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Dispersion in House Price and Income Growth across Markets
Facts and Theories

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2.1 Introduction

One of the most striking patterns in the American socioeconomic landscape since World War II involves the skewness of long-run house price growth. Real house prices in metropolitan statistical areas (MSAs) such as San Francisco, Boston, and New York have appreciated at rates well above the national average over the postwar period. Indeed, this time period has witnessed two very different patterns of urban success: one pairs strong population expansion with mild house price appreciation, but the other involves very high house price growth with relatively little population growth.

This latter phenomenon is especially intriguing, because high house price growth in an MSA implies that new residents have to pay ever-increasing amounts to live there, especially relative to the MSAs with greater population growth. Of course, basic price theory tells us that consistently high prices require some limits on new supply. After all, if land were plentiful and homebuilders could supply new units whenever prices rose sufficiently above

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production costs to provide them a competitive return, prices would never exceed construction cost in the long run. Others have studied supply side constraints, and there is no doubt that many localities have become expert at imposing a myriad of hurdles that raise the cost of developing new housing (Glaeser and Gyourko 2003; Glaeser, Gyourko, and Saks 2005a, 2005b; Gyourko, Saiz, and Summers 2008; Saks 2008).

While inelastic supply is necessary for above-average long-run house price growth, it is not sufficient. Some factor must drive demand for living in the high price growth MSAs so that households are willing to pay an increasing house price premium to live there. In this chapter, we consider four potential explanations that stem from recent urban research. One possibility is that the value of agglomeration is rising in some inelastically supplied cities. Another is that these cities simply have become more productive but not due to agglomeration. A third possibility is that the level of amenities in these cities has grown. And the fourth explanation is that the dispersion in house price growth arises from an increasing number of high-income families at the national level, combined with households sorting across metropolitan areas. In this case, the rich households ultimately outbid others for the scarce slots available in supply-constrained metropolitan areas. We will conclude that the evidence suggests that this sorting mechanism is at least partially responsible for the urban outcomes we see, but it also is clear that much more work is needed to pin down the relative contributions of these basic factors.

We begin in the next section by describing some basic facts about the long-run evolution of house prices over time by MSA.[1] There is considerable heterogeneity in long-run house price growth across MSAs, and those cross-MSA differences persist. We show that many MSAs that experienced high house price growth had little population growth and vice versa. Following Gyourko, Mayer, and Sinai (2006), we classify a subset of MSAs with high house price growth and low population growth as "superstar cities." These cities experienced growing demand that was capitalized into land prices rather than manifested as new construction.

In section 2.3, we use a spatial equilibrium structure developed by Glaeser and Tobio (2008) to decompose the patterns of income, population, and housing unit growth to shed light on how superstar cities differ from other cities in regard to growth in their amenities, productivity, and housing supply. This framework implies that superstar cities have much lower housing supply growth than other cities. It also shows little difference between superstars and other cities in the growth rate of amenities or productivity.

The spatial distribution of income growth is brought to bear in section 2.4 as another set of stylized facts that needs explaining. Not only do long-run income growth rates vary widely across MSAs, but those MSAs with

1. Because we use decennial census data, our empirical analysis stops before the recent housing market bust. While this cycle is very interesting for a variety of reasons, our story and analysis are much more about trends that are not dependent on short-run dynamics.

growing house prices experience more rapidly growing average incomes, as well as a right shift in the entire income distribution. This fact is not true for any high-demand MSA, only those where it is difficult to construct new housing.

In sections 2.5 and 2.6, we discuss how the various possible explanations for urban growth—growing amenities, greater productivity, agglomeration benefits, or growth in the right tail of the national income distribution—comport with the stylized facts we established earlier. Section 2.7 briefly concludes.

2.2 Stylized Facts on the Growing Dispersion in House Prices

2.2.1 House Price Growth

We use and discuss a variety of data from the U.S. decennial censuses, aggregated to the level of the metropolitan area, which corresponds to the local labor market. We use a sample of 280 such areas that had populations of at least 50,000 in 1950 and that are in the continental United States.[2] Information on the distribution of house values, family incomes, population, and the number of housing units were collected.

Since the definitions of metro areas change over time, we use one based on 1999 county boundaries to project consistent metro-area boundaries forward and backward through time.[3] Data were collected at the county level and aggregated to the metropolitan statistical area, or to the primary metropolitan statistical area (PMSA) level in the case of consolidated metropolitan statistical areas. Data for the 1970 to 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

2. 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 in the following text. (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 to 2000 time period. While the point estimates naturally differ from those previously reported, 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 in the following text. 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.

3. We use definitions provided by the Office of Management and Budget (OMB), available at: http://www.census.gov/population/estimates/metro-city/90mfips.txt. One qualification is that in the case of New England county metropolitan areas, the entire county was included if any part of it was assigned by the OMB.

hard-copy volumes of the Census of Population and Housing. Both sources are based on 100 percent population counts. All dollar values are converted into constant 2000 dollars.[4]

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 dollars, assuming a uniform distribution of families within the bins. Since 1980 had among 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 dollars. Middle poor are those families with incomes between \$39,179 and \$78,358; middle-income families have incomes between \$78,359 and \$117,537; and middle-rich families lie between \$117,538 and \$156,716. Finally, rich families have incomes in excess of the 1980 real topcode of \$156,716.

Using these data, we begin by detailing the remarkable dispersion—and even skewness—across MSAs in house price growth over the 1950 to 2000 period. Figure 2.1 plots the kernel density of average annual real house price growth between 1950 and 2000 for our sample of 280 metropolitan areas. The tail of growth rates above 2.6 percent is especially thick, and the distribution is right skewed. Table 2.1, 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 fifty 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.[5]

These annual differences in house price growth rates 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 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 fifty most populous metropolitan areas.[6] Figure 2.2, which plots a kernel density estimate of the 280 metropolitan areas average house values in 1950 and 2000, shows

4. We also use some data for 1940. Population and housing unit data for that year are based on 100 percent counts, but housing values are averages from the 1940 sample provided by the Integrated Public Use Microdata Series (IPUMS) housed at the University of Minnesota. We do not yet use any family income data for 1940.

5. A complete list of house price appreciation rates by metropolitan area, along with 1950 and 2000 mean housing prices, is reported in the appendix table 2A.1.

6. 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 and 1980 are as follows: (a) San Francisco, 3.65 percent; (b) San Diego, 3.49 percent; (c) Los Angeles, 3.20 percent; (d) Oakland, 2.99 percent; and (e) Seattle, 2.88 percent.

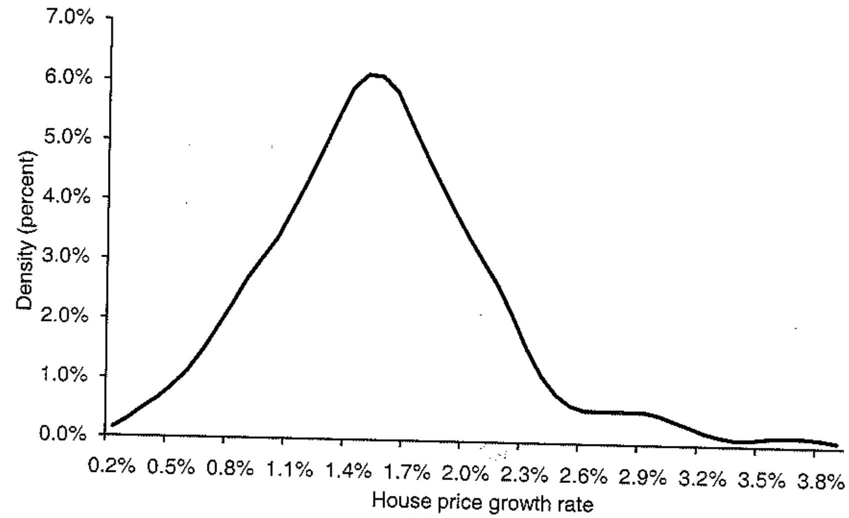

Fig. 2.1 Density of 1950–2000 annualized real house price growth rates across MSAs with 1950 population > 50,000

Table 2.1 Real annualized house price growth, 1950 to 2000, top and bottom ten MSAs with 1950 population > 500,000

Top 10 MSAs by price growth Annualized growth rate, 1950–2000		Bottom 10 MSAs by price growth 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

Note: Population-weighted average of the fifty MSAs in this sample: 1.70.

that skewness has increased over the last fifty years, with a relative handful of markets ending up commanding enormous price premiums. Figure 2.3 normalizes the means and standard deviations of the 1950 and 2000 house value distributions so that they are equal and then 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 also is long-run persistence in the markets that exhibit above-average price growth. Across the two thirty year periods from 1940 to 1970

