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# SUPERSTAR CITIES

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## ABSTRACT

Differences in house price and income growth rates between 1950 and 2000 across metropolitan areas have led to an ever-widening gap in housing values and incomes between the typical and highest-priced locations. We show that the growing spatial skewness in house prices and incomes are related and can be explained, at least in part, by inelastic supply of land in some attractive locations combined with an increasing number of high-income households nationally. Scarce land leads to a bidding-up of land prices and a sorting of high-income families relatively more into those desirable, unique, low housing construction markets, which we label "superstar cities." Continued growth in the number of high-income families in the U.S. provides support for ever-larger differences in house prices across inelastically supplied locations and income-based spatial sorting. Our empirical work confirms a number of equilibrium relationships implied by the superstar cities framework and shows that it occurs both at the metropolitan area level and at the sub-MSA level, controlling for MSA characteristics.

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Over the last 50 years, the number of families in U.S. metropolitan areas doubled, with the number making more than $140,000 in real ($2000) terms increasing more than eight-fold according to the U.S. Census. Gains in income growth have been concentrated in those high-income families. Piketty and Saez (2004) estimate that the fraction of income attributable to the top one percent of U.S. households rose from 11.4 percent in 1950 to 16.9 percent in 2000.

Concurrently, two other patterns arose. First, there has been a large dispersion in real house price appreciation rates across metropolitan areas and towns, with some appreciating at very high rates. For example, real house price growth in the San Francisco primary metropolitan statistical area (PMSA) averaged about 3.5 percent per year between 1950 and 2000, more than 2 percentage points higher than the national average. 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. Indeed, the gap in prices between the most expensive metropolitan area (San Francisco) and the average across all areas doubled between 1970 and 2000. San Francisco in 2000 had an average house price of almost $550,000, more than three times higher than the average. Second, real income growth rates between 1950 and 2000 and changes in the income distribution also varied widely across locations. For example, in the San Francisco PMSA the share of families earning over $110,000 (in constant 2000 dollars) grew by 21 percentage points between 1970 and 2000 versus 9 percentage points across all metropolitan areas.

In this paper, we provide evidence that these patterns of spatial dispersion in house price and income growth are related: they are the inevitable result of increasing scarcity of land in certain metropolitan areas and towns, combined with a growing number of high income families nationally. In places that are desirable but have low rates of new housing construction, families with high incomes or strong preferences for that location outbid lower willingness-to-pay families for scarce housing, driving up the price of the underlying land. 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. By contrast, in municipalities where construction is easier, any family who wishes to live there – rich or poor – can buy in at the cost of constructing a new house and, instead of growth in house prices, the area exhibits growth in the quantity of houses. Land prices act as a clearing mechanism, so lower-income households are disproportionately excluded from cities that have limited supply, leaving behind concentrations of higher-income households. In this sense, living in a superstar city is like owning a scarce luxury good.

Over time, the gap in house prices between cities can keep increasing. Even if each family individually is willing to pay only a fixed premium for a location, when the absolute number of rich families in the country increases and their incomes rise, there are more families who will pay a higher premium for the same perceived difference between cities. Thus, a changing composition of residents in supply-constrained cities toward higher income families supports the growth in land prices.

This process can continue as long as the growth in the income-weighted demand for a location exceeds the addition in supply, either in the original location or in a close substitute. Indeed, the inelastically supplied city need not be more desirable on average than any other city, nor do workers in the city need to enjoy increased productivity by moving there. As long as the city appeals to a large enough clientele of families, a growing price gap and a shifting of the local income distribution to the right will occur. We label metropolitan areas and towns where demand exceeds supply and supply growth is limited, “superstars.” These superstar cities and towns are ones in which residents are willing to pay a premium to live and into which high-income superstar-earners disproportionately sort. These markets do not allow for increasing density through construction, cannot infinitely expand their borders, *and* have few close substitute locations. Our results emphasize that even seemingly generic MSAs, for some portion of the population, are not perfectly substitutable.

This correlated skewness in house prices and the income distribution is a modern development at least at the metropolitan area level, because even the densest coastal markets had plenty of land available for development throughout much of the twentieth century. Once these MSAs “filled up”, in the sense that adding units to the housing stock became difficult, both because of geographical limitations and local restrictions on increases in density, growth in house prices accelerated.

We begin the analysis by documenting the long-run trends in house price and income growth and the spatial skewness that has arisen since 1950. Next, we outline a simple two location model that shows how inelastic land supply can link these stylized patterns. This model is similar in spirit to Epple and Platt (1998), but allows for differences in the elasticity of supply across locations, and generates a set of empirically testable predictions. Systematic patterns in the data are consistent with the equilibrium predictions of this superstar cities model.

First, the income-sorting predictions of the model are borne out in the data. Income distributions in superstar cities are skewed to the right, and skew relatively more when the national number of high-income families rises. Recent movers into superstar cities tend to be higher-income, on average, than recent movers into other cities, and recent movers out of superstar cities are drawn disproportionately from the bottom tail of the city’s income distribution.

Second, not only do superstar cities enjoy higher long-run house price growth, but prices in those markets are a higher multiple of current rents, suggesting that homebuyers there anticipate more rapid long-run rent and price growth. In addition, when the total number of high-income families living in the U.S. grows more rapidly, the gap in house prices between superstar cities and other housing markets widens the most.

These patterns are repeated when we compare superstar towns to other towns within their metropolitan areas. “Superstar suburbs” typically have more high-income households and fewer poor ones, and experience a greater rightward shift in their income distributions and more rapid growth in their house prices when the number of high-income households in their MSAs rises. They, too, have higher price-to-rent ratios. That we find similar evidence of ‘superstar suburbs’ is an important differentiator from models of urban agglomerations because labor productivity is unlikely to vary geographically based on where workers live within a given labor market area.

Consistent with the model’s predictions, once an elastically supplied city or town “fills up” and future supply growth becomes limited, price-to-rent ratios increase, and income sorting and house price dispersion accelerates. A number of jurisdictions in our sample undergo this transition into superstar status. For example, Los Angeles and San Francisco are the first major metropolitan areas to become supply-limited, and that happened between 1960 and 1980. The areas around Boston and New York followed between 1970 and 1990.

The implications of the superstar cities framework are fundamentally different from those of existing urban models. For example, standard compensating differential models attribute differences in prices across markets to variation in amenities and other local traits. [Roback (1982), Blomquist *et al* (1988), Gyourko and Tracy (1991)] By contrast, the superstar cities view implies that limited land supply results in a rightward shift in the income distribution and rising land prices that are neither due to changes in the innate attractiveness of living there nor in local productivity, but follow from an increasing number of high willingness-to-pay families in the population. Second, the superstar cities intuition reverses the causality of typical agglomeration models in which moving to a location enhances a worker's productivity. [Glaeser *et al* (1992, 1995), Henderson *et al* (1995), Rauch (1993), Moretti (2004a,b,c), Rosenthal and Strange (2001, 2003)] Instead, high human capital (high income) workers concentrate in superstar cities because they can outbid less productive workers. We do not claim that alternative explanations involving the potential impacts of human capital spillovers, production agglomeration effects, or preference externalities on housing markets are not valid, but we do show empirically that they cannot completely account for the patterns observed in the data.

## 1. Skewness and dispersion in house prices, incomes, and their long-run growth rates

We begin by detailing the remarkable dispersion – and even skewness – across MSAs in house price and income growth over the 1950 to 2000 period. Figure 1A plots the kernel density of average annual real house price growth between 1950 and 2000 for the 280 metropolitan areas with populations over 50,000 in 1950.[1] The tail of growth rates above 2.6 percent is especially thick and the distribution is right-skewed. Table 1, which lists the average real annual house price growth rate between 1950 and 2000 for the ten fastest and ten slowest appreciating metropolitan areas out of the 50 MSAs with populations of at least 500,000 in 1950, documents that the dispersion seen in this figure is not an artifact of a few areas that were small initially and then experienced abnormally rapid price growth.

These annual differences compound to very large price gaps over time even within the top few markets. For example, San Francisco's 3.5 percent annual house price appreciation

[1] The Census data that underlies these calculations is described in Section 3.

implies a 458 percent increase in real house prices between 1950 and 2000, more than twice as large as seventh-ranked Boston at 212 percent, which itself still grew 50 percent more than the sample average of 132 percent for the 50 most populous metropolitan areas.[2] Figure 2A, which plots a kernel density estimate of the 280 metropolitan area average house values in 1950 and 2000, shows that skewness has increased over the last 50 years, with a relative handful of markets ending up commanding enormous price premiums. Figure 2B normalizes the means and standard deviations of the 1950 and 2000 house value distributions so they are equal and plots them against each other. In 2000, the right tail of the MSA house value distribution extends to four times the mean, more than twice the highest MSA from the right tail of the 1950 Census. The left tail ends at about half the mean in both years, although it is slightly more skewed in the 2000 Census.

There is also long-run persistence in the markets which exhibit above-average price growth. Across the two 30-year periods from 1940-1970 and 1970-2000, average annual percentage house price growth has a positive correlation of about 0.3. Moreover, of the MSAs in the top quartile of annual house price growth between 1940 and 1970, half were still in the top quartile and nearly two-thirds remained ranked in the top half between 1970 and 2000.[3]

Income growth rates, as well, demonstrate wide dispersion across MSAs over the long-run. Figure 1B plots the kernel density of average annual real income growth over the 1950 to 2000 period. Growth rates range from 0.8 percent per year to 3.1 percent, and the distribution also evinces some right-skew.

[2] It is worth emphasizing that the extremely high appreciation seen in the Bay Area, southern California, and Seattle markets is not restricted to the past couple of decades. The top five markets in terms of annual real appreciation rates between 1950-1980 are as follows: (1) San Francisco, 3.65 percent; (2) San Diego, 3.49 percent; (3) Los Angeles, 3.20 percent; (4) Oakland, 2.99 percent; and (5) Seattle, 2.88 percent.

[3] Over short horizons, such as a decade, MSAs can experience large price swings. The correlation in house price growth rates across contiguous decades often is significantly negative.

## 2. Superstar Cities

We turn to a simple model to show that the stylized facts in the previous section may be linked through the elasticity of supply of land. In our model, households vary by their incomes and tastes for two locations which differ by whether they have available land. Epple and Platt (1998, henceforth known as EP) 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 in one, we emphasize the testable empirical implications of differences in the elasticity of supply. In addition, our results do not depend upon the reasons for location preferences or inelasticity of supply, so we neither attempt to discern why some families prefer certain cities nor address the causes of limited supply.

### *A. A Simple Model of Superstar Cities*

There are two cities: a red city ($R$) and a green city ($G$). The red city does not allow new development and has a fixed size of $K$ units of housing. The green city has a perfectly elastic supply of new housing units.[4]

There are $N$ workers in the economy, with a continuum of worker skills. Wages are increasing in skill, but are independent of a worker's location, so worker productivity is unrelated to the number or concentration of high-skilled workers in $R$ or $G$. Define $n(W)$ as the distribution of workers who earn wage $W$. Thus $\int_{w=0}^{\infty} n(W)dW = N$.

[4] While we realize that land is not perfectly elastically supplied anywhere, the ease with which builders construct new units clearly differs across the country, as shown by Gyourko and Glaeser (2003), Glaeser, Gyourko, and Saks (2005b), and Saks (2005).

Each worker has an intensity of preference, $c$, uniformly distributed between 0 and 1, to live in the red versus green city.[5] The higher is $c$, the more that a worker prefers to live in $G$. The preference to live in $R$ or $G$ is independent of income.

Workers choose two items in their consumption bundle: a city to live in ($R$ or $G$), and a quantity of the composite good, $A$. The price of $A$ is normalized to 1. The rental cost of agricultural land is $l$. By assumption, land is perfectly elastically supplied in $G$ so that residents can always acquire an additional lot at rent $l$ in the green city. If more than $K$ households prefer the red city, residents of $R$ must pay a per-period rent $r+l$ with the rent premium $r>0$ determined based on bidding as described below.

We assume that a worker gets utility from consumption of $A$, as follows:

$$U = \begin{cases} U^R \equiv (1-c)f(A) \text{ and } A=w-r & \text{if worker resides in city } R \\ U^G \equiv cf(A) \text{ and } A=w & \text{if worker resides in city } G. \end{cases}$$

For simplicity, we normalize $w= W-l$. This specification assumes that a worker obtains higher utility from consumption when its preference for its current location is stronger. However, all of our results presented below still hold if consumption benefits from location and all other goods were separable.

