# SUPERSTAR CITIES

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**Abstract**

Large long-run differences in average house price appreciation across metropolitan areas over the past 50 years have led to wide spatial dispersion in house prices. We show this can be explained in large part by inelastic supply of land in some attractive locations combined with an increasing number of high-income households nationally. The resulting high house prices crowd out lower-income households from living in high price growth superstar housing markets, inducing a right-shift in the local area income distribution. We observe the same pattern among municipalities within a metropolitan area when the number of high income households in the metropolitan area grows. These facts suggest that disparate local house price and income trends can be driven by aggregate demand, not just changes in local factors such as productivity or amenities.

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A striking feature of urban housing markets post World War II is the considerable dispersion across U.S. metropolitan areas and towns in long-run real house price appreciation rates. In Figure 1, which plots the kernel density of average annual real house price growth for 280 U.S. metropolitan areas between 1950 and 2000, average real house price appreciation ranged from about 0.2 percent to over 3.8 percent per year, with an especially thick right tail of growth rates above 2.6 percent. This distribution is not an artifact of a few small areas that grew very rapidly. For example, Table 1, which reports the annualized house price growth rates for the top and bottom ten Metropolitan Statistical Areas (MSAs) with populations above 500,000 in 1950, shows that San Francisco enjoyed an average annualized real house price appreciation rate of more than 3.5 percent.[1] By contrast, Buffalo realized barely 0.5 percent average annual real price growth. Overall, a small group of MSAs experienced real house price growth rates that exceeded the average for large MSAs by anywhere from 0.5 to 1.25 percentage points per year.

These differences in long-run rates of appreciation led to an ever-widening gap in the price of housing between the most expensive metropolitan areas or communities and the average ones. Figure 2 plots the distribution of mean real house values across metropolitan areas in 1950 and 2000. In 1950, house prices in the most expensive cities were twice the national average. By 2000, the gap had risen to four times the national average. A similar evolution occurred between 1970 and 2000 among U.S. municipalities.

Why house price dispersion has increased so much over such a long time span is not well understood. Most existing research focuses on cross-MSA differences in the levels of house prices rather than growth rates. These cross-sectional differences in house price levels are usually assumed to be due to differences in local fundamentals. For example, standard

[1] The Census data underlying these figures is described more fully below. All monetary amounts are in constant 2000 dollars throughout the paper. The 280 metropolitan areas in Figure 1 had populations of at least 50,000 in 1950.

compensating differential models in urban economics attribute differences in house prices across markets to differences in the economic value to a household from living in one MSA versus another, with that value driven by factors such as inherent local productivity (and thus wages), amenities, or fiscal policies.[2] In addition, differences across markets in the elasticity of housing supply could lead to differences in capitalization of the economic value into land prices. However, in order to extrapolate this cross-sectional logic to explain differences in house price growth, long-run changes in local productivity, amenities, or housing supply elasticities would have to match the pattern of dispersion in long-run house price appreciation rates. There is little empirical evidence on whether that is the case.[3]

In this paper, we propose a simple mechanism that generates dispersion in long-run house price growth rates without relying on persistent changes over time in local fundamentals. Instead, we show that changes in the aggregate demand for housing create demand pressure at the local level. Because some localities have inelastic housing supply and because localities are differentiated in the sense that households have heterogeneous preferences over where they would like to live, a change in aggregate housing demand is manifested in different local house price growth rates. Consider the number of high income families in the U.S. as reflecting part of aggregate housing demand. When the number of high income families nationally grows, the number of households who would like to reside in any given community increases, presuming the distribution of households' preferences over where to live is constant. If the growth in latent

[2] Rosen (1979) and Roback (1982) provide the classic formulation using wages and natural amenities. Amenities could also include consumption agglomerations, such as in Waldfogel (2003), or local fiscal policy such as in Epple and Sieg (1999).

[3] For example, Van Nieuwerburgh and Weill (2010) find that the dispersion in metropolitan area-level wages has been large enough to account for the spatial distribution in house prices from 1975-2004, but they do not link growth in wages and growth in house prices at the individual MSA level. In addition, there is no empirical evidence that amenities grow at different rates over long periods of time. Natural amenities such as the weather or physical traits such as coastal location clearly do not change. Consumption agglomerations have been estimated only in the cross-section. [Waldfogel (2003)] Nor is there any evidence that household valuations of a given amenity have increased (e.g., see Glaeser and Tobio (2008) on the rise of the South).

housing demand for a particular location exceeds the growth in local housing supply due to supply inelasticity, house prices must rise to clear the market.[4]

We label areas where demand exceeds supply and supply growth is limited, "superstars." Our simple mechanism generates a number of powerful implications for superstars versus other locations. First, the gap in house prices between cities or towns can keep increasing. This occurs even when the inherent value of any particular location is unchanged, the housing supply has not become more inelastic, and the willingness-to-pay for each location by any individual family is unchanged. Instead, when the absolute number of rich families in the country increases, there simply are more households with a higher (but possibly unchanged) willingness-to-pay for the locations they prefer. High willingness-to-pay households outbid low willingness-to-pay ones, changing the composition of a location's potential residents. This will persist as long as aggregate housing demand grows faster than the supply of superstars.

Second, our mechanism implies that a change in the clearing house price induces a change in the local income distribution. This stands in contrast to prior research which assumes that local productivity growth yields higher wages that are then capitalized into house prices. In our model, land prices act as a clearing mechanism by which higher-income households crowd-out lower income households from a scarce location. In supply-constrained areas, families with high incomes or strong preferences for that location outbid lower willingness-to-pay families for scarce housing. As the number of high income families grows nationally, existing residents are outbid by even higher-income families, raising the price of land yet further. This process induces a shift to the right in the local income distribution.

[4] For our purposes, it does not matter what drives the differences in supply elasticities. It could be topography, regulatory supply restrictions, or some combination of the two.

Third, in asset market equilibrium, the dispersion in expected house price growth rates should yield differences in the price-to-rent ratio for houses. If home buyers in superstar cities expect their houses to appreciate over the long run, they should be willing to pay more (relative to the rental service flow), today.

We use U.S. Census data from 1950-2000 at the metropolitan area and municipality levels to test the implications of our model. Our main empirical result exploits the fact that our model predicts that a single national demand shock should have differential effects on metropolitan areas depending on their superstar status. We find that when the aggregate number of high-income households in the U.S. grows, house prices in superstar MSAs increase by more than in non-superstar MSAs, and both the average and right tail of the income distributions in superstar cities increase relatively more than in non-superstar cities. In addition, this mechanism explains a substantial portion of the increase in house price dispersion over the last 50 years.

Another important result is that this empirical pattern also holds within a metropolitan area. We find that an increase in the high-income population in a metropolitan area yields increasing price and income dispersion across municipalities within that area, with price growth, income growth, and income skewness in 'superstar suburbs' outpacing those in non-superstar localities.

We also document empirical evidence of several other consequences of our framework. First, house prices in superstar MSAs and municipalities (within an MSA) are a higher multiple of current rents, suggesting that homebuyers there anticipate more rapid long-run rent and price growth.[5] When aggregate housing demand increases, those multiples expand more for superstar

[5] This is not a violation of asset market equilibrium because superstar markets do not necessarily have higher risk adjusted returns. Rather, they are like growth stocks in the sense that higher expected capital gains come at the cost of greater risk and lower dividend (rent) yields. It is interesting that estimates of MSA-level housing returns in

MSAs than for non-superstars. Second, we allow for time-varying superstar status. When a metropolitan area transitions to being a superstar, we see an acceleration in house prices and in the right-shift of the income distribution. Third, in the cross-section, superstar metropolitan areas or municipalities have higher house prices and a higher-income population.

It is difficult for standard mechanisms of urban housing demand, such as productivity shocks or growth in agglomerations, to generate the empirical patterns we establish. They typically depend on local shocks to housing demand, and it would be unusual for those shocks to match the propagation from higher to lower geographies that we find. In addition, since productivity should benefit all households in a metropolitan area, productivity growth-based theories do not generate the house price growth dispersion across communities within the local labor market area that we observe. However, the evidence we present in favor of the Superstar Cities mechanism does not preclude these other possible explanations of urban housing demand. Indeed, it is likely that other factors are operating in addition to the mechanism we demonstrate.

In addition, we emphasize that our superstar mechanism is intended to explain differences in long-run trend growth rates of house prices, not short-run boom/bust cycles. Although superstar MSAs have higher long-run trend house price growth rates than other MSAs, this does not mean that house prices in superstars increase every year. It is clear in metropolitan area-level house price index data that superstar MSAs have experienced considerable short-run house price volatility, with prices that cycle around positive appreciation trends.

The plan of the paper is as follows. The next section outlines a simple two location model that shows how heterogeneity in supply elasticity combined with growing aggregate demand can combine to generate the patterns in the data described above. Section 3 then

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Campbell et al. (2009) are higher on average for the MSAs we consider to be superstars, but those estimates do not adjust for risk.

discusses the data used in our analysis, most of which is from the decennial censuses between 1950 and 2000. Section 4 reports the results. There is a brief summary and conclusion.

## 2. Superstar Cities: A Simple Model

To focus on the economic forces central to our hypothesis, we simplify the model to a few key elements. We consider two locations that differ in their elasticity of land supply and their innate productivity. These locations could be metropolitan areas, in which case aggregate growth would occur at the national level, or towns within a given MSA, in which case aggregate growth takes place at the metropolitan area level.

We label our two locations R and G. G, the "green" city, is perfectly elastically supplied, and housing can always be obtained at a normalized rent of zero. R, the "red" city, by contrast, has a capacity of $K(r)$ households. That capacity can be increased if rents, $r$, are high enough to make new construction worthwhile, so $K'(r) \geq 0$, with there being perfectly inelastic supply if this holds as an equality.[6]

Households vary by their innate productivity and their tastes for the two locations. There are $N$ workers in the economy, each with type $w_i \sim F(\cdot)$ on $[0,\infty]$. Each also has a preference for the G or R city, denoted by $c_i \sim U(0,1)$. A higher $c_i$ corresponds to a greater taste for city R. We assume that $c_i \perp w_i$, so that households of all abilities have the same distribution of preferences over the two cities.[7] Households are paid a productivity wage, and we allow for the possibility

[6] Epple and Platt (1998) present a more formal and extensive treatment of a similar model, but assume that land supply is perfectly inelastic in all jurisdictions. By limiting the model to two cities and allowing for elastic supply, we emphasize the testable empirical implications of differences in the elasticity of supply.