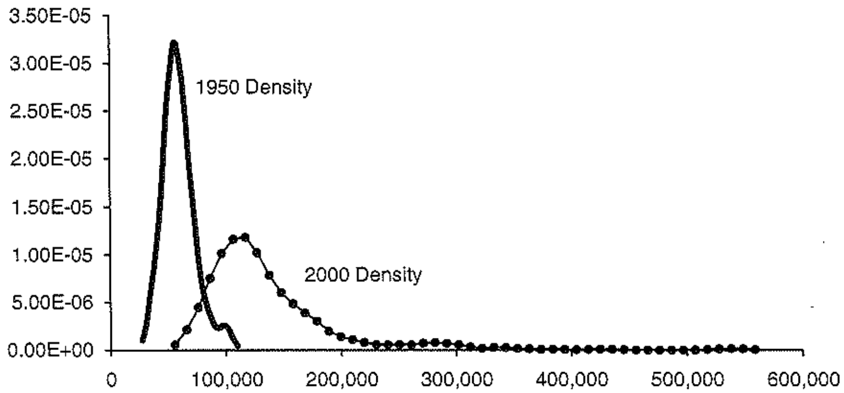

Fig. 2.2 Density of mean house values across MSAs, 1950 versus 2000

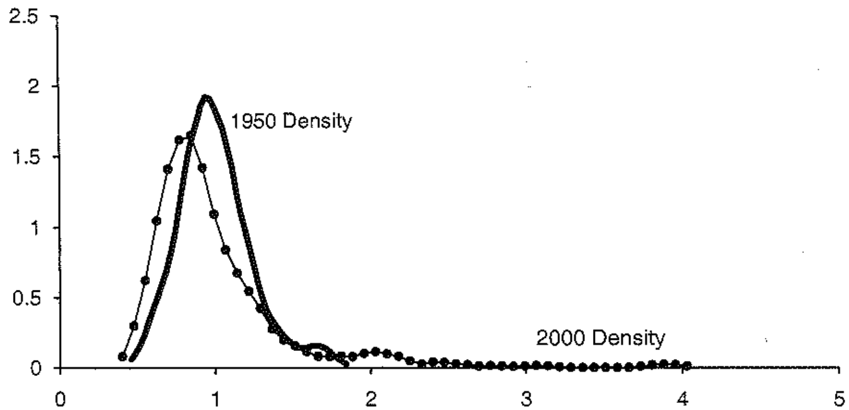

Fig. 2.3 Skewness in mean house values across MSAs, 1950 versus 2000

and 1970 to 2000, average annual percentage house price growth has a positive correlation of about 0.3. The root of this latter result can be seen in table 2.2, which reports the transition matrix for MSAs ranked by their average real house price growth rates computed over the two thirty year periods of 1940 to 1970 and 1970 to 2000. Most high-appreciation areas do not move very far in their relative price growth ranking. For example, of the thirty-two 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. Outside of the top growth rate areas, there is more movement across the distribution.[7]

7. Over shorter horizons such as a decade, MSAs can experience large price swings. In fact, the correlation in house price appreciation rates across decades is often negative.

Table 2.2 Thirty-year house price appreciation rate transition matrix

	1970 to 2000			
1940 to 1970	Top quartile	Second	Third	Fourth
Top quartile	16	6	6	4
Second	8	8	7	9
Third	4	7	7	14
Fourth	4	11	12	6

Note: The underlying sample for this table includes only 129 metropolitan areas due to limitations on data available back to 1940.

2.2.2 House Price and Housing Unit Growth

Typically, the markets with high long-run house price growth have not experienced much growth in the number of housing units, although that relationship has evolved over time, as housing supply has presumably become more inelastic in some cities. In table 2.3, we document the relationship between housing price and housing unit growth over time for the high price appreciation markets. To estimate this relationship, we regress the decadal growth in the number of housing units at the MSA level on the long-run growth in house price, allowing a different intercept and slope for those areas in the top quartile of the price appreciation distribution. Specifically, we estimate:

(1) $$\%\Delta H_{i,t} = \alpha + \beta^{*}\%\Delta P_i + \gamma^{*}(\text{TopQuartile}_i) + \delta^{*}(\%\Delta P_i{}^{*}\ \text{TopQuartile}) + \varepsilon_{i,t},$$

where $\%\Delta H_{i,t}$ is the percentage change in housing units in metropolitan area i during decade t, $\%\Delta P_i$ is the percentage house price growth in metropolitan area i between 1960 and 2000, and TopQuartile is a dummy indicator for whether the metropolitan area is among the top quartile of areas in terms of house price appreciation over the 1960 to 2000 period.

These results show that the price growth/unit growth relationship for the top quartile of the price appreciation distribution has essentially disappeared between the 1960s and the 1990s. For the bottom 75 percent of the price growth distribution, the relationship between average price growth and unit growth is positive, and with the exception of the 1980s, it is flat over the decades. The MSAs in the top quartile in terms of price appreciation start out in 1970 with a slightly less positive correlation than for the lower 75 percent (11.12 – 3.12 = 8.0 correlation). By the 1970s, however, the highest price growth markets are already in negative territory (17.18 – 18.14 = –0.96), while there still is a large positive relationship between long-run price growth and housing unit production for the other metropolitan areas. The negative correlation for the top quartile increases over time, to –3.62 in the 1980s and –3.89 in the 1990s.

Table 2.3 **The relationship between high long-run price growth MSAs and the change in the number of housing units, by decade**

	1960s	1970s	1980s	1990s
Average house price growth, 1960–2000	11.12	17.18	11.73	9.37
	(4.76)	(3.77)	(2.19)	(1.51)
In top quartile of average price growth	6.10	35.23	31.99	24.99
	(16.02)	(12.68)	(7.38)	(5.08)
Average price growth × in top quartile	–3.12	–18.14	–15.35	–13.26
	(7.91)	(6.26)	(3.64)	(2.51)
Adjusted R^2	0.04	0.10	0.16	0.15

Notes: The left-hand-side variable is the decadal percent change in the number of housing units. Standard errors in parentheses. To be in the top quartile, average real house price growth must have exceeded 1.75 percent over the 1960 to 2000 period.

2.2.3 Classifying "Superstar Cities"

We now turn to other work we have done (Gyourko, Mayer, and Sinai 2006) to identify those markets with high house price growth and low housing unit growth. Such markets are termed "superstar" markets in that research, and they are markets that are in high demand and those in which something prevents the development of many new homes.[8] Thus, house price growth is very high, but housing unit growth is not.

Because we do not observe the true state of demand and the literature does not provide high quality estimates of the elasticity of supply, the following two measures are combined to determine whether a market is a superstar. First, a market is classified as in high demand if the sum of its housing unit and housing price growth is above the sample median for the relevant period of analysis. Second, a metropolitan area is defined to have a low elasticity of supply if its ratio of housing price growth to housing unit growth is at or above the ninetieth percentile of the distribution for all metropolitan areas over the relevant period of analysis.

Each of these measures is constructed using data from the two decades prior to the year for which a superstar designation is made. Thus, the status of each metropolitan area is classified from 1970 to 2000, with 1970 being the first year, because the underlying data begin in 1950.[9] Figure 2.4 documents the outcome of this methodology for the most recent period—using 1980 to 2000 data to determine superstar status in 2000. Average real annual

8. That something could be a natural constraint such as an ocean or a man-made constraint in the form of binding growth controls on housing development.

9. Because the empirical task here is to document whether equilibrium relationships implied by our model exist in the data rather than to identify causal mechanisms for why a place becomes a superstar, the use of lagged data is not driven by endogeneity concerns (which these lags would not deal with effectively in any event). Rather, we wish to be able to classify superstar status in the most recent census data from the year 2000, and we suspect that any relationship between income segregation and house price effects occur after the superstar market has filled up.

Fig. 2.4 Real annual house price growth versus unit growth, 1980 to 2000

house price growth between 1980 and 2000 is on the y-axis, with housing unit growth over the same two decades on the x-axis. The single downward-sloping line reflects the boundary between markets with a sum of price and unit growth above the sample median across all our MSAs for 1980 to 2000. Any metro area lying below that line is a relatively low-demand place by definition. The left-most and steepest positively sloped line from the origin captures the elasticity of supply at the ninetieth percentile of the distribution of the ratio of price growth to unit growth. For this twenty-year period, the MSA at the ninetieth percentile has a ratio of real annual house price growth to unit growth above 1.7. The right-most and flattest positively sloped line from the origin reflects the inverse of the ninetieth percentile ratio value (i.e., 1/1.7, or 0.59).

Cities in the region marked A, which is both above the boundary determining low-demand status and above the boundary marking significant inelasticity of supply, are composed of many coastal markets including San Francisco, New York, and Boston that have experienced very strong house price appreciation (indicating high latent demand) but little supply response in terms of new construction over the past two decades. The other markets in relatively high-demand areas are divided into two groups for the purposes of the following empirical analysis. What we term "nonsuperstars" are the metropolitan areas in the C range, which include markets with relatively high housing unit production and relatively low housing price growth. These high-demand markets, which include Las Vegas and Phoenix, build sufficient new housing to satisfy demand so that real price growth is low. The remaining high-demand markets are in between the superstars and nonsuperstars and lay in the B range in figure 2.4. They have experienced relatively high demand and have both built at least a modest amount of new units and experienced a moderate amount of real house price appreciation. The final set of metropolitan areas are in low demand and lay in the region below the negatively sloped line in figure 2.4.

This nonlinear categorization is useful, because it allows us to observe how MSAs evolve over time. It seems natural that metropolitan areas could become more inelastically supplied as they grow and begin to fill up in the face of geographic constraints or politically imposed restrictions on development. This would appear as a market moving over time from area C to B to A in figure 2.4. We do observe such an evolution over time. In 1980, only San Francisco and Los Angeles clearly qualified as superstars, with the other markets filling up over time.

2.3 Characteristics of Superstar Market Growth: Decomposing the Roles of Productivity, Amenities, and Housing Supply

As a first pass in understanding what determines the unique price growth of superstar markets, we apply a strategy developed by Glaeser and Tobio

(2008). Their approach uses structure imposed by a Rosen/Roback-style theory to transform MSA differences in house price growth, population growth, and income growth into implied differences in the growth of MSA-specific amenities, productivity, and housing supply. We use this decomposition to see how superstars vary from other cities on these dimensions.

