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Housing supply and affordability: Evidence from rents, housing consumption and household location

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ABSTRACT

We examine the effects of housing supply constraints on housing affordability, which we measure directly using quality-adjusted rent as well as indirectly using structure sizes, lot sizes and household location choices. Empirically, we find that housing supply constraints have only modest effects on rents and housing consumption despite their larger effects on city growth and the price to purchase homes. Calibration of a dynamic, spatial equilibrium model shows that supply constraints increase price-rent ratios because investors expect future rents to increase more with expected demand growth. Because rent is what matters for affordability, supply constraints have reduced affordability less than is commonly understood despite their sizable effects on the purchase prices of homes.

1. Introduction

A large literature shows that housing supply constraints—strict zoning and permitting rules, as well as geographic barriers such as mountains and oceans—have driven up house prices over the last 40 years (*e.g.*, Glaeser and Gyourko 2003, Quigley and Raphael 2005, Ihlanfeldt 2007, Zabel and Dalton 2011, Hilber and Vermeulen 2016, and Albouy and Ehrlich 2018). In this paper, we assess the effect of supply constraints on quality-adjusted rents, housing consumption, and household location choices. Our estimated effects on these outcomes are significantly smaller than the effects of supply constraints on house price and city growth rates. Because rent is what matters for affordability, the effect of supply constraints on affordability is smaller than has been recognized in studies examining prices only.

Prior research has defined housing affordability in a variety of ways. In our view, the most appropriate measure of affordability is the quality-adjusted rent for a unit of housing services, since the consumption of housing services is the housing outcome that matters most directly for a consumer's welfare. The rent for housing services can be observed directly for renter-occupied housing units. However, rent cannot be observed directly for owner-occupied homes since owners pay for housing services indirectly through the cost of owning and maintaining their property. Observed rent of rental units serves as an imperfect proxy for the implicit rent of owner-occupied housing in the presence of segmentation between the two markets. Therefore, we also examine housing consumption and location decisions, as these choices are determined in part by the implicit rent of owner-occupied homes. As we discuss in Section 2.1, we do not measure affordability as rents relative to income because higher housing costs, *per se*, make consumers worse off.

We start by documenting the empirical relationship between housing supply constraints and housing affordability. Our empirical strategy exploits differences in regulatory and geographic constraints across metropolitan areas in the US. To reduce concerns about omitted variable bias we examine changes in housing market outcomes from the 1970–1980 period to 2000–2016. Our regressions control for housing demand growth at the metro level over this time, and we drop low-demand metros where supply constraints likely did not bind.

Our headline empirical result is that a one-standard-deviation increase in either a regulatory or a geographic supply constraint increases rents by less than 5 percentage points. These estimated effects are much smaller than the analogous effects on the value of homes, which are around 10 percentage points, implying that supply constraints increase price-rent ratios substantially. The rent effects are not only small relative to the price effects, but also small relative to the average rent growth over our analysis period, which is more than 10 times larger. They remain small when we restrict to metros without rent control, to households who moved recently, and to single-family homes or to 2-bedroom apartments. Consistent with these relatively small effects on rent, we also find only small effects of supply constraints on various measures of housing consumption, including structure size, lot size, structure type (single-family or multifamily), housing unit quality, and household size. These results strongly suggest that the effects of supply constraints on

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the implicit rent paid for housing services by owner-occupiers are also small.

As in prior studies (Mayer and Somerville 2000; Saks 2008; Jackson 2016) we do find large negative effects of regulatory and geographic constraints on the number of housing units in a metro area—that is, constraints lead cities to be smaller than they otherwise would be. However, we estimate small effects of supply constraints on sorting by income and education, which is surprising given that Gyourko et al. (2013) and Ganong and Shoag (2017) predict such sorting theoretically. Gyourko et al. (2013) find much stronger sorting by income into "superstar cities," places with both tight supply constraints and high demand growth. Our analysis suggests that supply constraints on their own have not caused most of the sorting observed in superstar cities, which reduces the scope for supply-side policies to ameliorate affordability problems in these superstar locations. We also examine location choices within metro areas to see if households offset high rent by choosing less-desirable neighborhoods. Geographic constraints skew new construction toward Census tracts with more crime and worse schools, but closer to the metro center. In contrast, the effect of regulatory constraints on most neighborhood amenities that we examine is small and statistically insignificant.

Why are effects on housing market outcomes related to affordability so much smaller than effects on the price to purchase homes? To answer this question, we calibrate a model in the spirit of Gyourko et al. (2013) in which households choose between living in a regulated and an unregulated city. We enrich their framework by including structure and lot sizes as outcomes, and by explicitly modeling dynamics to quantify the effects of supply constraints over a 30-year period. Consequently, the model illustrates how and why supply constraints affect house prices, rents, housing consumption, and household location. In our model, a supply constraint is a limit that the local government imposes on the growth of either the number of housing units or the land area of all housing units. By modeling constraints this way, we directly capture government-imposed limits on city growth without appealing to reduced-form specifications of housing supply. In the model, secular demand growth increases rents more when supply constraints are tighter because the constraints bind more over time. Since the price to purchase a home reflects expected future rent growth, supply constraints push up the ratio of house prices to current rent.

In our calibrated model, both constraints raise rents about half as much as prices over 30 years. Regulatory constraints have small effects on housing characteristics, as in the data, because households offset higher housing costs primarily through cutting non-housing consumption. Interestingly, the model predicts a much sharper decline in lot sizes from geographic constraints than what appears in the data, while under-predicting the magnitude of the effect of these constraints on city population. Factors outside our model, such as minimum lot size requirements or the durability of housing, may prevent households from reducing their lot consumption in practice. As a result, geographic constraints may be more costly to households than they are in our model.

To our knowledge, this paper is the first to systematically document that housing supply constraints have had only small effects on housing affordability in the US, using evidence on housing consumption and location choices in addition to evidence on rents. Some prior papers have demonstrated weak correlations between regulatory constraints and rents (Malpezzi, 1996; Malpezzi and Green, 1996; Green, 1999; Pendall, 2000; Somerville and Mayer, 2003; and Xing, Hartzell and Godschalk, 2006), but without discussing the implications for housing affordability. In more causal contexts, Schuetz (2009) finds little effect of multifamily zoning on median rents across towns in Massachusetts, while Severen and Plantiga (2018) find no effect of the California Coastal Act on multifamily rents in California. Other empirical research has studied effects on the ratio of prices to rents. Büchler, von Ehrlich, and Schöni (2019) and Hilber and Mense (2021) find that increases in demand result in large increases in the price-to-rent ratio in supply-constrained cities in Europe. Gyourko et al. (2013) document growth in the price-to-rent ratio in US cities with strong demand and tight supply, but do not speak to the magnitude of rent growth on its own.

In addition, we contribute to the literature by providing theoretical justification for why the effects we find are so small. Somerville and Mayer (2003) and Gyourko et al. (2013) present models that show how supply constraints increase rent, but neither paper offers a quantitative theoretical prediction, which is the focus of our model and necessary to understand the magnitudes of our empirical estimates.

2. Empirical strategy and data

2.1. Outcomes reflecting housing affordability

The term "housing affordability" is used in a variety of ways by researchers and policy analysts. We define housing affordability as the quality-adjusted rent for a unit of housing services.[1] By housing services, we mean the shelter and space (*e.g.* structure and lot size) as well as the access to local amenities (*e.g.* local schools, proximity to jobs) that a housing unit provides. We focus on the rent for housing services—and not the price to buy housing outright—because the consumption of housing services has a more direct effect on consumer welfare than property ownership.

Our definition of affordability does not normalize housing costs by income, which contrasts with the approach of some other researchers.[2] The rise in quality-adjusted rents, *per se*, makes households worse off regardless of income. Even if incomes rise the same amount as quality-adjusted rents, housing has still become less affordable according to our definition, because households are worse off than if incomes had risen but rents had not. Similarly, spending on housing can remain constant even as quality-adjusted rents rise if households reduce the size of the house they occupy or move to cheaper and less desirable locations.[3] In this case, our definition measures a decline in housing affordability, while an approach using housing expenditures normalized by income does not.

Our goal is to measure the causal effect of metro-level supply constraints on changes in housing affordability over the past several decades. Following our definition of affordability, we regress rent growth on metro-level supply constraints, controlling for physical characteristics of the housing units as well as changes in the value of amenities in the metro area. The purpose of the controls is to quality-adjust the sample of housing units for which we observe rent, which includes adjusting for differences in amenities that rents reflect.[4] By construction, the regression using rent data excludes owner-occupied housing since rents are only observed for renter-occupied housing. One possible way to measure the implicit rent of owner-occupied housing would be to estimate the cost of owning and maintaining a housing unit (as in Himmelberg, Mayer, and Sinai (2005)). However, certain elements of the user cost, such as depreciation and expectations of future house price growth, are difficult to observe in practice. Instead, we indirectly estimate the effects of supply constraints on the implicit rent for owner-occupied housing by examining how homeowners shift their consumption of housing and location choices, since an increase in the implicit rent should lead them to consume less housing or move to an area where the cost is lower.

[1] Another name for this concept is the spot price for a unit of housing services. We use "rent" in place of "spot price" to avoid confusion, as we compare rents to purchase prices throughout the paper.

[2] For example, Somerville and Mayer (2003) look at rent relative to area income, while Anthony (2018) and Bieri and Dawkins (2019) look at housing expenditures as a fraction of household income.

[3] Davis and Ortalo-Magné (2011) present a model in which this situation occurs.

[4] The metro controls also address the endogeneity of supply constraints, as we discuss in Section 2.2.

To measure changes in the consumption of physical housing characteristics, we regress changes in structure and lot size on metro-level supply constraints, controlling for changes in the value of metro amenities and for household income, since changes in income would independently affect housing consumption. In this exercise, our sample is single-family homes, most of which are owner-occupied. To measure changes in the location choices of households, we regress growth in metro population on supply constraints, controlling again for changes in the value of metro amenities. This regression captures the extent that some households would prefer to live in a metro area but choose to live elsewhere because supply constraints have raised the rent for housing services too much. We further examine population growth by income and education, as recent work has focused on the welfare losses of poor households who leave desirable areas due to housing costs (Favilukis et al., 2019; Bilal and Rossi-Hansberg 2021). We examine the consumption of local amenities (*e.g.*, crime and school quality) that vary within a metro by examining whether metro-level supply constraints induce households to shift to lower-amenity neighborhoods.

To map these estimates to changes in affordability, we develop a model in which house prices, rents, structure sizes, lot sizes, and household location all adjust endogenously to housing supply constraints. We calibrate the model using estimates of housing production and consumer utility functions that are consistent with existing research. The model quantifies the changes in rent, housing consumption and location that we should expect from a tightening of supply constraints that raises the purchase price of housing by a given amount. Therefore, the model connects the empirical results on housing consumption and location to our driving question, which is the effect of supply constraints on housing affordability.

2.2. Identification

Our goal is to estimate the effect of housing supply constraints on the housing outcomes described in Section 2.1. To do so, we exploit the large heterogeneity in regulatory and geographic constraints across metropolitan areas in the US. We cannot regress the outcomes of interest on supply constraints alone in the cross-section because the constraints correlate with other aspects of local housing markets that affect the outcomes (Saiz 2010; Davidoff 2016). This correlation might occur by chance, or productivity differences could cause differential growth in regulation across metro areas, as in Parkhomenko (2020). Therefore, we focus on changes in the outcomes over time—which controls for time-invariant factors that correlate with supply constraints—and we directly control for changes in productivity and the valuation of amenities. We write this identification strategy as:

$$Y_{imt} = \delta_m + \delta_t + \beta_z Z_{mt} + \beta_{x1} X_{mt} + \beta_{x2} X_{it} + \varepsilon_{imt}, \tag{1}$$

where Y_{imt} is an outcome for household i in metro m at time t, δ_m is a metro dummy, δ_t is a time dummy, Z_{mt} is a vector of supply constraints in metro m at time t, and X_{mt} is a vector of metro-level controls for productivity and amenities. As discussed above, we include controls for housing characteristics and household income in some specifications; these constitute X_{it}.[5] The coefficient of interest is β_z.

We lack detailed data at the metro level on how regulatory constraints have changed over time. However, many local government regulations present in the 2000s were instituted in the 1980s or 1990s (Glaeser and Ward 2009; Jackson 2016; Ganong and Shoag 2017).[6] Therefore, our analysis compares observations from 1980 ($t = old$) to observations in the 2010s ($t = recent$). We use a supply constraint measure from the 2000s, Z_m, to proxy for the change over time, $Z_{m,recent} - Z_{m,old}$. This substitution allows us to rewrite the above specification as

$$Y_{imt} = \delta_m + \delta_{t=recent} + \beta_z 1_{t=recent} Z_m + \beta_{x1} 1_{t=recent} \Delta X_m + \beta_{x2} X_{it} + \varepsilon_{imt}, \tag{2}$$

where ΔX_m equals the change in metro-level productivity and amenity valuation between 1980 and the 2010s.

Our analysis does not assume that housing supply was entirely unconstrained in 1980, and indeed, Glaeser and Ward (2009) and Ganong and Shoag (2017) document regulatory restrictions in the 1960s and 1970s. Rather, we assume that metro areas with tighter regulation in the 2000s experienced stronger growth in regulations over our sample period. We validate this assumption directly for 60 metros that researchers surveyed about permit approval times in both the 1980s (Linneman et al., 1990) and 2006 (Gyourko et al., 2008). Table 1 shows that permitting times increased by a factor of 3 to 4 between the 1980s and 2006. We regress this increase on the level of permitting time in 2006 and find coefficients between 0.87 and 0.95.[7] The proximity of these coefficients to 1 implies that any bias from using 2006 regulation to proxy for the increase since the 1980s is small.

Our empirical strategy also uses geographic constraints in the 2000s to proxy for the change in effective geographic constraints since 1980.The topography of the land itself changes quite slowly over time, but Cosman et al. (2018) demonstrate theoretically that even a static geographic constraint binds more sharply over time in an expanding metro area. The gradual use of vacant land parcels close to the city center—infill development—exemplifies this process. Fig. 1 documents widespread infill development by plotting housing unit density in cen-

Table 1
Months from Application to Permit Issuance for SF construction.