[7] Our main empirical predictions are robust to this assumption and reasonable alternatives to a uniform distribution of tastes amplify the income sorting predictions. To see this, suppose the Red city is preferred to the Green city by all workers. Then, only high-wage workers end-up in R because they are the only workers that can afford to live there. Of course, as Epple and Platt (1998) point out, a single preference model cannot literally be true, otherwise we would observe pure income sorting. Intermediate cases in which higher income workers have a moderate preference for R versus G would not change our qualitative predictions.

that R and G are differently productive in the sense that the same worker would be more productive in one city than the other. Differences in productivity are not the focus of this paper, but it is useful to allow for them in the model to clarify what mechanisms we can distinguish between empirically. In our model, a worker of type $w_i$ produces $w_i$ if she works in G, but $\beta w_i + \alpha$ if she works in R. This exogenous difference in productivity could be due to a variety of factors ranging from a production agglomeration to simple natural advantage. Obviously, the special case of $\alpha = 0$ and $\beta = 1$ reduces to all households being equally productive in either city.

The utility for household $i$ is denoted by $V_i$ and is a function of being in the preferred location and of non-housing consumption. Household utility in city G is given by $V_i^G = (1 - c_i)w_i$, and in city R, by $V_i^R = c_i(\beta w_i + \alpha - r)$. Thus, if $c_i = 1$, the household would prefer city R to the exclusion of all else. We will make the common simplifying assumption that there are no costs of moving, so the household chooses whichever city gives it the most utility: $V_i = \max\{V_i^R, V_i^G\}$. This framework further implies that the marginal rate of substitution between housing and non-housing consumption is zero and that housing can be consumed only in a fixed quantity. This also is a common simplification – see, for example, Sinai and Souleles (2005) – and in our context emphasizes the households' choice of location.[8]

In choosing to live in the city where their utilities are highest, households trade off rental costs against their preference for that city, their income, and any productivity difference. We will focus on the case where latent demand to live in R exceeds the space that would be available if rent were zero. If demand for R were not in excess of capacity, it would be free to live there

[8] The utility functions were chosen for ease of exposition. More general functions do not engender additional insight.

and households would sort between the two cities based on differences in their taste and productivity differences alone.[9]

Each household has a cutoff taste level for the red city, $\underline{c}(w_i)$. If their taste, $c_i$, is less than $\underline{c}(w_i)$, they would not be willing to sacrifice non-housing consumption to live in R. That cutoff taste level is solved for by equating the utility received from living in R and G:

$$\underline{c}(w_i) = \frac{w_i}{(1+\beta)w_i + \alpha - r} \tag{1}$$

If $\beta w_i + \alpha \geq r$, so income is greater than the market rent, then there exists a taste for city R, $\underline{c}(w_i)$, such that $V_i^R = V_i^G$ and the fraction of the mass of households of that productivity type with tastes above the cutoff prefers R. If more households want to live in R than there are spaces, in equilibrium rents must be at the level where R is just full:

$$N \int_{\frac{r-\alpha}{\beta}}^{\infty} [1 - \underline{c}(w)] f(w) dw = K(r) \tag{2}$$

Prediction 1: Rents, the average wage, and the share of workers who are high income are higher in *R* than in *G*. The difference increases with the inelasticity of supply in R.

Since rent is zero in G and greater than zero in R due to excess demand for the scarce locations in *R*, rent is higher in R than G by assumption as long as $K'(r) < \infty$. This rent premium is due to the underlying scarcity of land, not the cost of housing structures, which is similar across markets.[10]

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[9] For example, in the absence of productivity differences, any household with $c_i \leq 0.5$ weakly prefers G and so at least half the households choose to live in G, rent-free. The other half prefer to live in R, but if $K(r) < {}^{N}/_{2}$, they need to pay *r* to locate there.

[10] House price differences across markets are much greater than construction cost differences. (Gyourko and Saiz (2006))

The differences between R and G in average wages and the income distribution follow from the difference in rent. A higher rent in R means that, for a given taste for the red city, a household needs to have a higher income to be willing to live there. This can be seen by rewriting equation (1) in terms of the cutoff wage for a given taste, $\underline{w}(c_i)$, rather than the cutoff taste for a given wage. A household with taste $c_i$ would be willing to live in R as long as its type exceeded $\underline{w}(c_i) = \frac{(r-\alpha)c_i}{(1+\beta)c_i-1}$. Since $\frac{d\underline{w}(c_i)}{dr} > 0$, the cutoff wage is higher in R, where r>0, for all tastes. Since taste is independent of rent or income, the average wage rises with rent.

Differences between the income distributions in R and G follow from the nonlinearities in the tradeoff between income and rent. Each worker trades off its intensity of preference for the red city with the rent premium required to live there. From equation (1), the cutoff taste for a given wage, $\underline{c}(w_i)$, increases with rent, because $\frac{d\underline{c}(w_i)}{dr} = \frac{w_i}{((1+\beta)w_i+\alpha-r)^2}$. The increase is largest at low levels of $w_i$ and declines as $w_i$ rises above $\frac{r-\alpha}{\beta}$. Since the distribution of tastes is independent of income, a larger growth in the cutoff means that fewer households at that income are willing to live in R. Thus, higher rent displaces more low-income than high-income households from R, and this effect is larger the greater the difference in rent. This skews the income distribution in *R* to the right. For example, any worker with income less than *r* is better off in the free green city, no matter what its value of *c*. A low-wage worker with *w* just above *r* will choose *R* only if its *c* is close to one, and a high-income worker with *w* well above *r* will choose *R* as long as its *c* is at least slightly above 0.5. We would obtain this result for any distribution of *c* as long as the aggregate demand for *R* at zero rent exceeds $K(r)$. Note that this sorting occurs even when a given worker is equally productive in *R* and *G* and worker preferences are independent of income.

Prediction 2: Aggregate population growth causes rent growth in R, and more skewed wages in $R$ relative to $G$. The differences are larger the more inelastic is supply in R.

Growth in population increases the support of households with taste for R. The higher aggregate demand for R raises the clearing rent. This result can be derived by totally differentiating (2), substituting in (1), and solving:

$$\frac{dr}{dN} = \frac{K(r)/N}{N\int_{\frac{r-\alpha}{\beta}}^{\infty}\frac{w}{((1+\beta)w+\alpha-r)^2}f(w)dw+K'(r)} > 0. \qquad (3)$$

All terms in the numerator and denominator are positive. The terms excluding $K'(r)$ reflect how rents increase with population more when the latent taste for the location at the prior rent level, $K(r)/N$, is higher, but the effect is mitigated by the increase in the cutoff taste level (the integral in the denominator). A lower elasticity of supply (lower $K'(r)$) also yields a higher $\frac{dr}{dN}$ because higher demand is met by increases in rent rather than more new construction. Holding the distribution of productivity constant, a greater taste for the red city combined with a lower elasticity of supply yields the most sensitivity of rents to aggregate population growth.

The effect of the higher clearing rent propagates through the income distribution. Prediction (1) showed that a higher rent in R raised the cutoff productivity across the taste distribution, yielding a higher average income. It also showed that more low-productivity households would be displaced than high-productivity ones. Written in terms of $dN$:

$$\frac{d\underline{w}(c_i)}{dN} = \frac{c_i}{(1+\beta)c_i-1}\frac{dr}{dN} \geq 0. \qquad (4)$$

A higher cutoff productivity for every $c_i$ implies that the average wage in R must increase. By the same logic as in Prediction 1, an increase in the clearing rent without a commensurate increase in productivity means that the cutoff taste increases more for low-income households than for high-income households and the income distribution shifts to the right. Population growth leads to an even more skewed distribution of wages for workers living in *R* relative to *G*. Some families who previously had a strong preference to live in *R* will no longer have the income necessary to cover the rent, and others will no longer prefer R at the higher rent. Families with the lowest incomes are disproportionately priced out of *R* as the national population grows. This can be seen in:

$$\frac{d\underline{c}(w_i)}{dN} = \frac{w_i}{\left((1+\beta)w_i + \alpha - r\right)^2}\frac{dr}{dN} > 0 \qquad (5)$$

where the effect is greater at lower values of $w_i$.

More elastic supply in R reduces the responsiveness of rents to changes in aggregate population, and that propagates through all the predictions. If rents do not rise as much with population, then the effect of the increase in rent on the income distribution in R is also mitigated. That diminished increase in rent also means that the $\frac{dr}{dN}$ term in Equations (4) and (5) is smaller so that the cutoff and average wage do not rise as much and the income distribution does not shift as much to the right.

<u>Prediction 3:</u> A thicker right tail in the aggregate wage distribution leads to higher rents and wages in *R* relative to *G*. The differences are larger the more inelastic is supply in R.

Even without population growth, an increase in the skewness of the aggregate income distribution raises the average income. The rent premium in *R* rises because the willingness-to-pay of the marginal worker who prefers *R* goes up, but the number of families who prefer *R* does not increase. The higher rent, in turn, displaces relatively more low-wage workers in favor of high wage workers.

A simple proof of this point makes use of the fact that $\frac{d\underline{c}(w)}{dw} < 0$. Starting with equation (2), suppose part of the productivity distribution, $f(w)$, is shifted to the right by epsilon. That lowers the average cutoff wage in the integral in equation (2) since more of the mass of the aggregate productivity distribution is at high $w_i$, and thus increases demand for R. That higher demand yields a higher clearing rent. That higher rent has the same effect on the income distribution as in Prediction 2.

<u>Prediction 4:</u> When aggregate population growth and/or a spreading to the right of the overall income distribution is anticipated, *R* will have a higher price/rent ratio than *G*.

Expected long-run risk-adjusted returns to investing in housing in the two cities, where rent is analogous to the dividend paid by a house, are equated by the market. If workers anticipate that rents in *R* will grow faster than rents in *G*, they will bid up house prices so that the overall return for a house in *R* is equal to the return on a house in *G*. If *R* has a faster growth rate of rents than *G*, that market will also have the same faster stationary growth rate in prices. Priced fairly, a house in *R* earns a lower current yield (lower rent/price ratio), but a higher future capital gain due to the faster rent and price growth than in *G*.