Following Glaeser and Tobio (2008), every market in the United States is characterized by a location-specific productivity level of A and firm output of $AN^{\beta}K^{\gamma}Z^{1-\beta-\gamma}$, where N represents the number of workers, K is traded capital, and Z is nontraded capital. Traded capital always can be purchased for a price of 1. The location has a fixed supply of nontraded capital equal to $\overline{Z}$.

Three equilibrium conditions can be derived involving households, firms, and the housing market. One involves consumers who are presumed to have Cobb-Douglas utility defined over tradable goods and housing, the nontraded good. The next equations assume the following utility function defined over traded goods (C), housing (H), and city amenities (θ): $\theta C^{1-\alpha}H^{\alpha}$. Standard optimizing behavior assumptions yield indirect utility of $\alpha^{\alpha}(1-\alpha)^{1-\alpha}\theta W p_H^{-\alpha}$. Spatial equilibrium requires household utility to be the same everywhere, with the level determined by the utility available (denoted $\underline{U}$) in the reservation market, which always is open to any household or firm.

The second equilibrium condition involves firms, which are presumed to behave competitively, so they cannot earn excess profits in any one market in equilibrium. Hence, their labor demand function is derived from the firm's first-order conditions, as usual.[10]

An important innovation of Glaeser and Tobio (2008) that is quite relevant for this chapter is its introduction of housing supply heterogeneity into the classic urban spatial equilibrium framework. Specifically, housing is produced competitively with height (h) and land (L) so that the total quantity of housing supplied equals hL. There is a fixed quantity of land in the market area, denoted $\overline{L}$, which will determine an endogenous price for land (p_L) and housing (p_H). The cost of producing hL units of structure on L units of land is presumed to be $c_0h^{\delta}L$. Given these assumptions, the developer's profit for producing these hL units of housing is $p_H hL - c_0 h^{\delta}L - p_L L$, where $\delta > 1$. Of course, this must equal zero, given that we have presumed free entry of developers. The first-order condition for height then implies the area's housing supply.

The firm's labor demand equation, the equality between indirect util-

10. As in Rosen (1979) and Roback (1982), the spatial equilibrium assumption does not mean that wages corrected for local price (real wages) are equal across space but that higher real wages in some places are offsetting lower amenity levels. However, spatial equilibrium is presumed to hold at every point in time, which does imply that housing prices are sufficiently flexible to offset differences in wages and amenities, not that labor or capital has perfectly adjusted at all times and places.

ity in the town and reservation utility, and the housing price equation are three equations with the three unknowns of population, income, and housing prices. Solving these equations for the unknowns yields equations (2) through (4) from Glaeser and Tobio (2008):

$$(2)\quad \mathrm{Log}(N) = K_N + \frac{(\delta + \alpha - \alpha\delta)\mathrm{Log}(A) + (1-\gamma)[\delta \mathrm{Log}(\theta) + \alpha(\delta - 1)\mathrm{Log}(\overline{L})]}{\delta(1-\beta-\gamma) + \alpha\beta(\delta - 1)},$$

$$(3)\quad \mathrm{Log}(W) = K_W + \frac{(\delta - 1)\alpha \mathrm{Log}(A) - (1-\beta-\gamma)[\delta \mathrm{Log}(\theta) + \alpha(\delta - 1)\mathrm{Log}(\overline{L})]}{\delta(1-\beta-\gamma) + \alpha\beta(\delta - 1)},$$

and

$$(4)\quad \mathrm{Log}(p_H) = K_p + \frac{(\delta - 1)[\mathrm{Log}(A) + \beta \mathrm{Log}(\theta) - (1-\beta-\gamma)\mathrm{Log}(\overline{L})]}{\delta(1-\beta-\gamma) + \alpha\beta(\delta - 1)},$$

where K_N, K_W, and K_p are constant terms that differ across cities but not over time within a city, and all other terms are as defined previously.

These static relations are transformed into dynamic ones by presuming that changes to productivity, amenities, and housing supply are characterized by the following growth equations:

$$(5)\quad \mathrm{Log}\left(\frac{A_{t+1}}{A_t}\right) = K_A + \lambda_A S + \mu_A,$$

$$(6)\quad \mathrm{Log}\left(\frac{\theta_{t+1}}{\theta_t}\right) = K_\theta + \lambda_\theta S + \mu_\theta,$$

and

$$(7)\quad \mathrm{Log}\left(\frac{\overline{L}_{t+1}}{\overline{L}_t}\right) = K_L + \lambda_L S + \mu_L,$$

where S is a dummy variable reflecting superstar market status as defined previously, the terms K_A, K_θ, and K_L are constants, the terms λ_A, λ_θ, and λ_L are the expected difference in growth rates for superstar markets, and μ_A, μ_θ, and μ_L are standard error terms. Given this, equations (2) through (4) imply the following:

$$(8)\quad \mathrm{Log}\left(\frac{N_{t+1}}{N_t}\right) = K_{\Delta N} + \chi^{-1}\{(\delta + \alpha - \alpha\delta)\lambda_A + (1-\gamma)[\delta\lambda_\theta + \alpha(\delta - 1)\lambda_L]\}S + \mu_N,$$

$$(9)\quad \mathrm{Log}\left(\frac{W_{t+1}}{W_t}\right) = K_{\Delta W} + \chi^{-1}\{(\delta - 1)\alpha\lambda_A - (1-\beta-\gamma)[\delta\lambda_\theta + \alpha(\delta - 1)\lambda_L]\}S + \mu_W,$$

and

$$(10)\quad \mathrm{Log}\left(\frac{P_{t+1}}{P_t}\right) = K_{\Delta P} + \chi^{-1}(\delta - 1)[\lambda_A + \beta\lambda_\theta - (1-\beta-\gamma)\lambda_L]S + \mu_P,$$

where $\chi = [\delta(1-\beta-\gamma) + \alpha\beta(\delta-1)]$.[11]

Equations (8) through (10) enable us to transform differential changes in population, incomes, and house prices across superstar and other cities into differences in innovations in productivity, amenities, and housing supply over time. Each of the equations can be estimated using ordinary least squares (OLS) by regressing each of log population, income, or house price growth on a constant and a superstar indicator variable, recovering the estimated coefficients on the superstar dummy, which are B_{pop}, B_{inc}, and B_{val}, respectively. Then, some algebra yields that the connection between superstar status and productivity growth (λ_A) equals $(1-\beta-\gamma)B_{pop} + (1-\gamma)B_{inc}$, where B_{pop} and B_{inc} are the estimated coefficients on a superstar market dummy variable from the population and wage change regressions, respectively. The weight on the population regression coefficient is the share of production associated with immobile capital. The weight on the income regression coefficient is the share of production associated with labor plus immobile inputs.[12]

The connection between superstar status and changing amenities is given by λ_θ, which equals $\alpha B_{val} - B_{inc}$, where α is the share of expenditure going toward housing, and B_{val} is the coefficient from the house price change regression. Given that traded goods always cost 1 and that housing is the only nontraded good, this difference reflects the change in real wages. If real wages are decreasing, then amenities are rising, so the basic insight of the static Rosen/Roback compensating differential model also holds in this more dynamic context.[13]

The connection between housing supply growth and superstar status, λ_L, equals $B_{pop} + B_{inc} - [\delta/(1-\delta)]B_{val}$, where δ reflects the elasticity of housing supply. In this equation, population directly affects housing supply one for one, as everyone in the market has to live in a housing unit. Hence, if superstar markets have relatively low population growth, the B_{pop} term will be negative. The population/housing supply relationship is then adjusted for income and price effects. Higher relative income growth in superstars will raise the estimate of λ_L. However, house price growth that is substantially higher in superstar markets will lower the value of λ_L, with the weight determined by the elasticity of supply.[14]

11. The interested reader should see Glaeser and Tobio (2008) for more detail on the derivation of these equations.

12. In the results reported next, we follow Glaeser and Tobio (2008) in presuming that labor's share of input costs (β) equals 0.6, with that for mobile capital (γ) being 0.3.

13. In the results reported next, we presume that $\alpha = 0.3$, which Glaeser and Tobio (2008) also used, based on their examination of Consumer Expenditure Survey data over time.

14. We presume that $\delta = 3$ in the following analysis. Supply would be perfectly elastic if $\delta = 1$, which clearly is not the case in at least some markets or for the nation on average. Glaeser

To estimate B_{pop}, B_{inc}, and B_{val}, for each decade, we regress the decadal log change in population, mean income, or mean house price on a dichotomous dummy for whether the market *ever* was a superstar during our sample period. Thus, the superstar indicator is constant within each MSA. We also allow for a number of controls, including the beginning of period mean population, mean income, mean house price, and the share of the adult population with a college degree. Those regression coefficients are reported in table 2.4. The results typically were not economically or even statistically different if we omitted the controls.

It is worth noting that our definition of a superstar market as described in the preceding section is a function of the prior two decades' house price and housing unit growth. Since our data starts in 1950, our first decade where superstar status is fully predetermined is 1970. However, since we are using an indicator for whether an MSA *ever* was defined as a superstar, we feel comfortable backcasting the superstar identification to 1960. When we use a time-varying definition of superstar status in the next section, we will restrict our attention to 1970 and later.

In the 1960s, population growth in markets that ultimately became superstars was not materially different from those that did not. However, it has been appreciably lower in every subsequent decade, with the gap widening over time. These estimated coefficients are reported in the first four columns of the top panel of table 2.4. Superstar MSAs had almost 4 percentage points lower population growth (relative to other MSAs) in the 1970s, almost 5 percentage points lower in the 1980s, and almost 8 percentage points lower in the 1990s. To smooth out some decade-to-decade fluctuations, the last two columns of table 2.4 pool the 1960s and 1970s decades and the 1980s and 1990s decades. Over the 1960 to 1980 period, superstars had statistically insignificantly lower population growth. But during 1980 to 2000, superstars' population growth averaged almost 5.5 percentage points lower than other MSAs.

