Housing Inequality

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Abstract

Inequality in U.S. housing prices and rents declined in the mid-20th century, even as home-ownership rates rose. Subsequently, housing-price inequality has risen to pre-War levels, while rent inequality has risen less. Combining both measures, we see inequality in housing consumption equivalents mirroring patterns in income across both space and time, according to an income elasticity of housing demand just below one. These patterns occur mainly within cities, and are not explained by observed changes in dwelling characteristics or locations. Instead, recent increases in housing inequality are driven most by changes in the relative value of locations, seen especially through land.

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1 Introduction

In this paper, we examine a dimension of inequality that has received surprisingly scant attention – inequality in housing outcomes. We find that measures of inequality in housing prices and rents in the United States exhibit a U-shaped pattern over the last 85 years, resembling patterns of income and wealth inequality, often referred to as a "great compression" followed by a "great divergence" (Piketty and Saez (2003), Saez and Zucman (2014)). Housing-value inequality fell from 1930 to 1970 as home ownership expanded, but has subsequently risen. Rent inequality also fell, but it has risen only slightly since. Combining both measures into a rental equivalent, we again see a U-shape.

To understand the fall and subsequent rise of housing inequality, we use decomposition techniques to quantify the impacts of key variables. Changes in housing inequality have occurred primarily within cities and are not explained by *observable* changes in dwelling characteristics. Thus, changes in the desirability of particular neighborhoods, reflected in land values, appear to be the main contributor to changes in housing inequality, although we cannot rule out changes in unobserved housing quality. Using a series of simple regressions, we also find that local housing inequality is related with local income inequality at magnitudes implied by reasonable values for the income elasticity of housing consumption.

Knowledge of housing inequality sheds light on larger issues concerning consumption and wealth inequality. It informs debate over whether consumption inequality has grown as much as income inequality over the last few decades.[1] Housing accounts for a large share of consumption, and has done so more stably than other items, such as food or health care.[2] Housing may represent permanent income particularly well as it is durable (Friedman (1957), p 208). The great compression and great divergence in housing inequality are of roughly similar magnitude, commensurate with income changes. However, housing inequality has less to do with tangible dwelling characteristics — such as living space — and more to do with what people pay to live

[1] Krueger and Perri (2006) and Meyer and Sullivan (2010) argue that consumption inequality has increased much less than income inequality using the Consumer Expenditure Survey. Aguiar and Bils (2011) propose a correction for measurement error that results in a consumption inequality measure that mirrors income. Work using PSID consumption measures by Attanasio and Pistaferri (2014) and earlier evidence by Cutler and Katz (1992) also suggest that consumption inequality has increased in line with income inequality.

[2] As a fraction of Personal Consumption Expenditures (PCE), "Housing and utilities" rose from 16.6 to 18.1 percent between 1959 and 2014. Similar fractions for "Food and beverages purchases for off-premises consumption" are 19.4 to 7.5 percent; "Clothing and footwear," 8.0 to 3.1 percent, "Motor vehicles and parts," 5.9 to 3.7 percent; "Health care," 4.7 to 16.5 percent. Depending on the survey, the budget share of housing roughly one-sixth, in the PCE, to one-third, in the Consumer Expenditure Survey (CEX), of average consumer expenditures (Albouy and Lue (2015).)

in different locations. These locations offer different "intangibles" such as access to employment and local amenities, such as schools, safety, and natural features.

There has also been recent debate over whether wealth inequality has increased as much as income inequality.[3] Housing informs this debate as it accounts for much of the overall capital stock and is the principal asset for most Americans with savings.[4] Our evidence that housing values have diverged indirectly supports the view that wealth inequality has increased, albeit to levels lower than before World War II, due to increases in home-ownership.[5]

To our knowledge, our paper is the first to document inequality in housing prices and rents over such a long period and to relate them to measures of income inequality over space and time. Our analysis of housing expenditures sheds light on consumption inequality prior to World War II – before widely available household-level consumption data – providing direct evidence of a great compression in consumption inequality contemporaneous with similar changes in income and wealth.[6] While several studies (e.g. Van Nieuwerburgh and Weill (2010), Moretti (2013), and Gyourko, Mayer and Sinai (2013)) have examined recent changes in housing-price inequality across cities, our analysis extends for longer, covers rents, and examines dwelling characteristics and variation in prices within cities.

2 Data, Inequality Measures, and Empirical Techniques

2.1 Housing Data and Sample Selection

Our data are drawn from the full 1930 and 1940 Census, the long form of the 1960 through 2000 Censuses, and the American Community Survey (ACS) for 2009-12. These surveys ask owners to report the current value of their home and renters to report their monthly rent. Renters from 1970 onward and home owners from 1980 onward also report their utility costs. Home values

[3] Kopczuk (2004) find a great compression of wealth inequality but little divergence afterwards. Using capitalization methods, Saez and Zucman (2014) find greater divergence, although Kopczuk (2015) disputes this.

[4] Housing accounts for roughly one third of total household wealth and roughly 40 percent of the capital stock. Housing is almost two thirds of wealth for the middle three quintiles (Wolff, 2014). In 2004, 62 percent of housing wealth was held by the bottom 90 percent, and only 9.8 percent by the top 1 percent; for stocks and mutual funds, the comparable numbers are 14.6 and 44.8 percent (Wolff 2009, p. 160).

[5] Differences in wealth due to inequality in housing values have more complex implications than differences due to other types of capital. An appreciation in home prices will only increase a home-owner's permanent wealth if they have a less expensive alternative to living in their now more expensive house. Rognlie (2014) and Bonnet et al. (2014) have emphasized this point in critiquing Piketty and Zucman (2014). One interesting feature of our paper is our finding that home owners have alternatives that are observably quite similar but much less expensive. This suggests that the distinction is less important.

[6] Goldin and Margo (1992) used methods similar to ours to highlight and examine the great compression in incomes in the 1930's and 1940's. Piketty and Saez (2003) examine the great compression of top incomes, particularly from capital.

are recorded as intervals from 1960 through 2000 and monthly rents are reported as intervals for 1960, 1980, and 1990. In all other years the questions record a continuous measure with relatively little top coding.[7]

We restrict our sample to focus on residential homes and to maximize consistency across years. This involves three restrictions. First, we restrict the sample to the continental United States. Second, we eliminate all farms and homes used for commercial activities, such as dental and medical offices. Fourth, we remove owner-occupied units in multi-family structures. Appendix table A.1 lists the number of houses in each category. We remove farms in all years, which is our most important sample restriction. The 1930 and 1940 data do not include dwelling characteristics, nor do they indicate the presence of businesses, so we cannot remove businesses and multi-family structures in these years. These two categories account for only 6 percent of owner-occupied houses in 1960.[8]

2.2 Interpolation and Extrapolation Procedures

The Census often asks questions about home values and rents in terms of intervals. Even when questions are asked in terms of continuous dollars, the data are top coded, and respondents often round. To account for these issues, we use a Pareto interpolation procedure to allocate responses within intervals. Where y are values distributed according to $F(y)$, this procedure fits $\ln[1-F(y)] = \alpha_j[\ln(k_j) - \ln(y)]$, where $\alpha_j > 1, k_j > 0$ are parameters for an interval j. In other words, it fits a linear spline of the "tail" function $\ln[1-F(y)]$ to $\ln(y)$. For high values of y, the α_j parameters are fairly constant, implying that the Pareto distribution provides a good fit. To improve comparability and handle rounding problems, we also interpolate in years with continuous data, using 25 artificial intervals, with 4 percent of the data in each.[9]

At the top of the distribution, we use standard Pareto extrapolation procedures (e.g. Atkinson, Piketty and Saez (2011)). In years that we have information about the mean of top coded values, we use the estimate of $\alpha_J = E[y|y>k]/(E[y|y>k]-k)$. In other years, we extrapolate α_J for the top coded bin from the α_j from intervals in the top 10 percent of the distribution.[10]

[7]The home value is the owner's estimate. We discuss below how question changes impact our analysis. We take data from the ACS from 2009 (not 2008) through 2012 to reflect conditions after the latest housing boom and bust.

[8]Enumerator instructions for 1940 instruct respondents to exclude the value of units rented out and to also exclude the area of the house that is used for business purposes if this is a "considerable portion" of the house. These instructions are re-printed in the data appendix.

[9]Because of rounding, these intervals can sometimes contain only one value. In these cases, we decrease the number of groups until each interval has a top value at least 2.5 percent higher than its bottom value.

[10]The one exception to this are rent values in 1930 and 1940, where we hard code the top Pareto distribution

For the bottom interval we extrapolate values using a uniform distribution to deal with bottom coding and problems associated with zero values. We set the minimum of this interval as a proportion of average household income in that year. More details are in Appendix B.