Percentile	Application for Rezoning		Application for Subdivision	
	< 50 units	≥ 50 units	< 50 units	≥ 50 units
		1980s		
10th	1	2	1	1
50th	2	2	2	2
90th	3	3	3	2
		2006		
10th	3.9	4.8	3.6	3.8
50th	6.4	8.0	5.6	6.8
90th	10.7	13.0	9.0	10.7
		Change from 1980s to 2006		
10th	1.7	2.4	2.2	2.6
50th	4.7	5.8	4.1	5.2
90th	8.0	10.2	6.7	8.7

Note: Sample includes the 60 metropolitan areas that appear in both surveys. Data from the 1980s are from a survey conducted by Linneman et al. (1990) and data from 2006 are from a survey conducted by Gyourko et al. (2008).

[5] To allow income to affect housing consumption in a flexible manner, we include indicators for the decile of income in the national income distribution, interacted with time dummies. We use household income with Census/ACS outcomes and median tract income with CoreLogic outcomes. For older homes in CoreLogic, we use 1980 Census income data imputed to 2010 tracts via the crosswalk of Logan, Xu and Stults (2014), and for newer homes, we use 2012-2016 ACS income data. We do not control for changes in the age of household heads but doing so does not alter our main results.

[6] Specifically, Jackson (2016) finds that most regulations that affect the size, location, or density of the housing stock in California were established after 1985, while Glaeser and Ward (2009) show that most cluster zoning regulations, wetlands bylaws, and septic system requirements in Greater Boston were adopted in the 1980s or later. In addition, Ganong and Shoag (2017) report that the fraction of state appellate court cases that contain the phrase “land use” increased by about 60 percent from 1980 to 2010.

[7] Although Table 1 compares results of the 2006 Wharton survey to an earlier survey conducted in the 1980s, we do not use these data on changes in regulation in our main analysis because this comparison is only sensible for a single survey question; the other sets of survey questions are not readily comparable across the two surveys. Moreover, only 60 metro areas are observed in both surveys; we use a wider set of metro areas in our analysis so that we can identify effects from more heterogeneity in supply constraints.

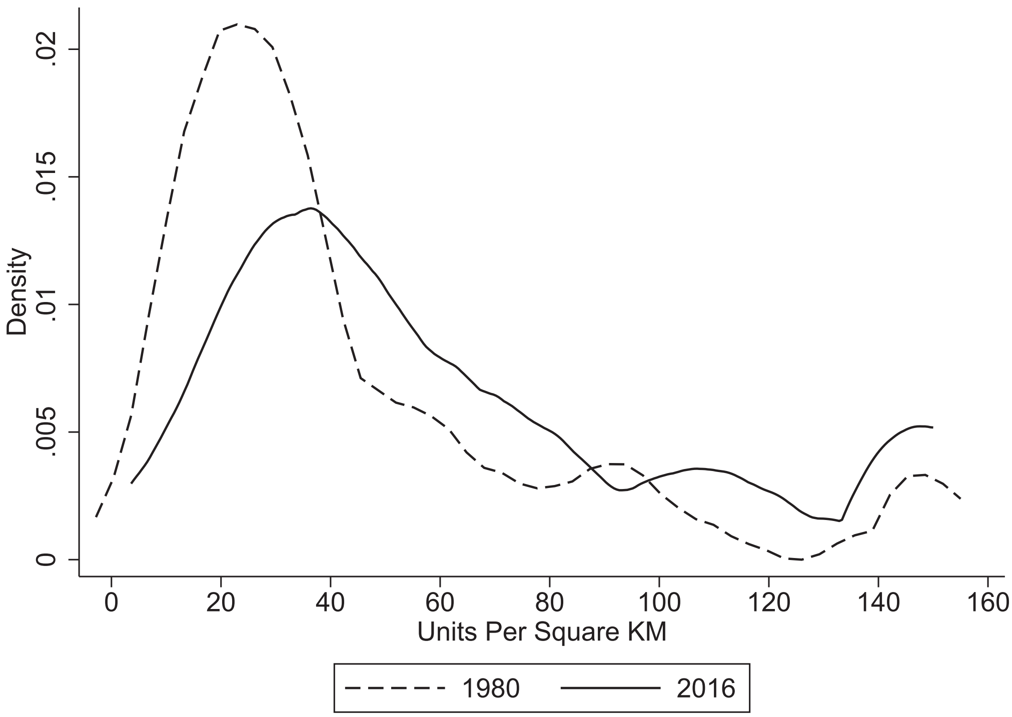

Fig. 1. Distribution of Housing Unit Density Among Central Parts of Metropolitan Areas. *Note*. The figure shows the distribution of housing units per square kilometer across metropolitan areas in 1980 and 2016. In each metropolitan area, density is calculated only among counties that are designated as "central" according to the 2013 OMB delineation. The sample is restricted to metropolitan areas for which not all counties are designated as central.

tral parts of metro areas in 1980 and 2016.[8] Whereas two-thirds of areas had a density less than 40 units/km^2 in 1980, only one-third did by 2016. Other research has also reported the prevalence of infill development (Brueckner and Rosenthal 2009; Burchfield et al., 2006; Hilber et al., 2018; McDonald and McMillen 2000).

Eq. (2) identifies β_z when $E(\varepsilon_{imt}|Z_m, \Delta X_m, X_{it}) = 0$. The controls must explain all the changes in the outcomes over time that correlate with the supply constraints but are not caused by the supply constraints. Otherwise, our estimated effects of supply constraints will be biased. In Appendix B.1 we assess the potential extent of this bias with an exercise in the spirit of Altonji, Elder and Taber (2005).[9] Moreover, to make this identification assumption more likely to hold, we exclude low-demand metro areas from our analysis. Following Gyourko et al. (2013) and Charles et al. (2018), we calculate housing demand as the sum of the percent changes in the number of housing units and the median home value from 1980 to 2016.[10] Low-demand areas are those in the bottom quartile of the demand distribution; these appear as hollow circles in Fig. 2. These metros differ in hard-to-measure ways from growing metros, and supply constraints likely did not bind there during our sample period.

2.3. Data on supply constraints

To measure regulatory constraints, we use the Wharton Residential Land Use Regulatory Index (Gyourko et al., 2008). In 2006, local government officials answered survey questions about residential land use and the political process through which governments enact these rules. The index, which is available for 259 metro areas, combines answers to these questions into a single measure of regulatory stringency.

The Wharton index has some potential drawbacks. Given our focus of comparing the effects on rents to the effects on house prices, the primary concern is that the survey might capture regulations that affect single-family housing (which is primarily owner-occupied) more than multi-family housing (which is primarily renter-occupied), perhaps because the municipalities in the survey are more likely to be suburban than urban. However, the index includes restrictions that are relevant in urban areas, like regulation of multifamily construction, in addition to those relevant in suburban areas, such as minimum lot sizes. Furthermore, regulations that target the owner-occupied housing market spill over to the rental market when these markets are connected, which seems likely to be the case over the long timeframe we examine (Rosenthal 2020). Nonetheless, we present results for single-family rental homes (which are likely in the same neighborhoods as owner-occupied homes) to address this concern. Another potential drawback is reverse causality: one component of the index measures permit approval times, and permit delays may be longer in areas with strong construction activity. However, absent other regulatory constraints, local governments should be able to adapt their provision of services to strong demand over the 35-year period that our analysis covers.

To measure geographic constraints, we use the data underlying Saiz's (2010) estimates of the fraction of land that is unavailable for construction because it is on a steep slope or covered by water.[11] Not only are the estimated effects of geographic constraints interesting on their own, but including this measure sharpens the identification of the effects of regulation. Regulatory and geographic constraints are correlated across metros (Saiz 2010), and the mountains and water bodies

[8] In the 2013 designation of which counties are in metropolitan areas, the Census Bureau identifies some counties in each metropolitan area as "central". We use this indicator to define central counties and limit this analysis to metropolitan areas for which not all counties are designated as central.

[9] An alternate concern is that we are controlling for too many factors because our controls partly reflect endogenous responses to supply constraints. However, the fact that we obtain similar results regardless of the controls (see Appendix B.1) suggests that bias from over-controlling is not large.

[10] Data are from the 1980 Census and 2016 American Community Survey. We take published data by county and aggregate to the 2013 metro area definitions. House value is calculated as the housing unit-weighted average of county median values.

[11] Saiz (2010) calculates these constraints for a radius of 50 kilometers around the center of each of 100 metropolitan areas. We alter this calculation slightly by calculating the fraction of unavailable land for all of the land area in the metropolitan area, which allows us to compute geographic constraints for a larger set of metropolitan areas.

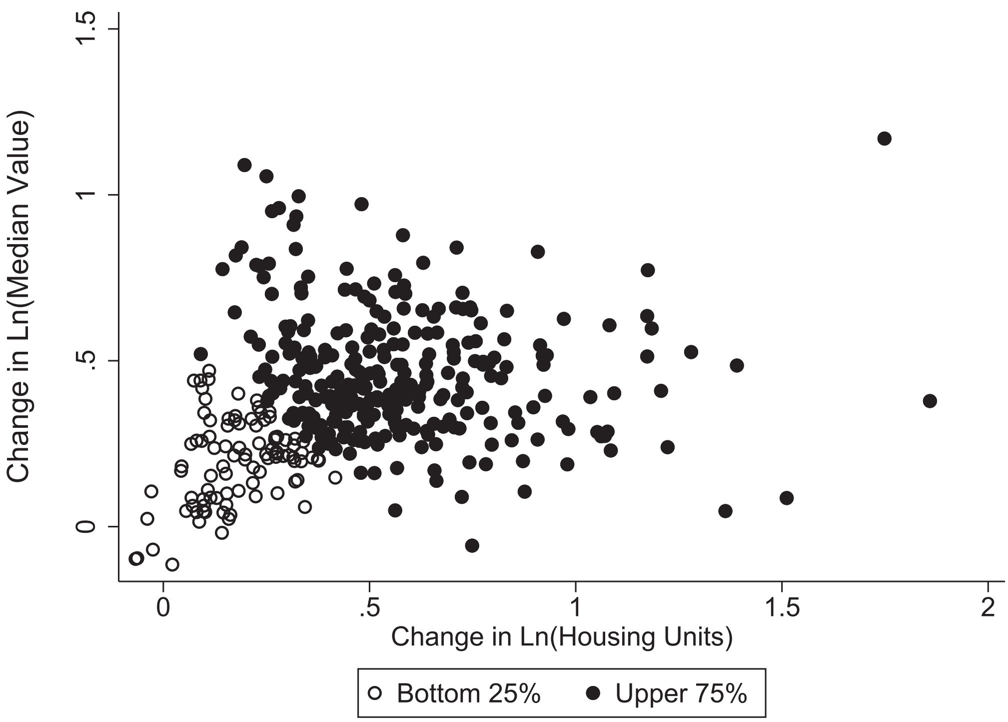

Fig. 2. Identification of Low-Demand Areas Based on Growth in Housing Stock and House Value 1980–2016. *Note.* Housing units include single-family and multifamily units. Median value is expressed relative to the price index for personal consumption expenditures.

that make construction more difficult may have become increasingly valuable amenities over the time period we are studying (Cosman et al., 2018).

To facilitate the interpretation of our coefficient estimates, we standardize each constraint variable to have a mean of zero and a standard deviation of one.[12]

2.4. Data on outcomes

We use data from the 1980 Census and the 2012–2016 American Community Survey (ACS) on rent and property value, both deflated by the price index for personal consumption expenditures from the Bureau of Economic Analysis.[13] We use gross rent, which adds utilities costs to contract rent in cases when utilities are not already included, to ensure comparability across units.[14] To interpret results as effects on constant-quality rents and prices, we include dummy variables for all available property characteristics: single-family, decade of year built, number of rooms, and number of bedrooms.

To quantify sorting across metro areas, we also use Census/ACS data on income, education, and occupation. For each metro and survey wave, we compute the fraction of the population age 15+ in each decile of the national income distribution, the fraction of the population age 25+ with at least four years of college, and the fraction of the working population age 16+ (*i.e.*, those age 16+ who worked in the past 5 years) with a high occupation score, a measure the Census Bureau created using median incomes by occupation category in the 1950 Census.

Housing consumption outcomes come from a 2014 cross-section of tax assessor data collected by CoreLogic. Tax assessors record property characteristics to determine property values and taxes. We use data for single-family homes on unit square footage, lot square footage, and construction year. The dataset covers the vast majority of single-family housing in the US.[15] We assign a value of $t = old$ to any house built between 1960 and 1980 and a value of $t = new$ to any house built on or after 2000. We drop units built before 1960 or between 1980 and 2000. We do not observe the income of the household living in each housing unit, so we control for median Census tract income instead of household-level income when using these data.

Our CoreLogic dataset has two drawbacks. First, we observe housing units built in the 1960s and 1970s only as they were in 2014. Teardowns and renovations between 1980 and 2014 might bias our results. Second, the dataset excludes multifamily housing. We address these drawbacks by using additional data on housing consumption from the Census/ACS and the American Housing Survey (AHS).[16] Both datasets report contemporaneous information on housing units, so teardown and renovation bias does not affect them. Both sources also provide data on multifamily homes. However, the Census/ACS data do not report unit or lot square footage, so we use the number of rooms to proxy for unit size and the number of rooms per adult (age 22+) to proxy for housing consumption per person. While we can observe unit and lot square footage in the AHS, the limitation of this data source is that it covers less than 1/3 of the number of metros in our main sample. Appendix A.1 describes the

[12] In Appendix Table B3, we show that results are qualitatively similar when specifying the constraints as indicators for each quartile of their national distributions.

[13] Data obtained from the IPUMS USA (Ruggles et al. 2018). To harmonize the definition of metropolitan area over these two samples, we construct a crosswalk from four-digit metropolitan delineations based on 1990 OMB definitions (IPUMS variable METAREAD) to the 2013 OMB delineations (IPUMS variable MET2013).

[14] For outcomes derived from Census and ACS data, we use only occupied units, which by definition contain a single household each. With minor exceptions, price and rent data are only collected for occupied units. Moreover, our income controls are specified at the household level and would not be defined for a vacant unit.

[15] To limit the influence of outliers, we drop observations with units larger than 10,000 square feet or lots larger than 175,000 square feet (about 4 acres). We also drop units with extremely small lots (less than 2000 square feet) and units with very high ratios of floor area to lot size. For computational reasons, we use a 25% random sample with 19 million usable observations. In contrast with the Census and ACS data, we include both vacant and occupied units, as the dataset lacks occupancy information.

[16] As with the Census/ACS data, we include only occupied housing units in the AHS analysis.

AHS in more detail and quantifies potential teardown/renovation bias in CoreLogic using this source.

