Homeownership, Polarization, and Inequality*

Andrii Parkhomenko†

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Abstract

The rise of income inequality and job polarization have been more pronounced in large U.S. cities. I offer a new explanation: when price-rent and price-wage ratios grow faster in large cities, middle-income households increasingly cannot afford to own a house there. They move to smaller cities and the middle of the income distribution in large cities hollows out, making them more polarized and unequal. I document that (1) commuting zones with higher price growth experienced larger polarization and increase in inequality since 1980 and (2) middle-income households migrate more often to cheaper states for housing-related reasons than low- or high-income households. Using a quantitative spatial equilibrium model with tenure choice and skill heterogeneity, I find that disproportionate growth of prices relative to incomes and rents in large cities accounts for about one-half of the gap in inequality growth and polarization between large and small cities.

Key Words: homeownership, job polarization, income inequality, house prices, spatial equilibrium

JEL Classification: J24, J31, R21, R23, R31

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†University of Southern California, Marshall School of Business, Department of Finance and Business Economics; Los Angeles, CA 90089. Email: parkhomenko.andrii@gmail.com

1 Introduction

Since the 1980s, the labor market in the United States has become more unequal and polarized. Individual differences in labor earnings have widened, while the shares of low- and high-income jobs have increased at the expense of middle-income jobs. Moreover, this labor market polarization and increase in income inequality have been more pronounced in large cities (Baum-Snow and Pavan, 2013; Autor, 2019). Most previous work on the topic emphasized the role of technology and offered explanations that rely on skill-biased technical change (Baum-Snow, Freedman, and Pavan, 2018; Cerina, Dienesch, Moro, and Rendall, 2022) or external labor demand shocks (Davis, Mengus, and Michalski, 2020). A central feature of this literature is that large cities have become increasingly more attractive for workers with high skills compared to those with lower skills.

In this paper, I propose a novel explanation for the disproportionate rise in income inequality and employment polarization in large cities. It emphasizes the role of the housing market and, unlike the previous literature, does not rely on features of the production function. Since 1980 large cities have experienced faster growth in house prices, both in absolute terms and relative to wages and rents. I argue that rapid price growth has made homeownership out of reach of more and more middle-income households. These households have increasingly chosen smaller and more affordable cities where they could buy a house. At the same time, low-income households who struggle to buy even in affordable cities and high-income households who can buy even in expensive cities were not affected as much as the middle class. This hollowed out the middle of the income distribution of big cities, making them more polarized and unequal.

This mechanism is supported by empirical evidence. I document that the decline in middle-income employment shares was more pronounced in commuting zones (CZ) where prices, price-wage, and price-rent ratios rose faster between 1980 and 2019. I also find that such cities saw higher increases in wage inequality. These results do not merely pick up the fact that prices grew more in large cities and hold even after controlling for the CZ population in 1980. In addition, I find that greater polarization and higher inequality growth in big cities can be attributed to out-migration of middle-income households. Using interstate migration data, I show that a doubling of house prices, price-rent, or price-wage ratios in the state of origin relative to the state of destination raises the probability that a middle-income household migrates for housing-related reasons by 50–80% relative to the probability that a low- or high-income household makes the same move.

Next, I show that a standard static spatial equilibrium model with two extensions–skill heterogeneity and tenure choice–can account for the empirical evidence outlined above. In the model, households are heterogeneous in their skill level which determines their income. They choose consumption of a traded good and housing, and also decide in which city to live (*location choice*) and whether to own or rent housing (*tenure choice*). Buying a house has financial advantages but is subject to minimum-size and payment-to-income constraints. As a result, only households with sufficiently high income can own a house. The relationship between location and tenure choices leads to a peculiar sorting pattern of households across cities. The income of low-skilled households is insufficient to buy a house even in cities with low prices. The high-skilled can afford to buy a house in all cities, even the most expensive ones. Thus, location and tenure choices of these two skill groups are independent. It is the middle-skilled households who can buy a house in a city with low prices but cannot do so in a more expensive one. As a result, location and tenure choices of the middle-skilled depend on each other. Subsequently, many middle-skilled households choose to settle in cities where house prices are lower relative to wages or rents. This empties out the middle of the income distribution in expensive cities leading to greater local labor market polarization and higher income inequality. Thus, larger polarization and inequality in locations with high price-wage and price-rent ratios is an equilibrium outcome of the model.