2.3 House Values, Gross Rents, and Consumption Equivalents

We present all of our results separately for housing prices and rents. To integrate the two and account for changes in home ownership (which mainly changed from 1940 to 1960), we impute a rental equivalent measure for home owners, based on a constant user cost of 0.0785 times the value of the house and plus utility payments.[11] We then divide these rental measures by a household equivalence scale to provide a per-person measure of housing consumption.[12]

2.4 Inequality Measures

To describe inequality in housing expenditures we use three scale and population invariant measures: the variance of logs, the Gini coefficient, and the Theil entropy index.[13] We decompose the variance of logs and the Theil index to show how much overall inequality is due to variation across versus within areas. Note that the variance of logs is particularly sensitive to the bottom of the distribution while the Gini coefficient and Theil mainly measure changes in the middle of the distribution (Atkinson (1970)).

parameter to be 2.5. In these years we have a continuous distribution of rents (and home values) with very few top codes; parameters estimated from the mean procedure lead to suspiciously high inequality statistics.

[11]This commonly-used value is based on Peiser and Smith (1985). User costs of home ownership are foregone interest, depreciation, and property taxes, minus price appreciation. User costs vary over space, time, and possibly occupant, but there are various empirical and conceptual challenges in calculating year-by-city user costs (e.g. those examined in Verbrugge (2008) and Poterba and Sinai (2008)). We choose a constant number so as to avoid the data being overly influenced by our choice of methodology, recognizing that scale invariance of the inequality measures will help to undo differences among owners.

[12]Equivalence scales are designed to take into account economies of scale in consumption, such as from the sharing of common spaces, kitchens, etc. We use the OECD equivalence scale: $1 + 0.7(A - 1) + 0.5C$ where A is the total number of adults in the household and C is the number of children (14 years old or below).

[13]The Theil index is computed by taking a weighted average of the log of the (normalized) expenditure on housing by each household. Where $\bar{y} \equiv E[y_i]$:

$$T = \frac{1}{N} \sum_{i=1}^{N} \left[\frac{y_i}{\bar{y}} \ln \left(\frac{y_i}{\bar{y}} \right) \right]$$

The Gini coefficient and Theil index satisfy the principle of transfers, so a transfer from a rich to a poor person always decreases inequality. We decompose Theil entropy indices and variances of logs by calling inequality in mean levels of housing expenditures across areas the between (areas) component, and inequality within areas the within component. As Cowell (2011) notes, the variance of logs is only decomposable with constant means of logged values, not levels.

2.5 Dwelling Characteristics and Location Measures

Dwelling characteristics are provided only from 1960 onwards. They include the age of the building, the number of rooms, the number of bedrooms, the presence of complete plumbing, and what heating system, if any, was installed (gas, oil, wood, electric, etc.).

Measures of location extend back to 1930. We consider the lower 48 states, and 722 commuting zones (CZs). CZs are defined like metropolitan areas, corresponding to local labor markets, but include rural areas, and are constant over time.[14]Some locational advantages may be permanent, such as climate and natural features. Others, such as safety or employment proximity, may have changed considerably since 1930. We remain agnostic about which amenities households value, mainly because we can measure so few of them.

2.6 Re-weighting Analysis

To account for how observable changes in housing characteristics have affected inequality, we use the propensity-score re-weighting approach of DiNardo, Fortin and Lemieux (1996). This approach estimates what the distribution of housing prices would be if the observed characteristics of houses had remained identical to earlier years, and those characteristics had been priced as in later years. In this way, it rules out general-equilibrium effects (such as changes in demand) affecting prices. Nonetheless, it is a useful accounting method, as changes from re-weighting tell us how well observable characteristics could affect inequality.

The re-weighting makes the observable characteristics of a sample of houses in a later "current" year, t (e.g. 2010), resemble characteristics from a previous "target" year, t' (e.g. 1970). The weights are the odds of a house being observed in the target year relative to the current year, which we determine using a logit regression on the pooled sample in years t and t'. Fortin, Lemieux and Firpo (2011) provides detailed conditions for identification and implementation details. The main requirement for identification is conditional independence – after conditioning on all characteristics, a house's price is independent of the year we observe it in.

[14]We use 1990 Commuting zones, which are more fully explained in Tolbert and Sizer (1996). They are made up of counties and designed to be places where people both live and work. For 1930 and 1940 we are able to assign every house to one commuting zone. In 1960 they are not available in public PUMS samples. From 1970 onward some houses are identified as being in PUMA's or county groups in the IPUMS data that cut across multiple commuting zones. For these years we follow Dorn (2009), Autor, Dorn and Hanson (2013), and others in probabilistically assigning houses to commuting zones based on the proportion of responses in their most detailed geographic category that were in one commuting zone or the other. For most of our specifications we also report statistics using states. We are able to match each house to a state for each year.

3 Empirical Results

3.1 General Trends over Time

Table 1 provides basic characteristics of the sample. The first row shows how home-ownership fell after the Great Depression and rose dramatically after World War II, hovering just above 60 percent for over fifty years. Household size consistently fell (from 3.8 in 1930, 3.3 in 1960, to 2.5 in 2012) and the number of rooms per house rose slowly after 1960 (from 5 to 5.75) along with the number of bedrooms. Indoor plumbing was common but not ubiquitous in 1960, but became so by 1980. Taken together, these trends imply Americans consumed much more housing per person. The fraction living in the South and West also ballooned from 35 to 60 percent, while the Midwest and Northeast lost its former predominance.

Figure 1 graphs Lorenz curves for various measures of housing outcomes and incomes in 1930, 1970, and 2012. We present Lorenz curves because they show how each part of the distribution has changed over time.

Panel A shows that, among home-owners, 2012 and 1930 have almost identical levels of inequality, with 50 percent of housing value accruing to the top 20 percent. Inequality is uniformly lower in 1970 with 40 percent going to the top 20 percent. To better understand the distribution of housing assets (if not equity) Panel B includes renters as zeroes. Here we see 1930 is considerably less equal, with 80 percent of owner-occupied housing wealth accruing to 20 percent of households, resembling the original "Pareto Principle," for 19th-Century landowners. In comparison, inequality in 2012 is much lower, although changes in the number of farms may influence this number.

Panel C shows that rents were quite unequal in 1930, but that they were much more equal in 1970. Since then, rent inequality has only grown slightly, primarily for costlier units. Panel D shows consumption equivalents, which summarize much of the earlier discussion: 1930 had the highest inequality, 1970 the least, and 2012 resembles 1930 at the top of the distribution but 1970 at the bottom.

Panels E and F describe household wage income (not available in 1930) and total income (not available in 1930 or 1940). Total income inequality is generally smaller, especially at the bottom (partly due to lack of zeroes), and increased less than wage inequality between 1970 and 2012.

Figure 2 graphs our preferred inequality statistics in all years. Generally these show U-shaped patterns from 1930 to 2012. Before 1970 there was a great compression in housing consumption, similar to trends in the inequality of household income shown in Panel D.

From 1930 to 1970 the Theil entropy index and the variance of the log of home prices roughly halved. Each statistic increases after 1970 — with a blip in 1990 that seems due to regional housing booms — and settles in 2012 at a level slightly below its value in 1930. It is especially remarkable that home-ownership waxed considerably during the great compression, while it did not wane during the great divergence.

Rents exhibit a different pattern. While inequality in rents declined dramatically between 1930 and 1960, it increased less than home values in the period starting in 1980. Since inequality changed more at the top than at the bottom, this may relate to increased levels of housing assistance for low-income households, or rent control in major cities like New York and San Francisco.

The consumption equivalent measure accounts for changes in demographics and home ownership, and exhibits a U-shaped pattern that is slightly less extreme in the latter half of the U. This measure shows the lowest levels of inequality in 1980, while the other measures bottomed-out closer to 1960. Inequality in consumption equivalents appears to be currently at its highest level since World War II and seems to be increasing.

While we only have household wage income in 1940 (and nothing in 1930) it is worth noting that inequality in our housing measures fell *more* between 1940 and 1960 than measures of income. Subsequent increases in housing inequality since 1960 have been comparatively gentler.

3.2 Decomposition over Space

In Figure 3 and Table 3 we use a spatial decomposition to see how much inequality is due to differences across areas as opposed to within them. Differences across cities are likely labor market driven, since CZs are designed to resemble local labor markets. Differences within cities are likely due to dwelling characteristics, local amenities, and commuting opportunities.

In all cases, within-area inequality is much larger than between-area inequality, such that the within statistics are generally between three to ten times as large. The U-shaped patterns observed at the national level for each measure are reflected both within and across states and commuting zones. However, given the relative magnitudes, changes in inequality are mainly driven by differences within metro areas. In contrast, much of the literature (examples include Van Nieuwerburgh and Weill (2010), Diamond (2012), Gyourko, Mayer and Sinai (2013), and

Moretti (2013)) focuses on growing inequality between metro areas. Between-metro changes did figure prominently in 1990 blip, which occurred in rents as well as prices, but have otherwise been dwarfed by changes within metros.