Superstar markets also experienced higher income and house price growth, as can be seen in the middle and bottom panels of table 2.4, respectively. However, all of the higher growth came in the 1960s and 1980s. Indeed, during the 1970s and 1990s, superstar markets had income and price growth below that of other cities (with the exception of house price growth in the 1970s). However, the more rapid growth for superstars in the 1960s exceeded the decline in the 1970s, and the growth in the 1980s exceeded the decline in the 1990s. Thus, in the last two columns of table 2.4, which average across decade pairs, superstars had income and house price growth that typically exceeded that of other MSAs. Over the 1960 to 1980 period, superstars had

and Tobio (2008) also worked with δ = 3. The value of δ does affect the magnitude of the housing supply innovations, although no reasonable value changes the relative magnitudes of the contributions of productivity, amenities, or housing supply.

Table 2.4 **Decadal population, income, and house price growth regressions**

	1960s	1970s	1980s	1990s	1960–1980	1980–2000
	Population growth on superstar market dummy					
B_{pop}	0.0046	–0.0394**	–0.0483**	–0.0771**	–0.0096	–0.0542**
	(0.0159)	(0.0167)	(0.0125)	(0.0146)	(0.0143)	(0.0110)
	Income growth on superstar market dummy					
B_{inc}	0.0205**	–0.0127	0.1085**	–0.0110	0.0016	0.0384**
	(0.0090)	(0.0091)	(0.0125)	(0.0082)	(0.0051)	(0.0063)
	House price growth on superstar market dummy					
B_{val}	0.0773**	0.0284	0.3510**	–0.0777**	0.0492**	0.0794**
	(0.0129)	(0.0247)	(0.0289)	(0.0262)	(0.0132)	(0.0117)

**Significant at the 5 percent level.

almost no excess income growth but had almost 5 percentage points higher house price growth. Over the 1980 to 2000 period, superstars experienced almost 4 percentage points higher income growth and almost 8 percentage points higher house price growth.

The decade-to-decade volatility in the estimated superstar coefficients is not so surprising, given the well-known mean reversion in house prices. If superstars have higher trend income and house price growth but also greater volatility around that trend, then excess growth in one decade should be followed by less growth the next. This effect is compounded by our observing house prices and incomes only once per decade. Instead, what table 2.4 shows is that the *long-run* trends for superstars in income and house price growth are above those of other MSAs, while their long-run population growth is below that of other markets on average.

Next, we apply equations (8) through (10) to convert the estimated coefficients in table 2.4 into innovations in productivity, amenities, and housing supply in table 2.5.[15] At the decadal frequency, superstar markets do not exhibit consistently higher productivity or amenity growth (the first two panels). The estimates are positive in some decades and negative in others. For productivity, only in the 1980s did superstar MSAs seem to experience sizeable excess productivity growth. The decadal amenity results are small in general, indicating that superstar markets are not very different from the average along this dimension.

When we look at the twenty-year periods, in the last two columns of table 2.5, the pattern becomes clearer. Superstars effectively had no excess productivity growth during the 1960 to 1980 period, but they did have 2.2 percentage points higher productivity growth during the 1980 to 2000 period.

15. All regression coefficients and assumptions regarding consumption and sector shares are taken at face value in these calculations, which is why no standard errors are reported for these figures. They should be interpreted as stylized facts, not as precise estimates.

Table 2.5 Growth decomposition: Productivity, amenities, and housing supply

	1960s	1970s	1980s	1990s	1960–1980	1980–2000
Innovations to productivity						
Superstar, with controls	0.019	–0.013	0.071	–0.015	0.0002	0.022
Innovations to amenities						
Superstar, with controls	0.003	0.021	–0.003	–0.012	0.013	–0.015
Innovations to housing supply						
Superstar, with controls	–0.091	–0.095	–0.466	0.029	–0.082	–0.135

By contrast, superstars' amenity growth is not much different from that of other cities and over the 1980 to 2000 period was actually below that of nonsuperstar markets.

Superstar markets are most consistently different from other areas in terms of their housing supply growth, as can be seen in the bottom panel of table 2.5. It was much less (9 percentage points) even in the 1960s, before these places filled up, according to our measure of "superstarness." Relative housing supply was similarly low in the 1970s, with these markets building dramatically less in the 1980s. The results for the 1990s indicate a marked change in this pattern, although the estimate is only slightly positive at 2.9 percentage points. This discrepancy is swamped by the overall trend, as can be seen in the last two columns. Over 1960 to 1980, superstars' supply growth was 8.2 percentage points lower than for other cities. That difference rose to 13.5 percentage points during 1980 to 2000.

In sum, the only clear pattern is that Superstars have long had much less housing production than other markets. There is some evidence that productivity growth was higher for superstars in the last two decades, but as noted before, the productivity growth results are sometimes positive and sometimes negative, with only the 1980s generating the bulk of the higher measured productivity growth. Thus, not only are the magnitudes of the productivity differences smaller than the housing supply effects, but there is less of a clear pattern indicating that superstar markets are more (or less) productive than other markets.

2.4 The Distribution of Income within Metropolitan Areas: Superstars versus Nonsuperstars

What enabled us to distinguish productivity and amenity growth in section 2.3 was the relationship between the growth of average income and average house prices. If house price growth were large relative to income growth in a given MSA, one could conclude that amenities were improving since the after-housing income would have declined. If income or population growth were high, that indicates greater local productivity leading to greater demand for living in the city. In large part, what tables 2.4 and 2.5 tell us is that house price growth and income growth must have been highly correlated within MSA. Indeed, the distribution of income growth rates across MSAs looks very much like that of house price growth, with wide dispersion and some right skew. This partly can be seen in figure 2.5, which plots the kernel density of average annual real income growth over the 1950 to 2000 period by MSA. It shows that growth rates range from 0.8 percent per year to 3.1 percent.

However, another important stylized fact is that the entire distribution of income, not just the average, has been changing differentially for superstar MSAs, even relative to the nation as a whole. Over the last fifty years, the United States has experienced growth in the absolute number, population share, and income share of high-income households (Autor, Katz, and Kearney 2006; Piketty and Saez 2003; Saez 2004). The left panel of figure 2.6 shows that the aggregate distribution of family income across all MSAs in the United States 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 2.6 then displays the evolution of the number of families 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. Two canonical MSAs—San Francisco and Las Vegas—provide a vivid contrast. San Francisco experienced low levels of new construction and high house price growth (figure 2.7). Between 1950 and 1960, the San Francisco 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 spiked in San

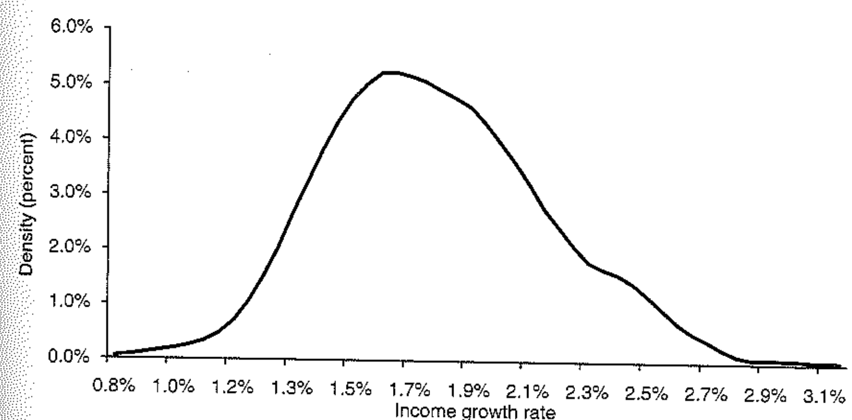

Fig. 2.5 Density of 1950 to 2000 annualized real income growth rates across MSAs with 1950 population > 50,000