***B. Solution:***

A worker will choose to live in $R$ and pay rent premium $r$ if and only if $U^R > U^G$, or $(1-c)f(w-r) > cf(w)$. If $N/2<=K$, $r=0$ since the red city still has open land and residents sort into $R$ and $G$ solely based on whether $c$ is less than or greater than 1/2. We will restrict our attention to the case of $N/2>K$, so that the expected rent premium in the red city will be strictly positive.

[5] Reasonable alternatives to a uniform distribution of tastes exacerbate the income sorting predictions. 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.

The market-clearing rent premium, $r^*$, equates the number of workers desiring to live in *R* with the number of lots available by solving:

$$\int_{w=0}^{\infty} c^*(w)n(w)dw \leq K . \quad (0.1)$$

The function $c^*(w)$ is the maximum *c* such that a worker with wage *w* will choose to live in *R* and pay rent premium $r^*$. When $w \leq r^*$, then $c^*(w) = 0$; that is, workers cannot afford to live in *R* unless their wage is greater than the rent required to live in *R*. When $w > r^*$, $c^*(w)$ represents the preference of a worker of a given wage who is just indifferent between living in *R* or *G*. So workers with wage *w* and preference $c < c^*(w)$ will choose to live in *R*.

### *C. Simulation Results:*

To demonstrate the effect of inelastic supply of land on land prices and income sorting, we perform a simple simulation. The simulated economy has 100,000 workers, but only 30,000 spaces in city *R*, and a truncated normal wage distribution with discrete $1,000 increments, a mean wage of $40,000, a standard deviation of $40,000, the lowest wage truncated at 0, and the highest wage truncated at $150,000. As above, wages are defined as compensation earned in excess of the agricultural rent, *l*. The location preference *c* is uniformly distributed between 0 and 1, and $f(A)=A$. Solving for the market-clearing rent premium yields $r^* = \$19,257$, or almost 40 percent of the average wage.[6]

<u>Prediction 1</u>: Rents, the average wage, and the share of high income workers are higher in *R* than in *G*.

<u>Explanation for Prediction 1</u>:

[6] The average wage in the economy is actually $51,246 given that the lower truncation wage of $0 removes more of the low wage workers relative to the upper truncation wage of $150,000.

Figure 3 graphs the wage distributions in the red and green cities, with the number of residents in *G* equal to the difference between the two solid lines. A disproportionate share of higher income workers, and no one at all earning below $19,257, lives in the red city.

This result is purely due to the scarcity of locations in *R*. At zero rent premium, any worker with $c<0.5$ would prefer to live in the red city. Since more workers prefer *R* than there are spots, the clearing rent premium is strictly positive, and each worker trades off its intensity of preference for the red city with the rent premium. 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 *c* is close to zero, and a high-income worker with *w* well above $r^*$ will choose *R* as long as *c* is at least slightly below 0.5. Thus the income distribution in *R* is skewed to the right.[7]

Note that this sorting occurs even though a given worker is equally productive in *R* and *G* and worker preferences are independent of income.[8] Indeed, with a uniform distribution of *c*, more than half of the high wage workers live in the green city. This is because half of the workers actually prefer the green city and those on the cusp choose to live in the green city versus paying a rent premium $r^*$ to live in the red city. High-income residents comprise a smaller *share* of the green city since it is larger than *R*, with well more than half of the low-income workers living there.

<u>Prediction 2:</u> Population growth leads to a higher rent premium, higher prices, and more skewed wages in *R* relative to *G*.

[7] Epple and Platt (1998) obtain a similar partial sorting by income. In EP, sorting arises because families have preferences over a bundle of public goods and tax rates which are provided in different amounts across inelastically supplied locations. In our illustrative model, we allow for differences in the elasticity of land supply but do not specify why a household might prefer one location over another.

[8] Because we do not incorporate peer effects or increasing returns to skill, [Moretti (2004b,c)] there is no countervailing pecuniary incentive for high wage workers with a preference for *G* to live in *R* anyway. Given that the density of high wage workers is higher in *R* but the absolute number of high wage workers is higher in *G*, it is unclear where such effects would be greater.

Explanation for Prediction 2:

Suppose that population doubles from 100,000 to 200,000 but the number of spots in *R* is unchanged. The equilibrium rent premium increases from $19,257 to $41,263 as the number of households with $c<0.5$ doubles.[9] Figure 4 illustrates that the wage distribution in the red city also shifts to the right. Thus, 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 $r^*$, and others will no longer prefer it at the higher rent. Families with the lowest incomes are disproportionately priced out of *R* as the national population grows.

Assuming house prices equal the present discounted value of rents, markets with higher rent levels will also have higher house prices. Rent and price premiums are due to the underlying scarcity of land, not the cost of housing structures, which is similar across markets.[10]

Prediction 3: A thicker right tail in the aggregate wage distribution leads to higher rents and wages in *R* relative to *G*.

Explanation for Prediction 3:

Even without population growth, an increase in income inequality raises the average income and thus the willingness-to-pay of the marginal worker who prefers *R*. Thus the rent premium rises in *R*, but less so than in the case of population growth because the number of families who prefer *R* does not increase. Higher rent, in turn, displaces relatively more low-wage workers in favor of high wage workers. This process is illustrated in Figure 5, where the standard deviation of the truncated wage distribution is raised to $80,000.

[9] The specific percentage change in rent is dependent on the parameter values. Eventually the cutoff rent must grow more slowly than the population because the upper support of the truncated normal distribution does not change.

[10] Gyourko and Saiz (forthcoming) show that the cost of construction has been declining in real terms, while real house prices have risen almost everywhere in the U.S.

Prediction 4: 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*.

Explanation for Prediction 4:

The comparative statics in predictions 2 and 3 demonstrate that population growth or a right-skewing of the income distribution lead to higher rents in *R* ($r^*>0$). This prediction assumes that expected long-run risk-adjusted returns to investing in housing in the two cities are equated by the market, where rent is analogous to the dividend paid by a house. If workers anticipate that rents in *R* will grow faster than agricultural rents, 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*. Thus, when the number of high-income families is growing, the price/rent ratio should be higher in *R* than *G*. In fact, house price levels are higher in *R* for two reasons: both land rents and the price-to-rent ratio are higher in *R* than in *G*.

Prediction 5: An unexpected increase in the relative growth rate of rents in R implies a higher steady state growth rate in prices in R and an increase in the price-to-rent ratio.

Explanation for Prediction 5:

With stationary growth in rents, the price/rent ratios will be fixed. If there is an unanticipated shock to the growth rate of rents, the price/rent ratio and the growth rate of prices can deviate from its steady-state trend. If a city runs out of developable land, thereby transitioning from a city like *G* to a superstar city like *R*, the growth rate of rents (and prices) will rise accordingly. In the short-term, house prices will grow more quickly than rents as the price/rent ratio rises to reflect the new higher growth rate of rents. Owners in the newly-created superstar city will earn a one-time capital gain.

## 3. Data description

We use data from the U.S. decennial census, aggregated to three different levels: the metropolitan area, which corresponds to the local labor market, the Census-designated place, which is a political entity such as a city or town, and the household. At the metro area and the census-designated place levels we obtain information on the distribution of house values, family incomes, population, and the number of housing units.[11] For the analysis across metropolitan areas, we use a sample of 280 such areas that had populations of at least 50,000 in 1950 and are in the continental United States.[12]

[11] Census house price data are imperfect in that they are self-reported and not quality adjusted. We use them because the length of the panel available allows us to observe the evolution of superstar markets over time. While correlations between constant quality and unadjusted series can be weak at annual frequencies, the correlation over the decadal periods, which are the unit of analysis here, is quite high. For example, from 1980-1990 and 1990-2000, the sole time periods for which both Census and constant quality data from the Office of Federal Housing Enterprise Oversight are available, the correlation in appreciation rates for a set of consistently defined MSAs is 0.94 in the 1980s and 0.87 in the 1990s.

[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-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.

Since the definitions of metro areas change over time, we use one 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 are obtained from GeoLytics, which compiles long-form data from the decennial *Censuses of Housing and Population*. We hand-collected 1950 and 1960 data from hard copy volumes of the *Census of Population and Housing*. Both sources are based on 100 percent population counts. For the analysis within MSAs, we extract place-level data for 1970-2000 from the GeoLytics CD-ROMs.[15] All dollar values are converted into constant 2000 dollars.

Household-level data comes from the *Integrated Public Use Micro Samples* (IPUMs), which provide a set of matched variables using common definitions across decades. We use family income and the MSA of residence five years prior in an analysis of recent movers reported below. If the resident lived in a different MSA than the current one five years ago, that individual is an in-migrant to the current MSA and an out-migrant from the host MSA five years previously. We restrict the household sample to 1980 and 1990 because the 'MSA-five-years-ago' variable did not exist prior to 1980 (except for a few MSAs in 1940), and in 2000 the number of MSAs identified in the IPUMs was drastically reduced.

[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 for those few areas with that designation.
[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.

In each data set, we divide the distribution of real family incomes into five categories that are consistent over time. The income categories in the original Census data change in each decade. We set the category boundaries equal to 25, 50, 75, and 100 percent of the 1980 family income topcode, and 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 topcode in real terms, using it as an upper bound reduces miscategorization of families into income 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.

## 4. A case study of San Francisco and Las Vegas

A case study of two cities illustrates how the superstar city dynamic plays out in practice. Over the last 50 years the U.S. has experienced growth in the absolute number, population share, and income share of high-income households. [Autor *et al* (2006), Piketty and Saez (2003), Saez (2004)] The left panel of Figure 6 shows that the aggregate distribution of family income across all MSAs in the U.S. has been shifting to the right in real dollars as the right tail of the income distribution has grown much faster than the mean. The right panel of Figure 6 displays the evolution of the number of families, rather than the share, in each of the income bins. Most of the growth in the number of families was among those earning more than the $78,358 median value for our sample.

These changes in the national high-income share were accompanied by very disparate patterns at the metropolitan area level. San Francisco, a canonical superstar city, experienced low levels of new construction and high house price growth. Between 1950 and 1960, the San Francisco primary metropolitan statistical area (PMSA) expanded its population by about 48,000 families. Over the subsequent *four* decades, San Francisco grew by only 44,000 families, with two-thirds of that growth taking place between 1960 and 1970. Real house prices (in constant $2000 dollars) spiked in San Francisco after 1970, growing between 3 and 4 percent per year between 1970 and 1990, about 1.5 percentage points above the average across all MSAs, and 1.4 percent per year between 1990 and 2000, almost one percentage point above the all-MSA average.

By contrast, over the same time period, Las Vegas was a canonical high-demand, elastically supplied non-superstar city. Las Vegas saw explosive population growth, growing from fewer than 50,000 families in 1960 to the size of San Francisco by 2000. Yet it experienced modest real house price growth that was well below the national average.

Consistent with the income distribution predictions of the superstar cities model, as the number of high-income families in the country increased, San Francisco's share high-income grew disproportionately. San Francisco (Figure 7), which always had relatively more rich families and fewer poor families than Las Vegas (Figure 8), became even more skewed toward high income families between 1960 and 2000. Since the number of families in the San Francisco MSA did not grow by much, the MSA actually experienced an increase in the number of rich families and a reduction in the number of lower income ones. In fact, only the richest groups, with incomes of $78,358 and above, increased their share of the number of families in the San Francisco MSA.

By contrast, the overall income distribution in Las Vegas did not keep up with the nation (left panel of Figure 8), leaving Las Vegas progressively more poor relative to both San Francisco and the U.S. metropolitan area aggregate. The large numbers of new families in Las Vegas were both rich and poor, leading to *pro rata* growth in the number of families across Las Vegas' income distribution. Relative to the national income distribution, which shifted right, the growth in Las Vegas was skewed towards poorer families.

In the remainder of this paper, we show empirically that these patterns and the equilibrium predictions of the model generalize to all MSAs and towns.

## 5. How do we determine if a city is a superstar?

Following the model in Section 2, superstars must be in high demand, relative to supply, with demand manifested more in price growth than in housing unit growth because of binding restrictions on the development of new sites. We neither observe the true state of demand nor the elasticity of supply, so we define a superstar city using housing market outcomes. Growth in mean real prices and housing units at the MSA level is measured 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 match each growth rate to the characteristics of the market at the end of the window so, for example, the 1950-70 growth rates are matched to 1970 data.[16]

A MSA is categorized as a superstar if it exhibits high demand, defined as whether its sum of price and quantity growth over the prior two decades is above the sample median, *and* it

[16] We chose this algorithm because the model suggests that the predicted income segregation and house price effects occur after the superstar market has 'filled up'. The use of lagged data helps guard against us misclassifying an area as a superstar too early. Also, 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.

has a low elasticity of supply, indicated by a high ratio of price growth to quantity growth. We allow the high-demand cutoff to vary over time to account for changes in the aggregate economy. By contrast, the cutoff for having a low elasticity of supply should not vary over time since aggregate changes in demand should not affect the ratio of price growth to unit growth. Hence, we use the 90$^{th}$ percentile of the distribution of price growth to quantity growth for all metropolitan areas over the entire period, which is about 1.7.