Housing is supplied by developers who either sell it to homeowners or lease it to renters. Local prices and rents depend on the productivity of developers and the purchasing power of households. While prices and rents are endogenous, I do not model expectations of future rent growth and, therefore, local price-rent ratios are exogenous.

To understand the role of housing markets and tenure choice in shaping differences in polarization and inequality between large and small cities, I build a quantitative version of the model for years 1980, 2000, and 2019. The model has two locations that represent large and small CZs. In the model, large CZs experienced faster growth in house prices as a result of a lower construction productivity growth and higher labor productivity growth. The growth of labor productivity in large CZs occured primarily at the top of the skill distribution, which represents skill-biased technical change (SBTC).

Then I run two counterfactual experiments. In the first counterfactual, I fix parameters that govern local returns to skills at the level of 1980, thereby shutting down SBTC. In this experiment, there are almost no differences in the evolution of polarization and inequality between large and small CZs since 1980. This aligns with the results in the earlier literature that finds that SBTC can account for most of the disproportionate polarization and the rise of inequality in big cities. The second counterfactual allows for SBTC but equalizes changes in price-rent and price-wage ratios for large and small CZs between 1980 and 2019. When disproportionate price growth in large CZs is shut down, the excess polarization in big cities falls by 54% and the excess rise of inequality falls by 43%. In other words, even if SBTC is a major driver of disproportionate polarization and inequality in big cities, its effect is significantly *amplified* by declining housing affordability in these cities and would be about one-half smaller if price-wage and price-rent ratios did not grow faster in large cities. The largest losers from rising price-rent and price-wage ratios in big CZs are middle-skilled workers who either lost the opportunity to own a home or moved to less productive CZs in order to buy a house.

Why should we be concerned about polarization and inequality *within* cities? First, understanding these phenomena at the local level may help our understanding of the mechanisms that are responsible for polarization and inequality at the aggregate level. Second, skill mix at the city level matters for its productivity. Rossi-Hansberg, Sarte, and Schwartzman (2019) and Fajgelbaum and Gaubert (2020) show that local productivity spillovers depend on the skill mix and may produce inefficient skill sorting across cities. In turn, the distribution of productivity levels across cities determines aggregate productivity (Hsieh and Moretti, 2019). Third, greater job polarization in large cities implies that some essential middle-income workers, such as teachers, may be undersupplied (Florida, 2017). Finally, local polarization and inequality may determine other important outcomes. For instance, Glaeser, Resseger, and Tobio (2009) show that more unequal cities have higher crime rates and lower self-reported happiness.

Three recent studies are most related to this paper. Baum-Snow, Freedman, and Pavan (2018) build a model where local productivity depends on skill-specific agglomeration externalities. They find that the increase in the bias of agglomeration economies toward high-skilled workers (i.e., SBTC) accounts for about 80% of the disproportionate increase in wage inequality in large cities between 1980 and 2007. Cerina, Dienesch, Moro, and Rendall (2022) construct a spatial equilibrium model where workers differ by skill. The simultaneous increase in low and high-skilled employment in a given location is driven by complementarity of low- and high-skilled workers in job tasks, based on the evidence from Eeckhout, Pinheiro, and Schmidheiny (2014), as well as consumption complementarities that link the income of the high-skilled with the demand for services performed by the low-skilled. They find that SBTC accounts for 67% of observed disproportionate polarization in big cities. I also find that SBTC generates large differences in polarization and the rise in inequality between big and small cities, but argue that its effect would be much smaller without the larger growth in price-rent and price-wage ratios in big CZs. Finally, Davis, Mengus, and Michalski (2020) develop a framework that simultaneously produces higher labor market polarization and greater skill concentration in large cities in response to an external labor demand shock, without relying on SBTC.