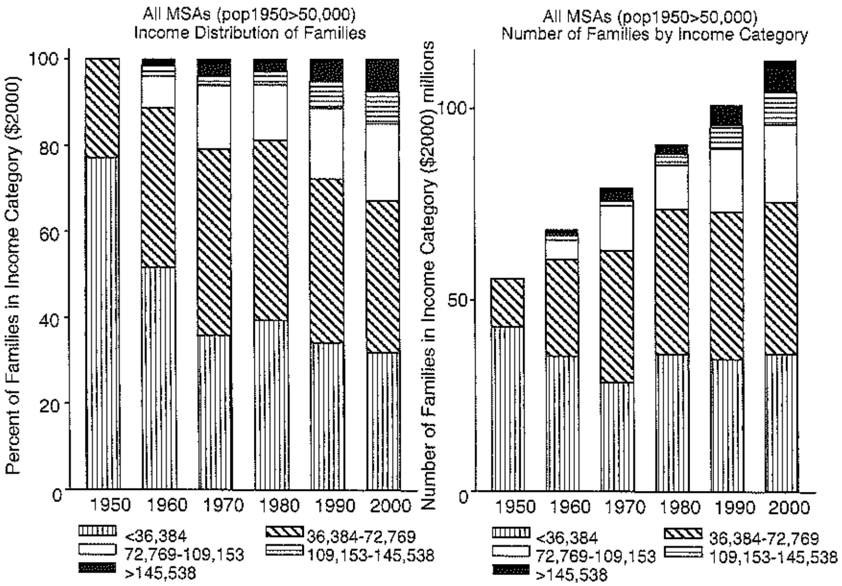

Fig. 2.6 The evolution of the national income distribution

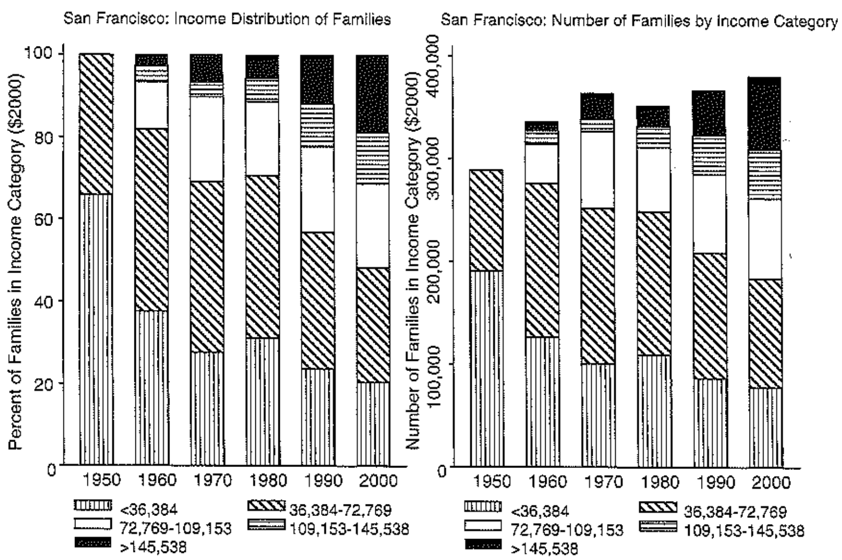

Fig. 2.7 San Francisco (big price growth) gains rich, loses poor

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 1 percentage point above the all-MSA average. By contrast, over the same time period, Las Vegas saw explosive population growth, expanding from fewer than 50,000 families in 1960 to the size of the San Francisco PMSA by 2000 (figure 2.8). Yet, it experienced modest real house price growth that was well below the national average.

Note that San Francisco's high-income share grew disproportionately. San Francisco, which always had relatively more rich families and fewer poor families than Las Vegas, 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.

In stark contrast, the overall income distribution in Las Vegas did not keep up with the nation (left panel of figure 2.8), leaving that metropolitan area 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 substantial growth in the number of families across the income distribution of Las Vegas. Relative

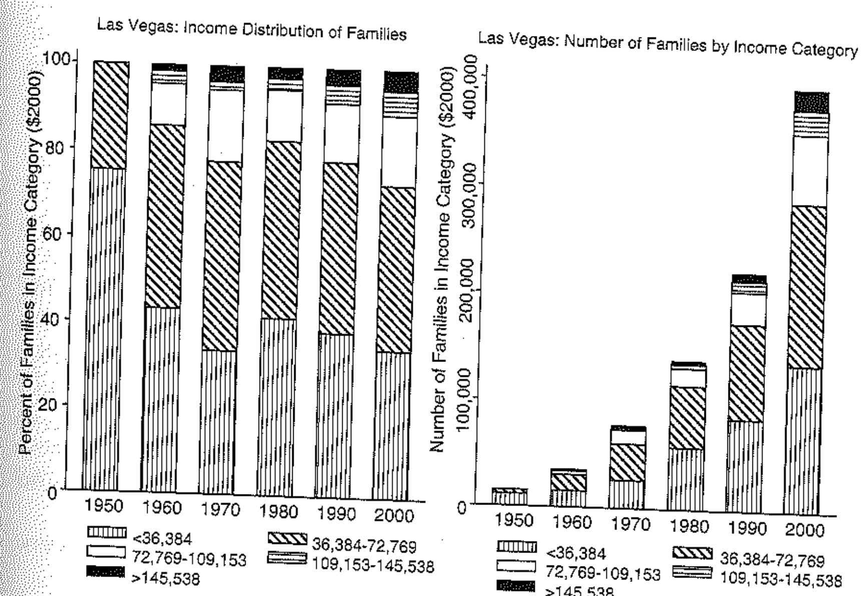

Fig. 2.8 Las Vegas (big unit growth) gains rich and poor, shares stay constant

to the national income distribution, however, the growth in Las Vegas was skewed toward poorer families.

We can generalize this pattern beyond San Francisco and Las Vegas by comparing the evolution of the income distribution in our superstar MSAs to other MSAs. Table 2.6 reports regression results on the link between income distributions and house prices using our earlier categorization of cities into superstar versus nonsuperstar status. We start with the cross-sectional relationship and then examine the data over time. The specification in equation (11) investigates whether a typical superstar market's household income is skewed to the right of the U.S. income distribution, as we saw was the case for San Francisco. Specifically, we estimate the following regression for MSA i in year t:

$$(11)\quad \frac{\#\text{ in Income Bin}_{yit}}{\#\text{ of Households}_{yit}} = \beta_1(\text{Superstar}_i) + \beta_2(\text{Nonsuperstar}_i) + \beta_3(\text{Superstar}_{it}) + \beta_4(\text{Nonsuperstar}_{it}) + \gamma_1(\text{Low Demand}_i) + \gamma_2(\text{Low Demand}_{it}) + \delta_t + \varepsilon_{it}.$$

Essentially, this regression relates the share of an MSA's families that are in each income bin to its superstar status and controls for total demand.[16]

The first column of the top panel of table 2.6 is based on a pooled cross-section of 1,116 MSA × year observations.[17] As in table 2.4, this regression treats superstar status as a (nonexclusive) fixed MSA characteristic, including indicator variables for whether the MSA ever was a superstar over the 1970 to 2000 period, whether it was ever in the nonsuperstar range, whether the MSA ever moved inside the low-demand area, and time dummies. The group of intermediate, high-demand MSAs from region B of figure 2.4 is the excluded category in all the regressions reported in table 2.6.

The difference in income distribution between superstars and all other MSAs is pronounced. Those 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 of families who are 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

16. See the appendix table 2A.2 for summary statistics on all variables used in these regressions.

17. This represents 279 MSAs in each census year from 1970 on.

Table 2.6 **The income distribution in superstar MSAs**

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

Notes: Number of observations is 1,116, for four decades (1970 to 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 ninetieth 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. Nonsuperstar_{it} is equal to 1 when the price growth/unit growth ratio is below 1/1.7, and nonsuperstar_i is an indicator of whether nonsuperstar_{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 twenty 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 twenty years was below the median; LHS = left-hand side.

have a nearly 9 percentage point lower share of families who are poor (row [1], column [5]), almost 21 percent less than the other MSAs.

Nonsuperstar 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 second panel of table 2.6 adds time-varying superstar, nonsuperstar, and low-demand indicator variables to the previous specifications. Prior to becoming superstars, MSAs that eventually will become superstars are richer on average, with a 1.3 percentage point greater share of families who are rich and a 7.1 percentage point lower share of families who are poor (row [1] of panel 2). When these areas are actually in the superstar region, the share of families who are rich goes up by an additional 2.8 percentage points, and the share of families who are poor declines further by 4.1 percentage points (row [4] of panel 2). As a baseline, superstar cities have a 43 percent higher share of families who are rich, declining monotonically to a 17 percent lower share of families who are 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 versus not, or separate year dummies for superstars/nonsuperstars/low-demand MSAs.

2.5 Urban Productivity Differences and the Skewing of House Prices and Incomes

We now turn to a discussion of existing theories of urban growth and how consistent they are with the set of stylized facts that we have established. We first consider growth in amenities as an explanation and then turn to differences in productivity across MSAs. Finally, we consider dynamic agglomeration economies. In the next section, we will discuss a less traditional story that links national growth in the high-income population to the presence of housing supply constraints in some labor market areas to induce income-based sorting.

The standard spatial equilibrium model in urban economics developed by Rosen (1979) and Roback (1982) suggests that house price differences across markets are a function of amenity and wage (productivity) differentials. Glaeser and Saiz (2003) and Shapiro (2006) investigate the effect of amenities on the growth of population and employment. Both conclude that the link between education and metro-area population/employment growth largely is due to productivity, with amenities playing a smaller role. Going beyond the reduced-form OLS estimation standard in the literature, Shapiro (2006) calibrates a neoclassical urban growth model and estimates that

about 60 percent of the impact of a higher local population share of college graduates on metropolitan-area employment growth is due to productivity, as reflected in wage growth. This does leave room for improvements in the quality of life to play a role, too, and they appear related to "consumer city"-type attributes, as reflected in various local cultural traits (Glaeser, Kolko, and Saiz 2001).

In our context, growth in amenities conceivably could cause the excess growth in house prices in superstar markets. However, this seems unlikely, since the results of the decomposition in section 2.3 indicate that amenities play little—if any—role. This makes intuitive sense: the growth in amenities in some MSAs would have to be substantial in order to match the patterns of long-run house price growth we observe. In addition, the amenities would have to be favored by high-income households in order to generate the cross-MSA changes in income distributions.