Superstar markets as of 2000, determined using 1980-2000 growth rates, lay in the region marked *A* in Figure 9, which plots average real annual house price growth between 1980 and 2000 against housing unit growth. Thus high-demand cities are far from the origin and inelastically supplied markets are close to the y-axis. Region *A* is both above the downward-sloping boundary determining high growth status and above the leftmost upwards-sloping line marking significant inelasticity of supply. The cities in *A* include many coastal markets such as San Francisco, New York, and Boston.

A metro area has a high elasticity of supply if it builds sufficient new housing to satisfy demand so that real price growth is low and housing unit production is relatively high, placing it close to the x-axis in Figure 9. We label these cities with high demand but with a ratio of price growth to quantity growth being less than 1/1.7 (about 0.59) as 'Non-superstars'. Non-superstars are in the *C* range, below the less-steeply upwards-sloped line and above the downward-sloped demand cutoff. They include markets such as Las Vegas and Phoenix. The remaining high demand markets, in-between the superstars and non-superstars, lay in the *B* range. They have experienced relatively high demand, and have built at least a modest amount of new units and experienced a moderate amount of real house price appreciation. The final category consists of metropolitan areas that are in low demand, defined as the sum of price and quantity growth below the sample median, and lies in the *D* region below the negatively-sloped line.[17]

We chose to use a discrete method of identifying superstar cities to ease the interpretation of the empirical results. As will be discussed in the results section, our findings are not affected by this decision.

At the Census place level, we use a parallel methodology to determine which places are superstars. 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. It is a superstar place if it is both high-demand and inelastically supplied, defined as the ratio of price growth to unit growth exceeding the 75th percentile, or 4.06. Some places experience high price growth but declines in the number of housing units. To keep the ratio greater than zero, in such places we set the ratio equal to the sample maximum ratio. Similarly, non-superstar places have high demand and elastic supply, with a ratio below the inverse of the 75th percentile. If housing unit growth is positive but prices have fallen, we set the ratio of price growth to unit growth equal to the lowest positive sample value. Since place data is available only for 1970 to 2000, we assign superstar or non-superstar categories to places in 1990 and 2000.

In the face of geographic constraints and politically-imposed restrictions on development, it seems natural that high-demand metropolitan areas could become more inelastically supplied over time as they grow and begin to "fill up". This process would appear as a market moving over time from area *C* to *B* to *A*. Comparing Figures 9 and 10, we observe such an evolution. In 1980, only San Francisco and Los Angeles clearly qualified as superstars, as can be seen in

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[17] We do not distinguish between low-demand areas on the basis of inelasticity of supply. As Glaeser and Gyourko (2005) note, the existence of durable housing makes most cities appear to be inelastically supplied when demand falls. Thus inelastic supply in a low-demand city does not necessarily reflect constraints on new development.

Figure 10 which plots the price growth-to-unit growth relationship over the 1960-1980 period.[18] Between 1980 and 2000, twenty more MSAs filled up, becoming superstars.

## 6. Implications of superstar cities: income distributions and house prices

An important set of predictions of our framework is that a superstar city's household income should be skewed to the right of the U.S. income distribution, and should become more skewed as the right tail of the national income distribution becomes thicker and as the MSA fills up.

### *A. Income distributions across MSAs*

To see if this pattern holds across all MSAs, we estimate the following regression for MSA *i* in year *t*:

$$\frac{\#\text{ in Income Bin}_{\text{yit}}}{\#\text{ of Households}_{\text{yit}}} = \beta_1(\text{Superstar}_{\text{i}}) + \beta_2(\text{Non-superstar}_{\text{i}})$$
$$+\beta_3(\text{Superstar}_{\text{it}}) + \beta_4(\text{Non-superstar}_{\text{it}}) + \gamma_1(\text{Low Demand}_{\text{i}}) + \gamma_1(\text{Low Demand}_{\text{it}}) + \delta_t + \varepsilon_{it}$$

This regression relates the share of a MSA's families that are in each income bin to its superstar status, and controls for total demand. The model implies that superstar cities should have relatively larger shares of rich or middle-rich families (highest and second-highest income bins, respectively) and lower shares of those in the lowest income bins.[19]

The first column of the top panel of table 2 is based on a pooled cross section of 1,116 MSA × year observations.[20] This regression treats superstar status as a (non-exclusive) fixed MSA characteristic, including indicator variables for whether the MSA ever was a superstar over the 1970-2000 period, whether it is ever in the non-superstar range, whether the MSA ever

[18] Enid, OK, barely makes it into 'superstar' territory in this time period. This appears to be the result of an extraordinary, but temporary, oil industry-related shock, as this area is not a superstar later.
[19] See Appendix Table 1 for summary statistics on all variables used in these regressions.
[20] This represents 279 MSAs in each census year from 1970-on.

moved inside the low-demand area, and time dummies. The intermediate, high demand MSAs from region *B* are the excluded category in all the metro area regressions.[21]

The difference in income distribution between superstars and all other MSAs is pronounced. MSAs that ever were superstars have a 2.5 percentage point greater share of their families that are in the rich category relative to the excluded high-demand cities (row 1, column 1). This effect is largest at the high end of the income distribution and declines in magnitude as incomes fall. For example, as reported in square brackets in row 1, the high income share of superstar MSAs is about 83 percent more than the 3 percent share rich for the average MSA that is not a superstar. The share of the next-highest income category is 69 percent greater in superstars relative to the average of other MSAs, and 34 percent higher in the middle category. Markets that have ever been superstars also have a nearly 9 percentage point lower share of poor families (row 1, column 5), almost 21 percent less than the other MSAs.

Non-superstar cities appear similar to the in-between group (row 2). Those coefficients are relatively small and do not exhibit a clear pattern. Low-demand MSAs are less high-income and poorer relative to all of the high demand categories of MSAs, although the magnitudes are modest (row 3).

The superstar cities model suggests that superstar cities should become richer and less poor when they transition into the superstar region. The second panel of Table 2 addresses this hypothesis by adding time-varying superstar, non-superstar, and low demand indicator variables to the previous specifications. Prior to becoming superstars, MSAs that eventually will become a

[21] Our qualitative results and statistical significance in this table and those below are robust to changing the cutoffs between the regions, including continuous measures of the degree of superstardom, or removing from the superstar (or non-superstar) ranks any city that failed to qualify as such in at least two consecutive periods. For example, we have tried including the ratio of price growth to quantity growth, the sum of price and quantity growth, and the interaction of the two, as superstar fundamentals. We have also tried including price growth and quantity growth separately. These specifications lead to the same conclusions, though they are more difficult to describe concisely. The results are available from the authors.

superstar are richer on average, with a 1.3 percentage point greater share rich and a 7.1 percentage point lower share poor (row 1 of panel 2). When these areas are actually in the superstar region, their share rich goes up by an additional 2.8 percentage points and their share poor declines by a further 4.1 percentage points (row 4 of panel 2). Thus superstar cities, as a baseline, have a 43 percent higher share rich, declining monotonically to 17 percent lower share poor, than other MSAs. After their transition to superstar status, these MSAs have an additional 80 to 90 percent greater share of the top two income groups and an 8 to 10 percent lower share of the bottom two income categories. As before, this pattern of results is robust to adding a host of controls for potential unobservables, such as MSA fixed effects, differential time trends for superstars vs. not, or separate year dummies for superstars/non-superstars/low-demand MSAs.

The data do not indicate nearly as much income skewing among non-superstars or low demand MSAs relative to the omitted group. For example, when MSAs transition into being non-superstars or low demand MSAs, they appear to lose a small share of rich relative to poor, although not all of these coefficients are statistically different from zero at conventional levels.

***B. Income distributions across places within MSAs***

Next, we turn to analogous regressions for superstar places within MSAs. Examining changes in house prices and income distributions at the census-designated place level has several clear advantages over the MSA level. The most important is that by using sub-MSA variation, we can control for MSA-level factors, such as agglomeration or other production externalities that affect the common labor market. By including MSA × year fixed effects, we compare places within an MSA in a given year. Another advantage is that places exhibit much more variation in changes in the overall income distribution than do MSAs. On the downside, the place-level data is noisier than the MSA data, and covers a shorter time period.

When we regress the share of households in an income category on the time-invariant measure of place superstar status, using the full 1970 to 2000 sample and controlling for MSA × year effects, places that were ever a superstar have a higher fraction of their families in the richer categories and a lower percentage in the poorer categories. The estimates are reported in the first row of the first panel of Table 3. Superstar places have a 5.2 percentage point higher share rich than do places in the same MSA and year that are in the in-between omitted category, an increase of nearly 150 percent from the sample mean. These places have a 28 percent greater share in the middle-rich category, and anywhere from a 3 to 11 percent lower share in the three poorest categories. The non-superstar and low-demand places show the opposite pattern, except in the poorest category, with generally a lower share of high-income, and a higher share of low-income, families. Both of these patterns are statistically different from zero at conventional levels.

In the second panel of Table 3, we add the time-varying superstar variables. Even when they are not yet superstars, superstar places are relatively more high-income and relatively less poor. In the years that a place is a superstar, it has an even larger share of its families in the highest income category. For example, relative to the omitted in-between group, a place that will eventually be a superstar has a 3.7 percentage point, or more than 80 percent, greater share in the rich category. When that place is a superstar, the share in the rich category increases by 4.2 percentage points, or 85 percent of the mean. Once again, we observe the reverse pattern for the non-superstar places. The patterns are somewhat less distinct because we are limited to the small sample of 7,584 observations over 1990 to 2000, but one can see that the same general pattern holds at both the MSA and place levels, and using the time-varying or time-invariant definitions of superstar status. Finally, the bottom panel shows that we obtain similar cross-section results whether we use the full sample or the smaller 1990-2000 places sample.

### *C. What happens to local house prices and the share rich when the aggregate number of rich rises?*

Another implication of the superstar cities model is that when the *number* of rich families in the country increases, land prices should rise fastest in superstar MSAs since the clearing price goes up to equilibrate the limited supply of houses with the increased demand. Similarly, the income distributions in the superstar cities should shift to the right more than in other cities when there are more rich families at the national level—as long as some of the added rich families have a preference for the inelastic markets. The superstar cities model also predicts analogous patterns at the place level, with the number of rich families at the MSA level positively correlated with the growth of prices and the rich share of the families in the superstar places.

First, we examine whether house values in superstar MSAs are linked to the number of rich families at the national level. We regress a proxy for the entry price of a house – the 10$^{th}$ percentile house value – on the time invariant city status variable (superstar, non superstar, and low demand) interacted with the national number rich, plus year and MSA fixed effects, for the 1970-2000 sample period, with the results reported in Table 4. Note that the MSA fixed effects subsume the non-interacted superstar indicator variables and the year dummies subsume the non-interacted national number rich, so our estimates are identified from MSA × year variation.

The results in column 1 show that entry level houses in superstar cities are even more expensive relative to other cities when the U.S. has more rich families. Indeed, when the national number of rich families is 10 percent higher, the gap in the 10$^{th}$ percentile house value between the MSAs that are ever superstars and the in-between MSAs is 1.1 percent greater.[22]

[22] We find similar results using the average house value rather than the 10$^{th}$ percentile.

However, one should note that our true variation is limited since we observe only four changes in the number of rich families for the metropolitan U.S. as a whole and are merely observing that something is happening disproportionately to superstar MSAs at those times.

This is not the case at the place level, where each of the 279 "parent" MSAs has its own pattern of growth in the number of rich families over four decades. Once again, the 10th percentile house price for each place is regressed on the interaction of place superstar status and the number of rich families in the MSA. We include place fixed effects, and MSA × year effects to control for MSA-level dynamics. We use all four census years and the time-invariant definition of superstar places.

The places results in column 2 of Table 4 show that the entry house price is 0.98 percent higher in superstar places relative to the in-between places in the same MSA in the years when an MSA's number rich is 10 percent greater. The in-between places have 10th percentile prices that are 1.81 percent higher relative to the non-superstar places when the MSAs' number rich is 10 percent higher. We obtain very similar results when we restrict the sample to those places that appear in our data in all four decades (column 3) and when we exclude places with fewer than an average of 500 families (not shown).