We follow the tradition in the housing literature in presuming that in asset market equilibrium house price equals the expected present value of future rents plus a risk adjustment:

$$P_0^m = \int_0^\infty r(t)^m e^{-\delta t}\, dt + \pi^m \tag{6}$$

where δ is the discount rate and $\pi^m$ is the MSA-constant risk premium.[11] If rents grow at a constant rate so that $r_t^m = r_0^m e^{g^m t}$, we obtain the continuous-time Gordon Growth Model with an additional adjustment for risk:

$$\frac{P_0^m}{r_0^m} = \int_0^\infty e^{-(\delta - g^m)t}\, dt + \pi^m = \frac{1}{\delta - g^m} + \pi^m. \tag{7}$$

From equation (7), $d\frac{P_0^m}{r_0^m}/dg^m > 0$. Rent growth, $g^m$, is higher in *R* because $g^m = \frac{dr^m}{dt} = \frac{dr^m}{dN} \cdot \frac{dN}{dt}$, $\frac{dN}{dt}$ is the same everywhere, and we established earlier that $\frac{dr^m}{dN}$ is greater for *R*. Thus, expected aggregate population growth is manifested in a higher price-rent ratio in *R* than in *G*. The logic is the same for changes in the aggregate income distribution.

## 3. Data description

Our primary data source is the six decennial United States Censuses taken between 1950 and 2000. We obtained information on the distributions of house values, rents, family incomes, population, and the number of housing units at two levels of geographical aggregation: metropolitan areas, and Census-designated places, which are municipalities such as cities and towns. All dollar values are converted into constant 2000 dollars using the CPI-U price index.

The MSA data used in our empirical analysis consists of a panel of 279 areas that had populations of at least 50,000 in 1950 and are in the continental United States.[12] Since the

[11] See Meese and Wallace (1994), Sinai and Souleles (2005), and Ortalo-Magne and Prat (2011) for examples.
[12] Thirty-six areas with populations under 50,000 in 1950 were excluded from our analysis because of concerns about abnormal house quality changes in markets with so few units at the start of our period of analysis. Those MSAs are: Auburn-Opelika, Barnstable, Bismarck, Boulder, Brazoria, Bryan, Casper, Cheyenne, Columbia, Corvallis, Dover, Flagstaff, Fort Collins, Fort Myers, Fort Pierce, Fort Walton Beach, Grand Junction, Iowa City, Jacksonville, Las Cruces, Lawrence, Melbourne, Missoula, Naples, Ocala, Olympia, Panama City, Pocatello, Punta Gorda, Rapid City, Redding, Rochester, Santa Fe, Victoria, Yolo, and Yuma. That said, none of our key results are materially affected by this paring of the sample. Similar concerns account for our not using data from the first *Census of Housing* in 1940 in the regression results reported below. (All individual housing trait data from the 1940 census were lost, so we cannot track any trait changes over time from that year.) However, we did repeat our MSA-

definitions of metro areas change over time, we use a definition based on 1990 county boundaries to project consistent metro area boundaries forward and backward through time.[13] Data were collected at the county level and aggregated to the metropolitan statistical area (MSA) or primary metropolitan statistical area (PMSA) level in the case of consolidated metropolitan statistical areas.[14] Data for the 1970-2000 period were obtained from GeoLytics, which compiles long-form data from the decennial *Censuses of Housing and Population*. We hand-collected data spanning 1950 and 1960 from hard copy volumes of the *Census of Population and Housing*. Both sources are based on 100 percent population counts. At the Census place level, we extracted data for 1970-2000 from the GeoLytics CD-ROMs.[15]

Because the house price data is central to our analysis, it bears discussing its strengths and weaknesses. The primary strength of using house price data from the decennial censuses is that it is available on a consistent basis over the half century-long period needed for our analysis. The weakness of this source for home values is that the underlying observations are both self-reported and not quality adjusted. However, correlations between constant quality and unadjusted house price series are high over decadal-length periods. For example, the correlation across house price appreciation rates for a large set of consistently defined MSAs in our Census

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level analysis over the 1940-2000 time period. While the point estimates naturally differ from those reported below, the magnitudes, signs, and statistical significance are essentially unchanged. Finally, the New York PMSA is missing crucial house price data for 1960, and is excluded from the analysis reported below. The census did not report house value data for that year because it did not believe it could accurately assess value for cooperative units, the preponderant unit type in Manhattan at that time.

[13] We use definitions provided by the Office of Management and Budget, available at http://www.census.gov/population/estimates/metro-city/90mfips.txt.

[14] All our conclusions are robust to aggregating to the CMSA level.

[15] While states differ in the extent to which local jurisdictions control new construction or even whether they can change their boundaries, census-designated places provide a useful comparable sample. The 1970 data include only 6,963 out of 20,768 places. (Conversations with the Census Bureau suggest that the micro data on the remaining places has been lost or is not readily available.) Fortunately, these places account for more than 95 percent of U.S. population in 1970. In 2000, 161 million people lived in these 6,963 places, 206 million people in all places, and 281 million people in the entire U.S. We further limit the sample to places within a MSA.

data and the Federal Housing Finance Administration (FHFA) constant quality house price index is 0.94 in the 1980s and 0.87 in the 1990s.[16]

Income also is central to our analysis. To categorize the distribution of income, we divide real family incomes into five categories that are consistent over time. The income categories in the original Census data change in each decade, so we set the category boundaries equal to 25, 50, 75, and 100 percent of the 1980 family income top code, and then populate the resulting five bins using a weighted average of the actual categories in $2000 (assuming a uniform distribution of families within the bins). Since 1980 had amongst the lowest top code in real terms, using it as an upper bound reduces miscategorization of families into income bins. This results in the following bins. We call a family "poor" if its income is less than $39,179 in $2000. "Middle-poor" are those families with incomes between $39,179 and $78,358, "middle" income families have incomes between $78,359 and $117,537, "middle-rich" families lie between $117,538 and $156,716, and "rich" families have incomes in excess of the 1980 real topcode of $156,716. It is important to recognize that the quartiles of the 1980 income top code do not correspond to quartiles of the income distribution; there are far more families in the "poor" category than in the "rich" category. Thus, our choice of income bin boundaries provides more detail in the right tail of the income distribution.

## 4. Empirical evidence

The underlying conditions necessary for the superstar cities hypothesis to be true have been present in the post-WWII era. Between 1950 and 2000, the number of families in U.S. metropolitan areas doubled, with the number making more than $140,000 in constant $2000

[16] The FHFA data begin for a limited set of markets in 1975, so we cannot perform the same analysis on earlier decades.

dollars increasing more than eight-fold according to the U.S. Census. And, some metropolitan areas and local communities have more inelastic housing supply than others, either because of local regulation or geographic restrictions (e.g., Gyourko, Saiz, and Summers and (2008); Saiz (2010); Paciorek (2011)). Given that, we now take the model to the data and test the four predictions of the model.

### a. Defining Superstar Markets

Our first step is to define empirical proxies for the theoretical characteristics of superstar markets: high taste for the location (high demand) and inelastic supply. We use the fact that demand growth has to be manifested either in price growth or housing unit growth to construct these variables. We measure growth in mean real prices and housing units at the MSA level over 20-year periods. This window size gives us growth rates defined over four time periods: 1950-70, 1960-80, 1970-90, and 1980-2000. We identify high demand MSAs by applying a simple cutoff of whether the sum of price and quantity growth for the market is above the sample median. This definition captures the idea that both inelastically-supplied markets with very limited new construction but high price appreciation and highly elastic markets with minimal price growth but lots of construction should be categorized as in high demand. We allow the high-demand cutoff to vary over time in order to account for changes in the aggregate economy. In this case, the metropolitan area would be defined as being in high demand in 1970 if the sum of its price and housing unit growth from 1950-70 exceeded the sample median for that time span. We proxy for the supply elasticity as the ratio of price growth to housing unit growth. In an inelastically supplied city, demand growth would be manifested more in price growth than in housing unit growth, so this ratio should be high.[17]

We define an indicator variable for superstar status (*Superstar*) based on whether a MSA is in the "high demand" category and in the top decile of the ratio of price growth to housing unit growth based on growth over the prior two decades.[18] Due to the two-decade lag for computing growth rates, 1970 is the first year for which we can define a superstar.[19] The sample of superstars, broken down by decade in Appendix B, includes major metropolitan areas that are superstars in multiple years as well as smaller MSAs that enter and exit superstar status. To purge those noisy MSAs from our sample, we define the MSA-constant $Superstar_i$ as one if the time-varying $Superstar_{it}$ equals one in any <u>two</u> decades between 1970 and 2000, and redefine $Superstar_{it}$ to equal one only for MSAs that are superstars for at least two decades. However, we obtain very similar results when we define $Superstar_i$ as those MSAs that are in the superstar category for one or more census years. The estimated coefficients tend to be slightly lower and the standard errors slightly higher when we use the one-year definition of superstar, but they retain their economic and statistical significance. For parsimony, we report only the results using this baseline definition of superstar status.

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[17] We also experimented with non-time varying measures of supply elasticity such as produced by Saiz (2010). See below for a discussion of those results. Our pattern of findings is robust to this definition.

[18] We also tried using a continuous measure of 'superstar-ness', defined as the ratio of price growth to housing unit growth for high demand MSAs or places, rather than an indicator variable. This approach yielded comparable results to those reported below. Our selection of an indicator variable emphasizes the empirical variation due to large differences in elasticity of supply and also yields a more parsimonious exposition. However, the implication of the model in section 2 that continuous differences in the supply elasticity among high-demand MSAs or places also should induce differences in house price growth and changes in the income distribution as the aggregate number of high-income families increases does hold in our data.

[19] Using lagged data on price and unit growth helps guard against misclassifying an area as a superstar too early. Recall that the model suggests that the predicted income segregation and house price effects occur after the superstar market has 'filled up'. In addition, we wish to classify superstar status of metro areas in the most recent census year, 2000. That said, this choice is not critical to our results. For example, we could match 1950-1970 growth rates to metro areas as of 1960. That methodology generates superstar classifications from 1960-1990, rather than from 1970-2000. Our findings are robust to such changes.