An alternative explanation for our stylized facts is that urban productivity differentials are growing sufficiently to account for the increases in house price and income dispersion that we observe in the data. Van Nieuwerburgh and Weill (2006) investigate the role of productivity by developing a dynamic, general equilibrium version of the Rosen-Roback model in which they then run calibration exercises to see whether there has been enough growth in wage dispersion across labor markets to account for the growth in house price dispersion.[18] Essentially, they assume homogeneous physical markets receive unobservable exogenous productivity shocks, and they investigate whether their model can then match the increase in the coefficient of variation in house prices across markets between two steady states. This exercise yields a very good match of the mean annual increase in house prices between 1975 and 2004, as well as a tight fit of the increase in the coefficient of variation in house prices across markets. This simulation also results in a good match of the growth of population in the productive places with higher wages. Although the framework is dynamic, the essential insight of Rosen and Roback still holds—housing costs are the price one has to pay to access the productivity of a given labor market area.[19]

Although the results in Van Nieuwerburgh and Weill (2006) are consistent with growing urban productivity differentials being the cause of the growing house price dispersion across labor market areas, they are not conclusive in proving causality. In particular, their results are not consistent with the empirical fact in our table 2.3 and figure 2.4 that the MSAs that experience

18. Van Nieuwerburgh and Weill (2006) provide one of the first truly dynamic frameworks to analyze spatial equilibria. Glaeser and Gyourko (2006) also have produced a dynamic model, but it is designed to investigate higher frequency movements in house prices.

19. There are a host of other results, ranging from the role of supply-side constraints to the change in the ratio of house prices to construction costs. We do not review those findings here so as to stay focused on the relationship between the skewing of incomes and house prices across markets.

long-run house price growth often have little population growth and vice versa. A careful review of Van Nieuwerburgh and Weill's (2006) data indicates that the productive/high-wage markets to which the model predicts people should move include both high price growth/low population growth cities in the A section of our figure 2.4, as well as high population growth/low price growth cities in the C section. More generally, there is a mixture of both types of markets in Van Nieuwerburgh and Weill's (2006) predicted top-wage quintile. Thus, it appears that their model's ability to match the data is at least partially the result of it picking up much of the growing price dispersion from very high-price (and price appreciation) coastal markets that have very little homebuilding and population growth; analogously, it looks to be picking up much of the housing unit/population growth from large Sunbelt markets that have relatively low house price levels and that have experienced relatively little price appreciation. This suggests that it remains an open question whether the growing dispersion in house prices and matching dispersion in income growth are being driven exclusively by random productivity shocks.

Much has been written in urban economics and in the broader growth literature about agglomeration effects and the potential for increasing returns in some markets that conceivably could causally link the endogenous relationship between house price and income growth previously documented. Indeed, Lucas (1988) explicitly notes that cities are a natural laboratory in which to test growth models involving some type of productivity spillover. Glaeser et al. (1992), Glaeser, Scheinkman, and Shleifer (1995), and Henderson, Kuncoro, and Turner (1995) soon followed with analyses of dynamic agglomeration economies that extend across time. While there is much debate about the precise nature of the spillovers involved, there is widespread agreement that there are long-run effects from urban agglomerations.[20]

Much of the more recent agglomeration research starts with the basic fact that skilled cities grow more quickly, where growth is measured in terms of quantities such as population or employment. For example, Glaeser and Saiz (2003) document that at the metropolitan-area level, a 1 percentage point higher population share for college graduates is associated with about a 0.5 percentage point higher decadal population growth rate. Similarly, Shapiro (2006) shows that from 1940 through 1990, a 10 percent higher concentration of college graduates is associated with a 0.8 increase in future employment growth (also at the metropolitan-area level).

Since Rauch (1993), we have known wages in a market rise with the skill level of that market, holding constant individual worker skills. Moretti (2004) recently confirmed Rauch's basic correlation, identifying human capital externalities via an instrumental variables estimation that uses the presence of land grant universities as an instrument that proxies for human capital in the area but is plausibly exogenous to wages.[21]

Urban wage premia do appear to be relatively large. Glaeser and Mare (2001) estimate them to be on the order of 20 to 35 percent for workers in larger cities. Those authors also find that long-term residents in bigger cities earn a premium over new arrivals and that when long-term workers leave their city for another, the larger the size of their previous market, the higher their wages are in the new location.[22]

While there is much evidence consistent with the presence of dynamic spillovers, the agglomeration literature has not focused on the relationship between house price and income dispersion. However, it is not hard to see a natural link. If productivity differences across markets are growing, then the higher wages that result in the most productive agglomerations should be capitalized into land values (and thus house price) in markets where the supply of housing is constrained.

This story requires a very high rate of value growth, consistency in the location of agglomeration benefits in areas with inelastic supply sides to their housing markets, and firms that will not move to cheaper places. It certainly is not hard to understand how difficult it would be to recreate somewhere else the production or consumption externalities that lead to increasing returns. In the short run, this probably is impossible, although it seems more open to debate whether we should expect mobility of people and firms to be high over half-century-long periods. In addition, it is not immediately clear why such productivity would tend to occur in supply-constrained markets.

2.6 Household Sorting and Supply Constraints as Explanations for the Spatial Skewing of House Prices and Incomes

While a positive relationship between house prices and incomes across MSAs suggests that there might be innate differences in productivity across locations, it may be that productive people agglomerate rather than agglomerations make people more productive (Glaeser and Mare 2001). In addition, people may value grouping together for various reasons that do not have anything to do with production (Waldfogel 2003).

Given that, an alternative explanation for the stylized facts described earlier can be found in Gyourko, Mayer, and Sinai (2006). In that paper, the

20. See Rosenthal and Strange (2003) for an extensive review of the urban agglomeration literature.

21. That said, there is some debate about the strength of such externalities, with Acemoglu and Angrist (2000) finding small effects but at the state level. See Moretti (2003) for a recent review of the literature on human capital externalities in cities.

22. There is research on the firm side, too. For example, Henderson (1997) shows that concentrations of own-industry employment have measureable impacts on growth many years into the future.

growth in incomes and house prices across MSAs is due to inelastic supply in certain MSAs, heterogeneity in preferences for living in various MSAs across households, and a growing absolute number of high-income households at the national level. Importantly, neither the elasticity of supply nor the distribution of tastes for MSAs need vary over time for the Gyourko, Mayer, and Sinai (2006) hypothesis. Instead, changes in the income distribution at the national level percolate down to differences in the composition of families at the MSA level.

In addition, the comparative statics do not depend on the reasons for location preferences or the inelasticity of supply in the one market. All that is required is that some households prefer one city over the others and that there be some binding limit (natural or regulatory) on the supply of new housing units in some MSAs. Ultimately, the relatively rich with a preference for the market with an inelastic housing supply outbid the poor for the scarce slots. Gyourko, Mayer, and Sinai (2006) conclude that it is increases in the number of rich people nationally that should be correlated with the spatial skewing of prices and incomes. The intuition is that skewing can continue and increase as long as the growth in the number of rich people, at least some of whom have a preference for the supply-constrained market, exceeds the growth in supply in that market. The urban productivity model does not predict any such relationship with national aggregates.

That the right tail of the national income distribution has indeed been getting thicker over time is confirmed in figure 2.9, which reports data from Saez (2004) on the share of U.S. income by population percentile over time. The tax-return data Saez (2004) uses provides a very clear picture of changes

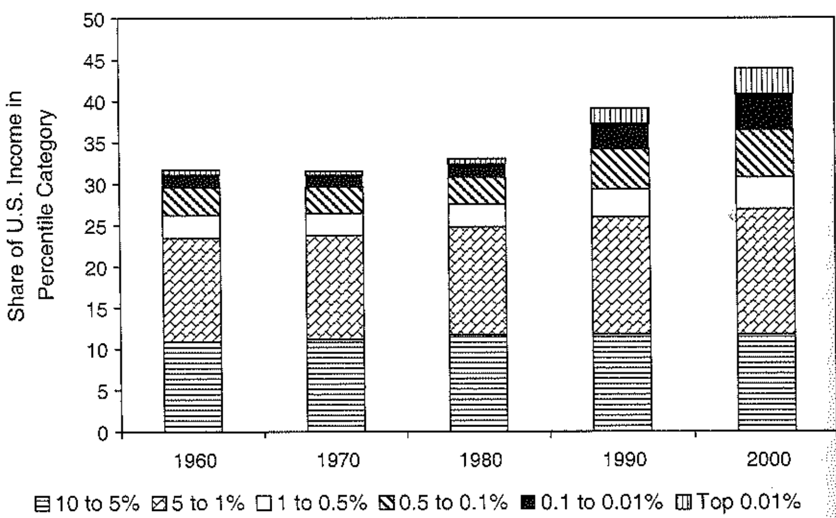

Fig. 2.9 Change in U.S. income distribution, 1960 to 2000 (from Saez [2004])

at the high end of the income distribution. The share of income held by the very top percentiles of the U.S. population—the top one-hundredth or 0.01 percentile, the 0.1 to 0.01 percentile, and the 0.5 to 0.1 percentile—all increased dramatically over the last forty years. The income share of the top 1 percent grew from under 10 percent in 1960 to almost 17 percent in 2000. Even the share of income held by the first to tenth percentiles of the population went up, from about 23 percent in 1960 to about 27 percent in 2000. While the income data reported in the decennial censuses in figure 2.6 are not nearly as fine or detailed as that available to Saez (2004), this source also shows skewing over time similar to that observed in the Internal Revenue Service data.

Gyourko, Mayer and Sinai (2006) show that changes in the national income distribution are correlated with more rapid house price growth in superstar markets. They regress a proxy for the entry price of a home (they use the tenth percentile house value in each metropolitan area) on a set of indicators for superstar/nonsuperstar/low growth status that are also interacted with the national number of rich families. Their findings imply that when the national number of rich families is 10 percent higher, the gap in the tenth percentile house value between MSAs that are ever superstars and those in-between markets is 1.1 percent greater.[23]

2.7 Conclusion

The growing dispersion in house price and income growth rates across MSAs is one of the most important stylized facts about metropolitan areas in America. The spatial sorting by income that it necessarily involves goes to the heart of how we live and organize ourselves socially. Whether these phenomena are due primarily to increasing value from amenities and productivity benefits or are the result of a growing number of high-income families willing to pay increasingly large amounts to live in a few supply-constrained markets is likely to have much to say about how many of us view this ongoing development.