In the right-hand panel of Table 4, we repeat the exercise with the share of the families in the MSA (or place) that are in the "rich" category as our dependent variable. Again, the income distribution in superstars shifts to the right the most when the number of rich families is the largest. Column 4 shows that, at the MSA level, a 10 percent rise in the national number rich is correlated with a 0.31 percentage point greater rise in the share rich for superstar cities relative to in-between cities in the same year. At the place level, a 10 percent rise in a MSA's number rich is correlated with a 0.22 percentage point greater rise in the share rich for its superstar places relative to its in-between places. Again, the place results are robust to including only those places that are in our sample for 1970-2000 (column 6) or excluding places with fewer than an average of 500 families.

### *D. Mobility and superstar cities*

The superstar cities model suggests that rising incomes in a city are due to a changing composition of families within superstar cities from an influx of highly productive high-income workers, rather than through gains in existing residents' productivity. Ideally, one could distinguish between these alternatives by comparing workers' wages before and after exogenously moving to a superstar city. If the superstar city had a positive influence on wages over and above what the worker earned prior to moving, that would provide evidence in support of agglomeration benefits. But, if the type of worker who moved to the city was already high-income so that his arrival changed the income distribution of the destination city, the pattern would be more consistent with superstar cities. Unfortunately, in our data we do not observe preexisting wages (or exogenous moves), so we compare the distributions of recent in-migrants and out-migrants in superstar cities and non-superstars to identify whether the share of in-migrants who are currently high-income is greater in superstar cities.

The top panel of Table 5 shows that the income distribution of recent movers into superstar cities is shifted toward relatively more "rich" families. Each column corresponds to the regression of the share of the MSA's recent movers (in-migrants in the top panel, out-migrants in the bottom panel) in a particular income bin on the MSA's superstar/non-superstar status, a year dummy, and an indicator for low demand status. The out-migrant regressions also include the share of the MSA's families in the income category as a control for the at-risk-of-moving population. The sample contains 231 MSAs with migration data in 1980 and 1990. Relative to recent in-migrants in the omitted intermediate *B* category or in non-superstars, superstar MSAs have fewer low-income in-migrants and more middle-to-upper income ones. This difference in income distribution is more than twice as thick as the average density of long-time residents on the rich end and half as thick at the low-income end (see the numbers in square brackets). The difference in the income distributions of in-migrants between superstar and non-superstar MSAs is statistically significant in all but the "middle-poor" income category.

There is not such a strong pattern for out-migrants. Superstar MSAs typically do have a lower fraction of rich out-migrants and a higher fraction of poor out-migrants. However, these effects are statistically distinguishable from the in-between MSAs in only three of the five columns and from the non-superstar MSAs in only one case at the 95 percent confidence level (and two more cases at the 90 percent level).

However, the difference in the income distributions of in-migrants and out-migrants varies considerably between superstar cities and non-superstars. In superstar MSAs, in-migrants are more often rich and less often poor than out-migrants, while in non-superstars there is little difference between in-migrants and out-migrants. This difference in *net* in-migration is statistically significant in four out of five cases, as reported in the bottom row of the table. This comparison is especially useful as it differences out MSA-level characteristics that affect the income distribution of in-migrants and out-migrants equally.

### *7. Implications of superstar cities: higher price-to-rent ratios*

Another implication of the superstar cities framework is that the price-to-rent ratio should be higher in superstar cities. If home buyers correctly anticipate that superstar cities have higher than average rent growth, they should be willing to pay a greater multiple of current rents to obtain a house. This is analogous to the price/earnings ratio being higher for stocks with higher expected growth in earnings.[23]

Table 6 reports results from regressing the log of the ratio of average house value to average annual rent on our indicators for superstar status and year dummies. At the MSA level, we find that metropolitan areas that became superstars at any time from 1970-2000 have higher price/rent ratios, consistent with the implication that superstar cities should experience higher expected rent growth. Relative to the intermediate *B* markets, the price/rent ratio is 22 percent (with a standard error of 1.4 percent) higher for MSAs that ever were superstars (first row), and 13 percent (1.2) lower for low demand MSAs (third row). There is no statistically or economically meaningful difference between price-to-rent ratios for non-superstar metros (second row) and the omitted group.

To show that the higher price/rent ratios are not a spurious characteristic of MSAs that happen to become superstars, in column two of Table 6 we add time-varying indicators for whether an MSA is classified as a superstar, a non-superstar, or low demand in each census year. The results confirm that MSAs' price-to-rent ratios rise when they become superstars. Specifically, MSAs that will become superstars have 10 percent higher price-to-rent ratios than the excluded group before they are superstars, but their price-to-rent ratios rise by another 23 percent (row 4) during their actual superstar period(s). Non-superstars have similar price-to-rent ratios to the in-between group of MSAs when they are not in the non-superstar category, but they have a 12 percent lower price-to-rent ratio in those years when their supply is most elastic (row 5). Finally, low demand MSAs exhibit their lowest price-to-rent ratios when they are in a low demand period (row 6). This pattern is robust to many specifications, including adding MSA

[23] In previous research, Sinai and Souleles (2005) show that a higher price/rent ratio is associated with a higher expected growth rate of rents, measured as the average rent growth over the first nine of the prior 10 years, holding constant other important factors including differences in risk (volatility of rents) across metro areas.

fixed effects, different linear time trends for each type of MSA superstars, non-superstars, and low demand, and different year dummies for each of the four categories of MSAs.

At the place level, we find a parallel result to the MSA-based analysis: the price-to-rent ratio is higher in superstar suburbs. We begin by regressing the log price-to-rent ratio on whether a place *ever* is considered a superstar, non-superstar, or low-demand, in column 3. We include indicators for MSA × year to control for unobserved dynamics taking place at the metropolitan area level, so in essence we are comparing price-to-rent ratios of superstar and non-superstar places within the same MSA and same year. Because of the short time series at the place level, we extrapolate superstar status in 1990 or 2000 back to 1970 and 1980. Relative to the omitted, intermediate high demand category, price-to-rent ratios are 14 percent higher for superstar (row 1) and 5 percent lower for non-superstar places (row 2). Price-to-rent ratios in low demand places are nearly 16 percent lower than the high-demand, in-between places (row 3). All of these results are highly statistically significant.

In column 4, we examine whether the places that transition in or out of superstar/non-superstar status experience a change in their price-to-rent ratio. Because we use lagged data to determine contemporaneous superstar status, we restrict the sample to the places for which we have data over the 1970 to 2000 period and use only 1990 and 2000 in the regression. These restrictions result in a drop from 30,539 to 7,584 observations. As with the MSAs, the census year in which a city achieves superstar status is associated with an increase in the price-to-rent ratio, although the coefficient is small and the standard error is relatively high. Including place fixed effects, in results that we do not report here, reduces that standard error sufficiently that the positive effect is statistically significant. Exiting non-superstar status raises the price-to-rent ratio by 10.3 percent (with a 3.7 percent standard error).

These time-varying place results do not appear to be an artifact of the restricted sample. As a consistency check, in column 5 we repeat the estimation strategy from column 3 using the smaller sample. We find qualitatively similar, and still statistically significant, results.[24]

## 8. Distinguishing superstar cities from alternative explanations

Taken in concert, the empirical evidence above indicates that the superstar cities phenomenon must be at least partially responsible for the skewness in growth rates in house prices and income sorting that we observe. While alternative theories of urban growth and agglomeration are consistent with some of the facts we have identified, none except for superstar cities matches the entire set. Of course, we do not claim that other potential hypotheses are not also valid; rather they cannot be the only explanations.

Unlike superstar cities, which contends that house price growth and changes in the income distribution at the MSA or place level is merely due to exogenous changes in the income distribution and sorting, typical urban theories postulate that there are locational differences in underlying value, either as consumption or through production. In the urban compensating differential literature discussed above, high-amenity locations should have permanently higher land prices. However, this literature does not typically address house price growth and there is no reason to believe that local amenities happen to improve the most when the number of high income people rises. Moreover, it is difficult to imagine that underlying amenities have

[24] Analogously, our MSA results are qualitatively unchanged if we rerun the regressions over the entire 1950-2000 time period using an indicator of supertar status that is extrapolated to the first two decades.

improved nearly enough to account for the dramatic increase in house price dispersion experienced across U.S. markets.[25]

Another way to generate persistent differences in house price appreciation is for some cities to have faster productivity growth. If a worker must live in a city to become more productive and land supply there is limited, workers will bid up the price of land, firms will have to pay higher wages, and land prices ultimately will capitalize the productivity-induced wage premium. If the productivity in the location increases over time, so will the willingness-to-pay to live there.

While we believe that differential agglomeration effects exist across urban areas, there are two main reasons why they cannot be the sole explanation for the variation seen in the data. First, the fact that we find similar patterns across places within a MSA strongly suggests that superstar cities effects exist independently of agglomeration effects. The effect of productivity growth on house prices should occur throughout the labor market area, even when agglomeration benefits accrue in the workplace, since MSAs are constructed according to how families commute to work. Income sorting and skewness in house price growth rates at the sub-MSA level must be due to some reason other than productivity growth. Second, there is no reason why the income benefits to productivity growth should accrue disproportionately to recent in-migrants, as in Table 6.[26]

Some related strands of research, in combination with the superstar cities concept, suggest that the broad theory articulated here may be a better fit of the data than the empirical

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[25] While changes in amenities cannot explain differential growth rates, amenities such as good weather or other people with similar preferences (Waldfogel 2003) may be characteristics that make some families prefer one city to another. That, plus growth in the right tail of the income distribution, is the mechanism for superstar cities.

[26] Combining these alternatives, Shapiro (2005) reports results consistent with other changes occurring with respect to the local quality life that could help retain high human capital workers who well could be essential to the agglomerated firms, thereby reducing their mobility.

results indicate. For example, if production requires a mix of high and low-skill workers, low-skill workers in superstar cities would earn a premium to enable them to afford living there. This theory could partially explain why superstar cities have a lower apparent poor household share, although superstar cities would still have to be the driving force as to why high-skill workers sort there in the first place. Consistent with this possibility, Lee (2005) shows that nurses earn large premiums to work in large cities, while doctors actually earn small discounts in the same cities. Ortalo-Magne and Rady (2006) develop a theory that helps explain why we observe some poor households remaining in the superstar cities. If a poor family owns its house, its wealth grows at the same rate as land prices in a superstar city and thus it can always afford to live in the city, even though its wage income alone would not support it.[27]

## 9. Conclusion

The dispersion in house price and income growth rates across locations and the skewness in house prices, especially the strong growth in the right tail, can be explained in part by inelastic land supply in some places combined with growth in the high-income population. The view that some cities and towns have turned into scarce luxury goods, which we label superstar cities, is supported by a number of consistent empirical facts. First, superstar cities and towns have higher mean incomes and income distributions that are skewed to the right, consistent with high land prices discouraging low-income households from living there. Income distributions at the MSA (or place) level shift right the most when the absolute number of high-income families rise at the national (or MSA) level. This pattern also kicks in more when a location fills up and transitions into superstar status. Second, superstar cities trade at higher price-to-rent ratios and

[27] Ortalo-Magne and Rady also note that their theory is consistent with in-migrants having higher incomes than existing residents.

that ratio expands further when those cities fill up. Third, superstar MSAs (towns) enjoy disproportionately high house price growth when the number of high-income families increases at the national (MSA) level. Lastly, recent movers into superstar MSAs are more likely to be rich and less likely to be poor than recent movers into other cities.

In this framework, house prices do not rise in superstar cities because there is increasing value from amenities or productivity benefits. Instead, the composition of families living in superstar cities shifts to those who are willing to pay more as high-income families become more numerous.

This analysis naturally raises a host of questions. Can the growth in the house price premiums for living in superstar cities and towns persist? On the demand side, the increasing house price gap for superstar cities is dependent on the thickness and length of the right tail of the income distribution, so that any reduction in the absolute number of high-income families or thinning of the right tail of the wage distribution will put downward pressure on this dispersion across cities. According to Piketty and Saez (2004), since 1940 there has never been a sustained drop in either the aggregate income or the average income earned by the top percentile of the U.S. income distribution (although the share of income held by that percentile has fallen). Further, U.S. cities may be ever-more dependent on the income distribution internationally, with superstar residents drawn from the highest income families worldwide.