To study sorting within metros, we measure neighborhood-level amenities in the 2010s. Using geocodes in CoreLogic, we compute the distance from each property to the center of the metro area as defined by Holian and Kahn (2015).[17] At the tract level, we use average commute times in the 2012–2016 ACS, and we take school quality and crime rates from Location Inc., which uses proprietary methods to create nationally comparable indices of school quality and crime for the year 2010 based on local test scores and law enforcement reports. We standardize the variables from Location, Inc. to have a mean zero and standard deviation one.

2.5. Data on controls for productivity and amenities

We include three measures of metro-level productivity growth as controls. The first is the share of the population age 25 or older with at least 4 years of college in 1980, which we take from the 1980 Census. The second is the share of local employment in 1990 in industries whose 1990–2016 national per-capita wage growth was in the top decile among industries. We obtain wages and employment by metro and industry from the annual files of the Quarterly Census of Employment and Wages, defining industries using 3-digit NAICS codes.[18] The third is employment growth over 1980–2016 predicted based on the industrial composition of the metro's 1980 labor force, following Bartik (1991). We create this measure using County Business Patterns data and the industry code concordances and employment imputations in Eckert et al. (2020).

We also use as controls two measures of the growth in the valuation of local amenities. The first is average January temperature. The value of warm weather seems to have increased since the 1970s (Glaeser and Gyourko, 2003) and many supply-constrained metros are in warm locales such as California. Temperature data come from the National Oceanic and Atmospheric Administration. We average weather station temperatures for the period 1981–2010 by county and then average across counties within each metro using county land area as weights. The second measure is the share of housing units that are seasonally vacant in the 1980 Census. Demand for seasonal housing has grown over time with the aging of the population and rising incomes, and seasonal housing tends to be in areas with tighter geographic or regulatory constraints.

Appendix Table B1 shows that all five measures positively and significantly correlate with the growth in housing demand between 1980 and 2016.

3. Empirical estimates

3.1. Effects on prices and rents

Much of our paper compares the effect of supply constraints on house prices to their effects on other outcomes, so we begin by estimating the house price effects in our data and then discuss their plausibility in the context of the existing literature. The first column of Table 2 reports the estimated effects of our two supply constraints on single-family house values in the Census/ACS data. In this table, and in all subsequent analysis that uses housing unit or property-level data, we cluster standard errors by metro area since the supply constraints are observed at the metro level. A metropolitan area with regulations that are one standard deviation tighter experienced 9 log point (about 10 percent) stronger house price appreciation over our sample period. The estimated effect of geographic constraints is similar. Results are broadly similar when we measure house prices using a repeat-sales price index instead of owner-reported house values in the Census/ACS (not shown).[19]

Our estimates for house prices are in line with Hilber and Vermeulen (2016), who find that a standard deviation of regulation raises house price growth by 14 percentage points in England from 1974 to 2008, and Zabel and Dalton (2011), who find that a 1-acre minimum lot size increases house prices by at most 20% in Massachusetts.[20] Nonetheless, our estimates imply that supply constraints explain less than one-third of the tripling of house prices in New York, Boston and San Francisco between 1980 and 2016. House price growth in these metros reflects strong demand growth as well as tight supply (Davidoff 2016), and we estimate larger coefficients on regulatory constraints when we drop controls for local demand (Appendix Table B2). Therefore, we view our estimates as in line with the literature even though they explain little of the outsized house price growth in certain metro areas.[21]

The remaining columns of Table 2 report the estimated effects of supply constraints on rent, our primary outcome of interest. The estimated effects are less than half of the estimated effect on house price growth, regardless of whether the sample includes only single-family rentals (the sample most comparable to the structures in the house price regression), all rentals, or 2-bedroom apartments (a common rental structure that is a more homogeneous sample). The price-to-rent ratio also increased more in metros with tighter constraints (Appendix Table B4). Furthermore, the effects on rent are small in absolute magnitude. They imply that 2 standard deviations of regulatory strictness increased rents by only 7 to 9 log points from 1980 to 2016, much less than the average increase in real rent of 49 log points among metros in our sample over this period. Even if we allow the effect of regulation to be non-linear, metros in the top quartile of regulation experienced only 8 to 12 log point higher rent growth over this period (Appendix Table B3). Thus, we find that supply constraints have only reduced housing affordability by a modest amount over this period.

One immediate concern is whether our measures of supply constraints may be poor proxies for true supply constraints, which would cause us to underestimate the effects on prices and rent. While there is surely some measurement error in our constraint variables, they are commonly used in academic research and are correlated with the elasticity of housing supply (Saiz 2010).[22] Moreover, the fact that our estimated effects on house prices are similar to estimates in the literature suggests that any downward bias owing to measurement error is fairly small. Specifically, if the measurement error is classical, then it depends only on the relative variance across metros of our supply constraint measures and true supply constraints. Any such error would thus bias down the price and rent coefficients to the same degree; a lack of

[17] Holian and Kahn (2015) define the CBD as the location returned when entering the central city name in Google Earth, which they found to be qualitatively "quite reasonable in all cases". The data are available for download at http://mattholian.blogspot.com/2013/05/central-business-district-geocodes.html.

[18] QCEW data by NAICS industry are unavailable prior to 1990. We could extend this measure back to 1980 using 1-digit SIC codes, but we would have only about 10 industry categories instead of 96.

[19] We use the repeat-sales index for single-family detached homes published by CoreLogic, converting the monthly index to annual averages and comparing 1980 to 2016. The estimated effect of regulation is very close to the estimate from the Census/ACS data, at 0.08. The estimated effect of geographic constraints is somewhat larger, at 0.23.

[20] Other research has found larger effects of supply constraints on house prices by looking at a combination of supply and demand (Glaeser, Gyourko and Saks 2006; Gyourko, Mayer and Sinai 2013).

[21] Because our estimated effects on prices are in line with the prior literature, it seems unlikely that omitted variables bias them substantially. By the same logic, it seems unlikely that omitted variables bias the estimated effects of regulation on *other* outcomes. The omitted variables would have to be correlated more strongly with these outcomes (including rent) than with prices, while also being correlated with the constraints and uncorrelated with the controls. We cannot think of factors that clearly fit these criteria.

[22] The papers introducing the regulatory index and the geographic constraint measure have been cited in at least 170 and 347 published journal articles, respectively.

Table 2
Effect of Housing Supply Constraints on House Prices and Rent.

	Ln(Value) SF Homes	Ln(Rent) SF Homes	Ln(Rent) All Homes	Ln(Rent) 2-Bed Apt.
2012–2016 indicator	0.496	0.501	0.489	0.458
	(0.024)	(0.015)	(0.014)	(0.016)
Indicator interacted with:				
Regulatory constraints	0.091	0.040	0.034	0.043
	(0.023)	(0.012)	(0.011)	(0.013)
Geographic constraints	0.110	0.018	0.042	0.046
	(0.022)	(0.011)	(0.011)	(0.013)
Controls for housing characteristics	Yes	Yes	Yes	Yes
Control for metro area productivity and amenities	Yes	Yes	Yes	Yes
Metro area fixed effects	Yes	Yes	Yes	Yes
Number of metro areas	133	133	133	133
Number of observations	2.2 million	0.38 million	1.2 million	0.35 million

Note: Standard errors are clustered by metropolitan area. Supply constraints are standardized to have a mean equal to zero and standard deviation equal to one. Controls for housing characteristics are indicators for decade built, indicators for number of rooms, and indicators for number of bedrooms. Value and rent are expressed relative to the price index for personal consumption expenditures. Controls for productivity and amenities are the variables listed in Appendix Table B1 interacted with the "recent" indicator. Observations are weighted to be nationally representative of the housing stock using the household weight provided by the Census Bureau.

downward bias in our house price regressions would therefore signal a lack of downward bias in our estimated effects on rents as well.

Another concern is that contractual rents are stickier than market prices. Leases fix monthly rents over the duration of the contract, and other frictions might prevent rents in the data from responding to supply constraints as much as prices. To address this concern, Appendix Table B5 replicates the first two columns of Table 2 for two subsamples. The first drops metros with rent control in 2014 (as reported on Landlord.com), and the second drops households in which the household head has lived in the unit for more than 5 years. In both cases, the effects on rent remain less than half the effects on prices.

Finally, the stronger effect on house values relative to rents could reflect disproportionate quality improvements in owner-occupied units relative to rental units that we are not capturing with the housing characteristics in the Census/ACS data. We address this issue using data from the AHS, which provides much more information on housing unit characteristics. Appendix Table A3 replicates Table 2, using price and rent per square foot as left side variables and controlling for additional housing unit characteristics. We continue to find much smaller effects on rents than on house prices.[23]

3.2. Effects on housing consumption

We turn now to the effects of supply constraints on housing consumption, which we measure using land and structure separately. Because our specifications control for household income, these specifications show how constraints alter the bundle of housing characteristics that a household with a given income consumes. Thus, this approach measures affordability in terms of real outcomes, which complements the approach above that measures affordability in terms of rents.

We measure land consumption using the lot sizes of single-family homes and using an indicator for whether a housing unit is single-family. Table 3 shows that regulatory constraints do not alter either measure. The effect sizes are indistinguishable from zero, and we can reject large negative effects. Geographic constraints negatively affect both measures of land consumption, but the effects are small relative to the effect of geographic constraints on house prices. Because the durability of housing may bias our results toward zero, we repeat the analysis of the single-family indicator while restricting to recently built homes in column 3. Regulatory constraints continue to have no effect, but the coefficient on geographic constraints becomes more negative, going from −0.015 to −0.029.

Table 4 shows results for measures of structure consumption. According to column 1, new homes are 28 log points larger in terms of unit square footage, but the effect of either constraint on unit square footage is a precisely estimated zero. Due to the drawbacks in the CoreLogic data (see Section 2.4), we repeat this analysis with Census data using the number of rooms as proxy for unit size. This sample is restricted to single-family homes since multifamily units tend to have fewer rooms than single-family units and we analyzed the effect of supply constraints on a single-family indicator in Table 3. The constraints have small negative effects (less than −2.5%) on the number of rooms, both for all homes and recently built homes.

The remainder of Table 4 documents small negative effects of both constraints on other aspects of structure consumption. Adults per household—which inversely measures structure consumption per capita—rise 1 to 2% per standard deviation of each supply constraint. Similarly, the constraints decrease rooms per adult by 1 to 3%.[24] Each constraint also lowers the quality of homes, defined as the first principal component of housing unit characteristics in the AHS (see Appendix A.2 for details). While these effects are statistically different from zero, they are economically small. A 1 standard deviation tighter constraint is only associated with about 0.1 standard deviation lower housing unit quality, much smaller than the increase in quality of 1.5 standard deviations over our sample period.

In summary, we do find some evidence that households reduce their land and structure consumption in response to housing supply constraints. However, the effects are small, consistent with the small effect of these constraints on the rent for housing services. The effects are larger in magnitude when we restrict to newly built homes, suggesting that durability frictions explain some of the small effect sizes, but the coefficient estimates remain small even in that sample. The small estimated effects on these outcomes also help reassure us our analysis

[23] To connect with work that defines affordability in terms of housing expenditures, we estimate the effects of supply constraints on expenditures in Appendix Table B6. A 1-standard deviation tighter constraint raises expenditures by only 3 to 6 percent over our sample period, and the effects are similar for owners and renters. The effects on expenditures are similar across the income distribution, while the effects on expenditures relative to income are largest for middle-income households (see Appendix Fig. B1).

[24] In these two columns, we control for income by dividing household income by the number of adults in the household and then calculating their decile in the national distribution. We do not control for total household income because it is mechanically related to the number of adults living there. In unreported analysis, we have confirmed that demographic changes are not driving the effects of constraints by estimating regressions at the individual level and controlling for age and sex. We also find similar results when we include multifamily units in addition to single-family.

Table 3
Effect of Housing Supply Constraints on Housing Lot Consumption.

	Ln(Lot Size) SF Homes	SF Indicator All Homes	SF Indicator Recently-Built Homes
"Recent" indicator	−0.159	−0.012	0.053
	(0.028)	(0.005)	(0.011)
Indicator interacted with:			
Regulatory constraints	0.023	0.001	−0.002
	(0.022)	(0.004)	(0.008)
Geographic constraints	−0.041	−0.015	−0.029
	(0.023)	(0.005)	(0.006)
Controls for income	Yes	Yes	Yes
Control for metro area productivity and amenities	Yes	Yes	Yes
Metro area fixed effects	Yes	Yes	Yes
Outcome data	CoreLogic	Census/ACS	Census/ACS
Number of observations	4.4 million	3.7 million	0.65 million

Note: Standard errors are clustered by metropolitan area. Supply constraints are standardized to have a mean equal to zero and standard deviation equal to one. Controls for income are indicators for deciles in the national distribution of income and interactions of these indicators with the "recent" indicator. When the outcome uses CoreLogic data, income is median household income by Census tract. When the outcome uses Census/ACS data, income is property-level household income. Controls for productivity and amenities are the variables listed in Appendix Table B1 interacted with the "recent" indicator. The third column restricts to homes built since 1970 in the 1980 sample and built since 2000 in the 2012–2016 sample.

Table 4
Effect of Housing Supply Constraints on Housing Structure Consumption.

	Ln(Unit Size) SF Homes	Ln(Rooms) SF Homes	Ln(Rooms) SF, Recently-Built	Ln(Adults per Household) SF Homes	Ln(Rooms Per Adult) SF Homes	Housing Unit Quality All Homes
"Recent" indicator	0.283	0.048	0.028	−0.024	0.066	1.53
	(0.012)	(0.004)	(0.006)	(0.005)	(0.005)	(0.08)
Indicator interacted with:						
Regulatory constraints	−0.000	−0.009	−0.003	0.007	−0.016	−0.118
	(0.008)	(0.003)	(0.005)	(0.004)	(0.004)	(0.041)
Geographic constraints	−0.007	−0.013	−0.023	0.023	−0.033	−0.145
	(0.008)	(0.003)	(0.004)	(0.004)	(0.004)	(0.043)
Controls for income	Yes	Yes	Yes	Yes	Yes	Yes
Control for metro area productivity and amenities	Yes	Yes	Yes	Yes	Yes	Yes
Metro area fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Outcome data	CoreLogic	Census/ACS	Census/ACS	Census/ACS	Census/ACS	AHS
Number of observations	4.4 million	2.7 million	0.48 million	2.7 million	2.7 million	0.24 million

Note: Standard errors are clustered by metropolitan area. Supply constraints are standardized to have a mean equal to zero and standard deviation equal to one. The measure of housing unit quality has a mean equal to zero and standard deviation equal to one, and is described in Appendix A. Controls for income are indicators for deciles in the national distribution of income and interactions of these indicators with the "recent" indicator (for AHS income is specified as quintiles instead of deciles). When the outcome uses CoreLogic data, income is median household income by Census tract. When the outcome uses Census/ACS or AHS data, income is property-level household income. Controls for productivity and amenities are the variables listed in Appendix Table B1 interacted with the "recent" indicator. The third column restricts to homes built since 1970 in the 1980 sample and built since 2000 in the 2012–2016 sample.

of home prices and rents in Census data is not biased by unobserved changes in housing unit quality.