The large increases in household wage inequality within areas in the late 20th century, mirrors those in Baum-Snow and Pavan (2013), who find income inequality grew the most within the largest U.S. cities. Meanwhile, inequality between metro areas declined considerably between 1940 and 1960, and did not change considerably afterwards outside of the 1990 blip.

3.3 The Role of Observable Characteristics

Although the share of income devoted to housing appears to have stayed relatively constant over the 20th century, patterns of housing consumption appears to have changed considerably. As pointed out in Table 1, while households have shrunk in (human) size, their housing units have gotten larger, and they have moved south and west.

Increases in housing price inequality since 1970 could be the result of two forces. First, some households may have moved into ever larger units, while others moved into ever smaller units. Second, Americans might have moved in ways that heightened inequality.

These hypotheses are examined in Figure 4 and Table 4. They show that if households lived in housing units with dwelling characteristics, locations, and household composition observably identical to those in 1970, housing values would be only slightly more equal. This accountable change is very small in relation to the overall changes.[15]

The re-weighting results in Table 4 show that dwelling characteristics can explain at most 30 percent of the change in the two inequality statistics using the consumption equivalent measure. The direction varies, however, with decreases in inequality among home owners and *increases* for renters. Generally, changes in the location of houses and household composition from 1970 to 2012 have tended to make households *more equal* in their housing outcomes. It is also interesting, even surprising, that neither location nor dwelling characteristics do much to explain changes in household wage inequality.

Our results on dwelling characteristics support previous reflections on this issue. For exam-

[15] The re-weighting specification we use allows for depreciation of housing by year at the cost of allowing for "vintage" effects of houses built in particular years. In an alternative specification we allow for these vintage effects. Davis and Heathcote (2007) find that spending on structural improvements in the US (roughly 0.8 percent) is very similar to a reasonable estimate of structural depreciation (roughly 1 percent). Our conclusions using vintages reinforce the idea that changes in dwelling characteristics have not driven the changes in housing inequality that we document.

ple, Glaeser and Gyourko (2008) find that per-capita square footage consumed by rich and poor households has become more equal over time. Since construction costs vary little within cities, much of the growing inequality in housing value seems to be due to growing inequality in land values, or the right to build on such land.

3.4 The Relationship between Income and Housing Inequality

The patterns documented in section 3.2 suggest a link between local income and housing inequality. Studies of housing demand (e.g. Polinsky and Ellwood (1979), Hanushek and Quigley (1980), and Mayo (1981)) have generally concluded that housing is a necessity, a regularity sometimes known as "Schwabe's Law." Most estimates typically fall between 0.3 and 1.0. So variations in income should be reflected in housing consumption. In fact, other things equal, the variance of log housing consumption should equal the square of the income elasticity of housing times the variance of log income.[16]

Patterns of income and housing inequality over time and space suggest a considerable relationship between the two. For instance, between 1970 and 2012, the variance of log income increased by 0.26, while the variance of log housing consumption increased by 0.09, consistent with an income elasticity of 0.59.

We examine this relationship spatially in Figure 5 and Table 5 by comparing how inequality within CZs for housing relate to income. Here we see that the two inequalities are strongly related, and share a relationship of roughly the same magnitude. Column three of Table 5 takes the square root of a regression of the variance of the logs of measure of housing consumption on the variance of logs of household income. This produces estimates of the income elasticity of housing expenditures in the range of 0.7 to 0.9, which are reasonable, if slightly higher than values from temporal variation.

4 Conclusion

Our results provide some refinements to the debate on inequality, particularly in terms of consumption and wealth. The similarity of housing and income inequality over space and time according to plausible income elasticities appears to support those arguing that consumption

[16]This exercise carries several caveats: General equilibrium effects may interact with consumer preferences to either dampen (Matlack and Vigdor (2008)) or amplify (Van Nieuwerburgh and Weill (2010)) the direct effects of changes in incomes. Additionally, since housing is so heterogeneous, it is difficult to quantify how much "housing service" a house of a given size or in a given neighborhood provide.

inequality does reflect income inequality. Additionally, changes in dwelling characteristics and differences between cities explain only a small fraction of recent increases in housing inequality. This suggests that the value of land plays an important role, even within cities.[17]

Several studies — e.g., Green, Malpezzi and Mayo (2005), Gyourko, Saiz and Summers (2008), and Saiz (2010) — have emphasized that regulatory and geographic constraints on housing supply may play an important role in price differences across cities. Our findings suggest constraints may play a role within cities, as new housing in the most desirable neighborhoods may be the most constrained. These may interact with findings by Rossi-Hansberg, PierreDaniel Sarte and Owens (2010), Guerrieri, Hartley and Hurst (2013), and Autor, Palmer and Pathak (2014) on how local externalities that can lead to substantial income sorting within cities. Generally, our findings suggest that researchers would do well to more closely examine differences in land prices across neighborhoods. An interesting research project would be to determine how much they are driven by local externalities, dwelling characteristics, and fixed neighborhood amenities.

The growing inequality in housing prices that we document also indirectly supports findings that wealth inequality has increased. High home-ownership levels do imply that inequality in housing wealth is still smaller than it was in 1930. Nevertheless, the windfall gains from unequal housing price changes, which benefited some homeowners relative to others, may help stir once-popular Georgeist concerns about unequal land-ownership from the beginning of the 20th Century. Moreover, it appears that housing inequality will continue to grow in line with any further increases in income inequality.

[17] Our result also supports findings by Watson (2009) and Reardon and Bischoff (2011) that segregation by income has increased since 1970. This contrasts with findings by Glaeser and Vigdor (2012) and others that black-white segregation peaked in 1970 and has since declined.