What about the supply of superstar cities? Our model is predicated upon cities being imperfectly substitutable, so that each has a clientele of potential residents that prefer it to others. However, as cities "enter" the market in response to population growth, they may locate close in product space to existing cities, siphoning off some of a city's clientele. The net effect will depend on the rate of growth of close substitutes, the growth in the high-income population, and the distribution of intensity of tastes. Second, most existing superstar cities could expand supply by increasing density, but choose not to. The political economy behind that decision is only just beginning to be studied. [Glaeser, Gyourko, and Saks (2005a), Ortalo-Magne and Prat (2006)]

In addition, this dynamic has profound implications for the evolution of urban areas because it implies that even large metropolitan areas might evolve into communities that are affordable only by the rich, just as exclusive resort areas have done. Is such an MSA sustainable, or does it lose the vibrancy that makes it unique? Should public policy ensure that living in a particular city is available to all families or, since superstar cities and towns are like luxury goods, is it reasonable that low income workers can no longer afford to buy homes in superstar cities?

## Selected References


Autor, David, Lawrence Katz, and Melissa Kearney (2006). "The Polarization of the U.S. Labor Market", *American Economic Review*, 96: 189-194.

Blomquist, Glenn, Mark Berger, and John Hoehn (1988). "New Estimates of the Quality of Life in Urban Areas", *American Economic Review*, 78(1): 89-107.

Epple, Dennis and Glenn J. Platt. (1998). "Equilibrium and Local Redistribution in an Urban Economy when Households Differ in both Preferences and Incomes", *Journal of Urban Economics*, 43: 23-51.

Glaeser, Edward and Joseph Gyourko (2003). "The Impact of Zoning on Housing Affordability", *Economic Policy Review*, 9(2): 21-39.

Glaeser, Edward and Joseph Gyourko (2005). "Urban Decline and Durable Housing", *Journal of Political Economy, 113(2): 345-375.*

Glaeser, Edward, Joseph Gyourko, and Raven Saks (2005a). "Why Have House Prices Gone Up?, *American Economic Review, 95(2): 329-333.*

Glaeser, Edward, Joseph Gyourko, and Raven Saks (2005b) "Why Is Manhattan So Expensive? Regulation and the Rise in House Prices", *Journal of Law and Economics*, 48(2): 331-370.

Glaeser, Edward, Hedi Kallal, Jose Scheinkman, and Andrei Shleifer (1992). "Growth in Cities", *Journal of Political Economy*, 100(6): 1126-1152.

Glaeser, Edward, Jose Scheinkman, and Andrei Shleifer (1995). "Economic Growth in a Cross-Section of Cities", *Journal of Monetary Economics*, 36: 117-143.

Gyourko, Joseph and Joseph Tracy (1991). "The Structure of Local Public Finance and the Quality of Life", *Journal of Political Economy*, 99(4): 774-806.

Gyourko, Joseph and Albert Saiz (forthcoming). "Construction Costs and the Supply of Housing Structure", *Journal of Regional Science*.

Henderson, J. Vernon, A. Kuncoro, and M. Turner (1995). "Industrial Development in Cities", *Journal of Political Economy*, 106(4): 667-705.

Lee, Sanghoon Conan (2005). "Ability Sorting and Consumer City," University of British Columbia working paper, October 28.

Moretti, Enrico (2004a). "Estimating the External Return to Higher Education: Evidence from Cross-Sectional and Longitudinal Data", *Journal of Econometrics*, Vol. 121.

______ (2004b). "Human Capital Externalities in Cities" in J.V. Henderson and J-F. Thisse (eds.) *Handbook of Urban and Regional Economics*, Volume 4.

______ (2004c). "Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions", *American Economic Review*, 94(3), 656-90.

Ortalo-Magne, Francois, and Andrea Prat (2006). "The Political Economy of Housing Supply", University of Wisconsin working paper, March 31.

Ortalo-Magne, Francois and Sven Rady (2006). "Heterogeneity within Communities: A Stochastic Model with Tenure Choice", University of Wisconsin working paper, February.

Piketty, Thomas and Emmanuel Saez (2003). "Income Inequality in the United States, 1913-1998", *Quarterly Journal of Economics* 118(1), 1-39.

__________ (2004). "Income Inequality in the United States, 1913-2002," UC Berkeley Working Paper.

Rauch, Jonathan (1993). "Productivity Gains from Geographic Concentration of Human Capital: Evidence from the Cities", *Journal of Urban Economics*, 34: 380-400.

Roback, Jennifer (1982). "Wages, Rents, and the Quality of Life", *Journal of Political Economy*, 90(2): 1257-78.

Rosenthal, Stuart and William Strange (2001). "The Determinants of Agglomeration", *Journal of Urban Economics*, 50: 191-229.

______ (2003). "Geography, Industrial Organization, and Agglomeration", *Review of Economics and Statistics*, 85(2): 377-393.

Saks, Raven (2005). "Job Creation and Housing Construction: Constraints on Metropolitan Area Growth", Finance and Economics Discussion Series 2005-49. Washington: Board of Governors of the Federal Reserve System.

Shapiro, Jesse (2005). "Smart Cities: Quality of Life, Productivity, and the Growth Effects of Human Capital", *Review of Economics and Statistics*, forthcoming.

Sinai, Todd and Nicholas Souleles (2005). "Owner Occupied Housing as a Hedge Against Rent Risk," *Quarterly Journal of Economics*, May 2005.

Waldfogel, Joel (2003). "Preference Externalities: An Empirical Study of Who Benefits Whom in Differentiated Product Markets" *RAND Journal of Economics*.

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: The income distribution in superstar MSAs

| | Left-hand-side variable: Share of MSA's families in income bin: | | | | |
|---|---|---|---|---|---|
| | Rich | Middle-rich | Middle | Middle-poor | Poor |
| Cross-section: | | | | | |
| $Superstar_i$ [Relative to mean share] | 0.025<br>(0.001)<br>[0.833] | 0.022<br>(0.001)<br>[0.688] | 0.042<br>(0.003)<br>[0.339] | -0.004<br>(0.004)<br>[-0.010] | -0.086<br>(0.007)<br>[-0.208] |
| $Non\text{-}superstar_i$ | 0.005<br>(0.001) | 0.003<br>(0.001) | 0.002<br>(0.002) | -0.023<br>(0.003) | 0.013<br>(0.006) |
| Low $Demand_i$ | -0.008<br>(0.001) | -0.007<br>(0.001) | -0.010<br>(0.003) | 0.007<br>(0.004) | 0.017<br>(0.007) |
| Adj. $R^2$ | 0.442 | 0.621 | 0.377 | 0.178 | 0.214 |
| Time-varying superstar/non-superstar status | | | | | |
| $Superstar_i$ [Relative to mean share] | 0.013<br>(0.002)<br>[0.433] | 0.011<br>(0.002)<br>[0.344] | 0.035<br>(0.004)<br>[0.282] | 0.013<br>(0.005)<br>[0.0325] | -0.071<br>(0.009)<br>[-0.171] |
| $Non\text{-}superstar_i$ | 0.005<br>(0.001) | 0.005<br>(0.001) | 0.002<br>(0.003) | -0.022<br>(0.004) | 0.010<br>(0.007) |
| Low $Demand_i$ | -0.006<br>(0.001) | -0.006<br>(0.001) | -0.009<br>(0.003) | 0.000<br>(0.004) | 0.021<br>(0.007) |
| $Superstar_{it}$ [Relative to mean share] | 0.028<br>(0.003)<br>[0.903] | 0.027<br>(0.002)<br>[0.818] | 0.017<br>(0.006)<br>[0.135] | -0.030<br>(0.008)<br>[-0.075] | -0.041<br>(0.015)<br>[-0.100] |
| $Non\text{-}superstar_{it}$ | -0.003<br>(0.002) | -0.006<br>(0.001) | -0.004<br>(0.004) | 0.010<br>(0.005) | 0.003<br>(0.009) |
| Low $Demand_{it}$ | -0.003<br>(0.001) | -0.003<br>(0.001) | -0.003<br>(0.003) | 0.015<br>(0.004) | -0.006<br>(0.007) |
| Adj. $R^2$ | 0.504 | 0.669 | 0.383 | 0.207 | 0.219 |
| Mean of LHS: $Superstar_i$=0 [$Superstar_{it}$=0] | 0.030<br>[0.031] | 0.032<br>[0.033] | 0.124<br>[0.126] | 0.400<br>[0.402] | 0.414<br>[0.409] |

Notes: Number of observations is 1,116, for four decades (1970-2000) and 279 MSAs. Standard errors are in parentheses. All specifications include year dummies. $Superstar_{it}$ is equal to 1 when an MSA's ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period exceeds 1.7 (the 90th percentile) and the sum of price and unit growth over that period exceeds the median. $Superstar_i$ is equal to 1 for an MSA if $superstar_{it}$ is ever equal to 1. $Non\text{-}superstar_{it}$ is equal to 1 when the price growth/unit growth ratio is below 1/1.7, and $non\text{-}superstar_i$ is an indicator whether $non\text{-}superstar_{it}$ is ever 1. To control for MSA-demand, the top panel includes an indicator variable for whether the MSA's sum of annual price growth and unit growth over any 20-year period fell below the median in that period. The bottom panel includes that variable plus a time-varying variable for whether the sum of the growth rates over the preceding 20 years was below the median.

Table 3 - Panel 1: The income distribution in superstar places

| | Left-hand-side variable: Share of place's families in income bin: | | | | |
|---|---|---|---|---|---|
| | Rich | Middle-rich | Middle | Middle-poor | Poor |
| Cross-section: | | | | | |
| $Superstar_i$ [Relative to mean share] | 0.052 (0.002) [1.486] | 0.011 (0.001) [0.282] | -0.004 (0.001) [-0.029] | -0.044 (0.002) [-0.107] | -0.014 (0.003) [-0.037] |
| $Non\text{-}superstar_i$ | -0.017 (0.002) | 0.005 (0.001) | 0.030 (0.001) | 0.040 (0.002) | -0.057 (0.003) |
| Low $Demand_i$ | -0.032 (0.001) | -0.014 (0.001) | -0.020 (0.001) | 0.009 (0.001) | 0.056 (0.002) |
| Adj. $R^2$ | 0.130 | 0.098 | 0.041 | 0.036 | 0.064 |
| Mean of LHS: $Superstar_i$=0 | 0.035 | 0.039 | 0.136 | 0.412 | 0.377 |

Notes: Number of observations is 31,200 over four decades (1970-2000). This is not a rectangular panel. Standard errors are in parentheses. All specifications include MSA x year dummies. $Superstar_i$ is equal to 1 if a place's ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period *ever* exceeds 2.06 (the 75$^{th}$ percentile) and the sum of price and unit growth over that period exceeds the median. $Non\text{-}superstar_i$ is equal to 1 if the price growth/unit growth ratio is ever below 1/2.06 and the sum of price and unit growth over that period exceeds the median. Low $demand_i$ is an indicator variable for whether the place's sum of annual price growth and unit growth over any 20-year period fell below the median in that period.