This chapter has documented the basic facts about the spatial distribution of house prices and incomes and has outlined several possible explanations for the patterns we see in the data. Our review concludes that it is unlikely that growth in urban amenities, urban productivity, or agglomeration benefits are the sole causal forces involved. Rather, the skewing of the income distribution nationally is interacting with binding supply-side constraints in certain (primarily coastal) markets to help generate the variation

23. Gyourko, Mayer, and Sinai (2006) report results from several other empirical tests that are designed to distinguish between growth in the value of a location (such as from productivity growth) and growth and willingness to pay for the same utility (such as a greater number of high-income households that must choose between MSAs). We refer the interested reader to that paper for details.

observed. However, the empirical importance of the different explanations remains unresolved. Parsing this out is an essential task for future research that will not be easy but that is important for our understanding of urban markets.[24]

More generally, these changes in the nature of metropolitan America have profound implications for the evolution of urban areas. If the skewing and dispersion continues to grow, even large metropolitan areas could evolve into markets that are affordable only to the rich. In effect, an entire labor market area could have the income distribution of an exclusive resort. We do not know whether such an MSA is sustainable. Moreover, should public policy ensure that living in a particular city is available to all, or, because superstar cities are like luxury goods, should we not care whether lower-income households can buy into those markets any more than we care whether they can buy a Mercedes? The answer also has important implications for views on policy issues such as tax-based subsidies to homeownership. While economists can justify subsidies based on positive externalities involving better citizenship or improved outcomes for children (DiPasquale and Glaeser 1999; Green and White 1997), the case becomes harder if one believes that the high prices in America's coastal markets are due more to preference-based sorting combined with binding local regulation on homebuilding than to productivity. These and other questions will provide fertile ground for thought and research by economists interested in urban agglomerations.

24. Even if preference-based sorting explains the moves of the rich into markets like San Francisco, it is possible that once the rich agglomerate in that market, productivity then increases. Hence, the two forces may interact in various ways.

Appendix

Table 2A.1 **House prices and appreciation**

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Abilene, TX	34.6	54,917	73,918
Akron, OH	93.9	69,720	135,174
Albany, GA	61.7	60,388	97,630
Albany, NY	62.3	75,522	122,604
Albuquerque, NM	132.6	64,411	149,835
Alexandria, LA	98.9	46,114	91,722
Allentown, PA	110.3	61,811	129,981
Altoona, PA	99.2	43,163	85,966
Amarillo, TX	54.4	61,713	95,299
Ann Arbor, MI	177.2	70,125	194,421
Anniston, AL	132.5	37,222	86,527
Appleton, WI	93.3	63,152	122,098
Asheville, NC	192.3	50,005	146,159
Athens, GA	191.4	49,138	143,184
Atlanta, GA	178.8	61,933	172,667
Atlantic City, NC	128.3	68,581	156,590
Auburn-Opelika, AL	151.5	50,779	127,708
Augusta, GA	138.9	45,543	108,814
Austin, TX	193.8	55,895	164,223
Bakersfield, CA	94.7	57,461	111,850
Baltimore, MD	148.6	65,817	163,594
Bangor, ME	113.3	43,328	92,403
Barnstable, MA	205.5	76,239	232,912
Baton Rouge, LA	115.3	56,276	121,178
Beaumont, TX	47.6	51,200	75,580
Bellingham, WA	276.4	49,780	187,380
Benton Harbor, MI	103.9	59,222	120,727
Bergen-Passic, NJ	196.0	98,065	290,265
Billings, MT	48.4	79,117	117,401
Biloxi, MS	170.4	39,205	106,029
Binghamton, NY	24.4	70,626	87,873
Birmingham, AL	178.1	47,949	133,362
Bismarck, ND	72.0	61,250	105,354
Bloomington, IN	112.1	61,691	130,870
Bloomington, IL	176.3	47,973	132,556
Boise City, ID	142.6	58,231	141,275
Boston, MA	212.4	76,168	237,974
Boulder, CO	377.2	61,206	292,063
Brazoria, TX	123.5	46,086	103,025
Bremerton, WA	280.4	51,233	194,886
Brownsville, TX	73.8	39,569	68,775
Bryan, TX	137.9	48,788	116,046
Buffalo, NY	31.1	79,254	103,880
Burlington, VT	131.9	65,502	151,915

(continued)

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Canton, OH	78.4	65,215	116,324
Casper, WY	37.8	72,285	99,579
Cedar Rapids, IA	76.4	69,121	121,942
Champaign, IL	49.6	75,056	112,277
Charleston, SC	236.8	47,790	160,960
Charleston, WV	56.0	67,951	105,994
Charlotte, NC	194.1	53,454	157,233
Charlottesville, VA	158.7	66,377	171,734
Chattanooga, TN	154.3	45,327	115,264
Cheyenne, WY	75.5	68,901	120,934
Chicago, IL	113.7	97,920	209,302
Chico, CA	173.8	53,621	146,827
Cincinnati, OH	76.2	82,734	145,774
Clarksville, TN	146.1	39,349	96,846
Cleveland, OH	57.0	91,687	143,988
Colorado Springs, CO	162.7	67,264	176,709
Columbia, MO	106.2	64,039	132,067
Columbia, SC	109.0	62,560	130,741
Columbus, GA	97.8	52,647	104,113
Columbus, GA	112.5	68,152	144,797
Corpus Christi, TX	60.8	52,261	84,055
Corvallis, OR	190.3	65,383	189,834
Cumberland, MD	78.8	45,269	80,950
Dallas, TX	138.4	60,875	145,125
Danville, VA	79.1	49,789	89,160
Davenport, IA	46.4	69,396	101,616
Dayton, OH	63.9	72,429	118,740
Daytona Beach, FL	100.2	56,285	112,670
Decatur, AL	39.7	59,324	82,878
Decatur, IL	162.9	39,426	103,651
Denver, CO	184.3	75,357	214,261
Des Moines, IA	104.8	59,610	122,069
Detroit, MI	123.8	72,666	162,595
Dothan, AL	132.9	41,834	97,447
Dover, DE	142.0	52,372	126,746
Dubuque, IA	55.7	71,399	111,178
Duluth, MN	77.0	50,214	88,899
Dutchess County, NY	103.9	84,876	173,021
Eau Claire, WI	106.0	53,068	109,346
El Paso, TX	21.9	68,651	83,652
Elkhart, IN	124.8	51,894	116,662
Elmira, NY	19.8	65,681	78,693
Enid, OK	35.4	52,425	70,985
Erie, PA	60.8	63,623	102,287
Eugene, OR	169.8	60,521	163,308
Evansville, IN	104.6	51,168	104,673
Fargo, SD	65.2	64,995	107,401

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Fayetteville, NC	163.0	44,821	117,882
Fayetteville, AR	131.1	46,057	106,439
Flagstaff, AZ	226.7	50,500	164,989
Flint, MI	108.4	52,717	109,844
Florence, AL	105.7	53,411	109,874
Florence, SC	143.6	41,008	99,881
Fort Collins, CO	246.9	58,103	201,557
Fort Lauderdale, FL	112.5	76,577	162,733
Fort Myers, FL	224.3	47,951	155,498
Fort Pierce, FL	164.5	55,601	147,065
Fort Smith, AR	123.3	38,849	86,732
Fort Walton Beach, FL	310.2	32,220	132,178
Fort Wayne, IN	81.9	58,417	106,245
Fort Worth, TX	125.2	51,794	116,627
Fresno, CA	110.9	61,792	130,339
Gadsden, AL	95.6	43,564	85,218
Gainesville, FL	131.6	52,261	121,013
Galveston, TX	73.9	62,502	108,689
Gary, IN	79.6	68,478	123,004
Glens Falls, NY	111.5	52,596	111,252
Goldsboro, NC	117.0	48,770	105,809
Grand Forks, ND	84.0	52,702	96,954
Grand Junction, CO	182.4	50,121	141,565
Grand Rapids, MI	122.4	61,120	135,937
Great Falls, MT	60.5	66,267	106,331
Greeley, CO	240.5	47,601	162,079
Green Bay, WI	92.0	69,589	133,603
Greensboro-Winston-Salem, NC	160.4	51,382	133,785
Greenville, NC	126.8	53,496	121,353
Greenville, SC	136.4	51,358	121,431
Hagerstown, MD	128.9	56,392	129,058
Hamilton, OH	101.9	67,859	136,985
Harrisburg, PA	104.5	60,176	123,036
Hartford, CT	85.9	94,780	176,237
Hattiesburg, MS	157.9	37,870	97,658
Hickory, NC	169.4	43,043	115,939
Houma, LA	161.1	36,392	95,011
Houston, TX	100.2	63,203	126,516
Huntington, WV	60.5	52,196	83,751
Huntsville, AL	204.2	41,005	124,754
Indianapolis, IN	123.2	60,474	134,977
Iowa City, IA	101.6	77,367	155,995
Jackson, MI	112.1	47,567	100,887
Jackson, MS	123.8	51,349	114,931
Jackson, TN	77.8	61,374	109,126
Jacksonville, FL	134.7	56,494	132,578

(continued)