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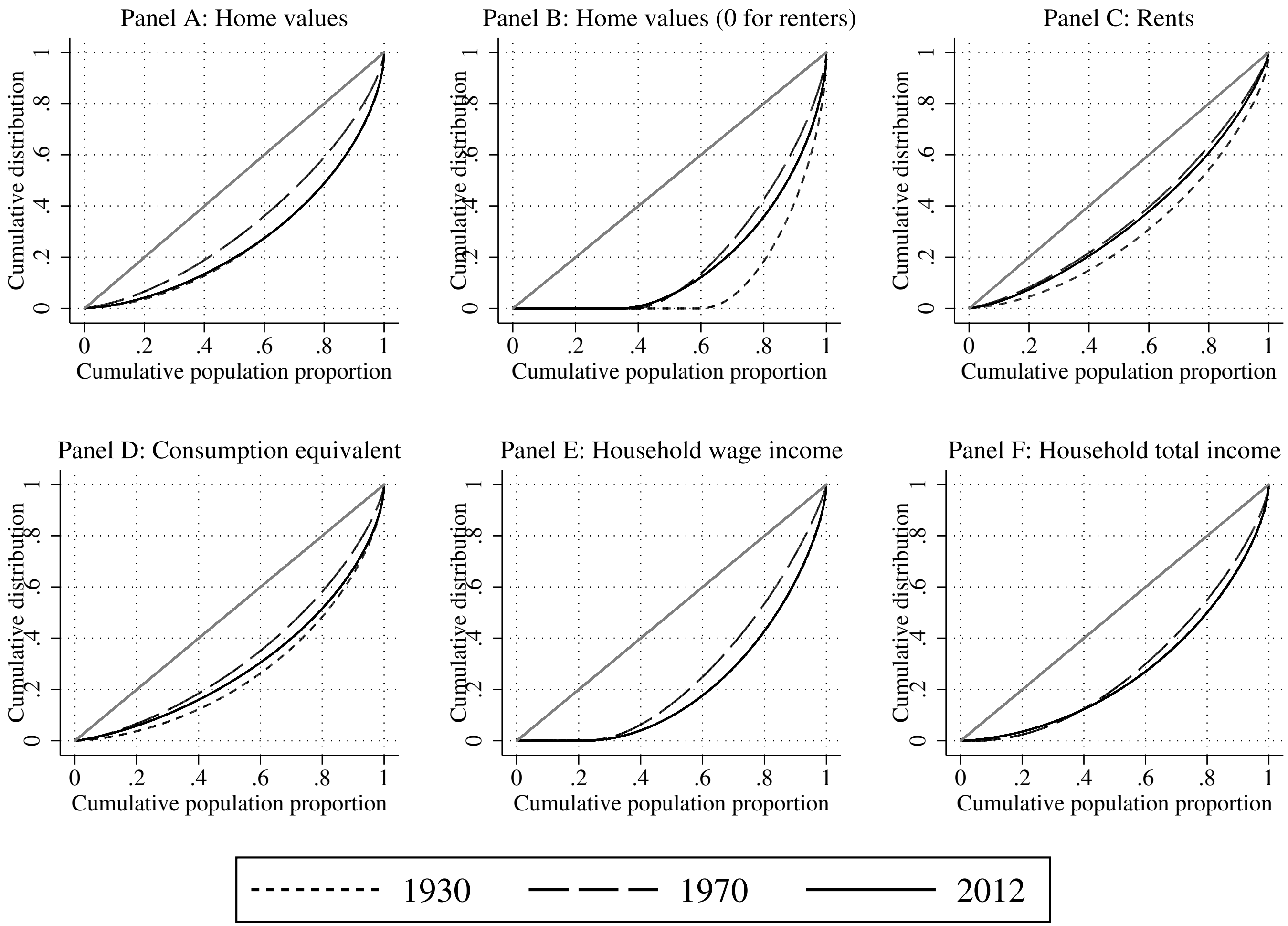
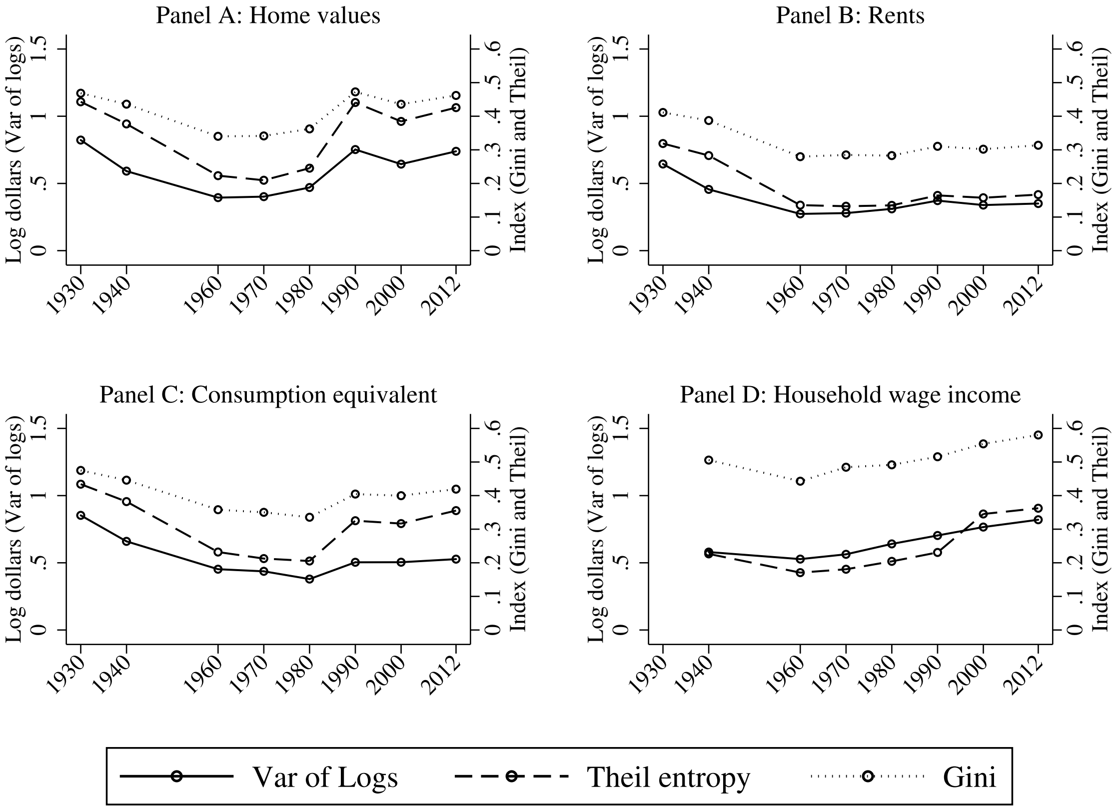
Figures

Figure 1: Lorenz Curves for Home Values, Rents, Housing Consumption, and Household Income



NOTE: These curves graph the cumulative percentage of housing expenditures (from lowest to highest), against the cumulative percentage of households. Panel A, is for owning households; Panel C is for renters. All others are for the sample of home owners and renters combined. Panel B includes renters with an implied home value of zero. Data are interpolated within intervals as described in the text. Data are from the Decennial Census and the 2009-2012 ACS. See the text and data appendix for more detail.

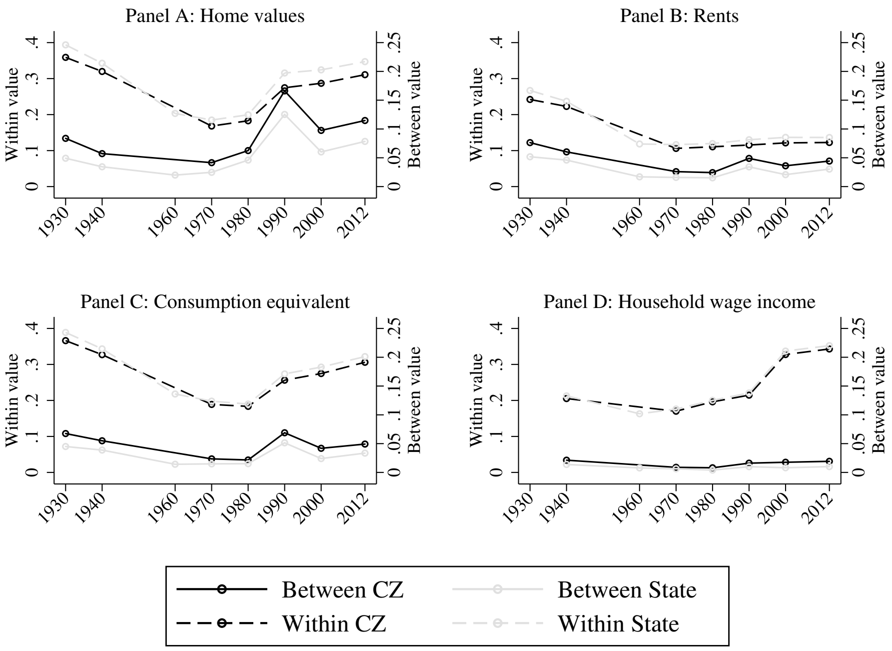
Figure 2: Inequality over Time in Home Values, Rents, Housing Consumption, and Household Income



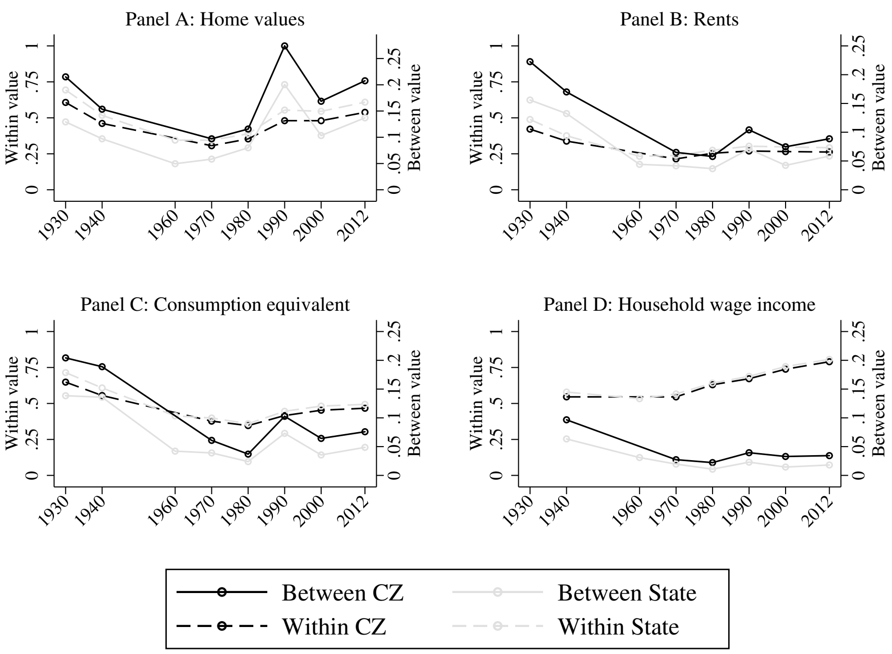
NOTE: Each presents inequality measures for separate samples. The first is for home owners and is the dollar value of their primary residence. The second is for renters and is their cash expenditure per month on rent and utilities. The final combines the two to compute an consumption measure per person, as explained in the text. Farms and houses used for business are excluded. Data are interpolated within intervals. The observation for 2012 comes from ACS for 2009-2012. See text and Data Appendix for more detail.

Figure 3: Decomposition of Values Between and Across Geographies.