The paper is also highly related to the work on increasing spatial dispersion of house prices, rents, and price-rent ratios (Van Nieuwerburgh and Weill, 2010; Gyourko, Mayer, and Sinai, 2013; Howard and Liebersohn, 2022). This strand of literature argues that some locations experienced faster growth in housing costs as a result of a combination of inelastic supply and extra demand, where the latter comes primarily from high-income workers. While this mechanism is present in my model, I argue that, when combined with tenure choice, it can also explain high inequality and polarization *within* large cities.

Besides, this study is connected to the broader work on polarization (Autor and Dorn, 2013; Goos, Manning, and Salomons, 2014) and rising inequality (Katz and Murphy, 1992; Piketty and Saez, 2003) at the national level. This paper also contributes to the literature on the spatial divergence in economic outcomes–termed by Moretti (2012) as the "Great Divergence"–that studies how and why in recent decades the U.S. has seen increasing local differences in productivity and wages (Moretti, 2011; Giannone, 2019; Gaubert, Kline, Vergara, and Yagan, 2021) and college shares (Costa and Kahn, 2000; Berry and Glaeser, 2005; Diamond, 2016). In addition, this paper is related to the literature that studies sorting of workers into large cities (Behrens, Duranton, and Robert-Nicoud, 2014; De la Roca and Puga, 2017). This paper also adds to the body of work that studies causes and consequences of rising income inequality within cities (Glaeser, Resseger, and Tobio, 2009; Baum-Snow and Pavan, 2013; Truffa, 2017; Baum-Snow, Freedman, and Pavan, 2018; Couture, Gaubert, Handbury, and Hurst, 2020). Moreover, it contributes to the literature on how differences in local housing markets affect the distribution of labor across space (Ganong and Shoag, 2017; Herkenhoff, Ohanian, and Prescott, 2018; Hsieh and Moretti, 2019; Parkhomenko, 2020). Finally, it adds to the small but growing number of quantitative studies that incorporate housing tenure choice into a spatial equilibrium framework (Giannone, Li, Paixao, and Pang, 2020; Mabille, 2021; Favilukis, Mabille, and Van Nieuwerburgh, 2022).

The paper is organized as follows: Section 2 presents empirical evidence on housing price growth, job polarization, and income inequality. Section 3 describes the theoretical framework and explains the mechanism that relates house price growth to local job polarization and income inequality. Section 4 builds a quantitative version of the model. Section 5 presents counterfactual experiments that evaluate the impact of rising price-wage and price-rent ratios on polarization and inequality in large cities. Section 6 concludes.

2 Empirical Evidence

This section documents empirical relationships between the growth in housing prices, job polarization, and income inequality. I look at three measures of housing prices:

(1) price index, (2) price-rent ratio, and (3) price-wage ratio. First, however, I revisit the evidence documented before and confirm that larger commuting zones (CZs) experienced greater job polarization, higher increase in income inequality, and also faster housing price growth. Then I show that CZs where prices advanced faster since 1980 also saw a greater increase in polarization and inequality. Finally, I provide evidence for a migration mechanism that links housing price growth to polarization and the increase in inequality.

2.1 Data

I perform empirical analysis at the level of commuting zones (CZs) or states. I focus on 465 larger CZs that have sufficient number of individual observations to build measures of polarization, inequality, wages, house prices, and rents. Appendix Section B.1 provides more details.

To study changes in housing costs, I compute hedonic price and rent indices using the Census and the American Community Survey (ACS) data, as well as mean annual wages for each CZ and year, and then construct three measures of house prices: prices, price-wage ratios, and price-rent ratios. Appendix Sections B.2 and B.3 discuss the details.

