it means $d \log r$ is not a complete measure of the housing costs faced by people or housing-producing firms. Our model interprets this mismeasurement as a shift in the location demand curve. Note that if ϕ or κ is large, i.e. there is a high degree of substitutability between types of housing, this shift is small.