Panel A: Theil entropy



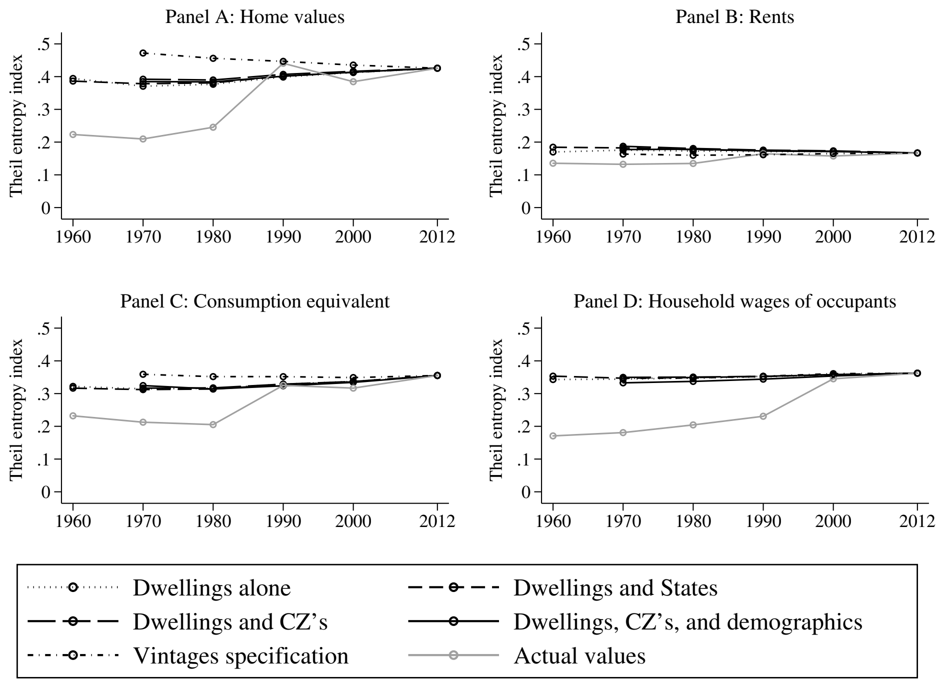
Panel B: Variance of logs



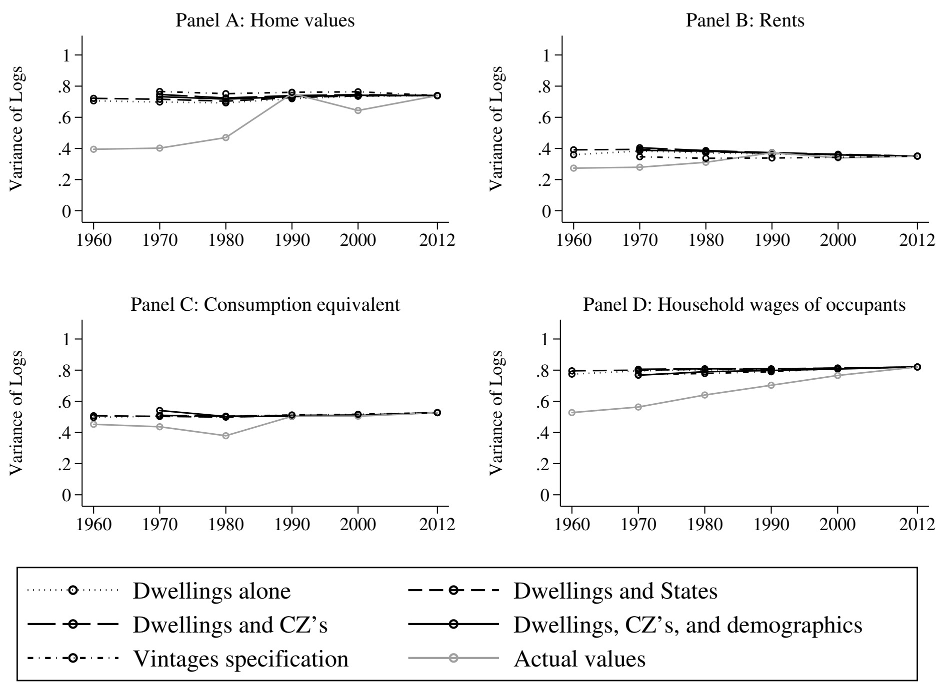
NOTE: Between and within decompositions of housing expenditures are shown for the Theil entropy index and the variance of logarithms. See earlier figure nots for details about the sample.

Figure 4: Explanatory Power of Observable Dwelling, Location, and Demographic Characteristics

Panel A: Theil entropy

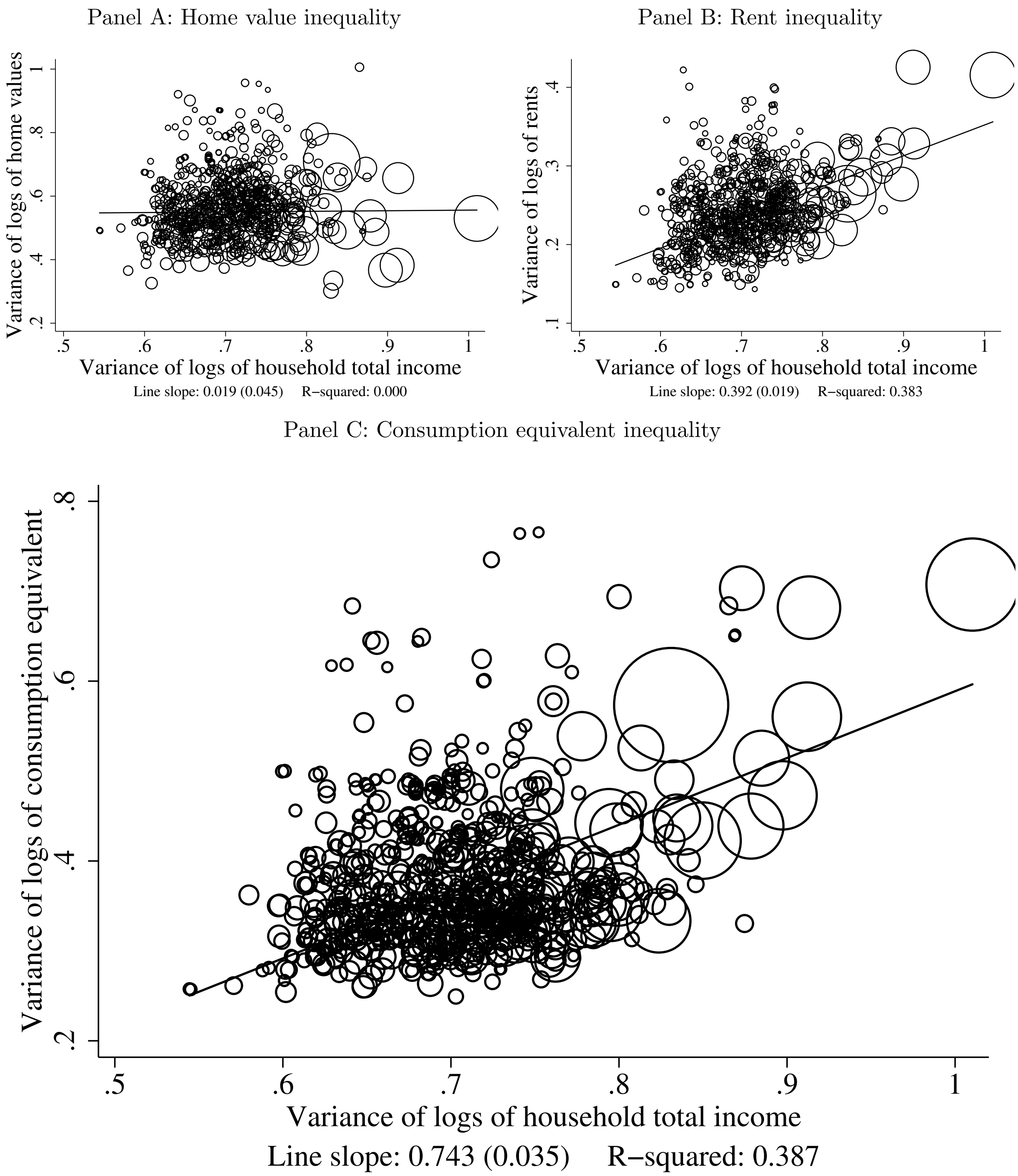


Panel B: Variance of logs



NOTE: Lines in black refer to re-weightings of the 2012 data to be comparable in composition in terms of the observed named variables. The line in grey refers to the actual values in the specified years. See Table 4 for variable descriptions. The solid line contains weights accounting for all of these which were computed as noted in the text, following DiNardo, Fortin and Lemieux (1996) and Fortin, Lemieux and Firpo (2011).

Figure 5: Local Inequality in Housing versus Income



NOTE: These panels display scatter plots for commuting zones with the variance of logs of total income recorded in the 2009-2012 ACS on the x axis and each measure of housing expenditure inequality on the y axis (with zeros excluded). Each variable is computed for its relevant population with the variance of the logs of household total income including both owners and renters in each graph. The size of each circle is proportionate to the number of (weighted) households in each commuting zone. The OLS regression line plotted incorporate these weights.