Table 3 - Panel 2: The income distribution in superstar places, 1990-2000

| | Left-hand-side variable: Share of place's families in income bin: | | | | |
|---|---|---|---|---|---|
| | Rich | Middle-rich | Middle | Middle-poor | Poor |
| Time-varying superstar/non-superstar status | | | | | |
| $Superstar_i$ [Relative to mean share] | 0.037<br>(0.005)<br>[0.804] | 0.008<br>(0.002)<br>[0.140] | -0.001<br>(0.003)<br>[-0.006] | -0.024<br>(0.004)<br>[-0.062] | -0.020<br>(0.007)<br>[-0.057] |
| $Non\text{-}superstar_i$ | -0.033<br>(0.005) | -0.001<br>(0.002) | 0.023<br>(0.003) | 0.038<br>(0.004) | -0.026<br>(0.007) |
| $Low\ Demand_i$ | -0.055<br>(0.003) | -0.021<br>(0.002) | -0.016<br>(0.002) | 0.039<br>(0.003) | 0.052<br>(0.005) |
| $Superstar_{it}$ [Relative to mean share] | 0.042<br>(0.005)<br>[0.857] | -0.001<br>(0.002)<br>[-0.017] | -0.022<br>(0.004)<br>[-0.137] | -0.027<br>(0.005)<br>[-0.070] | 0.008<br>(0.008)<br>[0.023] |
| $Non\text{-}superstar_{it}$ | -0.014<br>(0.006) | -0.004<br>(0.003) | -0.001<br>(0.004) | 0.009<br>(0.005) | 0.010<br>(0.008) |
| $Low\ Demand_{it}$ | -0.012<br>(0.003) | -0.015<br>(0.002) | -0.029<br>(0.002) | -0.008<br>(0.003) | 0.063<br>(0.005) |
| Adj. $R^2$ | 0.242 | 0.240 | 0.116 | 0.124 | 0.188 |
| Cross-section: | | | | | |
| $Superstar_i$ [Relative to mean share] | 0.066<br>(0.003)<br>[1.435] | 0.010<br>(0.001)<br>[0.175] | -0.012<br>(0.002)<br>[-0.075] | -0.041<br>(0.003)<br>[-0.106] | -0.023<br>(0.005)<br>[-0.066] |
| $Non\text{-}superstar_i$ | -0.042<br>(0.003) | -0.001<br>(0.001) | 0.027<br>(0.002) | 0.045<br>(0.003) | -0.028<br>(0.004) |
| $Low\ Demand_i$ | -0.065<br>(0.002) | -0.031<br>(0.001) | -0.034<br>(0.002) | 0.035<br>(0.002) | 0.096<br>(0.003) |
| Adj. $R^2$ | 0.233 | 0.229 | 0.093 | 0.119 | 0.172 |
| Mean of LHS: $Superstar_i=0$ [$Superstar_{it}=0$] | 0.046<br>[0.049] | 0.057<br>[0.059] | 0.160<br>[0.161] | 0.386<br>[0.384] | 0.351<br>[0.347] |

Notes: Number of observations is 7,584 over two decades (1990-2000), 3,792 places per decade. Standard errors are in parentheses. All specifications include MSA x year dummies. $Superstar_{it}$ is equal to 1 when a place's ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period exceeds 2.06 (the 75th percentile) and the sum of price and unit growth over that period exceeds the median. $Superstar_i$ is equal to 1 for a place if $superstar_{it}$ is ever equal to 1. $Non\text{-}superstar_{it}$ is equal to 1 when the price growth/unit growth ratio is below 1/2.06, and $non\text{-}superstar_i$ is an indicator whether $non\text{-}superstar_{it}$ is ever 1. Low $demand_{it}$ is an indicator variable for whether the MSA's sum of annual price growth and unit growth over the prior 20-year period fell below the median in that period. Low $demand_i$ is equal to 1 if low $demand_{it}$ ever equals 1.

Table 4: How Changes in the Number of the Nation's or MSA's Rich Differentially Affect House Prices and the Fraction Rich in Superstar and Non-Superstar Cities or Places

| Left-hand-side variable: | Log of the 10th Percentile House Value | | | Share of families that are in the "rich" category | | |
|---|---|---|---|---|---|---|
| Unit of observation | MSA × year | Place × year | Place × year | MSA × year | Place × year | Place × year |
| $Superstar_i$ × log(Number $Rich_{kt}$) | 0.140<br>(0.044) | 0.098<br>(0.010) | 0.119<br>(0.011) | 0.031<br>(0.002) | 0.022<br>(0.001) | 0.027<br>(0.001) |
| $Non\text{-}Superstar_i$ × log(Number $Rich_{kt}$) | -0.003<br>(0.036) | -0.181<br>(0.009) | -0.121<br>(0.011) | 0.004<br>(0.001) | -0.009<br>(0.001) | -0.016<br>(0.001) |
| Low $Demand_i$ × log(Number $Rich_{kt}$) | -0.176<br>(0.040) | -0.155<br>(0.007) | -0.123<br>(0.008) | -0.013<br>(0.001) | -0.025<br>(0.001) | -0.033<br>(0.001) |
| Fixed effects: | MSA, year | Place, MSA × Year | Place, MSA × Year | MSA, year | Place, MSA × Year | Place, MSA × Year |
| N | 1,116 | 31,190 | 15,170 | 1,116 | 31,200 | 15,170 |
| Rectangular sample? | Yes | No | Yes | Yes | No | Yes |
| Adj. $R^2$ | 0.259 | 0.093 | 0.203 | 0.233 | 0.127 | 0.162 |

Notes: The sample period is 1970-2000. At the MSA level, it covers 279 MSAs over four decades. At the place level, the rectangular sample uses the 3,792 Census-designated Places for which we have data over the entire period. The larger sample also uses places that enter the data set post-1970. Standard errors are in parentheses. $Superstar_i$ is equal to 1 for an MSA [place] if ever an MSA's [place's] ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period exceeds 1.7 [2.06] (the 90th percentile) and the sum of price and unit growth over that period exceeds the median. $Non\text{-}superstar_i$ is equal to 1 if ever the price growth/unit growth ratio is below 1/1.7 [1/2.06] and the sum of price and unit growth over that period exceeds the median. To control for demand, low $demand_i$ is an indicator variable for whether the MSA's [place's] sum of annual price growth and unit growth over any 20-year period fell below the median in that period. Each of these variables is interacted with the either the national number of families in the "rich" category (in the MSA specifications) or the MSA number "rich" (in the place-level specifications). The uninteracted variables are subsumed by the fixed effects.

Table 5: The difference among superstar MSAs in the income distribution of movers

| | Income Bins | | | | |
|---|---|---|---|---|---|
| | Rich | Middle-rich | Middle | Middle-poor | Poor |
| In-migrants: | | | | | |
| (i) $Superstar_{it}$ | 0.034 | 0.048 | 0.078 | 0.002 | -0.162 |
| [Relative to mean share | (0.013) | (0.009) | (0.020) | (0.030) | (0.037) |
| in income category] | [1.22] | [1.45] | [0.65] | [0.005] | [-0.39] |
| (ii) $Non\text{-}superstar_{it}$ | -0.002 | -0.006 | -0.006 | -0.009 | 0.023 |
| [Relative to mean share | (0.008) | (0.006) | (0.012) | (0.018) | (0.023) |
| in income category] | [-0.07] | [-0.18] | [-0.05] | [-0.02] | [0.06] |
| Adj. $R^2$ | 0.0632 | 0.1112 | 0.1354 | 0.0587 | 0.0657 |
| (A) With what confidence level is (i) – (ii) $\neq$ 0? | 99% | 99% | 99% | 27% | 99% |
| Out-migrants: | | | | | |
| (iii) $Superstar_{it}$ | -0.012 | -0.029 | -0.054 | -0.019 | 0.056 |
| [Relative to mean share | (0.017) | (0.010) | (0.023) | (0.029) | (0.029) |
| in income category] | [-0.42] | [-0.88] | [-0.45] | [-0.05] | [0.14] |
| (iv) $Non\text{-}superstar_{it}$ | -0.010 | -0.012 | 0.016 | 0.012 | 0.002 |
| [Relative to mean share | (0.010) | (0.006) | (0.014) | (0.018) | (0.017) |
| in income category] | [-0.38] | [-0.35] | [0.14] | [0.03] | [0.01] |
| Adj. $R^2$ | 0.1358 | 0.3005 | 0.2699 | 0.1468 | 0.2226 |
| (B) With what confidence level is (iii) – (iv) $\neq$ 0? | 5% | 90% | 99% | 70% | 93% |
| With what confidence level is (A) – (B) $\neq$ 0? | 91% | 99% | 99% | 58% | 99% |

Notes: The left-hand-side variable is the share of the MSA's number of in-migrants (or out-migrants) that are in the income category. The sample is restricted to 1980 and 1990 and the 231 MSAs per year for which we have migration data. Standard errors are in parentheses. All specifications include a year dummy and a control for low demand MSAs. Standard errors in parentheses. $Superstar_{it}$ is equal to 1 when an MSA's ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period exceeds 1.7 (the 90$^{th}$ percentile) and the sum of price and unit growth over that period exceeds the median. $Non\text{-}superstar_{it}$ is equal to 1 when the price growth/unit growth ratio is below 1/1.7. To control for MSA-demand, the regressions include an indicator variable for whether the sum of the growth rates over the preceding 20 years was below the median. The out-migrant regressions also include the share of the MSA's families in the income category as a control.

Table 6: Price-to-rent ratios and superstars

| Left-hand-side variable: | Log average house value/average rent | | | | |
|---|---|---|---|---|---|
| Unit of observation: | MSA × year | | Place × year | | |
| Definition of superstar: | Fixed MSA characteristic | Time-varying | Fixed place characteristic | Time-varying | Fixed place characteristic |
| $Superstar_i$ | 0.219<br>(0.014) | 0.100<br>(0.016) | 0.135<br>(0.011) | 0.159<br>(0.031) | 0.212<br>(0.021) |
| $Non\text{-}superstar_i$ | -0.004<br>(0.011) | -0.012<br>(0.012) | -0.045<br>(0.010) | -0.121<br>(0.031) | -0.165<br>(0.021) |
| $Low\ Demand_i$ | -0.131<br>(0.012) | -0.100<br>(0.013) | -0.155<br>(0.007) | -0.128<br>(0.022) | -0.241<br>(0.016) |
| $Superstar_{it}$ | | 0.227<br>(0.025) | | 0.048<br>(0.034) | |
| $Non\text{-}superstar_{it}$ | | -0.119<br>(0.015) | | -0.103<br>(0.037) | |
| $Low\ Demand_{it}$ | | -0.093<br>(0.012) | | -0.163<br>(0.022) | |
| Fixed effects | Year | Year | MSA × year | MSA × year | MSA × year |
| N | 1,116 | 1,116 | 30,539 | 7,584 | 7,584 |
| Sample period | 1970-2000 | 1970-2000 | 1970-2000 | 1990-2000 | 1990-2000 |
| Adj. $R^2$ | 0.450 | 0.548 | 0.065 | 0.153 | 0.135 |

Notes: Standard errors are in parentheses. $Superstar_{it}$ is equal to 1 when an MSA's [place's] ratio of real annual price growth over the previous two decades to its annual housing unit growth over the same period exceeds 1.7 [2.06] (the 90th percentile) and the sum of price and unit growth over that period exceeds the median. $Superstar_i$ is equal to 1 for an MSA if $superstar_{it}$ is ever equal to 1. $Non\text{-}superstar_{it}$ is equal to 1 when the price growth/unit growth ratio is below 1/1.7 [1/2.06], and $non\text{-}superstar_i$ is an indicator whether $non\text{-}superstar_{it}$ is ever 1. Low $demand_i$ is an indicator variable for whether the sum of annual price growth and unit growth over any 20-year period fell below the median in that period. Low $demand_{it}$ is a time-varying variable for whether the sum of the growth rates over the preceding 20 years was below the median.

Appendix Table A1: MSA Summary Statistics

| Variable | Mean | Standard deviation |
|---|---|---|
| MSA time-invariant characteristics: | | |
| Average Annual Real House Price Growth, 1950-2000 (N=279) | 1.57 | 0.56 |
| Average Annual Housing Unit Growth, 1950-2000 (N=279) | 2.10 | 0.98 |
| Average Annual Real Income Growth, 1950-2000 (N=279) | 1.82 | 0.35 |
| Ever a "superstar" | 0.165 [46] | 0.372 |
| Ever a "non-superstar" | 0.337 [94] | 0.474 |
| Ever "low demand" | 0.821 [229] | 0.384 |
| MSA time-varying characteristics: | | |
| 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 | 0.936 | 0.642 |
| Real house value | 111,329 | 54,889 |
| Average price/average annual rent | 17.00 | 3.99 |
| Year | # "superstars" | # "non-superstars" |
| 1970 | 3 | 55 |
| 1980 | 3 | 34 |
| 1990 | 30 | 43 |
| 2000 | 21 | 36 |
| 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
(Full sample: N=31,200)

| Variable | Mean | Standard deviation |
|---|---|---|
| Place time-invariant characteristics: | | |
| Average Real House Price Growth | 0.013 | 0.015 |
| Average Housing Unit Growth, | 0.015 | 0.023 |
| Average Real Income Growth | 0.028 | 0.029 |
| Ever a "superstar" | 0.113 | 0.316 |
| Ever a "non-superstar" | 0.113 | 0.316 |
| Ever "low demand" | 0.556 | 0.497 |
| Place time-varying characteristics: | | |
| Average 20-year Real House Price Growth | 0.013 | 0.016 |
| Average 20-year Housing Unit Growth | 0.016 | 0.023 |
| Average 20-year house price growth + housing unit growth | 0.029 | 0.030 |
| Mean real house value | 123,600 | 101,081 |
| 10th Percentile house value | 68,758 | 64,139 |
| Average price/average annual rent | 16.21 | 7.45 |
| Year | # "superstars" | # "non-superstars" |
| 1990 | 387 | 272 |
| 2000 | 837 | 870 |
| Income Distribution | Mean | Standard deviation |
| Share of an place's population that is "rich" | 0.045 | 0.084 |
| Share "middle-rich" | 0.043 | 0.046 |
| Share "middle" | 0.141 | 0.079 |
| Share "middle-poor" | 0.405 | 0.101 |
| Share "poor" | 0.365 | 0.167 |
| MSA number "rich" | | |
| 1970 | 16,216 | |
| 1980 | 10,072 | |
| 1990 | 19,963 | |
| 2000 | 30,499 | |