To illustrate where MSAs fall along the dimensions that make up a superstar city, Figures 3 and 4 plot average real annual house price growth against housing unit growth during the 1960-1980 and 1980-2000 periods, respectively. Three regions are outlined in each figure. Region C, below the negatively-sloped line, corresponds to low demand as defined above (i.e., they have sums of price and housing unit growth below the sample median for the relevant time period). Among the high-demand MSAs, regions A and B are, respectively, above and below the threshold that we use for our binary definition of a superstar city. That cut-off is the 90th percentile of the distribution of price growth to quantity growth for all MSAs over the time period – which is about 1.7. MSAs that have ratios above that level are considered highly inelastic because they experience much more price growth relative to housing unit growth. Thus, the markets in Region A are superstars because they are both in the high growth region and in the top decile of inelasticity of supply. By contrast, MSAs in the B range also have high demand, but they have more elastic supply since they are closer to the X-axis and have built more new units relative to the real house price appreciation they experienced.

Beyond providing snapshots of superstar status at two points in time, these two figures also illustrate some of the time series variation that we will exploit in our regression analysis. In the face of geographic constraints and politically-imposed restrictions on development, it seems natural that at least some high-demand metropolitan areas would become more inelastically supplied over time as demand for their scarce housing units becomes larger and they begin to "fill up". This process would appear as a market moving counter-clockwise around the origin over time. We do observe such evolutions. For example, Figure 3 shows that by 1980, San Francisco and Los Angeles qualified as superstars. In 1970 (which is based on data from 1950-

1970), both markets were in the B range of the plot. Figure 4 then shows that by the end of our sample period in 2000, 20 more high demand MSAs filled up, also becoming superstars.

At the Census place level, we categorize a place as a superstar if it is both high demand and is in the top quartile of price growth to unit growth. The methodology for determining which communities are "high demand" and for computing their supply elasticities is comparable to our MSA-level procedure.[20] However, the place data are available only from 1970 to 2000 so, after accounting for the two decades of lags required to compute these variables, our useable place-level sample covers only 1990 and 2000.

**b. Results**

Using these variables, we empirically test the four predictions of the model about how superstar areas should differ from other areas. The first prediction has implications for cross sectional differences in house prices and the income distribution; predictions 2 and 3 relate differences in superstar vs. non-superstar areas to changes in the aggregate income distribution; and the fourth considers the effects on the price-to-rent ratio.

We test these predictions at both the MSA level and the Census Place level. The superstar cities framework implies that the same patterns we observe at the MSA level should hold within a metropolitan area. Just like changes in the national income distribution should propagate into MSA-level housing demand, changes in the MSA income distribution should propagate into municipality-level housing demand as households sort among Census places.

To be faithful to the model in section 2, we compare the outcomes for superstar cities to all other metropolitan areas. In the model, cities with less demand than capacity are perfectly

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[20] A place is considered to be high-demand if its sum of price and housing unit growth exceeds that period's median across all places in all MSAs. The 75th percentile ratio of price growth to unit growth for places (2.0) is close to the 90th percentile for MSAs (1.7) because the distribution for places has thicker tails than for MSAs.

elastically supplied, whereas cities with excess demand can have varying supply elasticities. We compare the high-demand, inelastic cities to both low-demand cities and high-demand, elastic cities. In practice, not all low-demand cities appear to have elastic supply by our measures. This may be due to measurement error, or house prices being below construction cost as in Glaeser and Gyourko (2005). However, we have obtained comparable results even when including appropriate controls for low-demand areas.[21]

### i. Prediction 1: Do Superstar cities or suburbs have different prices or incomes?

Prediction #1 is that superstar MSAs or towns should have higher house prices and higher average incomes. In addition, the income distributions should be shifted more to the right – superstars should have relatively larger shares of their populations in the high-income bins and smaller shares in the low-income bins. We will first see if this prediction holds in the cross-section for MSAs, then for Census places, and then within MSAs as they change Superstar status.

We estimate the following bivariate regression using our panel of 279 MSAs over four two-decade periods (for a total of 1,116 MSA × year observations):

$$Y_{it} = \beta_1 \text{Superstar}_i + \delta_\text{t} + \varepsilon_\text{it}$$

for MSA $i$ in year $t$. The dependent variable, $Y_{it}$, takes a variety of outcomes, including the log house value, log income, and the share of families in each of the income categories.[22]

[21] Those controls paralleled the treatment of the superstar indicator variable. For example, when we used $Superstar_i$, we controlled for $Low\ Demand_i$, defined as a MSA or place ever being in the low demand region. If we interacted superstar status with the number of rich households in aggregate, we also controlled for the interaction of low demand with the number of rich households.

[22] See Appendix Tables 1A and 1B for summary statistics on all variables used in the paper.

Year dummies also are included and correspond to the final year of each two-decade estimation period as described above in the data section.  Thus, the estimated coefficient $\beta_1$ measures the average difference between MSAs that ever are superstars and other MSAs.

The results are reported in Table 2.  Superstar status is associated with higher average and 10th percentile house values, higher average income, a greater share of the MSA's residents in the high-income categories and a lower share in the low-income categories.  Moreover, the point estimates are economically large as well as statistically significant.  For example, in the first column, where the dependent variable is the log of the MSA's average house value, the estimated coefficient of 0.6053 for log house value (0.0729 standard error) implies that superstar MSAs have 60 percent higher average house values.  The second column uses the log of the MSA's 10th percentile house value as the dependent variable in an attempt to more closely reflect the changing minimum entry price for an MSA due to rising land values, as well as better control for differences in spending on the structure component of housing.[23]  The estimated coefficient is larger, 0.7844 (0.0855 standard error).[24]

In the cross-section, superstar MSAs also have income distributions that are shifted to the right relative to other MSAs.  In column 3, the differences in average incomes are nearly 24 percent with a standard error of about 3 percent.  We look at other points in the income distribution in columns 4 through 8.  The outcome variables in these columns correspond to each of the five income bins ($y$) in each MSA $i$ in year $t$: $Y_{it} = \frac{\#\ in\ income\ bin_{\mathrm{yit}}}{\#\ of\ households_{\mathrm{yit}}}$.  For example, in column 4, we find that the mean share of households in the 'rich' group in superstar MSAs is 3.4

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[23] The standard error is larger because the tail of the house value distribution is noisier due to house prices being reported in bins in the Census data.

[24] While our empirical results, in keeping with the prior literature, focus on house values, the model in section 2 is expressed in terms of rents.  We have obtained comparable results in this regression and in all other regressions in the paper when using log average rent as the dependent variable.

percentage points higher than in other MSAs. Since the income distribution outcome variables in columns 4 through 8 are not in logs, in those columns we report the estimated elasticity in addition to the usual point estimate. For example, since the share of the income distribution that is in the "rich" category averages just 3.3 percent, the estimated effect of 0.0339 amounts to a 102 percent increase in the "rich" share relative to the average. In addition, we find that superstars have an 80 percent higher share middle-rich households, 41 percent higher share middle-income households, and 26 percent lower "poor" households.

The findings reported in Table 2 establish that price growth and changes in the income distribution are happening concurrently in particular metropolitan areas, not just in terms of the aggregate distributions of price and income growth (as in Van Nieuwerburgh and Weill (2010)). Even so, many factors might differ between superstar and other MSAs in the cross-section that generate the patterns we see. One possible explanation that comes out of the model in Section 2 is differences in productivity across locations. If some MSAs are more productive than others, they would have both higher house values and higher wages.[25]

One way to distinguish between productivity-based explanations and a sorting-based model like ours is to examine the price/income/Superstar relationship at the Census Place level. Geographical differences in productivity could vary across MSAs, but not within MSAs since a MSA by design holds employment opportunities constant.[26] With Place-level data, our research design can control nonparametrically for any confounding unobservable factor that might vary

[25] Productivity differences may yield a different shape of the income distribution than our superstar hypothesis, but a more productive city should have an income distribution to the right of a less productive city. Given our data, and the lack of a prior on the distribution of tastes for cities, we would not be able to empirically distinguish between different patterns of right-shifts of the income distribution.

[26] Rosenthal and Strange (2003) finds that production agglomerations occur in very close proximity. However, workers in that production agglomeration can choose to live anywhere within the MSA since MSAs are defined by commuting patterns.

by MSAs or across MSAs over time, using only variation across towns within an MSA in a given year to identify our estimates.

The place-level version of our regression is:

$$Y_{kit} = \beta_1 \text{superstar}_k + \delta_{\text{it}} + \varepsilon_{\text{kit}}$$

The unit of observation is now Census place $k$ in MSA $i$ in year $t$. Superstar status is determined at the place level. MSA × year fixed effects also are included.

The Place-level results in Table 3 are comparable to the MSA-level results in Table 2. Superstar towns in an MSA have higher house values and average incomes than other towns in the same MSA and year. They also have income distributions that are shifted to the right. In particular, we find that average house values in superstar towns are 37 percent higher and incomes are 24 percent higher. The share of the population in the top two income categories is substantially greater – the fraction in the highest income category more than doubles – and the fraction of the population in the bottom two income categories experiences an offsetting decline.

Another approach to controlling for unobservable MSA-level characteristics is to see what happens when an MSA becomes a superstar. By using the time-varying definition of superstar, we can include MSA-level fixed effects, thus controlling for unobserved differences across MSAs that confound the relationship between demand, supply elasticity, and the outcome variables. Instead, the identification strategy measures how much the outcome variables change when the MSA is a superstar versus when it is not. In Table 4, we report estimates from the following regression equation:

$$Y_{it} = \beta_1 \text{Superstar}_{it} + \delta_{\text{t}} + \gamma_{\text{i}} + \varepsilon_{\text{it}}$$

Relative to Table 2, we have added a MSA fixed effect, $\gamma_{\text{i}}$, and allowed $\text{Superstar}_{it}$ to vary over time, as defined in the Data section.