Tables

Table 1: Descriptive statistics

	1930	1940	1960	1970	1980	1990	2000	2012
Sample size	1,146,534	1,436,399	451,066	2,237,327	3,589,168	4,172,556	4,749,600	4,410,452
Owner occupied	0.45	0.41	0.61	0.62	0.64	0.63	0.65	0.65
Median home value (thous)	53	40	74	83	113	111	130	154
Median monthly rent	312	292	361	433	472	572	609.18	649
Median annual consumption equivalent ($/person)	1,523	1,396	2,955	3,588	4,962	5,465	6,064	6,950
Median annual household wage income (thous)		14	29	35	32	35	37	33
Median annual household total income (thous)		14	34	41	40	46	50	47
Positive wage income		0.79	0.82	0.77	0.79	0.77	0.78	0.76
Household size	3.84	3.44	3.27	3.11	2.75	2.64	2.60	2.54
Number of rooms			4.92	5.09	5.31	5.37	5.45	5.74
Number of bedrooms				2.41	2.48	2.53	2.57	2.71
Plumbing facilities			0.88	0.95	0.99	0.99	0.99	1.00
Midwest	0.32	0.31	0.28	0.27	0.26	0.24	0.24	0.23
South	0.23	0.24	0.28	0.31	0.33	0.35	0.37	0.38
West	0.11	0.13	0.17	0.18	0.19	0.21	0.21	0.22

NOTE: Sample includes renting or home-owning households (when at least one resident is the owner-occupier). Data comes from the Decennial Census and 2009-2012 ACS. Blank cells indicate that the relevant statistic is not available. Values are means, and dollar values area deflated by the CPI excluding structures, unless otherwise specified.

Table 2: Inequality statistics

Home Values	1930	1970	2012
Variance of logs	0.823	0.402	0.739
Theil entropy	0.443	0.210	0.426
Gini coefficient	0.468	0.341	0.462
Ratio of 90 to 10th percentiles	11.159	5.399	9.295
Rent			
Variance of logs	0.645	0.279	0.351
Theil entropy	0.319	0.132	0.167
Gini coefficient	0.411	0.285	0.314
Ratio of 90 to 10th percentiles	8.066	3.989	4.619
Consumption equivalent			
Variance of logs	0.853	0.437	0.527
Theil entropy	0.434	0.213	0.355
Gini coefficient	0.475	0.350	0.419
Ratio of 90 to 10th percentiles	10.790	5.283	6.146
Household wage income	1940	1970	2012
Variance of logs	0.580	0.563	0.820
Theil entropy	0.227	0.181	0.362
Gini coefficient	0.506	0.484	0.580
Ratio of 90 to 10th percentiles			

NOTE: Home values refer to owner-occupied homes. Rents are gross and include the cost of utilities. Both are self reported. Consumption equivalents combine gross rents with imputed rents based on a percentage of the home value plus utility costs, divided by the equivalence scale $1 + 0.7(A - 1) + 0.5C$ where A is the number of adults and C is the number of children under 14. Household wage income refers is the sum of wages and salaries from all household members. Values are interpolated within intervals using standard procedures described in the text.

Table 3: Between-Within decomposition

Panel A: Home Values

	1930	1970	2012
Variance Overall	0.823	0.403	0.746
Variance Between	0.215	0.097	0.208
Variance Within	0.607	0.306	0.538
Theil Overall	0.443	0.210	0.426
Theil Between	0.084	0.042	0.115
Theil Within	0.359	0.168	0.311

Panel B: Rents

	1930	1970	2012
Variance Overall	0.645	0.280	0.351
Variance Between	0.223	0.065	0.089
Variance Within	0.422	0.215	0.262
Theil Overall	0.318	0.132	0.167
Theil Between	0.076	0.026	0.044
Theil Within	0.242	0.106	0.122

Panel C: Consumption equivalents

	1930	1970	2012
Variance Overall	0.853	0.438	0.543
Variance Between	0.204	0.061	0.076
Variance Within	0.648	0.377	0.467
Theil Overall	0.434	0.213	0.355
Theil Between	0.068	0.024	0.049
Theil Within	0.366	0.189	0.306

Panel D: Household wage income

	1940	1970	2012
Variance Overall	0.643	0.586	0.825
Variance Between	0.097	0.027	0.034
Variance Within	0.546	0.546	0.790
Theil Overall	0.227	0.179	0.362
Theil Between	0.021	0.009	0.019
Theil Within	0.205	0.170	0.343

NOTE: Between and within decompositions refer to the decomposition of each statistics to variation within states or commuting zones (CZs) versus between them. The sum corresponds to values in table 2.

Table 4: Re-weighting

Panel A: Theil entropy

	Consumption equiv	Rents	Home values	HH wages
2012	0.355	0.167	0.426	0.362
Dwellings	0.315	0.176	0.371	0.344
Dwellings and state	0.312	0.182	0.378	0.347
Dwellings and CZ	0.317	0.187	0.392	0.350
Dwellings, CZ, and demographics	0.325	0.177	0.385	0.333
1970	0.213	0.132	0.210	0.181

Panel B: Variance of logs

	Consumption equiv	Rents	Home values	HH wages
2012	0.527	0.351	0.739	0.820
Dwellings	0.505	0.383	0.698	0.796
Dwellings and state	0.503	0.394	0.716	0.800
Dwellings and CZ	0.510	0.404	0.746	0.806
Dwellings, CZ, and demographics	0.541	0.388	0.733	0.768
1970	0.437	0.279	0.402	0.563

NOTE: Statistics are taken of 2012 data, re-weighted to emulate the distribution of observable dwelling and location characteristics of previous years. The top and bottom row refers to the actual values in the specified years. Dwellings refers to: Indicators for the number of rooms, bedrooms, the decade of construction, plumbing facilities, and the heating system type. States and CZs include indicators for the geographic entities, and demographics is the interactions of the household type (single, a couple, a single parent, or non-related individuals) with indicators for the number of children and adults (separately). The solid line contains weights accounting for all of these which were computed as noted in the text, following DiNardo, Fortin and Lemieux (1996) and Fortin, Lemieux and Firpo (2011).

Table 5: Implied relationships with income inequality

	Home values	Rents	Consumption equivalent
1970	0.720	0.629	0.755
	(0.133)	(0.048)	(0.054)
1980	0.764	0.690	0.715
	(0.157)	(0.072)	(0.039)
1990	0.365	0.654	0.782
	(0.167)	(0.031)	(0.128)
2000	0.444	0.620	0.789
	(0.124)	(0.037)	(0.074)
2012	0.138	0.626	0.862
	(0.568)	(0.057)	(0.094)

NOTE: Each coefficient is the (re-signed) square root of the absolute value of the regression coefficient relating the variance of the log of household wage income within each CZ with the variance of the log of the variable within each CZ. Standard errors clustered by the state the plurality of the CZ's population lives in are in parenthesis. The unit of observation for each regression is a CZ year and each coefficients is from a different regression. Each is computed using the relevant sample for that variable while income inequality is computed using the universe of all home owners and renters. The third column represents an estimate of the income elasticity of demand for housing services. See tables 1 and 2 and figure 5 for more detail.

Appendix - For Online Publication

A Data appendix

A.1 Integrated Public Use Microdata Series samples

Our Census data are provided by the Integrated Public Use Microdata Series, from usa.ipums.org detailed in Ruggles et al. (2010). For each year we use the following samples.

- 1930: 5 percent sample
- 1940: 1 percent sample
- 1960: 1 percent
- 1970: 1 percent state and metro (depending on state or commuting zone) and format 1 or 2 (depending on the questions needed).
- 1980: 5 percent state sample
- 1990: 5 percent sample
- 2000: 5 percent sample
- 2009-12 ACS five year 2012 sample with interviews in 2008 dropped

A.2 Sample restrictions

As mentioned in the main text, we include households in the United States with three restrictions: We omit houses outside the continental US, we exclude houses used to generate revenue, and we similarly exclude owner occupied multiple family residences. Appendix table A.1 shows the percentage of houses we exclude for each year due to being used to generate revenue or encompassing multiple units. We present these separately for both owners and renters.

The first row for each panel shows the number of houses in the continental US that are included in our sample. this is quite high for each year, and in later years it is over 90 percent. The next few rows show reasons why houses are excluded. By far the most important reason is because they are farms. For example, in 1930 25 percent of households lived on a farm. Multiple family houses and houses used for commercial purposes are also excluded in our analysis for the years where the census identifies them. In 1960, the first year we can identify them, these housing categories made up roughly 6 percent of owner occupied housing.

The final few rows show categories of houses that were excluded from questions in some years. From 1960-1980 mobile homes and trailers were excluded and in 1970 condos were as well. In other years they are included. These categories, again, make up a small proportion of housing units in these years, They never reach six percent, and often are well below that mark.