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Jacksonville, NC	226.7	31,850	104,044
Jamestown, NY	31.3	58,609	76,940
Janesville, WI	76.8	62,627	110,704
Jersey City, NJ	136.8	72,622	171,946
Johnson City, TN	121.3	46,771	103,517
Johnstown, PA	65.9	45,873	76,127
Jonesboro, AR	128.9	43,218	98,938
Joplin, MO	143.5	34,162	83,176
Kalamazoo, MI	97.9	58,856	116,504
Kankakee, IL	70.3	68,181	116,145
Kansas City, MO	118.4	58,259	127,225
Kenosha, WI	93.3	71,148	137,515
Killeen, TX	100.3	44,527	89,207
Knoxville, TN	179.7	44,710	125,053
Kokomo, IN	129.7	45,759	105,114
La Crosse, WI	99.0	56,323	112,078
Lafayette, LA	155.4	39,681	101,363
Lafayette, IN	108.3	59,286	123,521
Lake Charles, LA	95.2	50,583	98,730
Lakeland, FL	101.7	49,523	99,883
Lancaster, PA	100.4	67,637	135,567
Lansing, MI	118.0	56,559	123,283
Laredo, TX	181.2	30,869	86,801
Las Cruces, NM	157.1	43,025	110,607
Las Vegas, NV	147.5	65,114	161,166
Lawrence, KS	187.3	49,050	140,902
Lawton, OK	72.7	48,036	82,946
Lewiston, ME	92.2	52,248	100,434
Lexington-Fayette, KY	113.7	60,367	129,025
Lima, OH	72.7	56,382	97,381
Lincoln, NE	105.5	61,336	126,018
Little Rock, AR	117.1	50,879	110,443
Longview, TX	123.2	37,678	84,102
Los Angeles, CA	236.6	85,150	286,633
Louisville, KY	113.4	60,413	128,893
Lubbock, TX	36.1	62,442	84,999
Lynchburg, VA	124.4	52,348	117,452
Macon, GA	133.0	44,416	103,502
Madison, WI	99.0	86,136	171,383
Mansfield, OH	49.3	64,370	96,099
McAllen, TX	99.9	33,393	66,759
Medford, OR	199.0	56,647	169,383
Melbourne, FL	114.9	55,488	119,262
Memphis, TN	100.7	61,886	124,183
Merced, CA	121.8	58,295	129,318
Miami, FL	95.2	83,286	162,594
Middlesex-Somerset-Hunterdon, NJ	185.6	80,437	229,739

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Milwaukee, WI	69.3	92,698	156,918
Minneapolis-St. Paul, MN	117.6	77,421	168,496
Missoula, MT	162.5	59,653	156,573
Mobile, AL	184.0	41,465	117,766
Modesto, CA	162.2	55,669	145,969
Monmouth-Ocean, NJ	160.2	77,938	202,758
Monroe, LA	101.7	49,470	99,781
Montgomery, AL	107.2	55,648	115,307
Muncie, IN	66.8	51,851	86,505
Myrtle Beach, SC	176.3	52,277	144,456
Naples, FL	406.7	51,144	259,155
Nashville-Davidson, TN	178.8	56,363	157,166
Nassau-Suffolk County, NY	167.6	99,692	266,806
New Haven, CT	185.4	103,118	294,297
New London, CT	132.5	74,479	173,185
New Orleans, LA	81.2	71,836	130,140
New York, NY	181.4	103,209	290,412
Newark, NJ	155.2	101,549	259,115
Newburgh, NY	125.2	70,748	159,289
Norfolk, VA	150.2	54,670	136,783
Oakland, CA	300.8	86,596	347,050
Ocala, FL	146.8	40,186	99,169
Odessa, TX	27.4	59,116	75,294
Oklahoma City, OK	65.8	58,078	96,278
Olympia, WA	194.8	57,586	169,788
Omaha, NE	104.3	59,470	121,483
Orange County, CA	356.1	72,185	329,206
Orlando, FL	122.8	61,908	137,919
Owensboro, KY	72.7	55,968	96,648
Panama City, FL	238.7	34,908	118,233
Parkersburg, WV	64.7	56,158	92,516
Pensacola, FL	185.6	40,422	115,431
Peoria-Pekin, IL	59.8	66,167	105,723
Philadelphia, PA	121.6	66,426	147,186
Phoenix, AZ	209.2	53,106	164,191
Pine Bluff, AR	113.6	33,106	70,724
Pittsburgh, PA	66.1	64,015	106,345
Pittsfield, MA	96.9	73,066	143,854
Pocatello, ID	71.7	60,819	104,417
Portland, OR	221.4	63,337	203,578
Portland, ME	169.3	60,377	162,576
Providence, RI	94.1	81,189	157,574
Provo-Orem, UT	207.3	61,174	187,982
Pueblo, CO	120.8	50,635	111,798
Punta Gorda, FL	215.2	39,342	124,010
Racine, WI	72.1	74,706	128,537

(*continued*)

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
Raleigh-Durham-Chapel Hill, NC	205.7	58,153	177,794
Rapid City, SD	89.5	59,458	112,668
Reading, PA	96.3	59,750	117,313
Redding, CA	168.0	52,416	140,465
Reno, NV	115.4	96,874	208,650
Richland, WA	117.2	60,700	131,811
Richmond-Petersburgh, VA	116.5	64,964	140,677
Riverside-San Bernardino, CA	173.7	59,725	163,483
Roanoke, VA	103.8	60,679	123,680
Rochester, MN	68.1	81,995	137,822
Rochester, NY	56.1	72,348	112,926
Rockford, IL	51.2	73,216	110,727
Rocky Mount, NC	109.4	50,538	105,837
Sacramento, CA	167.9	71,504	191,567
Saginaw, MI	90.4	54,865	104,471
Salem, OR	159.8	59,484	154,551
Salinas, CA	316.6	83,456	347,705
Salt Lake City, UT	157.1	70,810	182,029
San Angelo, TX	52.8	50,539	77,215
San Antonio, TX	75.2	56,397	98,829
San Diego, CA	262.4	78,640	284,952
San Francisco, CA	465.9	96,703	547,206
San Jose, CA	513.3	86,667	531,562
San Luis Obispo, CA	346.0	59,995	267,605
Santa Barbara-Santa Maria, CA	328.4	89,559	383,707
Santa Cruz, CA	522.0	68,494	426,041
Santa Fe, NM	284.9	66,127	254,503
Santa Rosa, CA	362.5	69,007	319,124
Sarasota, FL	166.7	62,131	165,729
Savannah, GA	153.5	53,867	136,552
Scranton, PA	111.5	49,142	103,948
Seattle, WA	285.7	70,684	272,603
Sharon, PA	58.4	56,123	88,901
Sheboygan, WI	84.6	67,042	123,742
Shermon-Denison, TX	119.4	38,321	84,065
Shreveport-Bossier, LA	61.6	57,812	93,411
Sioux City, IA	55.1	57,815	89,660
Sioux Falls, SD	87.5	64,197	120,400
South Bend, IN	66.4	62,322	103,678
Spokane, WA	119.0	60,147	131,739
Springfield, IL	83.1	60,736	111,198
Springfield, MA	93.7	72,294	140,063
Springfield, MO	128.5	47,932	109,543
St. Cloud, MN	135.0	48,134	113,132
St. Joseph, MO	126.5	39,063	88,484
St. Louis, MO	78.6	72,973	130,348

Table 2A.1 (continued)

MSA	% House price appreciation 1950–2000	1950 Mean value (2000 dollars)	2000 Mean value (2000 dollars)
State College, PA	145.6	54,367	133,541
Steubenville-Weirton, OH	34.4	57,706	77,550
Stockton, CA	171.8	60,531	164,517
Sumter, SC	93.4	47,929	92,696
Syracuse, NY	39.8	69,624	97,341
Tacoma, WA	201.6	58,269	175,746
Tallahassee, FL	137.0	53,971	127,889
Tampa-St. Petersburgh, FL	109.4	58,714	122,967
Terre Haute, IN	134.0	36,094	84,467
Texarkana, TX	123.4	35,200	78,620
Toledo, OH	80.4	65,783	118,705
Topeka, KS	72.1	54,593	93,969
Trenton, NJ	189.2	67,916	196,431
Tucson, AZ	130.5	63,094	145,417
Tulsa, OK	99.0	53,533	106,510
Tuscaloosa, AL	178.6	46,197	128,691
Tyler, TX	97.4	52,262	103,168
Utica-Rome, NY	30.6	64,791	84,587
Vallejo, CA	233.4	69,620	232,145
Ventura, CA	319.6	70,971	297,826
Victoria, TX	57.2	55,147	86,680
Vineland-Millville-Bridgeton, NJ	91.2	53,459	102,201
Visalia-Tulare-Porterville, CA	159.7	46,174	119,908
Waco, TX	70.1	48,552	82,577
Washington, DC	112.7	106,235	225,914
Waterloo-Cedar Falls, IA	40.2	64,682	90,685
Wausau, WI	114.3	51,753	110,908
West Palm Beach-Boca Raton, FL	159.7	73,275	190,261
Wheeling, WV	46.3	53,928	78,871
Wichita, KS	62.9	60,499	98,554
Wichita Falls, TX	57.4	47,826	75,266
Williamsport, PA	82.3	53,625	97,759
Wilmington, DE	90.8	82,087	156,661
Wilmington, NC	310.6	42,865	176,011
Yakima, WA	140.7	54,809	131,944
Yolo, CA	205.7	65,842	201,293
York, PA	104.8	60,915	124,730
Youngstown-Warren, OH	49.8	63,044	94,470
Yuba, CA	146.4	51,463	126,793
Yuma, AZ	156.6	44,473	114,101

Note: Decadal Census; all values in 2000 dollars.

Table 2A.2 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 nonsuperstar	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	**Number of superstars**	**Number of nonsuperstars**
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	

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