We find the same pattern in within-MSA differences over time that we observed across MSAs. MSAs experience increases in house prices and average incomes, and become more rich and less poor, when they are in the Superstar region. The effect on house values and average income are smaller than in Table 2, but still economically large and statistically significant. This pattern indicates that MSAs that become superstars had higher house prices and incomes than other MSAs prior to becoming superstars, and experienced an additional jump in house prices and average incomes after becoming superstars. The coefficients on the income bins are also smaller in Table 4 than in Table 2, though the fundamental pattern and significance is maintained. The share of an MSA's population in the top two income categories increases by about 90 percent when the MSA enters the superstar region, the middle-income category grows by about 6 percent, and the share in the bottom two income categories falls between 4 and 14 percent.[27]

### ii) Predictions 2 and 3: Are superstars differently affected when the aggregate income distribution changes?

At the national/MSA levels, the model implies that that when either the U.S. population or share of the population that is high-income increases, land prices should rise fastest and the local income distributions should shift to the right the most in superstar MSAs. We do not try to distinguish between the effects of population and income share in our empirical analysis, instead

[27] We also investigated the income distribution of migrants to and from superstars relative to non-superstars. The framework in section 2 suggests that rising incomes in superstars should be due to a changing composition of families associated with an influx of highly-productive, high income workers. Using data from the Individual Public-Use Microsample of the U.S. decennial Census, we found that the income distributions of recent in-migrants into superstar cities was shifted toward relatively more "rich" families, with fewer low income and more middle-to-upper income in-migrants, relative to elastically-supplied high demand MSAs or inelastically-supplied, low demand MSAs. There is not such a strong pattern for out-migrants, which is consistent with models that allow for investment in the local housing market. (Ortalo-Magne and Rady (2008)) However, the Census data reports income only subsequent to moving, so we could not ascertain whether in-migrants to superstar MSAs were high wage types prior to the move.

combining the two factors into one measure: the number of high-income families. We then look for empirical evidence at the national/MSA and then MSA/place levels.

Our national/MSA regression specification relates a time-varying MSA outcome to changes in the national income distribution and time-invariant differences across MSAs in their superstar status. The regression equation takes the following form:

$$Y_{it} = \beta_1 \text{Superstar}_i \times \ln(\#\ \text{Rich}_\text{t}) + \gamma_\text{i} + \delta_\text{t} + \varepsilon_\text{it}$$

for MSA $i$ in year $t$. The dependent variable, $Y_{it}$, takes the usual set of outcomes.
The first regressor interacts the time-invariant Superstar indicator with the log of the number of households at the national level that are in the "rich" income bin ($\ln(\#\text{Rich}_t)$). The Superstar indicator varies across MSAs and the number of rich households varies over time, so the interaction varies over time within MSA. Thus, the estimated coefficient $\beta_1$ measures how changes in the number of rich families at the aggregate level differentially affect superstar cities relative to all other cities. The MSA fixed effects ($\gamma_i$) control for MSA-level unobserved heterogeneity and the year dummies ($\delta_t$) absorb influences that vary only over time, such as aggregate macroeconomic factors. These fixed effects also subsume the uninteracted effects of supply elasticity or the aggregate number of rich families.[28]

The results, reported in Table 5, support Predictions 2 and 3. In the first column, where the dependent variable is the log of the MSA-average house value, the estimated coefficient of 0.3943 (0.0356 standard error) indicates that house values rise by more in more inelastic, high demand MSAs when the national number of rich families increases. We observe a smaller, though still statistically significant, effect on the 10$^{th}$ percentile house value.

To get a sense of the magnitudes, consider that between 1970 and 2000 the number of rich families in the U.S. grew by 160 percent. In the first column, the average house values in

[28] We obtain very similar results by taking first-differences within MSAs instead of including an MSA fixed effect.

superstar MSAs are estimated to rise by 39 percentage points more than in other MSAs when the number of rich families nationally doubles. In actuality, mean house prices in superstar MSAs grew 75 percentage points more than in other MSAs, so the pressure of the growing national income distribution accounts for more than 80 percent of the excess growth in house prices in Superstar cities in that specification.[29]

The remaining columns of Table 5 address the implications of Predictions 2 and 3 that the rise in house prices in superstar cities should also affect the distribution of local incomes. Column 3 uses the log of the mean income in the MSA as the dependent variable. The estimated coefficient of 0.1292 (0.0143) in the first row implies that doubling of the number of rich families in the country is associated with an 12.9 percentage point higher growth rate in average income in a superstar MSA. This represents all of the actual difference in the growth in average income between superstar MSAs and other MSAs over the 1970 to 2000 period.

Columns 4 through 8 report the estimated effects of growth in the national number of rich families at the various points in an MSA's income distribution. These results show that when the national number of rich families increases, the income distribution shifts to the right more in superstar MSAs. Relative to other MSAs, superstars experience a larger increase in their share of households that are in the highest-income categories and a bigger decline in their middle-low-income households. For example, the estimated coefficient of 0.0407 (0.0022) in the first row of column 4 implies that a doubling of the number of rich families nationally would increase the share of households in the "rich" category for superstar cities by 4 percentage points more than in other MSAs. A similar, but smaller, effect is found among the "middle-rich" households in column 5, and no effect on middle-income households.

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[29] $160 \times 0.3943 = 63.1$, which is 84.1 percent of 75.

At the other end of the income spectrum, a doubling of the number of national rich families would yield more than a 6 percentage point excess decline in the share of households in the "middle-poor" category, consistent with the higher-income households crowding out the lower-income ones. We discern little differential change between superstar MSAs and other MSAs in the share of households in the "poor" category.[30]

These results also help distinguish the superstar cities mechanism from other potential sources of local housing demand, such as those driven by productivity differences. It seems unlikely that local productivity growth (changes in the $\alpha$ or $\beta$ parameters from the model in Section 2) would match the geographic pattern, timing, and linkage to the national income distribution of MSA price growth that is predicted by the superstars framework. In addition, potential confounding effects due to defining superstar cities based in part on average house price growth over the entire sample period are mitigated by directly controlling for the superstar nature of an MSA, thereby identifying the effect from the interaction of those variables with changes in the national income distribution.

The 'superstar suburbs' logic implies that the number of rich families at the MSA level should be positively correlated with house price growth, income growth, and the rich share of families at the Census place level. The place-level version of our regression is:

$$Y_{kit} = \beta_1 \text{superstar}_k \times \ln(\#\,\text{Rich}_{it}) + \gamma_k + \delta_{it} + \varepsilon_{kit}$$

The unit of observation is now Census place *k* in MSA *i* in year *t*. Superstar status is determined at the place level, and $\text{Superstar}_k$ is set equal to one if the Census place is in the superstar region

[30] Ortalo-Magne and Rady (2008) provide one possible explanation for the stickiness of low-income households—namely, that low income households who bought more cheaply in previous years simply remain in their homes. In effect, their wealth (due to homeownership) rises to offset rising house prices. Lee (2010) and Eeckhout *et al* (2010) provide other potential explanations based on the complementarity of low- and high-wage workers.

in either 1990 or 2000. The aggregate growth in the number rich is measured at the MSA × year level. Place and MSA × year fixed effects also are included.

One drawback of this level of geography is that our place-level data date only to 1970, which makes it more difficult to assess within-town changes over time. Because $(\Delta P / \Delta Q)_{ki}$ requires two lagged decades to construct, we observe only one change per Census place – between 1990 and 2000. Essentially, we are estimating whether the change in the left hand side variable between 1990 and 2000 is related to the growth in the number of rich families in the "parent" MSA over that time period. Because each of the 279 "parent" MSAs experienced different rates of growth in the number of rich families between 1990 and 2000, we have plenty of variation to identify the effects on the Census places within those MSAs. We also have tried applying the measure of superstar status defined over the 1990-2000 period to the entire 1970 to 2000 sample, with consistent results.

The results reported in Table 6 reveal a similar pattern to Table 5. The magnitudes on the estimated coefficients are somewhat attenuated, but remain statistically significant. In sum, there is substantial evidence among towns within a given metropolitan area that aggregate, MSA-level changes have disproportionate impacts on prices, wages, and the share rich in superstar communities that have inelastic supplies and are in strong demand.

### iii) Prediction #4: Price-to-Rent Ratios in Superstar Markets

Lastly, we turn to Prediction #4, which stated that prices would be a greater multiple of rents in superstar markets if growth in rents was anticipated. Table 7 reports results that parallel the specifications in each of Tables 2 through 6, but that use the price-to-rent multiple as the left-hand-side variable.

Thus, the first column of Table 7 uses the cross sectional, MSA-level specification from Table 2, but with the log of the MSA-average price-to-rent ratio as the dependent variable. The estimated coefficient of 0.3145 from the first row indicates that, on average, prices are a 31 percent larger multiple of rents in superstar MSAs. Column 2 repeats the cross-section analysis at the Census place level, with MSA × year fixed effects. We find that superstar suburbs have a 26 percent higher price-to-rent ratio than other towns. This pattern persists when MSAs transition to superstar status (Column 3). In the years that MSAs are superstars, their price-to-rent ratios are 27 percent greater than in the years when they are not superstars.[31] The last two columns of Table 7 relate changes in the price-to-rent ratio at the MSA or Place levels to changes in the number of "rich" households at an aggregate geography. In both cases, when the number of "rich" households increases, the price-to-rent ratio goes up by more in superstar MSAs or Places.

In general, Table 7's results are consistent with the implication that the effect of superstar status on long-run price or rent growth is capitalized into the housing asset market. It is worth underscoring that this result, and the model in Section 2, follows from asset market equilibrium. Homeowners in superstar markets do not necessarily obtain a higher return; instead, they receive a higher expected capital gain at the expense of a lower current yield. In that way, superstar markets are like growth stocks in the equity investment universe.

### c) *Ex ante* versus *ex post* definitions of Superstar status

As a robustness check, we redefined our proxy for superstar status using *ex ante* MSA characteristics rather than *ex post* realizations of price and quantity growth. The model in

[31] This result does not appear to be due to simultaneity in *ex post* price growth generating both superstar status and high price-to-rent ratios. The results in Table 7 are robust to using price-to-rent ratios measured in the middle of the two-decade window over which price growth is computed.