Appendix Table A2: Place Summary Statistics
(Rectangular sample: N=3,792 per decade)

| Variable | Mean | Standard deviation |
|---|---|---|
| Place time-invariant characteristics: | | |
| 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" | 0.154 | 0.361 |
| Ever a "non-superstar" | 0.124 | 0.330 |
| Ever "low demand" | 0.618 | 0.486 |
| Place time-varying characteristics: (1970-2000) | | |
| 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 | 156,634 | 125,393 |
| $10^{th}$ Percentile house value | 90,703 | 79,105 |
| Average price/average annual rent | 17.75 | 7.60 |
| Year | # "superstars" | # "non-superstars" |
| 1990 | 381 | 272 |
| 2000 | 446 | 327 |
| Income Distribution (1970-2000) | Mean | Standard deviation |
| Share of an place's population that is "rich" | 0.062 | 0.092 |
| Share "middle-rich" | 0.065 | 0.048 |
| Share "middle" | 0.166 | 0.070 |
| Share "middle-poor" | 0.375 | 0.082 |
| Share "poor" | 0.332 | 0.154 |
| MSA number "rich" | | |
| 1970 | 16,214 | |
| 1980 | 13,358 | |
| 1990 | 26,765 | |
| 2000 | 39,549 | |

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

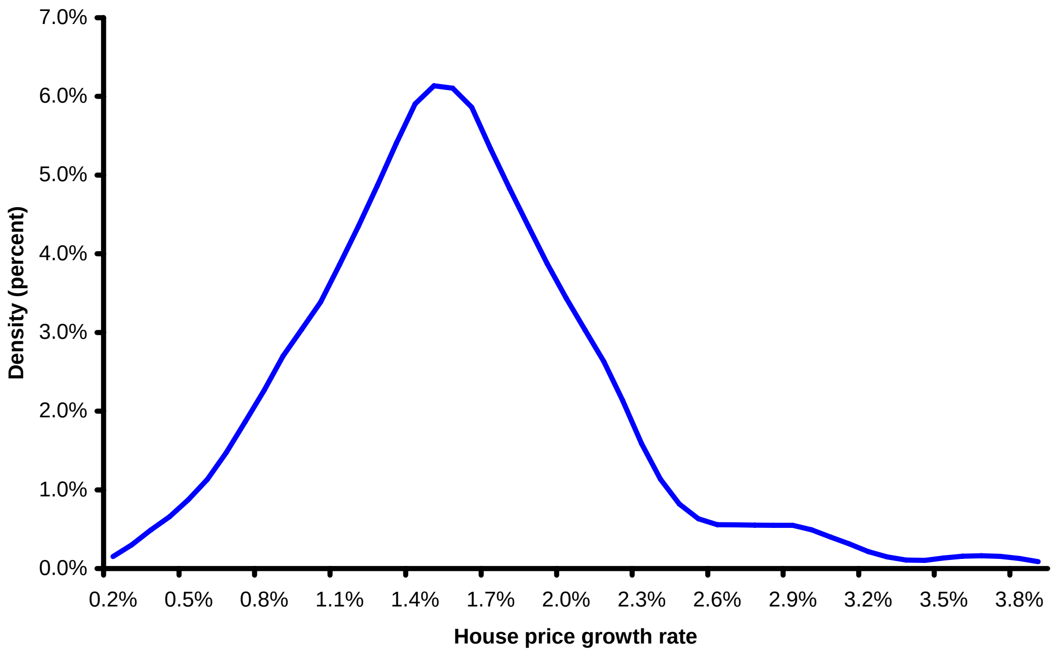



**Figure 1B: Density of 1950-2000 Annualized Real Income Growth Rates Across MSAs with 1950 population > 50,000**

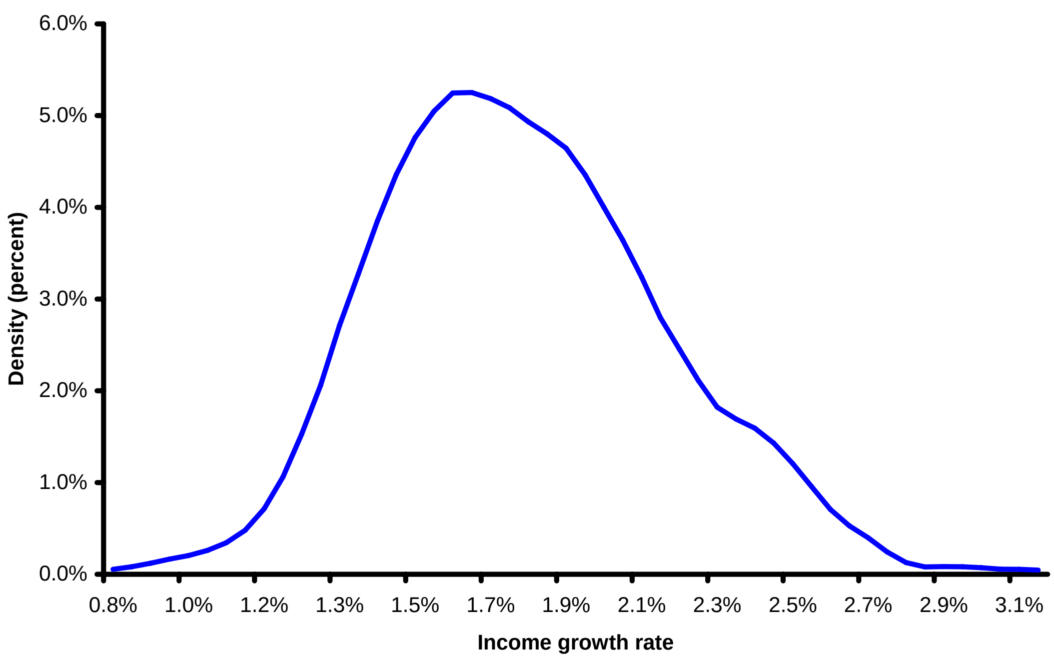


**Figure 2A**
**Density of Mean House Values Across MSA's**
**1950 versus 2000**

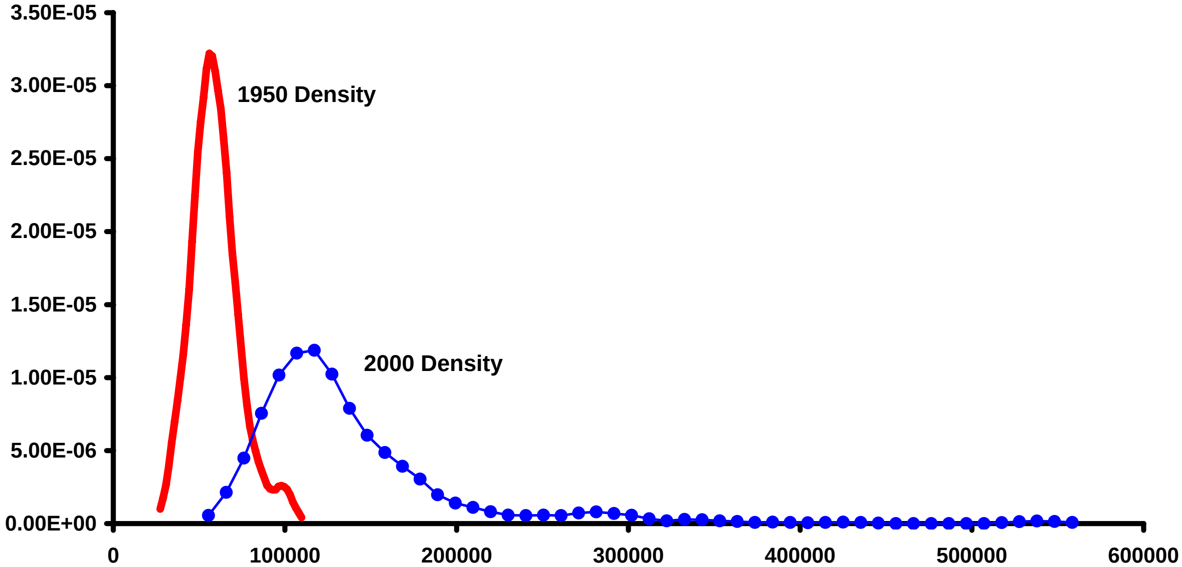



**Figure 2B**
**Skewness in Mean House Values Across MSA's**
**1950 versus 2000**

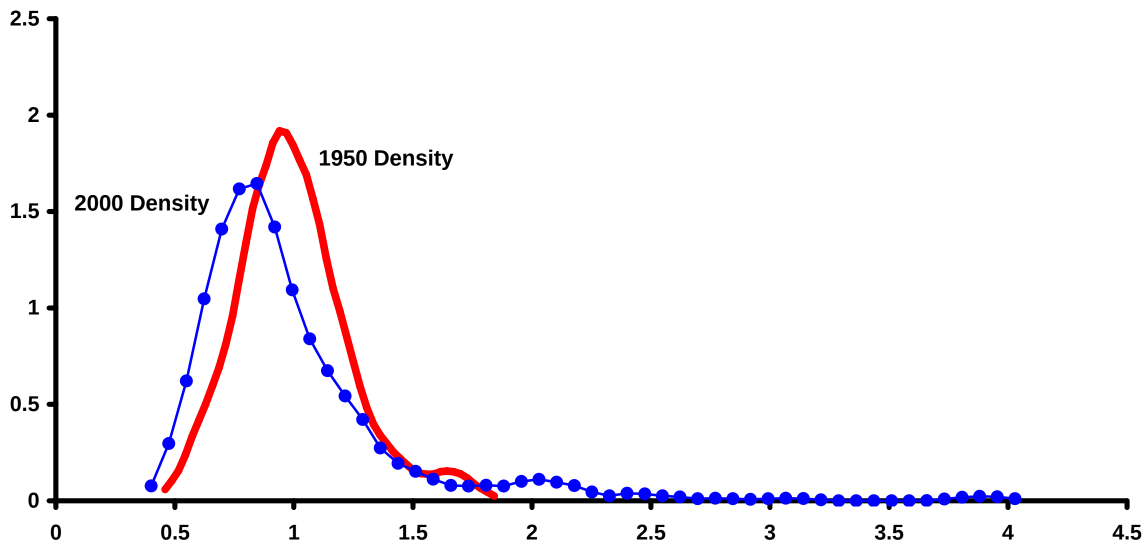
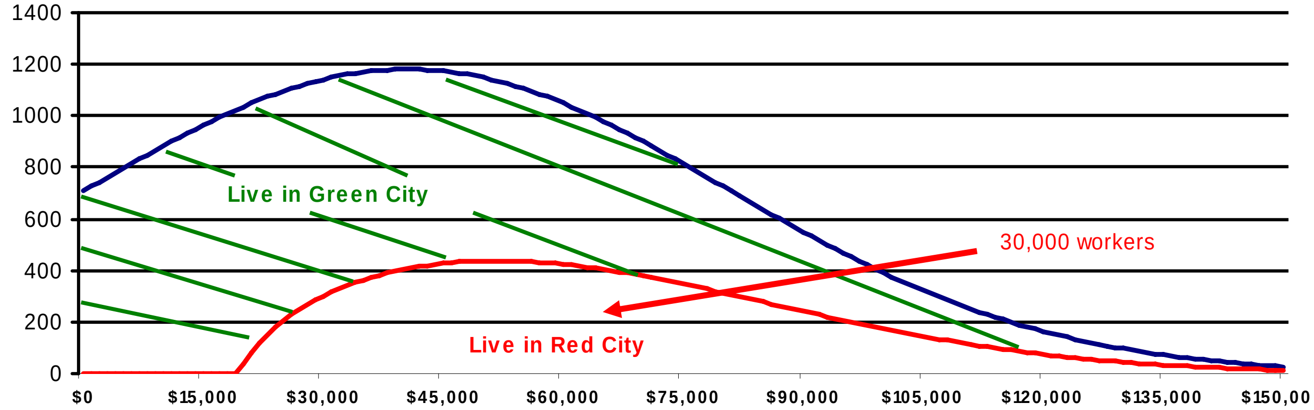
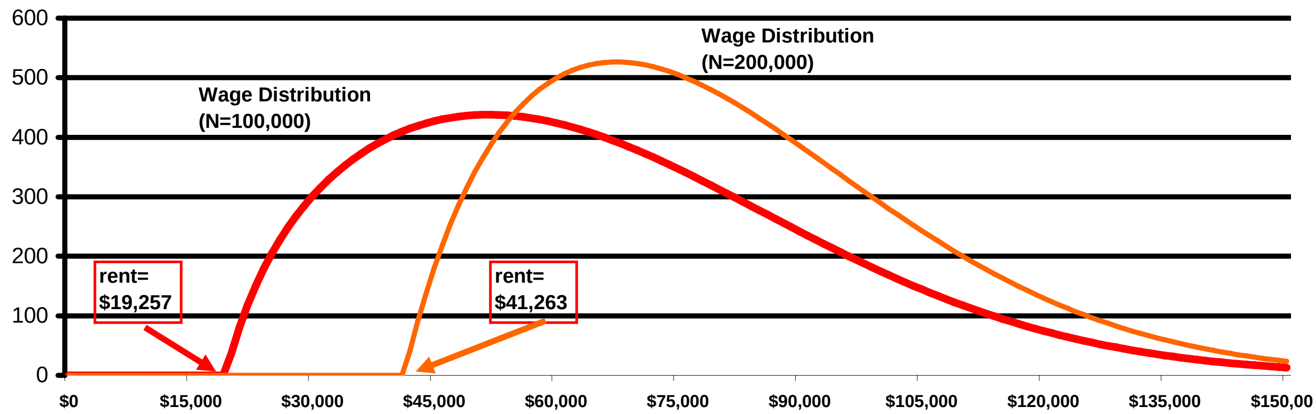