3.3. Effects on sorting across metropolitan areas

We next examine an additional real outcome that should be affected by affordability: a household's choice of metro area in which to live. We regress metro-level changes in average housing stock and population characteristics between 1980 and 2016 on our supply constraints, while continuing to control for metro productivity and amenities. We weight using the number of housing units in each metro (average of 1980 and 2012–2016) so that these results are comparable to earlier regressions that use household- and property-level observations.

As we report in the first column of Table 5, both supply constraints significantly reduce the growth in the metro's housing stock. A standard deviation of regulatory (resp. geographic) constraints reduces the housing stock by about 6% (resp. 10%).[25] This result is consistent with prior research finding that regulatory constraints reduce growth in the housing stock (Mayer and Somerville 2000; Saks 2008; Jackson 2016), although this work does not control for geographic constraints, which are correlated with regulatory constraints. Our results therefore demonstrate that regulatory constraints reduce metro growth even independently of geographic constraints.

To shed light on the mechanism behind this result, we estimate the effect of the supply constraints on migration to and migration from metro areas. To proxy for migration flows over the 1980s and 1990s, we sum retrospective 5-year migration rates by metro for 1990 and 2000 and then multiply by two.[26] As reported in Appendix Table B7,

[25] Results are similar if the dependent variable is the metro's population (not shown).

[26] We use Census data, which includes the location of residence five years earlier for the respondent. The Census Bureau last asked for this information in

Table 5
Effect of Housing Supply Constraints on Changes in Metropolitan Area Housing Stock and Population Characteristics 1980 to 2016.

	Ln(Housing Stock)	Fraction 4+ Years College	Fraction High Occupation Score	Ln(Average Real Income)	Ln(Median Real Income)
Constant	0.523	0.138	0.037	0.411	0.306
	(0.031)	(0.005)	(0.002)	(0.013)	(0.015)
Regulatory constraints	−0.058	0.007	0.001	0.028	0.020
	(0.026)	(0.004)	(0.002)	(0.011)	(0.012)
Geographic constraints	−0.106	0.003	−0.002	0.004	−0.018
	(0.023)	(0.003)	(0.001)	(0.009)	(0.011)
Control for metro area productivity and amenities	Yes	Yes	Yes	Yes	Yes
Number of observations	133	133	133	133	133

Note: The housing stock includes single-family and multifamily units. High occupation score is defined as above the 90th percentile of the national distribution of occupation scores in the same year. Metro areas with tight constraints are those in the top third of the distribution of constraints. Controls for productivity and amenities are reported in Appendix Table B1. Observations are weighted by the average number of housing units in 1980 and 2016.

a decrease in inflows drives the negative effect of constraints on metro population; we estimate zero effect on outflows. Frictions may keep people from migrating away from a metro once they are established there, and homeownership hedges homeowners against rising housing costs (Sinai and Souleles 2005). One consequence of the negative effect on migration inflows is that supply constraints reduce the boost to economic activity that in-migrants generate (Howard 2020).

The remainder of Table 5 examines sorting by education, occupation, and average and median real income. Existing theoretical literature suggests that high-income (Gyourko et al., 2013) and college-educated (Ganong and Shoag 2017) workers are more likely to stay in or move to areas with supply constraints. However, we estimate precise zero effects of geographic constraints on the college share and average income, while a standard deviation of regulatory constraints raises the college share only 0.7 percentage points and incomes only 2 to 3% between 1980 and 2016. These numbers are small relative to the average increase of 14% in the college share and 30–40% in real incomes.

Supply constraints could have large effects on a metro's income distribution without altering mean and median incomes. Therefore, we separately estimate the effect of the constraints on the fraction of a metro's population in each decile of the national distribution of income. In Panel A of Fig. 3, we document mild amounts of sorting by income in response to regulatory constraints. They raise the shares in the 9th and 10th deciles while lowering the shares in the 4th to 7th deciles, but these effects are small (less than a percentage point). We continue to find no evidence of income sorting in response to geographic constraints.[27]

Data from San Francisco, one of the most supply constrained metros in our sample, illustrate the small magnitude of our estimates. Regulatory constraints explain only 1/8 of the increase in the share of residents in San Francisco in the top decile of the national income distribution from 1980 to 2016. Similarly, they explain only 1/8 of the excess growth in the college share beyond the national average. Thus, little of the relatively strong growth in top incomes and the college share in the San Francisco metro seems due to supply constraints.

3.4. Effects on sorting within metropolitan areas

Finally, we investigate whether supply constraints make households more likely to live in less desirable neighborhoods. We answer this question by examining the level of amenities in neighborhoods where new housing is built. For this exercise, we merge CoreLogic with tract-level data on average commute times, crime, and school quality, and then use each tract characteristic as an outcome. We also examine distance to the central business district (CBD), which we observe at the property level. This specification measures the extent to which supply constraints shift housing demand, and therefore new construction, to less desirable neighborhoods.[28]

Table 6 reports the results. Regulatory constraints have a material negative effect on school quality but a precisely estimated zero effect on the other three amenities. Geographic constraints shift new homes 7% closer to the CBD and to tracts with 2% lower commute times. However, they also lead new homes to be in tracts with school quality and crime that are 0.1–0.2 standard deviations worse. That is, geographic constraints push new homes into neighborhoods that are nicer in some dimensions but less desirable in others. The effects on distance to CBD and commute times are small relative to the increases in distance and commute times over our sample period (as shown by the coefficient on the "recent" indicator). Therefore, we fail to find clear and consistent evidence that supply constraints cause households to live in either more or less desirable neighborhoods.

One important caveat to these results is that we do not observe variation in supply constraints across neighborhoods within a metro, and so our analysis may not account for the full effect of supply constraints on households' neighborhood choices. If supply constraints are systematically tighter in more desirable neighborhoods, then these constraints may move new housing into less desirable neighborhoods even if the degree of constraint on average in the metro is not tighter than other metros. This type of effect seems possible, as regulations are tighter in metros with more desirable amenities (Davidoff 2016), and the elasticity of housing supply is lower in Census tracts closer to the CBD (Baum-Snow and Han 2021).

2000, so we cannot extend this analysis past 2000. Because this analysis covers 20 years instead of 36 years, the magnitudes are not directly comparable to our baseline results.

[27] Metro-level productivity shocks affect local income, which complicates our interpretation of income results as reflecting sorting alone. That said, it is unlikely that our estimated effects of supply constraints reflect productivity differences across metros because we control for measures of productivity at the metro level.

[28] We find similar results when we use tract-level population growth instead of new construction to measure neighborhood demand. Banzhaf and Mangum (2019) also examine the relation between supply constraints and similar proxies for neighborhood amenities.

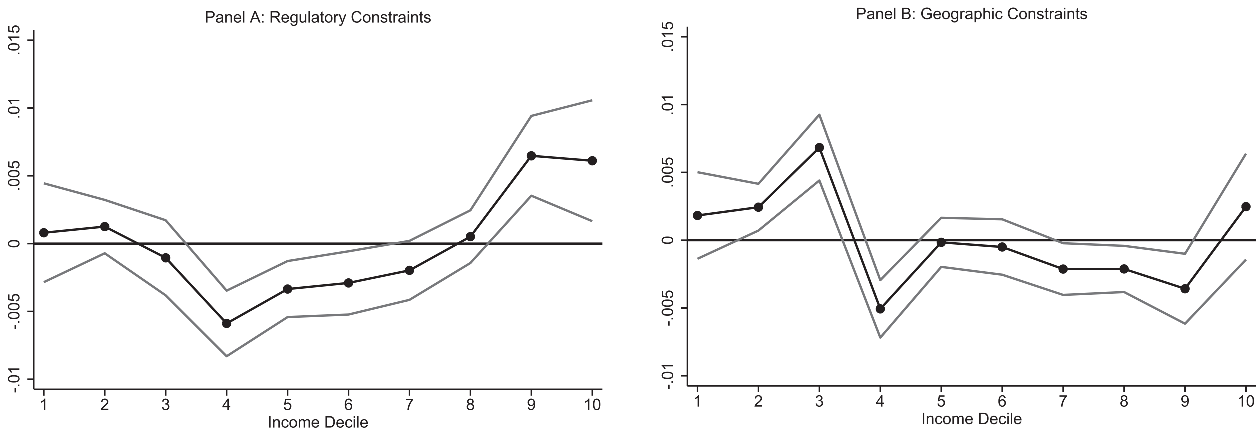

Fig. 3. Effect of Supply Constraints on the Distribution of Income. *Note*. The chart shows the estimated effects of each supply constraint on the change in the fraction of people in each decile of the national income distribution from 1980 to 2016. We calculate deciles of the national income distribution using Census/ACS data. Regressions control for the variables listed in Appendix Table B1. Regressions are weighted using the average number of housing units in 1980 and 2016. The outer bands show 95% confidence intervals.

Table 6
Effect of Housing Supply Constraints on Neighborhood Choice.

	Ln(Distance to Metro Center)	Ln(Average Commute Time)	Education Index	Crime Index
"Recent" indicator	0.327	0.081	0.093	−0.360
	(0.031)	(0.009)	(0.036)	(0.044)
Indicator interacted with:				
Regulatory constraints	−0.014	0.006	−0.080	0.030
	(0.026)	(0.005)	(0.026)	(0.032)
Geographic constraints	−0.076	−0.018	−0.115	0.153
	(0.019)	(0.005)	(0.021)	(0.026)
Controls for income	Yes	Yes	Yes	Yes
Control for metro area productivity and amenities	Yes	Yes	Yes	Yes
Metro area fixed effects	Yes	Yes	Yes	Yes
Outcome data	CoreLogic	CoreLogic	CoreLogic	CoreLogic
Number of observations	4.4 million	4.4 million	4.4 million	4.4 million

Note: Standard errors are clustered by metropolitan area. All reported right-hand-side variables are standardized to have a mean equal to zero and standard deviation equal to one. The education index and crime index are also standardized. Controls for income are median household income by Census tract interacted with decade indicators. Controls for productivity and amenities are the variables listed in Appendix Table B1 interacted with the "recent" indicator.

3.5. Robustness of empirical estimates

According to our analysis, supply constraints raise price-rent ratios and have at most small effects on housing consumption. In addition, they lead to little sorting by income despite causing metros to grow more slowly. Here, we show that most of these conclusions are robust to a variety of assumptions and specification choices in our empirical analysis. Results from this robustness exercise appear in Table 7.

In Panels A and B, we employ time-varying measures of regulatory constraints in place of the 2006 snapshot used in the main analysis. Panel A uses average permit approval time, which we observe in both the mid-1980s as well as 2006 (see Table 1). Panel B takes annual per capita counts of the phrase "land use" in state court cases from Ganong and Shoag (2017), using the 1976–1980 average for regulation in 1980 and the 2005–2009 average for regulation in the 2000s. We standardize each time-varying regulatory measure to have mean zero and standard deviation one. This exercise addresses bias arising from the assumption that regulation in the 2000s proxies for the growth since 1980 but comes at the cost of less cross-sectional variation in regulation (56 metros in Panel A and 43 states in Panel B).[29] In both panels, regulation continues to raise house prices at least twice as much as rent and to have much weaker effects on the single-family indicator, rooms per adult, and the fraction of the population in the top decile of the national income distribution. However, both regulatory measures raise lot sizes more than the baseline, although the effect of permit times is statistically insignificant. One potential explanation is that many state land use cases concern minimum lot sizes, increasing the correlation between regulation and lot sizes when we use this alternate measure.

Panel C includes metros in the bottom quartile of housing demand growth, which we drop in the baseline analysis. The effects of regulatory constraints remain essentially unchanged, while the effects of geographic constraints fall by about half, suggesting that geographic constraints bind less in low-demand areas. This finding supports our decision to drop these areas in the baseline.[30]

Panel D reports results that weight each metro equally, as opposed to weighting by the number of households. The estimated effects of the constraints are like the baseline, except that they raise house prices only 6–7% instead of 10%. The effect of geographic constraints on rents also shrinks, while the effect of regulatory constraints on rents is similar to the baseline. As a result, regulatory constraints increase the price-to-rent ratio less when we weight metros equally. It is possible that the same regulatory constraint compresses the housing risk premium more in a

[29] We cluster standard errors by state in Panel B because the court case measure is at the state level.

[30] For completeness, Appendix Table B8 reports effects on house prices and rents in each quartile of the demand distribution. Geographic constraints appear to bind the most in the top three quartiles, while regulatory constraints bind the most in the top half of the demand distribution. In each case where a constraint has a materially positive effect on house prices, the effect on rents is smaller in magnitude.

Table 7
Robustness to Alternate Specifications.