Section 2 implies that it is a combination of supply inelasticity and high demand that defines superstar status. Our *ex ante* definition of an inelastically supplied MSA is one that is in the top ten percent of Saiz's (2010) topography-based measure of the difficulty of building. We have two approaches to defining "high-demand" based on *ex ante* data. For one, we denote the top third of MSAs ranked by the sum of their price and housing unit growth in the pre-sample period of 1950-1970 as high-demand. In the other, we denote the top third of MSAs ranked by their mean January temperature as high-demand. Including our baseline definitions, we had two proxies for the elasticity of supply and three proxies for high demand. We replicated all the MSA-level tables using each of the six combinations of these definitions, with the exception of Table 4. Since neither the Saiz elasticity measure nor the *ex ante* high-demand proxies are time-varying, we could not use combinations of these variables to estimate the effect of changing superstar status.[32]

In Table 8, we report the estimated coefficients corresponding to the two combinations that used only the three new *ex ante* definitions. Using these alternative definitions does yield lower estimates than in our baseline results, but they still remain economically and statistically meaningful. The estimates from the specifications corresponding to Table 2 are reported in the top panel of Table 8. Each row corresponds to a different construction of Superstar status. Superstar MSAs exhibit higher house prices – about the same magnitudes as in Table 2 – and a right-shift in the income distribution that is about half the magnitude of that reported in Table 2. The bottom panel of Table 8 estimates the effect of growth in the national number of rich households on the newly-defined Superstar MSAs, akin to Table 5. These estimates are typically 40 to 50 percent lower in magnitude than in our baseline estimates, they are still economically and statistically significant. For example, in the first row of the bottom panel, the estimated

[32] For this reason, we do not use these definitions of superstar status in our baseline tables.

coefficient in the regression of log house value on the interaction of Superstar status with the log number of rich households nationally is 0.2563 (0.0355). This estimated coefficient implies that the 160 percent increase in the national number rich between 1970 and 2000 would yield a 41 percent increase in house prices in Superstar cities, or about 55 percent of the actual growth. In the third column, the estimated coefficient of 0.0758 (0.0142) corresponds to a 12 percent greater increase in log mean income for Superstar MSAs over the same time period.

## 6. Conclusion

The growing dispersion in house prices in the post-WWII era is an important economic and social phenomenon. Because high house prices skew the income distribution of potential residents, the evolution of entire metropolitan areas into superstars influences the way we spatially organize our society, both locally and nationally. This paper argues that this phenomenon is at least partially the consequence of aggregate population growth and the skewing of incomes nationally interacting with differences in local supply conditions. One interesting feature of this mechanism that is conceptually distinct from the prior literature is that in our model the house price growth in superstar cities is not due to an increasing service flow or greater productivity. Rather, it comes from a higher aggregate willingness-to-pay for the same service flow.

Although our analysis does not rule out a role for other factors such as persistent differences in local productivity, we provide empirical evidence at the MSA and Census Place geographies that is consistent with the superstar cities mechanism being one of the key forces in effect. First, we find that property values, mean wages and the share of workers who are high income are higher in superstar markets. Second, a combination of population growth and a thickening right tail of the wage distribution at the national or MSA level leads to greater growth in property values and wages in superstar MSAs and Census Places, respectively. Third, we find the same empirical patterns for house price-to-rent ratios. Our data suggests that as much as two-thirds of the growth in dispersion in house prices, and almost all of the growth in dispersion in average incomes, between superstar MSAs and others over the 1970-2000 period can be explained by the increase in high-income households at the national level.

Our framework also helps us understand the conditions under which widening dispersion in house prices can continue. For the superstars mechanism to be operative, metropolitan areas must be differentiated and in limited supply. In addition, there must be growth in aggregate housing demand. If a city that is a close substitute to a superstar city were to be created, it would siphon off some of the demand support for the superstar city.[33] The reduction in demand due to the substitute city would attenuate the growth of house prices in the superstar city in proportion to the growth of capacity in the substitute city. However, house price growth rates in superstar cities could fall below alternative MSAs only if growth in substitutes exceeded growth in aggregate demand.

Similarly, if the elasticity of supply were to increase in superstar cities – perhaps due to an increase in allowable density, abandoning growth controls, or loosening development restrictions – the excess price growth in superstar cities would be attenuated. However, because we have observed an increasing number of inelastically supplied MSAs over the past 50 years, it seems more likely that convergence in housing supply elasticities would come from non-superstar MSAs becoming less elastic rather than the other way around. In that case, house price growth rates would converge at a high level. However, it is important to note that no matter how

[33] The failure of close substitutes to superstar cities to arise over the last 50 years suggests it may be virtually impossible to replicate a superstar labor market area, perhaps because it involves many people, much human capital, and myriad social interactions.

convergence in supply elasticies happens, it would yield more convergence in the distribution of house price growth rates, but not in house prices.

Finally, our model suggests that Superstar cities are most sensitive to changes in aggregate demand. When housing demand increases, superstar cities and suburbs achieve disproportionate growth in house prices and changes in their income distributions. When housing demand contracts, the opposite should be true. The Great Recession reminds us that aggregate growth can falter substantially, both in terms of income increases and household formation. Even so, our model emphasizes that declines in per capita income can be offset by increases in the population to nonetheless yield higher aggregate demand. In addition, globalization expands the relevant market for superstar cities, inducing even more growth in aggregate demand. It is the waxing and waning of these factors which seem most likely to determine whether superstar cities maintain the same high long-run house price growth over the next 50 years as they did over the previous five decades.

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Table 1: Real annualized house price growth, 1950-2000,
Top and Bottom 10 MSAs with 1950 population>500,000

| Top 10 MSAs by Price Growth<br>Annualized growth rate, 1950-2000 | | Bottom 10 MSAs by Price Growth<br>Annualized Growth Rate, 1950-2000 | |
|---|---|---|---|
| San Francisco | 3.53 | San Antonio | 1.13 |
| Oakland | 2.82 | Milwaukee | 1.06 |
| Seattle | 2.74 | Pittsburgh | 1.02 |
| San Diego | 2.61 | Dayton | 0.99 |
| Los Angeles | 2.46 | Albany (NY) | 0.97 |
| Portland (OR) | 2.36 | Cleveland | 0.91 |
| Boston | 2.30 | Rochester (NY) | 0.89 |
| Bergen-Passaic (NJ) | 2.19 | Youngstown-Warren | 0.81 |
| Charlotte | 2.18 | Syracuse | 0.67 |
| New Haven | 2.12 | Buffalo | 0.54 |

Population-weighted average of the 50 MSAs in this sample: 1.70

Table 2: Pooled cross-section differences in superstar MSAs

| Left-hand-side variable: | Log House Value | Log 10th Percentile House Value | Log mean income | Share of MSA families in the ____ category: Rich | Middle-rich | Middle | Middle-poor | Poor |
|---|---|---|---|---|---|---|---|---|
| $Superstar_i$ | 0.6053<br>(0.0729) | 0.7844<br>(0.0855) | 0.2360<br>(0.0308) | 0.0339<br>(0.0058) | 0.0284<br>(0.0039) | 0.0524<br>(0.0066) | -0.0094<br>(0.0061) | -0.1053<br>(0.0137) |
| Relative to mean of LHS variable: | | | | 1.017 | 0.804 | 0.405 | -0.023 | -0.262 |
| Fixed effects: | Year | Year | Year | Year | Year | Year | Year | Year |
| Adj. $R^2$ | 0.4162 | 0.3149 | 0.4605 | 0.4151 | 0.5952 | 0.3584 | 0.1177 | 0.1969 |
| Mean of LHS: | 11.54 | 10.64 | 10.84 | 0.033 | 0.035 | 0.129 | 0.400 | 0.402 |

Notes: Number of observations is 1,116, for four decades (1970-2000) and 279 MSAs. Standard errors, clustered by MSA, are in parentheses. The specification is $Y_{it} = \beta_1 \text{Superstar}_i + \delta_t + \varepsilon_{it}$, where the superstar variable is defined at the MSA level and is not time-varying.

Table 3: Pooled cross-section differences in superstar places

| Left-hand-side variable: | Log House Value | Log 10th Percentile House Value | Log mean income | Share of MSA families in the ____ category: Rich | Middle-rich | Middle | Middle-poor | Poor |
|---|---|---|---|---|---|---|---|---|
| $Superstar_i$ | 0.3668<br>(0.0225) | 0.2723<br>(0.0163) | 0.2448<br>(0.0118) | 0.0759<br>(0.0032) | 0.0167<br>(0.0015) | -0.0006<br>(0.0022) | -0.0427<br>(0.0028) | -0.0493<br>(0.0047) |
| Relative to mean of LHS variable: | | | | 1.231 | 0.257 | -0.004 | -0.114 | -0.148 |
| Fixed effects: | MSA × year | MSA × year | MSA × year | MSA × year | MSA × year | MSA × year | MSA × year | MSA × year |
| Adj. $R^2$ | 0.4766 | 0.6804 | 0.3795 | 0.2535 | 0.4258 | 0.4040 | 0.2779 | 0.4381 |
| Mean of LHS: | 11.72 | 11.16 | 11.01 | 0.062 | 0.065 | 0.166 | 0.375 | 0.332 |

Notes: The sample period is 1990-2000 and covers 3788 Census Places over two decades (N=7,576). Standard errors are in parentheses. The specification is $Y_{kit} = \beta_1 \text{superstar}_k + \delta_{it} + \varepsilon_{kit}$, where the superstar variable is defined at the Census Place level and is not time-varying.

Table 4: Within-MSA changes when MSAs become superstars

| Left-hand-side variable: | Log House Value | Log 10th Percentile House Value | Log mean income | Share of MSA's families in income bin: Rich | Middle-rich | Middle | Middle-poor | Poor |
|---|---|---|---|---|---|---|---|---|
| $\text{Superstar}_{it}$ | 0.4427<br>(0.0304) | 0.2744<br>(0.0511) | 0.1224<br>(0.0127) | 0.0325<br>(0.0021) | 0.0316<br>(0.0020) | 0.0082<br>(0.0032) | -0.0543<br>(0.0062) | -0.0180<br>(0.0081) |
| Relative to mean of LHS variable: | | | | 0.977 | 0.895 | 0.063 | -0.136 | -0.045 |
| Fixed effects: | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year |
| Adj. $R^2$ | 0.8679 | 0.8738 | 0.9121 | 0.8203 | 0.8683 | 0.8948 | 0.7046 | 0.8584 |
| Mean of LHS: | 11.54 | 10.64 | 10.84 | 0.033 | 0.035 | 0.129 | 0.400 | 0.402 |

Notes: Number of observations is 1,116, for four decades (1970-2000) and 279 MSAs. Standard errors are in parentheses. The specification is $Y_{it} = \beta_1 \text{Superstar}_{it} + \delta_t + \gamma_i + \varepsilon_{it}$, where the superstar variable is defined at the MSA level and varies over time.