To measure polarization, I follow the methodology of Autor and Dorn (2013) and assign 3-digit occupations into income percentiles in 1980. I label occupations in the 1st–20th income percentile as "low-skilled," those in the 21th–80th percentile as "middle-skilled," and those in the 81st–100th percentile as "high-skilled." Then, using a consistent definition of occupations and keeping the assignment of each occupation into skill group constant over time, I compute the shares of each group for each CZ in years 1980 and 2019.[1] Finally, I calculate the difference in shares for the period of 1980–2019. Appendix Section B.4 provides additional details.

To measure inequality, I compute the Gini coefficient of annual wages and the variance of log annual wages for each CZ in years 1980 and 2019. More details can be found in Appendix Section B.5.

To study the relationship between migration and house prices, I use the 2001–2019 data from the Annual Social and Economic Supplement (ASEC) of the Current Population Survey (CPS). The CPS can only identify migration between states, not CZs. However, a key benefit of the CPS is that, unlike the ACS, it reports reasons for moving. This allows me to focus on households who move primarily for housing-related reasons. They constitute over 12% of the sample of interstate migrants. Appendix Sections B.6 and B.7 provide more details.

[1]Hereafter, 1980 variables were constructed using the 5% sample of the 1980 Census, while 2019 variables were constructed using the 5-year combination of 1% ACS samples from 2015 to 2019.

Table 1: Relationships between city size, polarization, inequality, and house prices

Panel A: Polarization and inequality

	(1) Mid-skl. chg.	(2) Gini coeff. chg.	(3) Var. log w chg.
Log initial population	-1.279***	1.281***	2.781***
	(0.109)	(0.0771)	(0.180)
R-squared	0.210	0.364	0.410

Panel B: House prices

	(1) Log price chg.	(2) Log p/r chg.	(3) Log p/w chg.
Log initial population	0.0350***	0.107***	0.0329***
	(0.0113)	(0.00974)	(0.00905)
R-squared	0.0340	0.206	0.0430

The table shows the results from first-difference OLS regressions for the 1980–2019 period. The number of observations in each regression is 465 (the number of CZs). In panel A, column (1) reports the coefficient from the regression of the change in 100× the middle-skilled share on log CZ population in 1980. Columns (2) and (3) report the coefficients for the change in 100× the Gini coefficient of annual wages and 100× the variance of log annual wages, respectively. In panel B, columns (1), (2), and (3) report the coefficients for the change in house prices, price-rent ratios, and price-wage ratios, respectively. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

2.2 Polarization, Inequality, and Housing Prices by CZ Size

Previous research has shown that large U.S. cities have experienced greater job polarization (Autor, 2019; Cerina, Dienesch, Moro, and Rendall, 2022) and higher growth in income inequality (Baum-Snow and Pavan, 2013) in recent decades. To verify these findings, I compute differences in skill shares, the Gini coefficients, and the variance of log wages between 1980 and 2019, and regress the change in skill shares and income inequality on log CZ population in 1980. The results are shown in panel A of Table 1. In column (1), we can see that larger CZs had more pronounced decline in the middle-skilled share, i.e., they experienced greater job polarization. Doubling CZ size is associated with a 1.3 percentage point greater fall in the middle-skilled share. In columns (2) and (3), we can see that larger CZs also experienced greater increase in income inequality. Doubling CZ size is associated with a 1.3 point higher growth in 100× the Gini coefficient and a 2.8 point higher growth in 100× the variance of log wages.

To complement these results, I also study the evolution of house prices as a function of CZ size. I compute differences in log prices, price-rent, and price-wage ratios from 1980 to 2019, and regress these differences on the CZ population in 1980. Panel B in

Table 1 demonstrates that larger CZs experienced faster price growth: doubling CZ size is associated with 3.5 percent higher price growth, 10.7 percent faster price-rent ratio growth, and 3.3 percent higher price-wage ratio growth. Appendix Section F contains maps of changes in prices, price-rent, and price-wage ratios, as well as skill shares and income inequality at the CZ level.