	Ln(Value) SF Homes	Ln(Rent) SF Homes	Ln(Lot Size) SF Homes	SF Indicator	Ln(Unit Size) SF Homes	Ln(Rooms Per Adult)	Fraction in Top Decile Income Dist.
Panel A: Measure Available in 1989 and 2006 Wharton Surveys (56 Metro Areas)							
“Recent” indicator	0.063	0.344	−0.234	0.009	0.291	0.129	−0.034
	(0.086)	(0.042)	(0.099)	(0.021)	(0.031)	(0.017)	(0.010)
Permit approval time	0.203	0.063	0.078	−0.007	0.023	−0.025	0.015
	(0.047)	(0.024)	(0.066)	(0.011)	(0.016)	(0.009)	(0.005)
Geographic constr. interacted with “recent”	0.021	−0.008	−0.041	0.002	−0.011	−0.018	−0.002
	(0.034)	(0.013)	(0.038)	(0.008)	(0.014)	(0.007)	(0.004)
Panel B: Mentions of Zoning in State Court Cases (Ganong and Shoag 2017)							
“Recent” indicator	0.499	0.507	−0.189	0.013	0.271	0.085	−0.005
	(0.034)	(0.022)	(0.028)	(0.009)	(0.012)	(0.005)	(0.004)
State-level index of cases	0.039	0.016	0.050	−0.018	0.019	−0.010	0.005
	(0.017)	(0.007)	(0.015)	(0.010)	(0.005)	(0.003)	(0.002)
Geographic constr. interacted with “recent”	0.112	0.023	−0.052	0.002	−0.013	−0.020	0.001
	(0.023)	(0.011)	(0.022)	(0.007)	(0.007)	(0.005)	(0.002)
Panel C: Including Low Demand Metro Areas							
“Recent” indicator	0.430	0.470	−0.122	0.002	0.295	0.081	−0.009
	(0.024)	(0.014)	(0.026)	(0.006)	(0.013)	(0.005)	(0.002)
Indicator interacted with:							
Regulatory constraints	0.116	0.042	0.004	−0.007	−0.003	−0.022	0.007
	(0.025)	(0.011)	(0.021)	(0.005)	(0.009)	(0.005)	(0.002)
Geographic constraints	0.062	0.009	−0.026	−0.004	0.000	−0.021	0.001
	(0.024)	(0.010)	(0.023)	(0.006)	(0.008)	(0.005)	(0.002)
Panel D: Weighting Each Metro Equally							
“Recent” indicator	0.513	0.502	−0.139	−0.012	0.251	0.056	−0.003
	(0.016)	(0.011)	(0.038)	(0.005)	(0.013)	(0.005)	(0.002)
Indicator interacted with:							
Regulatory constraints	0.063	0.045	0.012	0.004	0.010	−0.013	0.006
	(0.017)	(0.010)	(0.026)	(0.003)	(0.007)	(0.003)	(0.002)
Geographic constraints	0.069	0.010	−0.017	−0.006	−0.001	−0.020	−0.002
	(0.016)	(0.010)	(0.022)	(0.003)	(0.006)	(0.003)	(0.002)
Panel E: Controlling for Ex-Post Demand							
“Recent” indicator	0.478	0.517	−0.135	−0.014	0.280	0.053	−0.006
	(0.025)	(0.012)	(0.029)	(0.005)	(0.012)	(0.006)	(0.003)
Indicator interacted with:							
Regulatory constraints	0.089	0.037	0.038	0.007	−0.002	−0.020	0.007
	(0.030)	(0.014)	(0.020)	(0.005)	(0.008)	(0.004)	(0.002)
Geographic constraints	0.095	0.029	−0.039	−0.018	−0.007	−0.037	0.001
	(0.025)	(0.012)	(0.020)	(0.005)	(0.008)	(0.006)	(0.002)
Ex-post demand	0.097	0.036	−0.106	−0.004	0.011	−0.008	0.013
	(0.041)	(0.017)	(0.022)	(0.010)	(0.011)	(0.007)	(0.003)
Panel F: Measuring Supply Constraints using Superstar Indicator							
“Recent” indicator	0.413	0.504	−0.134	−0.012	0.278	0.093	−0.009
	(0.018)	(0.013)	(0.031)	(0.006)	(0.012)	(0.010)	(0.002)
Indicator interacted with:							
Superstar indicator	0.390	0.124	0.144	0.005	0.035	−0.058	0.026
	(0.028)	(0.025)	(0.062)	(0.017)	(0.027)	(0.025)	(0.004)
Ex-post demand	0.112	0.051	−0.112	−0.008	0.008	−0.016	0.013
	(0.026)	(0.017)	(0.023)	(0.010)	(0.012)	(0.012)	(0.003)
Panel G: Minimum Lot Size Constraints (2006 Wharton Survey)							
“Recent” indicator	0.496	0.500	−0.158	−0.012	0.283	0.066	−0.002
	(0.024)	(0.015)	(0.027)	(0.005)	(0.012)	(0.005)	(0.003)
Indicator interacted with:							
Min. lot size regulations	0.036	0.001	0.027	0.001	−0.001	−0.003	0.005
	(0.024)	(0.011)	(0.016)	(0.005)	(0.008)	(0.003)	(0.002)
Other regulations	0.084	0.045	0.011	0.000	0.000	−0.016	0.004
	(0.022)	(0.011)	(0.024)	(0.005)	(0.009)	(0.005)	(0.003)
Geographic constraints	0.109	0.012	−0.034	−0.015	−0.007	−0.032	0.003
	(0.024)	(0.011)	(0.022)	(0.005)	(0.007)	(0.004)	(0.002)

Note: Details for specifications shown in columns (1) and (2) can be found in Table 2. Details for columns (3) and (4) can be found in Table 3. Details for columns (5) and (6) can be found in Table 4. Details for column 7 can be found in Fig. 3. The state-level index of cases is the number of documents that mention zoning, standardized to the have mean equal to zero and standard deviation equal to one. We use the 1976–80 average for the 1980 data and the 2005–09 average (latest available 5 years) for the 2016 data. The “Superstar” indicator equals one for metro areas with demand above the median and supply in the tightest 10 percent. Standard errors are clustered by metro area for all panels except Panel D, in which standard errors are clustered by state.

larger metro area, raising the price-to-rent ratio in these areas. Nevertheless, constraints still raise prices more than rents when we weight metros equally.

In Panel E, we replace the controls for productivity and amenities with realized housing demand growth between 1980 and 2016 (the sum of price and quantity growth, as discussed in Section 2.2). By using realized demand growth, we address the concern that our results are biased towards zero because our controls only imperfectly capture demand. The estimates are close to the baseline across the board, although the effect of regulatory constraints on lot sizes rises slightly and becomes significant.

Panel F replaces the supply constraints with an indicator for whether the metro is a "superstar," defined following Gyourko et al. (2013) as a metro whose 1980–2016 house demand growth is above the median and for which the excess of house price growth over housing unit growth is above the 90th percentile. The superstar indicator addresses measurement error by measuring supply constraints using ex-post price and quantity growth instead of our survey-based measures. However, this indicator conflates tight supply with high demand growth. To mitigate this problem, we control for realized demand in place of the controls for productivity and amenities. The superstar indicator raises house prices by 39 log points. Consistent with our baseline results, it has much smaller effects on rent, structure consumption, and the fraction of the metro in the top national income decile. In contrast to the baseline, the superstar indicator has a large, positive effect (14 log points) on lot sizes of single-family homes, perhaps because minimum lot sizes are more common in superstar metros.[31] Meanwhile, superstar metros have 6% lower rooms per adult than other metros even though structure sizes themselves are about the same. These results show that beyond the previously-documented effect of superstar status on the price-to-rent ratio, living in these metros also alters certain dimensions of housing consumption.

Minimum lot size regulations would naturally have different effects on lot sizes than other types of regulation, since these restrictions make lots larger while other regulations should reduce lot sizes by making land more expensive. To see how the effects of minimum lot size rules differ from other regulations, we separate out the component of the Wharton index that measures minimum lot sizes.[32] As Panel G shows, lot sizes grew in metros with tighter minimum lot size rules, whereas other regulations do not affect lot sizes.

4. Model

In this section we develop a model of a housing market with supply constraints. Taking the effect of a supply constraint on house prices as given, the model allows us to quantify the resulting changes in rents, housing consumption and household location decisions. The ability to quantify the magnitude of these predicted effects is important because our empirical work has found many effects to be small, albeit statistically significant. Furthermore, the model clarifies the change in implicit rent of owner-occupied homes in the data by allowing us to translate a change in equilibrium housing consumption to a change in rents.

4.1. Environment and equilibrium

There are two cities, R (for "regulated") and F (for "free"). Time runs continuously from $t = 0$. The economy consists of N_t households, each living in one of these two cities. The utility of household i is

$$U_i = \int_{t_i}^{\infty} e^{-rt} \log\left(a_{i,j_{i,t}} v\left(c_{i,t}, h_{i,t}\right)\right) dt,$$

where t_i is the time the household is born, r is the discount rate, $a_{i,j}$ is its taste for city j, $c_{i,t}$ is non-housing consumption, and $h_{i,t}$ is the consumption of housing services. Flow utility from non-housing and housing consumption is Cobb-Douglas: $v(c_{i,t}, h_{i,t}) = c_{i,t}^{1-\alpha} h_{i,t}^{\alpha}$, where $\alpha \in (0, 1)$. The household receives income y_i that is constant over time. The distribution of income across households has a probability density function f. Income does not depend on the city in which the household lives, so the model abstracts from differences in productivity and labor demand across metro areas. This decision mirrors our empirical work, which controls for these differences. Households differ in their taste for each city:

$$a_{i,j} = a_j e^{\frac{\varepsilon_{i,j}}{\beta}},$$

where $\varepsilon_{i,R}$ and $\varepsilon_{i,F}$ vary as independent standard extreme value distributions and $\beta > 0$. City tastes are independent from household income and constant over time. Therefore, the model abstracts from income-based sorting between the two cities that might occur in response to the evolution of amenities or tastes over time.

Each household is part of a "dynasty," a collection of households with identical income and city tastes. At a given time, the dynasties contain the same number of households, and the number of households grows at a rate g. This population growth causes housing demand to rise over time. As we show later, it is a key force leading to price and rent growth in city R.

Each dynasty chooses cities and consumption levels for its households to maximize the sum of their utility. The dynasty can borrow against the future income of its households at a constant rate r, yielding the budget constraint

$$\int_0^{\infty} e^{-rt} \sum_{i \in d} \left(c_{i,t} + p_{j_{i,t},t}\left(h_{i,t}\right)\right) dt \le \int_0^{\infty} e^{-rt} \sum_{i \in d} y_i dt,$$

where $p_{j,t}(h)$ is the rental price of h units of housing in city j at time t, and the price of non-housing consumption equals one.[33] Although an artificial modeling device, the dynasty allows us to model population growth in a tractable manner and can be thought of as representing bequests between generations.

Competitive developers supply housing in each city using two inputs: land, l, and tradeable capital, q. Epple et al. (2010), Ahlfeldt and McMillen (2014), and Combes et al. (2016) find that a constant returns to scale, Cobb-Douglas function of these two inputs approximates the production process for housing very well. Thus, we assume the following production function in our model:

$$h(l, q) = l^{1-\gamma} q^{\gamma},$$

where $0 < \gamma < 1$.

Developers supply housing services in frictionless and instantaneous spot markets. Although housing is a durable asset, this assumption makes housing non-durable in our model. We make this assumption to avoid modeling adjustment costs, which would make the model much more complex. Owing to this assumption, the model's predictions for

[31] This regression also shows that metros with higher demand growth witness shrinking lot sizes. This result is surprising if demand increases income and richer households want to consume more land. We interpret this result as suggesting that strong local demand causes in-migration, which causes lot sizes to fall because not all new construction occurs on the metro's periphery. Also, demand growth could increase household formation, and new households might consume less land than established households, which have older and richer members.

[32] The Wharton survey records whether a municipality has any location with a minimum lot size greater than one acre. As Gyourko and Molloy (2015) discuss, this measure is coarse because minimum lot sizes vary widely across municipalities. Therefore, our exercise likely understates the effect of minimum lot size constraints on lot sizes. We measure "other" regulations as the residual from regressing the main regulatory index on the minimum lot size variable. We standardize both regulatory variables to have a mean zero and standard deviation one.

[33] Dynasties rent housing in spot markets, which is equivalent to buying and selling ownership claims to housing without transaction costs. Our model therefore abstracts from segmentation between the rental and owner-occupied markets. Such segmentation may be small in the long run, as many owner-occupied properties become rentals (Rosenthal 2020) and many single-family houses are rentals (Mills, Molloy, and Zarutskie 2019). Adding segmentation to our model would prevent us from making sharp predictions on the different effects of supply constraints on prices versus rents. Therefore, the model cannot address any demand factors that may differentially affect prices versus rents, such as purchases of single-family homes by institutional investors (Mills, Molloy, and Zarutskie 2019).

the effects of supply constraints on the housing stock may be an upper bound. We return to this point in Section 4.5.

The instantaneous rental cost of structure is k^q. A developer must pay two costs for land: the endogenous spot price for raw land, $p^l_{j,t}$, and the instantaneous cost to transform this land into a lot suitable for development, k^l. The total rental cost to the developer to obtain land that can produce housing is therefore $p^l_{j,t} + k^l$. While $p^l_{j,t}$ may vary across cities and over time, k^q and k^l do not.

In city F, the number of housing units and area of land used are unconstrained. In city R, regulators unexpectedly impose one of two restrictions on developers for all $t > 0$:

- The total number of housing units cannot grow at a rate greater than g^n.
- The total land used for housing cannot grow at a rate greater than g^l.

The first rule limits the speed at which developers may supply new housing, so it corresponds to permit limits or delays. It restricts the growth rate of the city's population because each household lives in one housing unit. We map theoretical predictions about this constraint to the empirical results on regulatory constraints. The second restriction limits the geographic expansion of the city, so we map theoretical predictions about this constraint to the empirical results on geographic constraints.

These rules come at the end of time 0, after developers and dynasties have made their initial decisions. In other words, prices and rents at time 0 reflect the belief that city R remains unconstrained forever; prices and rents after time 0 reflect the knowledge that the city has imposed the constraints. As we show below, prices discontinuously jump right after time 0 when this information is revealed, reflecting the anticipation of future rent growth resulting from the imposition of the constraints.

Developers must obtain a permit to supply a housing unit at time t. The endogenous permit price is $x_{j,t}$, with $x_{F,t} = 0$ due to the absence of regulations in city F. Unpermitted land available for development in city j trades among developers at the spot price $p^l_{j,t}$, which also equals zero in F.[34] Developer cost minimization pins down the rental price of housing:

$$p_{j,t}(h) = x_{j,t} + \gamma^{-\gamma}(1-\gamma)^{\gamma-1}\left(p^l_{j,t} + k^l\right)^{1-\gamma}(k^q)^\gamma h.$$

The price to buy housing outright equals the expected net present value of future rents:

$$p^{own}_{j,t}(h) = E_t \int_t^\infty e^{-r(t'-t)} p_{j,t'}(h) dt'.$$

Equilibrium consists of prices $p^l_{j,t}$, $x_{j,t}$, and $p_{j,t}(h)$ such that dynasties maximize utility subject to their beliefs and budget constraints, developers maximize profits while obeying the regulations in R, and the housing market clears in each city. At $t = 0$, dynasties expect prices that hold in an equilibrium without any regulation, while they expect the prices that hold in the regulated equilibrium for $t > 0$. Appendix C.4 characterizes equilibrium at $t = 0$.

4.2. Equilibrium effects of population constraints

To isolate the effect of the population constraint, we set $g^n < g$ so that the constraint binds, while assuming that g^l is sufficiently large so that the price of land in R equals zero (as it does in F). Proposition 1 describes household city choices given the path of permit prices (all proofs appear in Appendix C).

[34] The land price in F equals zero because no alternative use for land exists (such as farming). Our results remain identical if the opportunity cost of land is positive, as long as this cost remains constant and equal in the two cities. Adding this cost to the model is equivalent to increasing k^l.