Table A.1: Exclusions imposed in sample selection

Panel A: Home owners

	1930	1940	1960	1970	1980	1990	2000	2012
Included	0.748	0.758	0.843	0.873	0.881	0.910	0.900	0.922
Farm	0.252	0.242	0.093	0.051	0.029	0.023	0.019	0.017
Commercial use			0.013	0.010	0.015	0.020	0.033	0.015
Multiple families			0.051	0.065	0.075	0.047	0.048	0.046
Mobile home or similar			0.015	0.038	0.055	0.082	0.083	0.067
Condominium				0.002	0.007	0.015	0.018	0.032
Sample size	516,941	585,459	275,602	1,388,542	2,292,767	2,826,214	3,244,508	3,128,981

Panel B: Renters

	1930	1940	1960	1970	1980	1990	2000	2012
Included	0.798	0.837	0.977	0.986	0.988	0.989	0.986	0.993
Farm	0.202	0.163	0.023	0.008	0.005	0.004	0.003	0.002
Commercial use				0.007	0.007	0.007	0.011	0.005
Mobile home or similar			0.003	0.011	0.023	0.050	0.046	0.044
Condominium					0.017	0.045		
Sample size	629,593	850,940	175,464	848,785	1,296,401	1,346,603	1,505,211	1,281,471

NOTE: The gives the (unweighted) numbers of houses falling into categories that either merit exclusion or fall out of the universe of houses we have data for in some years. Farms, units used for commercial purposes, and multiple family owner occupied structures are excluded from our statistics. Mobile homes (as well as tents, vans, trailers, and boats) and condominiums are not asked about in certain years, so they are absent in those years but included when they are asked about.

A.3 Questionnaires

Relevant enumerator instructions for 1940:

Figure A.1: Enumerator instructions for 1940

431. ***Column 5. Value of Home, if Owned, or Monthly Rental, if Rented.***—If the home is owned, as indicated by the entry "O" in col. 4, enter in col. 5, on the line for the head of the household, the current market value of the home, as nearly as it can be ascertained. Unless the home has been recently purchased, it will be necessary to estimate its value. The estimate should represent the amount for which the home, including (except on a farm) such land as belongs to it, would sell under ordinary conditions—not at forced sale. The assessor's valuation, on which taxation is based, is usually not a safe guide.

432. Where a person owns a house with living accommodations for more than one household and his household occupies only a portion of the house, as where the owner of a two-family house rents part to another household, estimate the value of the portion of the house occupied by the owner's household (which for a two-family house may be about one-half of the total value), and enter this amount in col. 5 for the owner's household. The entry in col. 5 for the household or households renting a portion of the structure will be the amount paid in monthly rental. Where any considerable portion of the house is used for business purposes, such as a store, deduct the value of this portion—except that the value of one or two rooms used as an office by a dentist, lawyer, or contractor, etc., need not be deducted.

433. For the home of a farm operator who owns, and lives on, his farm (or who owns that part of the farm on which the dwelling stands), obtain an estimate of the value of the dwelling in which he lives, *excluding the land on which it is built.* (This figure should represent a reasonable fraction of the value of all farm buildings reported on the Farm schedule.)

434. Make it clear to your informant that the values returned on the census schedule are not to be used in any way in connection with taxation and are not open to public inspection.

435. If the home or dwelling unit is rented, as indicated by "R" in col. 4, enter in col. 5 to the nearest dollar the actual amount paid each month as rent, or enter one-twelfth of the annual rental, in case payment is not made monthly. *Do not enter fractions of a dollar.*

436. If no money rent is paid, as where a workman receives the use of a house as part of his wages, enter in col. 5 the estimated monthly rental value based on the monthly rental paid for similar dwelling units in the neighborhood.

437. In the case of a tenant farm operator, that is, one who pays rent in some form for the farm, including his dwelling (rather than for the dwelling alone), estimate the monthly rental value of the dwelling in which he lives. This estimate should be based, if possible, on the rent actually paid for similar dwellings nearby, making allowance for the fact that rents are usually lower in the open country than in town.

438. If there is no other basis for estimating the rental value of the home of a farm tenant (or in some instances a nonfarm tenant), you may consider that 1 percent of the total value of the dwelling is a fair monthly rental. For example, if $1,000 seems to be a reasonable estimate of the total value of the dwelling, enter $10 as the monthly rental value.

439. Whenever the value reported to you for a dwelling seems a great deal higher or lower than the value for similar structures in the same neighborhood, question your informant further to make sure that he has properly understood the question and that the value is the current market value of the living quarters.

B Pareto Interpolation and Extrapolation

Table A.2: House value interval boundaries over time

Year	Intervals
1960	10
1970	11
1980	24
1990	25
2000	24

NOTE: The gives the numbers of intervals for each year the census data are intervalled.

We use a pareto distribution to interpolate values both in years where data are intervalled and where they are continuous. Where data are intervalled, we interpolate within the specified intervals. Where data are continuous, we divide the data into equally size intervals. We start with 25, but decrease the number until each interval has a reasonable "width," or distance form its minimum to maximum value.[18]

[18]The precise definition is that the procedure will decrease the number of intervals until each interval has a max value that is 1.01 times its min value or greater. We do this because the procedure fails for intervals that are excessively "narrow" as sometimes occurs where respondents round values.

The pareto distribution's cumulative distriubtuion function (CDF) has the from $F(y) = 1-(k/y)^{\alpha}$ for $y \geq k$. It follows that the logarithm of the complementary CDF (or "tail" function) has a slope of $-\alpha$ with respect to $\ln(y)$. The greater the slope α, the faster observations "die off," and the less disperse the distribution. For any value y_i, define

$$p_i \equiv ln[1 - F(y)] = \alpha \ln(k) - \alpha \ln(y) \tag{A.1}$$

The interpolation method (Pareto (1896)) estimates α by differencing expression A.1 at the values for the two endpoints of a bracket $[y_i, y_{i+1}]$, where $i = 1, ..., I$ indexes the intervals, namely

$$\hat{\alpha}_i = \frac{\ln(y_{i+1}) - \ln(y_i)}{p_i - p_{i+1}}, i = 1, ..., I - 1, \tag{A.2}$$

and $\hat{k}_i = y_i p_i^{1/\alpha}$. Even when the distribution may not be considered Pareto globally, this procedure fits a simple line segment to the log survivor function in terms of $\ln(y)$.

Since the Pareto distribution is unbounded, determining a value of α beyond the top code, y_I in the data can be difficult. This problem is largely remedied if the mean is available, as it is for housing values in 1930, 1940, and 2012. There, the property that the mean value of $\bar{y}_I \equiv E[y|y \geq y_I] = \alpha y_I/(\alpha - 1)$, imples a value of

$$\hat{\alpha}_I = \frac{\bar{y}_I}{\bar{y}_I - y_I} \tag{A.3}$$

In other situations it is impossible to obtain a mean above a given cutoff. In these cases we infer a value of α by taking the average of values from the linear interpolation method (A.2) for the top 10 percent of the distribution that do not correspond to the top interval.[19]For rent values in 1930 and 1940, we code the top pareto parameter to be 2.5, which roughly corresponds to this.

For the bottom-most interval we employ a simple strategy of imposing a uniform distribution so our choices impact our results as minimally as possible. To do this we need to establish a minimum possible value for the variable we are concerned with. The bottom value is determined to be, for rents, 0.03 percent of average household incomes per year (corresponding to a household that makes 10 percent of the average household income and spends 1/3 of it on rent). For home values it is the same value, but divided by 0.0785, which is the rent to value ratio we use to convert housing values into user costs of housing. For household incomes it is the 0.1 times average household income in that year. Average (national) household incomes for this purpose across the many years in our sample come from Chao and Utgoff (2006). How we treat bottom values matters little except for in the variance of logarithms, which has undesirable properties at the bottom of the distribution (for instance, it cannot account for zero values).

Figure A.2 shows several illustrations of our imputation procedure for different types of situations. We plot both the CDF and the tail function, which is linear in the pareto distribution. The second plot is especially relevant for determining the fit in the very top of the distribution.

Panel A of Figure A.2 shows both the empirical cumulative density function for home prices in 2012 and the pareto CDF used in the paper. Note that this is a year where respondents reported a continuous quantity, though the distribution plot shows that many did round. The dashed lines show intervals in each bin used for rounding. As in other years, we divided the data into 25 bins to perform the CDF interpolation. The dashed lines show the min and max proportions for each bin, as well as its placement along the scale.