Table 5: How Changes in the Number of the Nation's Rich Differentially Affect Superstar MSAs

| Left-hand-side variable: | Log House Value | Log 10th Percentile House Value | Log mean income | Share of MSA families in the ____ category: Rich | Middle-rich | Middle | Middle-poor | Poor |
|---|---|---|---|---|---|---|---|---|
| $\text{Superstar}_i \times \log(\#\ \text{Rich}_t)$ | 0.3943<br>(0.0356) | 0.1992<br>(0.0578) | 0.1292<br>(0.0143) | 0.0407<br>(0.0022) | 0.0310<br>(0.0023) | -0.0003<br>(0.0036) | -0.0624<br>(0.0069) | -0.0090<br>(0.0091) |
| Relative to mean of LHS variable: | | | | 1.222 | 0.877 | -0.002 | -0.156 | -0.022 |
| Fixed effects: | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year |
| Adj. $R^2$ | 0.8555 | 0.8277 | 0.9110 | 0.8336 | 0.8591 | 0.8940 | 0.7060 | 0.8577 |
| Mean of LHS: | 11.54 | 10.64 | 10.84 | 0.033 | 0.035 | 0.129 | 0.400 | 0.402 |

Notes: The sample period is 1970-2000 and covers 279 MSAs over four decades (N=1116). Standard errors are in parentheses. The specification is $Y_{it} = \beta_1 \text{Superstar}_i \times \ln(\#\ \text{Rich}_t) + \gamma_i + \delta_t + \varepsilon_{it}$, where an indicator variable for an MSA ever being a "superstar" during the entire 1970-2000 period is interacted with the log national number of families in the "rich" category. The uninteracted variables are subsumed by the fixed effects.

Table 6: How Changes in the Number of an MSA's Rich Differentially Affect Census Places

| Left-hand-side variable: | Log House Value | Log 10th Percentile House Value | Log mean income | Share of Place families in the ____ category: "rich" | "less rich" | "middle" | "less poor" | "poor" |
|---|---|---|---|---|---|---|---|---|
| $Superstar_i$ × log(# $Rich_{kt}$) | 0.1565<br>(0.0126) | 0.0972<br>(0.0226) | 0.0857<br>(0.0114) | 0.0292<br>(0.0031) | -0.0009<br>(0.0023) | -0.0116<br>(0.0040) | 0.0016<br>(0.0056) | -0.0182<br>(0.0056) |
| Relative to mean of LHS variable: | | | | 0.473 | -0.014 | -0.070 | 0.004 | -0.055 |
| Fixed effects: | MSA × year, place | MSA × year, place | MSA × year, place | MSA × year, place | MSA × year, place | MSA × year, place | MSA × year, place | MSA × year, place |
| Adj. $R^2$ | 0.8123 | 0.6439 | 0.5804 | 0.4447 | 0.3689 | 0.3644 | 0.3412 | 0.4056 |
| Mean of LHS: | 11.72 | 11.16 | 11.01 | 0.062 | 0.065 | 0.166 | 0.375 | 0.332 |

Notes: The sample period is 1990-2000 and covers 3788 Census Places over two decades (N=7,576). Standard errors are in parentheses. The specification is $Y_{it} = \beta_1 \text{Superstar}_k \times \ln(\#\ \text{Rich}_t) + \gamma_{it} + \delta_k + \varepsilon_{ikt}$, where an indicator variable for a Census Place ever being a "superstar" during the 1990-2000 period is interacted with the MSA's log number of families in the "rich" category. The uninteracted variables are subsumed by the fixed effects.

Table 7: Price-to-Rent Ratio Results

| Table #: | 2 | 3 | 4 | 5 | 6 |
|---|---|---|---|---|---|
| Variation | Pooled Cross Section | Pooled Cross Section | Within-MSA changes | # Rich | # Rich |
| Geography | MSA | Place | MSA | MSA | Place |
| $Superstar_i$ | 0.3145<br>(0.0437) | 0.2661<br>(0.0196) | | | |
| $Superstar_{it}$ | | | 0.2717<br>(0.0216) | | |
| $Superstar_k \times \log(\# Rich_{it})$ | | | | 0.2222<br>(0.0253) | 0.1229<br>(0.0143) |
| Fixed effects: | Year | MSA × year | MSA, year | MSA, year | MSA × year, place |
| Adj. $R^2$ | 0.4030 | 0.2867 | 0.7936 | 0.7754 | 0.6639 |
| N | 1,116 | 7,576 | 1,116 | 1,116 | 7,576 |

Notes: The left-hand-side variable is the log average price/rent ratio.

Table 8: Robustness to alternative definitions of Superstar

| Construction of $\text{Superstar}_i$ | Log House Value | Log 10th Percentile House Value | Log mean income | Share of MSA families in the ____ category: Rich | Middle-rich | Middle | Middle-poor | Poor |
|---|---|---|---|---|---|---|---|---|
| Right-hand-side variable: $\text{Superstar}_i$ (corresponds to Table 2) | | | | | | | | |
| Saiz supply elasticity + January temp | 0.5031<br>(0.0928) | 0.6289<br>(0.1214) | 0.1004<br>(0.0366) | 0.0175<br>(0.0052)<br>[0.524] | 0.0130<br>(0.0043)<br>[0.369] | 0.0186<br>(0.0089)<br>[0.143] | -0.0201<br>(0.0050)<br>[-0.050] | -0.0290<br>(0.0182)<br>[-0.072] |
| Saiz supply elasticity + price growth 1950-70 | 0.5811<br>(0.0864) | 0.7607<br>(0.1081) | 0.1157<br>(0.0375) | 0.0194<br>(0.0054)<br>[0.582] | 0.0144<br>(0.0045)<br>[0.407] | 0.0205<br>(0.0093)<br>[0.159] | -0.0161<br>(0.0061)<br>[-0.040] | -0.0382<br>(0.0187)<br>[-0.095] |
| Fixed effects: | Year | Year | Year | Year | Year | Year | Year | Year |
| Right-hand-side variable: $\text{Superstar}_i \times \log(\#\ \text{Rich}_{kt})$ (corresponds to Table 5) | | | | | | | | |
| Saiz supply elasticity + January temp | 0.2563<br>(0.0355) | 0.1011<br>(0.0557) | 0.0758<br>(0.0142) | 0.0225<br>(0.0024)<br>[0.677] | 0.0131<br>(0.0024)<br>[0.372] | -0.0059<br>(0.0034)<br>[-0.046] | -0.0166<br>(0.0069)<br>[-0.041] | -0.0132<br>(0.0088)<br>[-0.033] |
| Saiz supply elasticity + price growth 1950-70 | 0.3089<br>(0.0366) | 0.1322<br>(0.0580) | 0.0937<br>(0.0147) | 0.0255<br>(0.0025)<br>[0.765] | 0.0151<br>(0.0025)<br>[0.427] | -0.0040<br>(0.0036)<br>[-0.031] | -0.0132<br>(0.0072)<br>[-0.033] | -0.0234<br>(0.0091)<br>[-0.058] |
| Fixed effects: | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year | MSA, year |
| Mean of LHS: | 11.54 | 10.64 | 10.84 | 0.033 | 0.035 | 0.129 | 0.400 | 0.402 |

Notes: Number of observations is 1,116, for four decades (1970-2000) and 279 MSAs. Standard errors are in parentheses. The specification in the first panel is $Y_{it} = \beta_1 \text{Superstar}_i + \delta_t + \varepsilon_{it}$, where the superstar variable is defined at the MSA level and is not time-varying. The specification in the second panel is $Y_{it} = \beta_1 \text{Superstar}_i \times \ln(\#\ \text{Rich}_t) + \gamma_i + \delta_t + \varepsilon_{it}$, where an indicator variable for an MSA ever being a "superstar" during the entire 1970-2000 period is interacted with the log national number of families in the "rich" category. The uninteracted variables are subsumed by the fixed effects. Marginal effects relative to the mean of the LHS variable are in square brackets.

Appendix Table A1: MSA Summary Statistics

| Variable | Mean | Standard deviation |
|---|---|---|
| MSA time-invariant characteristics (N=279): | | |
| Average Annual Real House Price Growth, 1950-2000 | 1.57 | 0.56 |
| Average Annual Housing Unit Growth, 1950-2000 | 2.10 | 0.98 |
| Average Annual Real Income Growth, 1950-2000 | 1.82 | 0.35 |
| Ever a "superstar" | 0.075 | 0.264 |
| Ever "low demand" | 0.738 | 0.440 |
| MSA time-varying characteristics (N=1,116): | | |
| Average 20-year Real House Price Growth | 1.50 | 1.04 |
| Average 20-year Housing Unit Growth | 2.10 | 1.20 |
| Average 20-year house price growth + housing unit growth | 3.60 | 1.86 |
| Average ratio of 20-year price growth to 20-year unit growth | 0.869 | 1.148 |
| Real house value | 111,329 | 54,889 |
| Average price/average annual rent | 17.00 | 3.99 |
| Year | # "superstars" | |
| 1970 | 0 | |
| 1980 | 2 | |
| 1990 | 21 | |
| 2000 | 20 | |
| Income Distribution | Mean | Standard deviation |
| Share of an MSA's population that is "rich" | 0.033 | 0.021 |
| Share "middle-rich" | 0.035 | 0.024 |
| Share "middle" | 0.129 | 0.043 |
| Share "middle-poor" | 0.400 | 0.050 |
| Share "poor" | 0.402 | 0.095 |
| National number "rich" | | |
| 1970 | 1,571,136 | |
| 1980 | 1,312,103 | |
| 1990 | 2,611,178 | |
| 2000 | 4,098,324 | |