**Figure 3**
**Wage Distribution in Red and Green Cities**



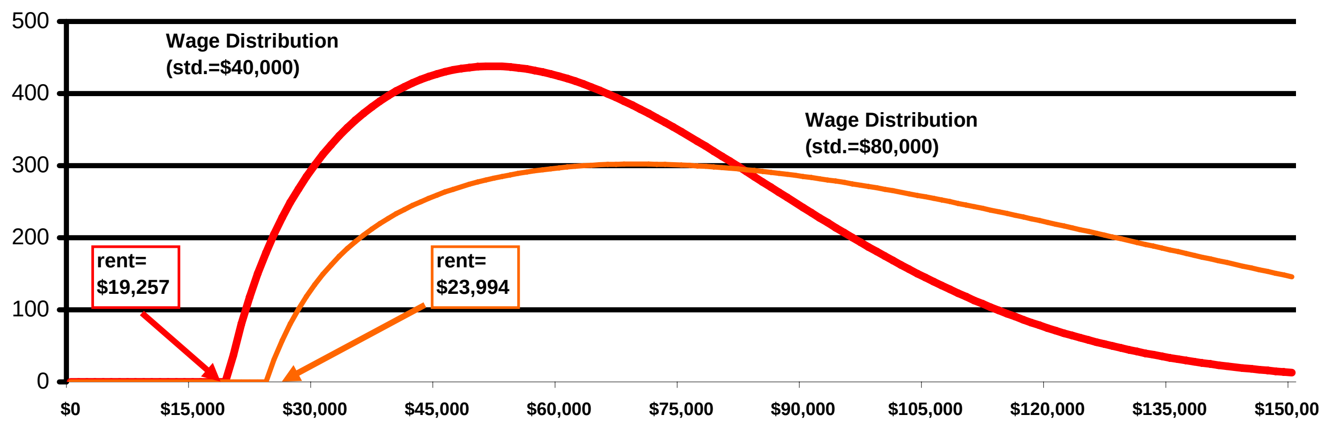

Note: 100,000 workers; truncated normal distribution; mean=40,000; std.=40,000, $w_L$=$0, $w_U$ =$150,000

**Figure 4**
**Wages and Rents in Red City, Alternate Populations**



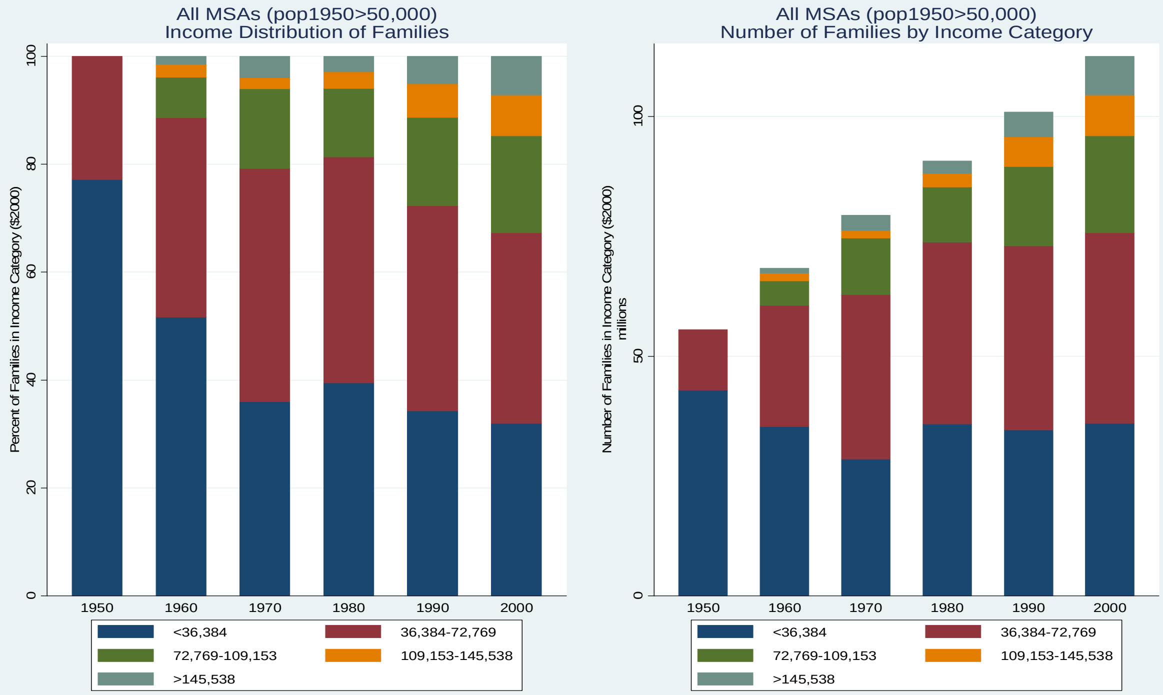

Note: truncated normal distribution; mean=40,000; std.=40,000, $w_L$=$0, $w_U$ =$150,000

**Figure 5**
**Wages and Rents in Red City, Fatter Tails**

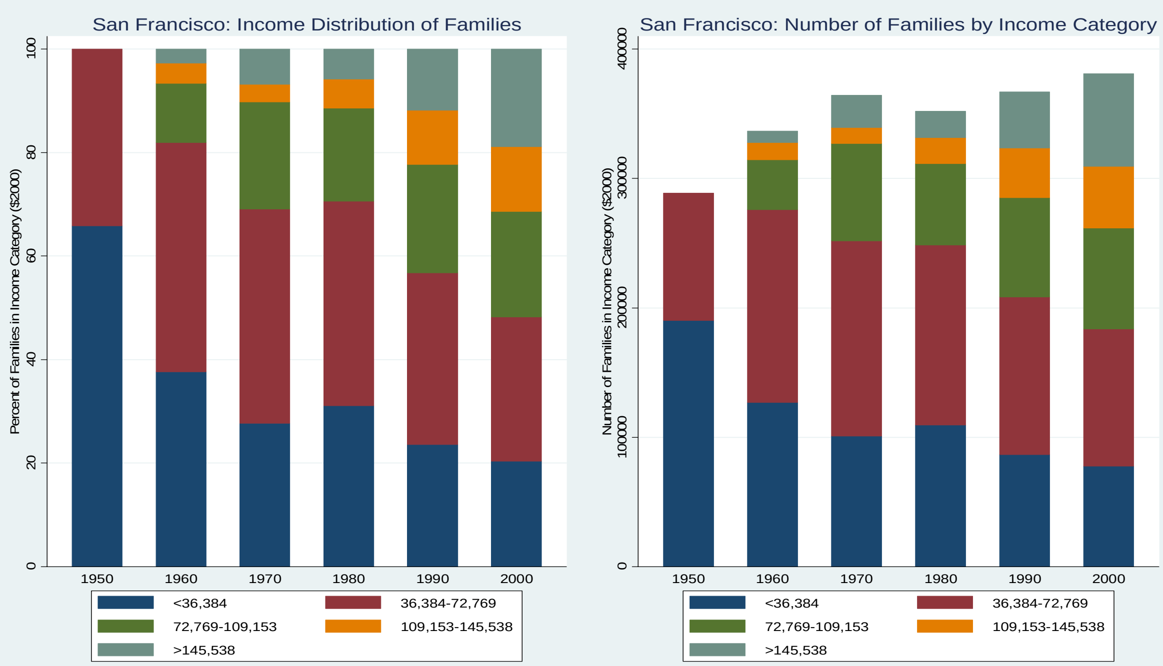



Note: 100,000 workers; truncated normal distribution; mean=40,000; $w_L$=$0, $w_U$ =$150,000

# Figure 6: The Evolution of the National Income Distribution




# Figure 7: San Francisco (big price growth) gains rich, loses poor



## Figure 8: Las Vegas (big unit growth) gains rich and poor, shares stay constant

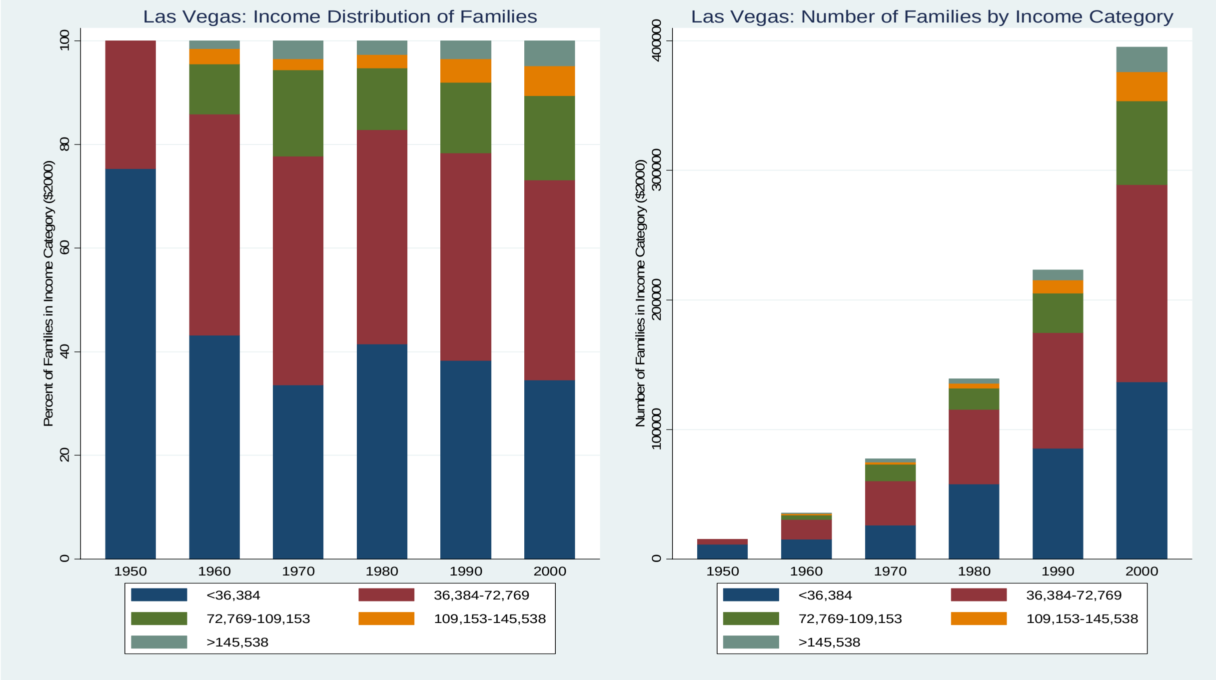



Figure 9: Real annual house price growth versus unit growth, 1980-2000

Figure 10: Real annual house price growth versus unit growth, 1960-1980