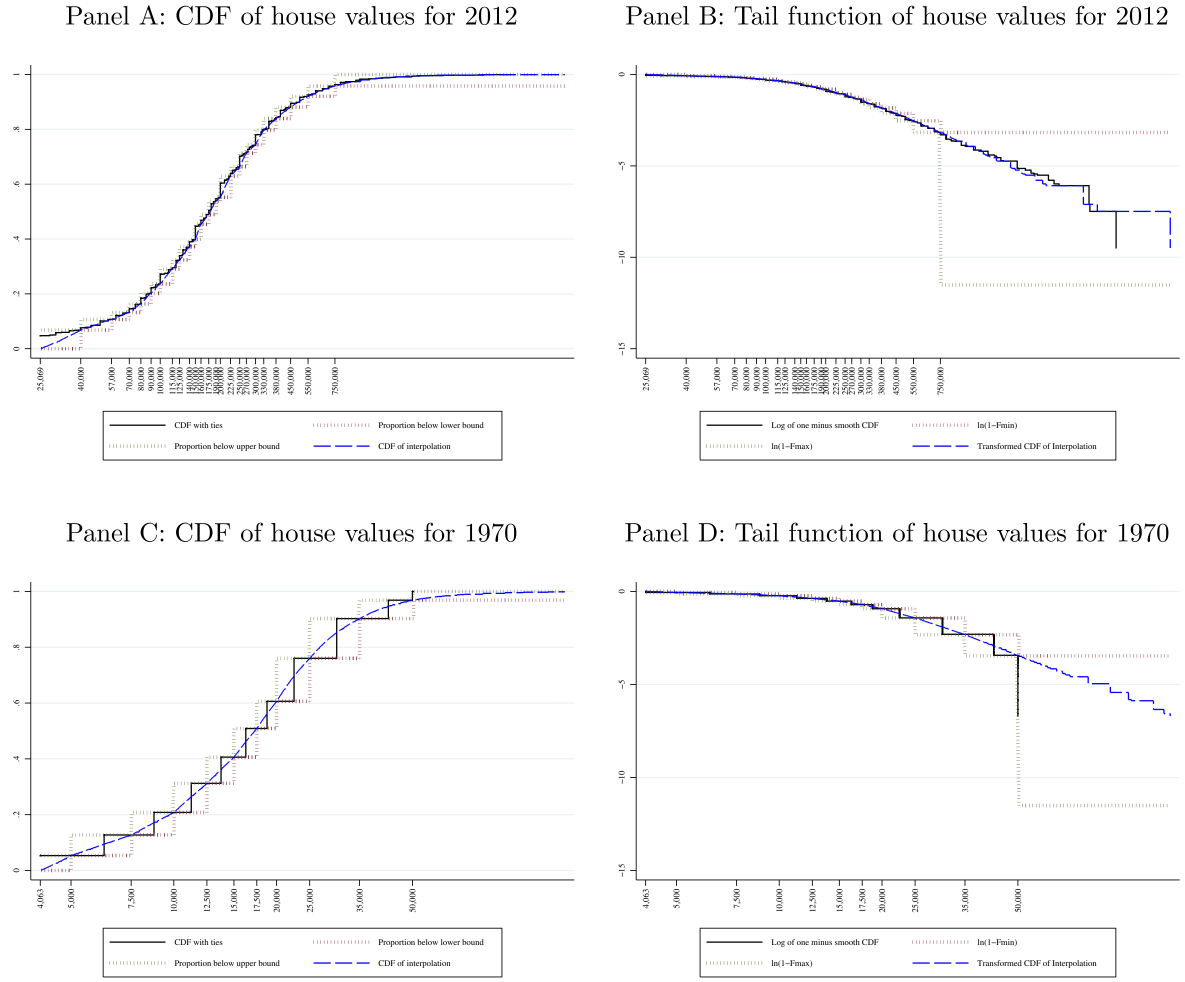
Figure Panel B, which shows a plot of the tail function, which shows how the Pareto distri-

[19]In the extremely rare case where all values in the top 10 percent are in the top bin, we check the top 11, 12, 13, etc. percent, stopping at the first percentile where an estimate exists.

bution matches the top of the distribution. Overall the fit is quite good, with the line tracking the distribution until it encounters the state by year topcodes for the top 0.5 percent of the distribution.

Similarly Panel C and Panel D show the same for the 1970 distribution where the variable is divided into 11 intervals. Here the distribution meets the interval boundaries exactly and the interpolation simply smooths the area between them. The top code extrapolation has the same slope as the one for 2012, but this slope matches the slope of the previous interval rather well, implying the extrapolation is reasonable for this year as well.

Figure A.2: Example CDF plots for the pareto interpolation



NOTE: The term "tail function" corresponds to the logarithm of one minus the the CDF.

C Geographic Assignment

We keep a consistent geographic sample across all years in the sample by primarily using 1990 local labor markets, or commuting zones, as described by Tolbert and Sizer (1996). Local labor markets are a natural geography for this analysis since housing values are closely related to local income levels. For 1970-2011 we match geographically using the probabilistic mapping made available by David Dorn via his website and used in, for example, Dorn (2009). For 2012 we replicate the probabalistis matching using updated PUMA definitions for the 2012 census and for 1930 and 1940 we use the direct county to commuting zone mapping in Tolbert and Sizer

(1996) since counties are available. Unfortunately it is not possible to match to commuing zones in for 1960 based on the publicly available samples, so we instead use states as our geographic entity where we use data from 1960 (this is generally marked in each table).

This mapping uses the most disaggregated geography available in each census to project this geography onto counties and then project these counties onto commuting zones. Unfortunately, the PUMAS and county groups available often contain multiple counties and these counties sometimes fall into separate commuting zones. In these cases we compute a probability that a given person resides in one commuting zone based on the proportion of people in her identified geography that in fact live in the given commuting zone based on non-restricted census summary tables. Where these probabilistic matches occur, we create multiple observations – one for each possible commuting zone – and weight them by the probability the original observation is in that commuting zone, times their initial weight if applicable. Samples for 1930 and 1940 contain county information so the match is exact and we avoid the first projection.

D Deflating

Since the inequality measures we use are scale invariant, deflating is generally unimportant. We deflate values using the Consumer Price Index excluding structures published by the BLS, from the Federal Reserve Bank of St.Louis' FRED system. The series mnemonic is: `CUUR0000SA0L2`. Before 1935, when structures were not identified separately, we combine the data series from the general CPI (`CPIAUCNS`) and the CPI for rent of primary residence (`CUUR0000SEHA`) by using an OLS regression to predict the shelters excluded series for the years it is available prior to 1941 based on the general CPI and the CPI for rent of primary residence. This regression has good out of sample prediction powers for years up to 1960, so we believe it is a reasonable approximation for the initial five years.

E Re-weighting decomposition specifics

Formally, using notation similar to Fortin, Lemieux and Firpo (2011), we have two groups of houses, one group of houses observed in t and another in t'. We have prices for each group and some houses may appear in both groups. We want to compute a statistic, $\nu(\mathcal{P})$, that is a function of a distribution of house prices, $\mathcal{P} \to \mathbb{R}$. With the above caveats in mind, we denote the distribution $\mathcal{P}_{t,t'}$ where the first subscript refers to the year we would like to apply prices from and the second year is the year we would like to match in terms of observables. So we re-weight observed houses in t so that they corresponded to the distribution of characteristics of houses in t'. Note that in this notation $\mathcal{P}_{t,t}$ is simply the distribution of houses in period t. Putting this together, we are seeking to recover:

$$\nu\left(\mathcal{P}_{t,t'}\right) \tag{A.4}$$

Conditional independence, or ignorability, in this context means that once we condition on all observable characteristics (S and L), the unobservable characteristics (ϵ) are independent of whether we observe the house in t or t'. Here this would imply that once we take into account each observable detail about the house there is no special trait which we omitted that differs systematically between t and t'.

To actually estimate $\nu\left(\mathcal{P}_{t,t'}\right)$, we compute re weighting factors following DiNardo, Fortin and Lemieux (1996) which Hirano, Imbens and Ridder (2003) and Firpo (2007) formally establish are efficient. $\Phi(S, L)$ with the following form:

$$\Phi(S,L) = \frac{\Pr(\tau = t'|S,L)/\Pr(\tau = t')}{\Pr(\tau = t|S,L)/\Pr(\tau = t)} \tag{A.5}$$

Where τ represents the year the house was observed in (either t' or t). The intuition is that we would like to heavily weight the observations from year t that look very much like the observations in year t'. We do this by using the odds that an observation came from t' given its observables.

We compute the probabilities using logit regressions that pool houses observed in both t and t'. By regressing a dummy indicator of a house being observed in t' on a flexible functional form of S and L In this context we mostly use dummy variables for different categories. we are able to compute predicted probabilities $\hat{\Pr}(\tau = t'|S, L)$ and $\hat{\Pr}(\tau = t|S, L)$. To compute $\hat{\Pr}(\tau = t')$ and $\hat{\Pr}(\tau = t)$ we simply use the sample proportions (appropriately weighted). Applying equation A.5 then gives a value of $\hat{\Phi}(S, L)$ that we use to re-weight each statistic.

We then multiply $\hat{\Phi}(S, L)$ by the weights already applied to the houses observed in t to simulate the density that would exist under the counter-factual that houses had identical characteristics to houses in t' but were priced in terms of the prices that prevailed in t.