Appendix Table A2: Place Summary Statistics

| Variable | Mean | Standard deviation |
|---|---|---|
| Place time-invariant characteristics (N=3,788): | | |
| Avg. Real House Price Growth (1970-2000) | 0.015 | 0.011 |
| Avg. Housing Unit Growth (1970-2000) | 0.017 | 0.019 |
| Avg. Real Income Growth (1970-2000) | 0.007 | 0.007 |
| Ever a "superstar" | 0.220 | 0.414 |
| Ever "low demand" | 0.618 | 0.486 |
| Place time-varying characteristics: (1990-2000; N=7,576)) | | |
| Average 20-year Real House Price Growth | 0.015 | 0.017 |
| Average 20-year Housing Unit Growth | 0.016 | 0.021 |
| Average 20-year house price growth + housing unit growth | 0.031 | 0.028 |
| Mean real house value | 156,736 | 125,401 |
| 10th Percentile house value | 90,757 | 79,123 |
| Average price/average annual rent | 17.76 | 7.60 |
| Year | # "superstars" | |
| 1990 | 653 | |
| 2000 | 580 | |
| Income Distribution (1990-2000) | Mean | Standard deviation |
| Share of an place's population that is "rich" | 0.061 | 0.035 |
| Share "middle-rich" | 0.069 | 0.030 |
| Share "middle" | 0.174 | 0.041 |
| Share "middle-poor" | 0.372 | 0.039 |
| Share "poor" | 0.323 | 0.085 |
| MSA number "rich" | | |
| 1990 | 26,789 | 36,031 |
| 2000 | 39,582 | 49,513 |

Appendix Table B: Superstar MSAs by year

| City name | 1970 | 1980 | 1990 | 2000 |
|---|---|---|---|---|
| Albany | | | X | X |
| Allentown | | | X | |
| Atlantic City | | | X | |
| Baltimore | | | X | |
| Bellingham | X | | | |
| Bergen-Passaic | | | X | X |
| Boston | | | X | X |
| Bremerton | X | | | |
| Detroit | | | | X |
| Dutchess County | | | X | X |
| Enid | | X | | |
| Glens Falls | | | X | |
| Hartford | | | X | |
| Jersey City | | | X | X |
| Lewiston | | | X | |
| Los Angeles | | X | X | |
| Louisville | | | | X |
| Middlesex-Somerset-Hunterdon | | | X | |
| Nassau-Suffolk County | | | X | X |
| New Haven | | | X | X |
| New London | | | X | X |
| Newark | | | X | X |
| Oakland | | | X | X |
| Orange County | | | X | |
| Philadelphia | | | X | X |
| Pine Bluff | X | | | |
| Pittsfield | | | X | X |
| Portland | | | X | |
| Providence | | | X | X |
| Reading | | | X | |
| Salinas | | | X | X |
| San Francisco | | X | X | X |
| San Jose | | | X | X |
| Santa Barbara-Santa Maria | | | X | X |
| Santa Cruz | | | X | X |
| Springfield | | | X | X |
| Trenton | | | X | X |
| Ventura | | | X | |

Notes: 241 MSAs that are never superstars are excluded from the table. Rows shaded in grey correspond to MSAs that achieve superstar status in two or more decades. This subset of MSAs are defined as superstars in our regression analysis. The empirical results are robust to defining all MSAs in this table as superstars. Expanding the definition yields slightly lower magnitudes of the estimated coefficients and slightly larger standard errors, but the results remain economically and statistically significant.

**Figure 1: Density of 1950-2000 Annualized Real House Price Growth Rates Across MSAs with 1950 population > 50,000**

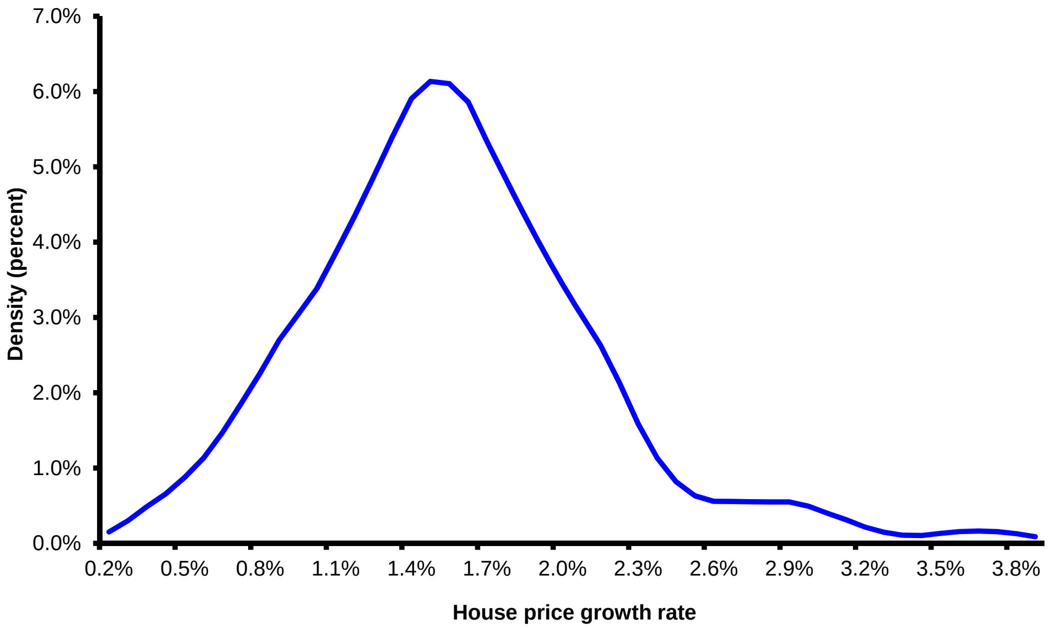


**Figure 2**
**Density of Mean House Values Across MSA's**
**1950 versus 2000**

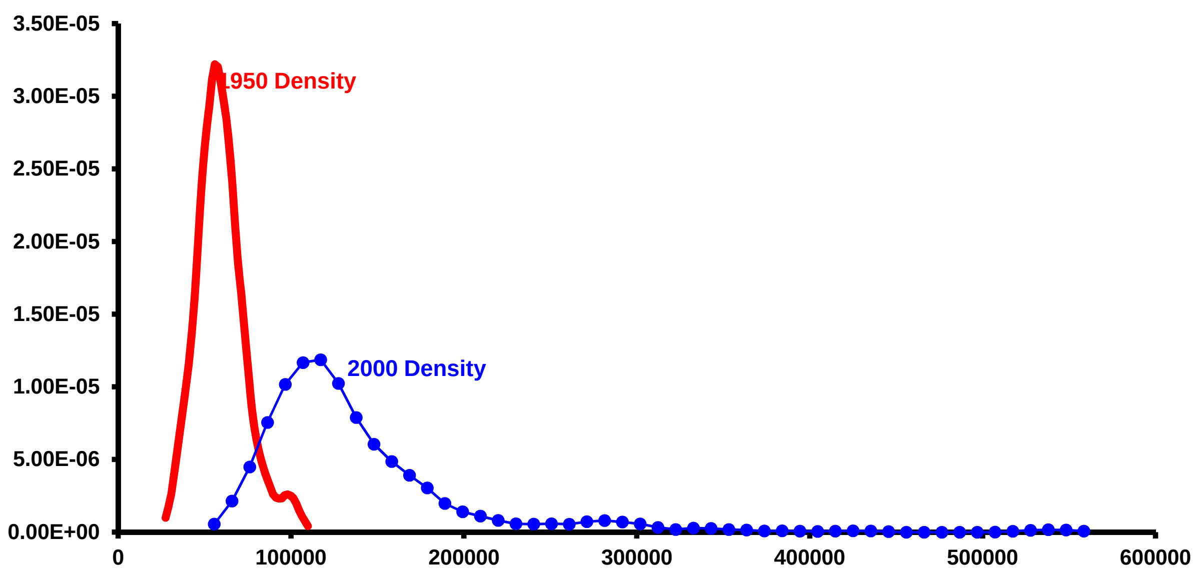

Figure 3: Real annual house price growth versus unit growth, 1960-1980

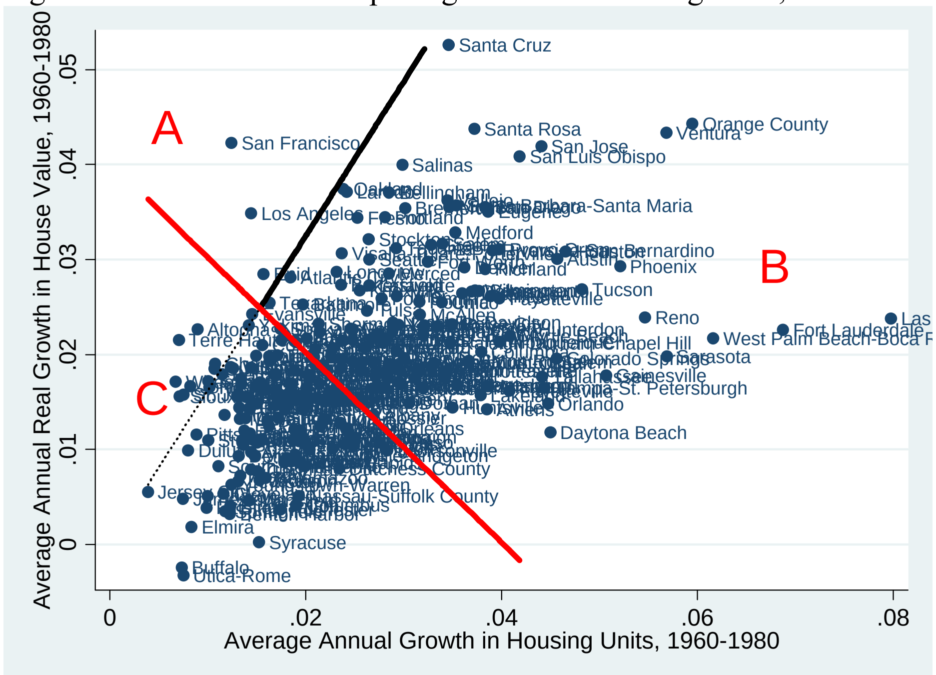


Figure 4: Real annual house price growth versus unit growth, 1980-2000