Proposition 1 (sorting). *If $a_{R,i} < a_{F,i}$, household i always lives in F. If $a_{R,i} \geq a_{F,i}$, household i lives in R only while $t \leq t^*_i$, which solves*

$$\log\left(\frac{a_{R,i}}{a_{F,i}}\right) = \frac{x_{R,t^*_i}}{y_i - \bar{x}\left(x_{R,t^*_i}\right)}$$

where $\bar{x}(x) \equiv \int_{(t|x_{R,t}\leq x)} (r-g)e^{-(r-g)t} x_{R,t} dt$.

According to the proposition, households with a greater taste for R live there until the permit price becomes too high. This threshold price is larger when the relative taste for R is greater or the household's income is higher. Because the threshold rises in income, regulation skews the city R income distribution to the right, inducing outmigration of poorer households. Qualitatively, Proposition 1 predicts a positive estimated effect of regulatory constraints on average real income and a negative estimated effect on the housing stock.

In equilibrium, the number of households choosing R equals the maximal number that city R allows. We calculate this maximum by growing the initial population (appearing in Appendix C.4) by a rate g^n over time. At time t, a household chooses R when its relative taste for that city is sufficiently high relative to the current permit price, x_t. We compute the number of such households by substituting in x_t for x_{R,t^*_i} in Proposition 1 and the integrating over the distribution of income and tastes. Equating the maximal population to household demand gives

$$e^{-(g-g^n)t} = \int_{\bar{x}(x_{R,t})}^\infty \frac{a_F^\beta + a_R^\beta}{a_F^\beta \exp\left(\frac{\beta x_{R,t}}{y-\bar{x}(x_{R,t})}\right) + a_R^\beta} f(y) dy.$$

This equation shows how the population constraint, g^n, pins down the permit price, $x_{R,t}$. When $g^n = g$—so that city R's population can grow at the economy's growth rate—the permit price, $x_{R,t}$, equals 0, and all households with a larger taste for city R always live there. However, if $g^n < g$, then city R's population cannot grow at its natural rate of g. To clear the market, the permit price, $x_{R,t}$, must rise to price out newly arriving households who would otherwise choose to live in city R. Mathematically, the left side of the equation decreases in t, which implies that $x_{R,t}$ increases over time because the right side decreases in $x_{R,t}$. Proposition 2 formalizes this result and shows that house prices increase more than rents.

Proposition 2 (prices versus rents). *The permit price, $x_{R,t}$, strictly increases in t. The effect of regulation on rents,*

$$\frac{p_{R,t}(h)}{p_{R,0}(h)} - 1 = \frac{x_{R,t}}{\gamma^{-\gamma}(1-\gamma)^{\gamma-1}\left(k^l\right)^{1-\gamma}(k^q)^\gamma h}$$

is therefore less than the effect of regulation on ownership prices,

$$\frac{p^{own}_{R,t}(h)}{p^{own}_{R,0}(h)} - 1 = \frac{\int_t^\infty re^{-r(t'-t)} x_{R,t'} dt'}{\gamma^{-\gamma}(1-\gamma)^{\gamma-1}\left(k^l\right)^{1-\gamma}(k^q)^\gamma h}$$

for all positive t and h.

Intuitively, the increase in rents from 0 to t depends closely on $x_{R,t}$, the permit price at time t. Because house prices capitalize future rents, the increase in house prices depends both on $x_{R,t}$ and on the path of permit prices after t. Because the permit price always increases, the forward-looking house price rises more since time 0 than rents, implying that the price-rent ratio is higher at any time $t > 0$ than at time 0. Mathematically, the integral in the equation for house price growth gives a weighted average of the future permit price, which exceeds the current permit price because $x_{R,t}$ increases over time. Qualitatively, Proposition 2 explains the key empirical result that regulatory constraints raise house prices more than rents.

Each household living in R subtracts some constant amount from its flow income to pay the permit price. This deduction corresponds to $\bar{x}$ in Proposition 1. The remaining income goes toward structure, lot, and non-housing consumption. Due to Cobb-Douglas preferences and production, the shares of remaining income going to these purposes are $\alpha\gamma$, $\alpha(1-\gamma)$, and $1-\alpha$, respecitively. Proposition 3 formalizes this argument.

Proposition 3 (housing characteristics). *Structure and lot sizes for household i in R are*

$$q_i^* = \alpha\gamma(k^q)^{-1}\left(y_i - \bar{x}\left(x_i^*\right)\right)$$

$$l_i^* = \alpha(1-\gamma)\left(k^l\right)^{-1}\left(y_i - \bar{x}\left(x_i^*\right)\right).$$

Both $E(q_i^* \mid y_i)$ and $E(l_i^* \mid y_i)$ strictly increase in y_i at each t, where the averages are over $a_{R,i}$ and $a_{F,i}$.

Holding income constant, regulation unambiguously decreases structure and lot sizes by increasing $\bar{x}(x_i^*)$, the annualized lifetime permit cost that household i pays to live in city R. This mechanism is an income effect: the permit price makes households poorer, leading them to consume less housing. The second part of Proposition 3 highlights that equilibrium characteristics rise in household income at a given time. Therefore, regulation could raise average structure and lot sizes in city R due to income sorting. This result explains why we control for income in our empirical work on housing consumption. According to the model, the estimated effects on structure and land consumption shown in Tables 3 and 4 should be negative, since those empirical estimates control for income. In fact, some of our point estimates are positive, but they are close to zero.

4.3. Equilibrium effects of geographic constraints

To isolate the effect of geographic constraints, we set $g^l < g$ so that the constraint binds, while assuming that g^n is sufficiently large so that the permit price in R equals zero. Proposition 4 describes household city choices given the path of permit prices.

Proposition 4 (sorting). *Household i lives in R only if*

$$\log\left(\frac{a_{R,i}}{a_{F,i}}\right) \geq \alpha(1-\gamma)\log\left(1 + \frac{p^l_{R,t}}{k^l}\right)$$

and lives in F when this inequality does not hold.

As with population constraints, geographic constraints lead some households with a higher taste for R to live in F. But different from the population constraints, this outmigration is independent of household income. Therefore, Proposition 4 matches the empirical results in Table 5: geographic constraints lower the housing stock but do not have meaningful effects on sorting by education and income. The housing characteristics for households in R clarify the lack of sorting in the model:

Proposition 5 (housing characteristics). *Structure and lot sizes for household i in R are*

$$q_i^* = \alpha\gamma(k^q)^{-1}y_i$$

$$l_i^* = \alpha(1-\gamma)\left(p^l_{R,t} + k^l\right)^{-1}y_i.$$

By driving up the marginal cost of assembled land ($p^l_{R,t} + k^l$), geographic constraints lead to smaller lot sizes. The proportional decrease in lot size is the same for all income groups and coincides with the term on the right side of the inequality in Proposition 4. This result holds because of Cobb-Douglas preferences and production. Another important modeling choice is the absence of minimum lot size requirements. With a minimum lot size, the geographic constraint would act as a fixed cost for poor households whose lot size is constrained to be the minimum.

Qualitatively, Proposition 5 explains the negative estimated effects of geographic constraints on measures of lot consumption in Table 3. However, it cannot explain the estimated negative effects of geographic constraints on structure consumption reported in Table 4. In Section 4.6, we relax the Cobb-Douglas functional forms of the production function and preferences so that geographic constraints may affect structure outcomes in the model.

To solve for the equilibrium price of land, we equate the total lot sizes of households choosing R with the maximal size that city R allows. The former comes from Propositions 4 and 5, while the latter comes from growing the initial city land size (appearing in Appendix C.4) by g^l. We obtain:

$$e^{-(g-g^l)t} = \frac{a_F^\beta + a_R^\beta}{\left(1 + \frac{p^l_{R,t}}{k^l}\right)\left(a_F^\beta\left(1 + \frac{p^l_{R,t}}{k^l}\right)^{\alpha\beta(1-\gamma)} + a_R^\beta\right)}.$$

Intuitively, the land price, $p^l_{R,t}$, equals 0 when $g^l = g$ because the demand to live in city R can grow at its natural rate g. When $g^l < g$, the demand for land in city R can no longer grow at its natural rate, and land prices must rise to clear the market. Higher land prices decrease the demand for land through two channels: lower lot sizes and smaller city population. These two effects account, respectively, for the two terms in the denominator. Mathematically, the right side of the equation deceases in $p^l_{R,t}$, so land prices always rise to balance the left side of the equation that decreases over time. The next proposition uses this equation to prove that prices must increase more than rents:

Proposition 6 (prices versus rents). *The effect of geographic constraints on rents,*

$$\frac{p_{R,t}(h)}{p_{R,0}(h)} = \left(1 + \frac{p^l_{R,t}}{k^l}\right)^{1-\gamma},$$

is less than the effect of regulation on ownership prices,

$$\frac{p^{own}_{R,t}(h)}{p^{own}_{R,0}(h)} = \int_t^\infty re^{-r(t'-t)}\left(1 + \frac{p^l_{R,t'}}{k^l}\right)^{1-\gamma} dt',$$

for all positive t and h.

The intuition for Proposition 6 is like that of Proposition 2. While rent growth reflects current land prices, price growth reflects current and future land prices. Because land prices always increase, prices grow from 0 to t more than rents, and the price-rent ratio is higher at any $t > 0$ than at time 0. Proposition 6 qualitatively explains the key empirical result that geographic constraints raise house prices more than rents.

4.4. Calibration

Although the model qualitatively explains many of the empirical results, we have not yet determined its quantitative match with the data. We aim to explain the smaller response of rents relative to house prices as well as the relatively small effects on housing consumption and location choices. To accomplish both objectives, we compare the predicted effects of supply constraints on rents, housing characteristics, and city choices given a predicted effect on ownership prices. Appendix C.11 gives details on how we quantitatively solve the model given parameter values. We choose these values as follows.

We use a discount rate of $r = 0.05$, which is roughly equal to the average real long-term interest rate over our sample period. We set the income distribution to a lognormal with mean \$50,000 and log standard deviation 0.96, which are roughly the mean and standard deviations of positive log household income in the 1980 and 2016 U.S. Census data samples. We take $\alpha = 0.25$ from Davis and Ortalo-Magné (2011), who find that this share of income is spent on rent in many cities from 1980 to 2000. We set β, which governs the distributions of preferences for R and F, equal to three, a value that is within the range estimated by Diamond (2016) by computing the elasticity of cross-city migration with respect to changes in wages and rents. We set $\gamma = 2/3$, the share of construction expenditure on structure that Albouy and Ehrlich (2018) estimate. The ratio a_R/a_F pins down the initial relative size of city R. We set this ratio to 1 so that the cities have identical populations absent regulations in R. The unconstrained growth rate of the number of households, g, equals 0.01, reflecting average annual population growth in the U.S. between 1980 and 2016. We do not choose specific values

Table 8
Reponses to Supply Constraints that Raise Prices 10% over 30 Years (Model Simulation, %).

	Population constraints	Land area constraints		
	(1)	(2)	(3)	(4)
Quality-adjusted rent (median)	6.0	5.8	5.9	5.7
Structure size, holding income constant	–1.7	0.0	2.1	–1.4
Lot size, holding income constant	–1.7	–15.7	–13.9	–6.6
Structure size, city average	1.6	0.0	2.1	–1.4
Lot size, city average	1.6	–15.7	–13.9	–6.6
Median city income	3.0	0.0	0.0	0.0
Population	–3.6	–2.1	–2.2	–2.1
Housing services consumption	–2.1	–7.5	–5.6	–5.4
Housing expenditure, holding income constant	7.3	0.0	2.1	2.1
Assumptions				
Housing/non-housing substitution elasticity	–	1	0.5	0.5
Lot/structure substitution elasticity	–	1	1	0.33

for k^q and k^l because the model outcomes we examine do not depend on the values of these parameters.

The final parameters are g^n and g^l, which describe the supply constraints. For each constraint, we choose the relevant parameter so that the constraint raises the ownership price of a constant-quality house (at the median of the quality distribution at time zero) by 10% over 30 years. We impose only one constraint at a time, so that results from the model correspond to the empirical regressions that estimate the marginal effect of each constraint while controlling for the other constraint. This methodology gives us values of $g^n = 0.0092$ for the model with the population constraint and $g^l = 0.0036$ for the model with the land area constraint. Recall that in Table 2, we find that separately tightening either constraint by 1 standard deviation is associated with about 10 percent faster price growth over a roughly 30-year period. By targeting the same price response in the model, we can compare the predicted effects on other outcomes in the model to the data.

Before proceeding, we check whether the implied value of g^n matches the 3- to 4-fold increase in permitting times between the 1980s and 2006 that we report in Table 1. In the simulation, we can think of $t = 0$ as mapping to 1980 in the data. Therefore, 1988 (roughly the year of the first survey) corresponds to $t = 8$ and 2006 (the second survey) corresponds to $t = 26$. In our simulation, the permit price at $t = 26$ is four times higher than it was at $t = 8$. In other words, our choice of parameters leads to a quadrupling of the regulatory constraint between 1988 and 2006, which is consistent with what we find in the data on permit issuance.[35]

4.5. Quantitative results

Table 8 reports changes in outcomes given each supply constraint: the case of population constraints in column 1, and the case of land area constraints in column 2. Under both supply constraints, the rent of the median unit rises much less than prices—by only about half. Quantitatively, this ratio is in line with our empirical results in Table 2, although the estimated effect of geographic constraints on rent is a little smaller than predicted by the model.

According to our model, about half of the effect of supply constraints on ownership prices comes from anticipation of future rent increases that the supply constraints are expected to cause. Fig. 4 illustrates this result by showing the evolution of prices and rents in response to the population constraint. Initially, rent is unchanged because the population constraint only affects future growth. But prices (and hence the price-rent ratio) jump by about 4 percent in response to anticipated future rent increases. Over time, prices and rents rise by similar amounts, so that the net increase in prices remains larger. Although the differential between prices and rents becomes a smaller fraction of rent as time goes on, it is still quite substantial after 30 years. Results are similar for the geographic constraint, not shown.[36]

Holding income constant, population constraints decrease structure and lot sizes by 1.7%. To compute this number, we calculate the reduction in structure and lot size for each household in R after 30 years and then take the average across households. The 1.7% decrease in structure and lot sizes is nearly an order of magnitude less than the increase in ownership prices and is significantly less than the increase in rents, in part because housing begins as only 25 percent of households' budgets, and households pay for the permit price by cutting back on both housing and non-housing consumption. Recall that the model's predictions for the changes in these housing characteristics are likely an upper bound because the model does not account for the durability of housing. Therefore, we would expect the estimated effects in the data to be even smaller than those predicted by the model.

The predicted effects of population constraints on housing consumption are close to the estimated effects of regulatory constraints on structure and lot size. Although the estimated effect on lot size is positive (see Table 3), the point estimate is small, and we cannot reject an effect equal to minus 1.7%. Table 4 finds no effect of regulatory constraints on the square footage of single-family homes, but we find that rooms per adult fall by 1.6%. Broadly speaking, we conclude that the model well explains the quantitatively small effects of regulatory constraints on housing consumption that we find in the data. Since the empirical estimates are based on a sample of largely owner-occupied homes, we conclude that the small changes in housing consumption are consistent with a small increase in implicit rent of owner-occupied homes.

In the model, population constraints reduce the number of households that choose to live in the regulated city by about $3\frac{1}{2}$ percent. Because poorer households are more likely to leave the regulated city, these constraints raise the median income in the city by 3.0%. Both effects are close to the corresponding empirical point estimates of minus 6 and positive 2 percent, and the model predictions fall within the 95% confidence intervals around these estimates.

[35] Because the model abstracts from frictions such as the durability of housing, the implied value of g^n is not perfectly comparable to the data on permit times. Given that the model matches the data on the quantity response to the population constraint (see below), this lack of comparability seems unlikely to be important quantitatively. The value of g^l we use implies that the developed land area in city R is 17% smaller after 30 years than it would have been absent the constraint. It is difficult to check this number against the data because we are not aware of any time-varying measures of the degree to which geographic constraints bind.

[36] In some models, convergence between prices and rents occurs much faster than in our model. See Rappaport (2004) for an example in which convergence occurs more quickly because it predicts the response to a one-time shock to the level of labor demand. By contrast, in our model, regulation constrains the population growth rate by a greater amount over time, so it takes longer for rents to catch up to the increase in prices.

Table 9
Reponses of Rent to Supply Constraints that Raise Prices 10% over 30 Years, Perfect Foresight (Model Simulation, %).

Constant interest rate		Declining interest rate	
Population constraints	Land area constraints	Population constraints	Land area constraints
10.4	10.0	0.7	0.8

Note: We calculate price and rent growth in city R relative to city F for the house at the median of the initial quality distribution in city R. We set $r = 0.05$ in the "constant interest rate" panel. In the "declining interest rate" panel, we compare the equilibrium with $r = 0.02$ at $t = 30$ to the equilibrium with $r = 0.1$ at $t = 0$. In all columns, we set $g_0^l = g^l$ and $g_0^n = g^n$. In each "population constraints" (resp. "land area constraints") column, we set $g^l = g$ (resp. $g^n = g$) and choose g^n (resp. g^l) so that prices rise 10% over 30 years.

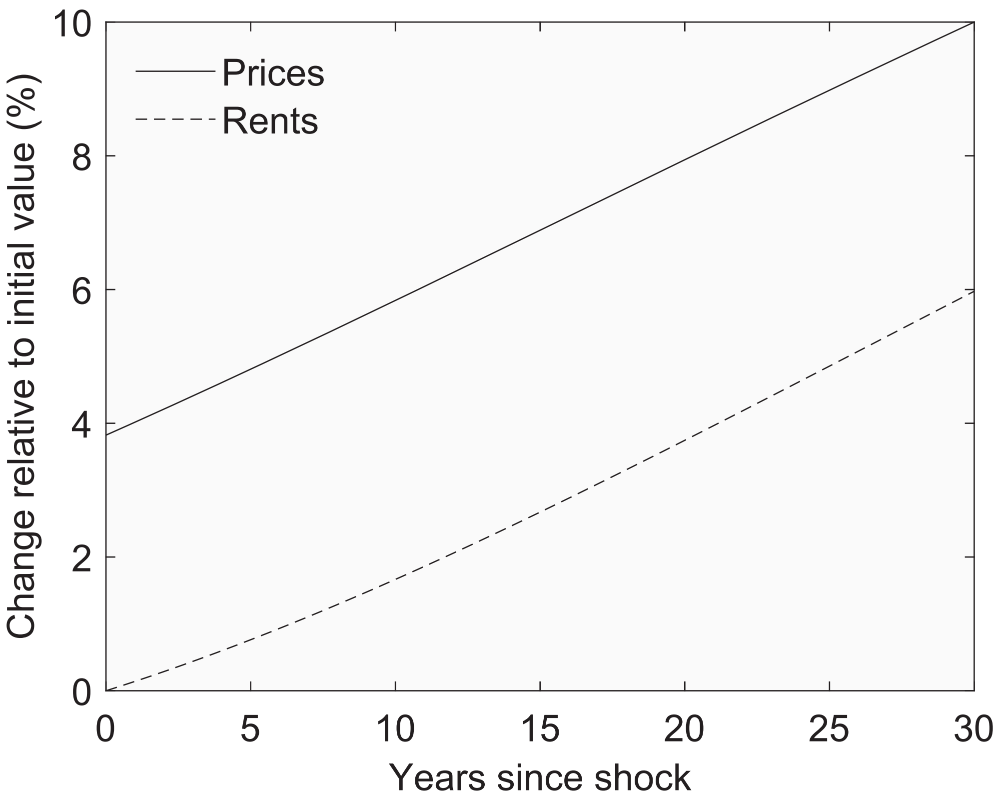

Fig. 4. Increases in House Prices and Rent in Response to an Unanticipated Population Constraint.

In column 2 of Table 8, the model predicts land area constraints to reduce lot sizes by 15.7%, which is much more than the effect on house prices. This type of constraint has no effect on structure size, housing expenditures, or median city income. The lack of adjustment along these dimensions results from our assumptions that preferences and the housing production function are Cobb-Douglas, so that an increase in the unit price of land leads only to less land consumption and some out-migration.

Relative to the empirical evidence, the model over-predicts the shrinking of lot sizes in response to geographic constraints. The empirical point estimate of the effect of geographic constraints on the lot size of single-family homes is minus 0.041, and we can soundly reject a decline of 15.7%. While Table 3 finds that geographic constraints lead to a smaller fraction of single-family homes, we are skeptical that this effect is substantial enough to account for the residual model-predicted decline in lot sizes.

We find more adjustment to geographic constraints in the data along margins other than lot size. Table 4 finds a 3% decrease in structure consumption operating through rooms per adult, and Table 5 estimates an 11% decrease in the housing stock. The model predicts no response in the first outcome and only a 2.1% decrease in the number of households. Households may find it easier to reduce the consumption of housing structure and non-housing goods rather than land, perhaps because of frictions in the adjustment of existing lot sizes or because of minimum lot size rules. Another possibility, to which we turn now, is that the Cobb-Douglas functional form assumptions are overly restrictive.

4.6. *Relaxing the Cobb-Douglas functional forms*

Although much of the literature has found that Cobb-Douglas functions are good approximations for both utility and production, the remaining columns of Table 8 explore the case of geographic constraints while relaxing the Cobb-Douglas assumptions. Instead, we use constant elasticity of substitution (CES) preferences or production, of which Cobb-Douglas is a special case. Appendix sections C.1 to C.4 solve this more general model.[37] Column 3 reports results when preferences are CES, in which case we take the elasticity of substitution between housing and non-housing consumption from Albouy et al. (2016). In column 4, we also use a CES production function, taking the elasticity of substitution between land and structure from Albouy and Ehrlich (2018). In both cases, we keep the initial expenditure share on structure and housing the same as in the baseline calibration.

[37] As we show there, the results for regulatory constraints remain the same when we use CES preferences or production. Proposition 1 continues to hold, implying the same path for $x_{R,t}$, and the change in each household's consumption bundle relative to $t = 0$ depends only on its income and the path of $x_{R,t}$.

With CES preferences, households cut lot consumption by 13.9%, still a large number but less extreme than before. In contrast to our empirical results this model predicts a 2.1% *increase* in structure sizes, which occurs because structure costs must scale with total housing costs given a Cobb-Douglas production function. Therefore, CES preferences move us closer to the data on lot consumption, but no closer on other outcomes.

When the housing production function also is CES (column 4), lot sizes only fall by 6.6% and structure sizes now fall 1.4%. CES production makes structure and lots strong complements, meaning that developers cut structure sizes in response to the increase in land prices. The lot size result moves within the 95% confidence interval of the effect of geographic constraints on lot sizes. However, the predicted decrease in structure size is outside the confidence interval around the estimated 3 percent decline in rooms per adult. Similarly, the model's predicted decrease in population is still smaller than the 10 percent decline we estimated in the data.

In summary, the CES extensions bring the model's predictions closer to the empirical results on the effect of geographic constraints on land consumption, but the magnitude of the decrease in land consumption in the model is still larger than we estimate empirically. Moreover, decreases in structure consumption and population in the model are smaller than we estimate in the data. It seems likely that factors outside the model (like minimum lot size, density restrictions, and adjustment costs) make it easier for households to adjust to higher land prices by altering household size or choosing a different location, rather than by cutting land consumption as much as they would like.

4.7. Robustness

This section clarifies the importance of two key parameters in generating our results: the discount rate, r, and the parameter that governs heterogeneity in preferences across locations, β. We also explore whether the results change if we decrease g^n and g^l to generate a sharper increase in house prices, which might matter due to nonlinearities in the model.

Appendix Table B10 reproduces Table 8 using a very high discount rate ($r = 0.1$) and a very low discount rate ($r = 0.02$). Under the high discount rate, rents rise between 7 and 8 percent in response to the supply constraints, implying a smaller increase to the price-rent ratio than in the baseline. When the discount rate is high, news about future rent growth has a smaller effect on house prices. As a result, a tighter constraint is necessary to generate the higher rent needed to raise house prices 10%. Consistent with this logic, rents rise only about 3 percent under the low discount rate. Population constraints decrease structure and lot sizes more sharply under the low discount rate, however, because households save more in anticipation of future increases in rents. In contrast, land area constraints have smaller effects on housing consumption with the low discount rate, as current rents are lower and consumption decisions reflect only current rents. Therefore, our baseline result of a small effect of supply constraints on rents grows stronger with a smaller discount rate, whereas the influence of the discount rate on other outcome depends on the type of constraint.

Appendix Table B10 also reproduces Table 8 using a high value of $\beta = 10$ and a low value of $\beta = 1$. When β is high, there is less heterogeneity in location preferences, so location choices are more sensitive to the difference in house prices between F and R. In both cases, the results on rents and household outcomes remain similar to the baseline. In contrast, the decline in the city's population is 10 times larger when $\beta = 10$ than when $\beta = 1$. Therefore, our predictions for household-level outcomes are robust to uncertainty about β, whereas our predictions for city-level outcomes depend more strongly on β.

The model calibration with the baseline value of $\beta = 3$ predicts that population constraints lower the city's population by 3.6%, which is close to the effect of regulatory constraints on the housing stock that we estimated in the data. The model with $\beta = 3$ also predicts an increase in median income that is similar to the empirical estimate. The similarity of these outcomes suggests that our baseline value for β is reasonable. However, the effect of geographic constraints on the housing stock is more negative in the data than in the model, even with the larger value of $\beta = 10$. While a very large β could explain the strong negative effect of geographic constraints on the housing stock that we estimate in the data, it is inconsistent with our estimated effects of regulatory constraints. Since underlying preferences for locations should be the same regardless of the types of supply constraints on housing, it seems unlikely that this preference parameter can explain why we estimate a larger population response to geographic constraints than the baseline model predicts.

In Appendix Table B11, we reproduce Table 8 but target price growth of 48% instead of 10%. This larger target corresponds to the average price growth of 39 log points in superstar cities that we report in Table 7. The effects on rent, housing consumption and household location scale up by about the same amount as prices, implying that nonlinearities are not an important concern for interpreting our results. The model predictions shown in Appendix Table B11 can also be compared to the empirical results on superstar cities in Table 7. The effect on rooms per adult is in line with the model's predicted effect of regulatory constraints on structure size, but the model generates stronger effects on rents and median income than appear in the data. The model also predicts declines in lot sizes (which are very large in the case of geographic constraints), whereas lot sizes actually rose by 14 log points more in superstar metros than in other areas. Some of the differences between the model predictions and the data could owe to the fact that superstar cities are identified as locations that experienced strong demand as well as tight supply, whereas the model predictions only pertain to the effects of tight supply.

4.8. Changing the information structure

As Fig. 4 shows, the price-rent ratio increases in our model due to information about the future, as prices capitalize news of future rent increases. This section clarifies this channel in two ways. First, we relax the assumption that households do not initially expect the supply constraints in city R. Second, we explore an alternate mechanism involving news about the discount rate instead of supply constraints.

Households initially believe at time 0 that the constraints in city R are g^n_0 and g^l_0. At the end of time 0 (after developers and dynasties have made their initial decisions), regulators in city R unexpectedly announce the final constraints g^n and g^l. When $g^n_0 = g$ and $g^l_0 = g$—that is, households do not expect binding constraints—this extension reduces to the main model. Households initially expect a binding constraint when $g^n_0 < g$ or $g^l_0 < g$. If $g^n_0 < g^n \le g$ or $g^l_0 < g^l \le g$, households learn that the corresponding constraint is looser than initially thought. Alternatively, if $g^n < g^n_0 \le g$ or $g^l < g^l_0 \le g$, households learn that the corresponding constraint is tighter than initially thought. The following proposition extends Propositions 2 and 6.

Proposition 7 (prices versus rents).

(a) **Population constraint.** Suppose $g^n < g$ and $g^l_0 = g^l = g$. For each positive t and h, there exist $g^n_* < g^n_{**} < g$ such that if $g^n_0 < g^n_*$, then $p^{own}_{R,t}(h)/p^{own}_{R,0}(h) < p_{R,t}(h)/p_{R,0}(h)$ and if $g \ge g^n_0 > g^n_{**}$, then $p^{own}_{R,t}(h)/p^{own}_{R,0}(h) > p_{R,t}(h)/p_{R,0}(h)$.

(b) **Land area constraint.** Suppose $g^l < g$ and $g^n_0 = g^n = g$. For each positive t, there exists g^l_* such that if $g^l_0 < g^l_*$, then $p^{own}_{R,t}(h)/p^{own}_{R,0}(h) < p_{R,t}(h)/p_{R,0}(h)$ for all $h > 0$ and if $g \ge g^l_0 > g^l_*$, then $p^{own}_{R,t}(h)/p^{own}_{R,0}(h) > p_{R,t}(h)/p_{R,0}(h)$ for all $h > 0$.

Therefore, households must expect a sufficiently light level of the constraint initially for our main result to hold. If households expect a sufficiently *tight* constraint at the outset, then prices increase *less* than rents, meaning that the price-rent ratio declines between 0 and t. Intuitively, rents rise between time 0 and time t because the final constraint (either g^l or g^n) limits the city's natural growth. Prices rise for the additional reason of initial news about the final constraint. If households learn that constraints will be much *less* severe than expected, then rents rise more than prices over time.

In recent years, some local governments have seemed to become more growth-friendly through public statements or rule changes.[38] Our model does not capture this trend exactly, because the model's supply constraints remain fixed after time 0 instead of changing over time. However, Proposition 7 suggests that becoming more friendly toward construction could reduce the growth rate of house prices relative to rents, and hence the price-rent ratio, to the extent that developers and households do not anticipate this trend.

The next exercise shuts down the information effect entirely by setting $g_0^n = g^n$ or $g_0^l = g^l$; that is, households completely anticipate the final supply constraints from the outset. We then solve for the constraint that increases prices 10% over 30 years and report the corresponding rent growth in the first two columns of Table 9. Rents rise as much as prices in this scenario, confirming that news about supply constraints is the driving force behind the result that the price-rent ratio grows in the main model.[39]

Up to this point, we have assumed a constant interest rate in the model, but the real rate fell considerably over the period we study in the data. When we subtract annualized inflation over the previous 2 years (as a proxy for expected inflation) from the average 30-year fixed mortgage rate, we calculate a decline in the real rate from about 10% in the mid-1980s to about 2% in 2012–2016 (see Appendix Fig. B2).[40] Theoretically, such a decline would also boost the price-rent ratio, and this increase may be larger in metro areas with tighter supply constraints initially. Therefore, a declining interest rate might explain why we find a larger effect on prices than on rents even in the absence of any news about constraints.

To investigate this possibility, we solve our model separately under the 10% and 2% interest rate regimes. We then compare the equilibrium at $t = 30$ in the $r = 2\%$ simulation to the equilibrium at $t = 0$ in the $r = 10\%$ simulation.[41] Throughout this exercise, we set $g_0^l = g^l$ and $g_0^n = g^n$ so that households have perfect foresight about the final supply constraints. In effect, we are isolating the effect of news about the interest rate.

The last two columns of Table 9 report the results. Under either constraint, rents now rise about 1% given a 10% increase in house prices in city R relative to city F. Therefore, an unexpected decline in the real rate can explain why prices rise more than rents in supply constrained metros, given perfect foresight about the constraints. If anything, the real rate story generates a larger increase in the price-to-rent ratio than we see in the data.

In our view, both mechanisms—news about constraints and news about interest rates—probably play some role in explaining why price-rent ratios have increased in constrained areas since 1980. We place more weight on news about constraints for two reasons. First, we are skeptical that households and developers in 1980 fully predicted the subsequent tightening of constraints, given the extent to which constraints tightened after 1980. For instance, rezoning applications took less than 3 months in the 1980s in 90% of the metro areas in Table 1. By the mid-2000s, rezoning times exceeded this length in nearly every metro area in the survey. Second, we find similar empirical results for prices and rent when we estimate effects over the longer period from 1960 to 2016 (see Appendix Table B12), even though the real interest rate was nearly as low in the early 1960s as it was in 2012–2016 (see Appendix Fig. B2). In any case, regardless of the exact type of news that drove the overall increases in the price-to-rent ratio, the differential outcomes across locations have been driven by differential supply constraints.

5. Conclusion

We have shown both empirically and theoretically that housing supply constraints have a smaller effect on housing affordability than on the purchase price of housing.[42] Supply constraints push up price-rent ratios and have only limited effects on housing consumption and location decisions, even as they keep cities smaller than they otherwise would be. Because rents are what matter for affordability, supply constraints have decreased affordability less than has been recognized in studies examining prices only.

Our results may seem surprising in light of the strong cross-sectional correlation between supply constraints and rents. Indeed, in our sample, the cross-sectional correlation between supply constraints and rents is three times larger than our panel estimates using controls for productivity growth and amenities. But locations with tight supply constraints tended to have had higher rent even back in 1980, so the changes in rent over time are not as strongly correlated with supply constraints as the current levels. Controlling for measurable differences in demand further reduces the estimated effects of supply constraints, suggesting that supply constraints are also correlated with strong housing demand.

One should not conclude from our analysis that housing affordability is not a problem in supply-constrained metropolitan areas. Rather, our results suggest that the supply constraints alone have not been the driving force behind high rents. Why are our estimated causal effects so much smaller than the effects suggested by the cross-sectional correlation between rent and supply constraints? One possibility is that our measures of supply constraints are not good proxies for true supply constraints. That said, the two constraints that we use are the most commonly used measures in the literature, and we still find relatively small effects when using other explicit measures of constraints or a measure based on ex-post housing market outcomes.

A second possibility is that supply constraints were at least somewhat binding even back in 1980, in which case we have underestimated the true effects of these constraints. Other research has documented the existence of some regulations prior to 1980—for example, Ganong and Shoag (2017) document the appearance of the words "land use" in state court cases as far back as 1950—and some geographic constraints were surely binding back then. But as we have shown, many constraints did become much stronger between 1980 and the 2000s.

A third possibility is that strong rent growth since 1980 is due largely to increases in demand. It is not possible for prices and rents to increase if supply is entirely unconstrained. Supply is constrained along some dimensions in most locations, however, not just in those that seem to be most constrained. For example, nearly all local governments have

[38] See, for instance, New York City's *Housing New York: A Five-Borough, Ten-Year Plan* announced in 2014, Minneapolis's "Minneapolis 2040 – The City's Comprehensive Plan" passed in 2018, and Seattle's Mandatory Housing Affordability ordinance adopted in 2019.

[39] In the baseline model, prices jump at time 0 while rents do not (see Fig. 4). When households correctly anticipate the final constraint, this jump disappears, and rent growth can exceed price growth. Appendix C.11 provides mathematical details on why rent growth exceeds price growth when households correctly anticipate the geographic constraint.

[40] The real rate was lower in the early 1980s, so using a rate from the mid-1980s gives an upper bound on the magnitude of this effect. We use a mortgage rate to determine borrowing costs because most borrowers finance at least 80 percent of a home purchase with a mortgage.

[41] An alternate exercise could involve feeding the interest rates from the data into the model. However, doing so would substantially complicate the model because it would need to accommodate stochastic interest rates.

[42] By making it particularly hard to buy a house, supply constraints may also have welfare costs from which we abstract in this paper. Entrepreneurs use housing wealth as collateral for small business ventures (Adelino, Schoar, and Severino 2015; Kerr, Kerr, and Nanda 2019). Homeownership may act as a forced saving mechanism, helping households achieve higher future consumption (Ghent 2015; Schlafmann 2016). In addition, homeowners invest more than renters in social capital (DiPasquale and Glaeser 1999), and their children obtain higher test scores and are more likely to graduate from high school (Haurin, Parcel and Haurin 2002; Aaronson 2000).

zoning regulations that separate residential land uses from other uses. In addition, the durability of existing structures can make land assembly challenging, especially in neighborhoods close to the urban center. Thus, demand might have sharply increased rent in many metropolitan areas in the US, even ones with relatively less restrictive supply constraints. Future research should examine the sources of rising demand in US metropolitan areas, the baseline level of constraints in all areas, and the connection with housing affordability.[43]

Beyond the results for rent, our research reveals interesting implications of housing supply constraints for housing consumption. We find much smaller reductions in housing unit size and lot size than many people might expect. People appear to adjust to a higher rent for housing services by living in larger households rather than by living in smaller homes. In addition, an inability to reduce land consumption as much as desired appears to have reduced the number of households able to live in geographically constrained metropolitan areas. Given that these restraints on city size may have important implications for both local and aggregate productivity (Hsieh and Moretti 2019), further work studying why structure size and lot size do not adjust in response to housing supply constraints would be fruitful.

Finally, and at a broad level, our results suggest that policies targeted solely at alleviating housing supply constraints in supply-constrained areas would likely not bring down rents in these locations by a material amount. Specifically, a shift in regulation of 3 standard deviations, which is roughly the difference between Boston and Indianapolis in our data, would only reduce rents by about 12 percent. Therefore, analysts and policymakers concerned with housing affordability should consider a broader range of issues, including demand-side factors, that might be boosting the rent for housing services. That said, modest increases in the housing supply could still have beneficial effects even if there is little impact on housing affordability. For example, allowing more people to move into supply-constrained areas would give these people access to the amenities in these locations and create greater agglomeration externalities. It is also possible that more dramatic changes in the regulatory posture of land use policy, beyond what has been seen so far in the United States, could boost housing supply by more and materially improve housing affordability.

Credit author statement

All three authors contributed as full authors.

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Appendix A. American Housing Survey

The American Housing Survey is a panel survey of housing units sponsored by the US Department of Housing and Urban Development (HUD). In addition to a biennial national survey, HUD periodically surveys large metropolitan areas. We use the metropolitan samples because the national survey is too small to provide a sufficient number of observations in a large number of metropolitan areas. Specifically, we combine the 1984 (earliest available), 1985, 1986 and 1987 surveys for data from the early period, and we combine the 2011, 2013 and 2015 surveys for data from the recent period. In this combined sample we can observe 39 metropolitan areas in both the early period and the recent period. Because the number of metropolitan areas is already so small, we do not drop low demand areas from the analysis.

A.1. Effects of survival and renovation bias on unit size and lot size

The AHS reports information on the unit size and lot size of single-family homes. We clean the lot size and unit size variables using the same restrictions as we used in the property tax records: We drop observations with a lot size less than 2000 square feet or greater than 175,000 square feet (about 4 acres), we drop observations with a unit size greater than 10,000 square feet, and we drop observations for which the ratio of unit size to lot size is greater than 5 (which are unreasonable values for single-family homes).

The potential bias in the property tax records results from only observing homes in 2014. Some homes built in the 1960s or 1970s might have been torn down or renovated, with the result that average unit size and lot size of homes observed in 2014 might not accurately reflect the actual characteristics at the time they were built. To assess the magnitude of this potential bias, we take all single-family homes in the AHS that were built in the 1960s and 1970s and calculate their average unit size and lot size by metropolitan area and survey time period. Next, we examine the correlation of growth between the two survey waves in average unit size and lot size by metropolitan area with our two supply constraints. If we were to find that changes in these characteristics were systematically different in areas with tight constraints compared with other areas, we would be concerned that differential survival and/or renovation of housing units could bias the results that we obtain with the 2014 property tax records.

Table A1 reports the results of regressing growth of average unit size and average lot size on the two supply constraints. None of the coefficients are statistically different from zero, although with only 39 metro areas and only 100 to 1000 housing units in each metro-by-time period, the standard errors are too large to draw precise conclusions. The coefficient on geographic constraints in the lot size regression is about 0.02, although it is not statistically significant. Recall that using the property tax records we estimated that lot sizes had fallen by more in areas with

Table A1
Correlation of Supply Constraints with Changes in Unit Size and Lot Size of Single-Family Homes in AHS data.

	ΔLn(Unit Size)	ΔLn(Lot Size)
Constant	0.005	−0.192
	(0.028)	(0.039)
Regulatory constraints	0.029	0.029
	(0.031)	(0.042)
Geographic constraints	0.003	0.017
	(0.026)	(0.035)

Note: Sample includes single-family homes built in the 1960s or 1970s, and changes in characteristics are calculated from metro-level averages in the 1980s to metro-level averages in the 2000s. Regressions are weighted using the number of housing units in the metro area.

Table A2
Factor Loadings on Housing Characteristics.

	Loading on First Component
Number bathrooms	0.34
Indicator for at least 1 half bath	0.21
Resident rating of unit quality	0.18
Presence of garage or other parking	0.31
Presence of porch	0.26
Presence of dishwasher	0.35
Presence of garbage disposal	0.26
Presence of clothes washer	0.36
Presence of clothes dryer	0.38
Presence of working fireplace	0.32
Presence of air conditioning	0.27

[43] For example, Howard and Liebersohn (2021) find that rising rents from 2000 to 2018 are largely explained by changes in where people want to live.

Table A3
Estimated Effects of Supply Constraints on House Prices and Rent Per Square Foot.

	Ln(Price Per Square Foot) SF Homes	Ln(Rent Per Square Foot) SF Homes	Ln(Rent Per Square Foot) All Homes	Ln(Rent Per Square Foot) 2-Bed Apt.
"Recent" indicator	0.257	0.427	0.235	0.192
	(0.079)	(0.045)	(0.049)	(0.065)
Indicator interacted with:				
Regulatory constraints	0.097	0.033	0.018	0.009
	(0.041)	(0.033)	(0.022)	(0.023)
Geographic constraints	0.137	0.030	0.036	0.049
	(0.042)	(0.027)	(0.020)	(0.020)
Controls for productivity and amenities	Yes	Yes	Yes	Yes
Controls for housing unit quality	Yes	Yes	Yes	Yes
Metropolitan area fixed effects	Yes	Yes	Yes	Yes
Number of observations	113,275	21,988	62,868	17,941

Note: Standard errors are clustered by metropolitan area. Regression controls for unit age and all of the measures of quality listed in Table A2. Unit age, number of bathrooms, and resident's quality rating are allowed to have non-linear effects by specifying an indicator for each possible value.

tighter geographic constraints. Taken at face value, the positive correlation that we estimate here means that lot sizes of the older homes in the property tax records have fallen by less in more geographically constrained areas. Thus, we might have found a less negative effect of geographic constraints on lot size had we been able to observe lot size in 1980 instead of 2014.

A.2. Housing unit quality

The AHS collects information on a variety of housing unit characteristics in addition to unit size and lot size. We use principal component analysis to derive a common factor from these characteristics that reflects housing unit quality. We use a sample that includes both multifamily and single-family homes; results are similar when liming to single-family homes. The first principal component has an eigenvalue equal to 4.05 and positive loadings on all housing attributes, indicating that this factor is probably a good measure of housing unit quality. Table A2 reports the factor loadings on each of the characteristics included in the model. We do not include unit size or lot size in the factor model because we examine those characteristics separately. We also exclude the number of rooms and number of bedrooms because they are strongly correlated with unit size.

A.3. Effects of supply constraints on house prices and rent per square foot

Because the AHS has data on unit square footage, we can control for housing quality in our price and rent regressions by estimating effects on prices and rent per square foot. We can also control for other measures of housing unit quality as described above. Table A3 shows that effects on rent per square foot are less than half the estimated effects on price per square foot. However, standard errors are fairly large, owing to the small number of metro areas and small number of homes per metro.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.jue.2022.103427.

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