2.3 House Prices, Polarization, and Inequality

2.3.1 House Prices and Polarization

Has disproportionately faster price growth in large cities displaced middle-skilled households? To answer this question, I estimate the following relationship between the change in prices from 1980 to 2019 and the change in the shares of middle-skilled workers:

$$\Delta n_i^M = \beta_0 + \beta_1 \Delta Q_i + \beta_2 \ln N_{i,1980} + \beta_3 \mathcal{X}_{i,1980} + \varepsilon_i. \tag{1}$$

In this expression, $\Delta n_i^M \equiv n_{i,2019}^M - n_{i,1980}^M$, and $n_{i,t}^M$ is the employment share of middle-skilled workers in CZ i and year t. The change in prices is denoted by $\Delta Q_i \equiv Q_{i,2019}/Q_{i,1980} - 1$, and $Q_{i,t}$ is either the price index, the price-wage ratio, or the price-rent ratio in CZ i and year t. The population of CZ i in year t is denoted by $N_{i,t}$. Finally, $\mathcal{X}_{i,t}$ is a vector of controls that includes 1980 share of manufacturing employment, share of female employment, share of college workers, share of foreign-born workers, and Census region fixed effects.[2]

OLS results. Table 2 shows the estimates. In the first three columns I report OLS results for prices (panel A), price-rent ratios (panel B), and price-wage ratios (panel C). First, I omit initial population levels and additional controls from equation (1), and regress the change in the middle-skilled share on the price change and the year fixed effect. Column (1) shows that there is a statistically significant negative relationship between the growth in all three measures of housing prices and the middle-skilled share.[3] The coefficient values are sizable. Doubling of prices is associated with a nearly 1 percentage point decline in the middle-skilled share, while doubling of the price-rent and price-wage ratio are associated with 12.2 and 3.9 reduction in the middle-skilled share.[4]

[2]This set of controls is similar to the one used in Autor, Dorn, and Hanson (2013).

[3]Lindley and Machin (2014) document a similar relationship between polarization and housing costs, showing that U.S. states that experienced a greater increase in employment polarization between 1980 and 2010 also saw a larger change in house prices. Schubert (2021) shows that cities with high prices experienced greater displacement of non-college workers by college workers. On the other hand, Feng, Jaimovich, Rao, Terry, and Vincent (2022) find that house price growth has been slower in manufacturing-heavy U.S. regions, though the decline in manufacturing is one of the major drivers of job polarization in these and other areas.

[4]To put these results in perspective, note that between 1980 and 2019 prices changed by 351% on average (with 284% and 402% at the 25th and the 75th percentiles, respectively), price-rent ratios by −34.8% (−45.7%

Table 2: Change in the middle-skilled share and house price growth

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	-0.990***	-0.522***	-0.829***	-3.598***	-2.922***	-4.618***
	(0.190)	(0.172)	(0.160)	(0.521)	(0.514)	(1.296)
Log initial population		-1.913***	-1.468***		-1.423***	-1.753***
		(0.138)	(0.153)		(0.226)	(0.229)
Mean of dependent variable	-2.761	-2.761	-2.761	-2.761	-2.761	-2.761
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0640	0.334	0.567			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.0520	0.789	0.0480

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	-12.24***	-7.785***	-3.465***	-33.73***	-25.84***	-48.40**
	(1.059)	(1.122)	(1.101)	(7.766)	(7.235)	(21.87)
Log initial population		-1.475***	-1.313***		-0.211	-0.118
		(0.138)	(0.160)		(0.555)	(0.679)
Mean of dependent variable	-2.761	-2.761	-2.761	-2.761	-2.761	-2.761
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.270	0.403	0.554			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.122	0.0150	0.653

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	-3.861***	-2.836***	-3.276***	-12.50***	-10.18***	-14.89***
	(0.870)	(0.813)	(0.727)	(1.779)	(1.515)	(3.684)
Log initial population		-1.962***	-1.461***		-1.815***	-1.659***
		(0.138)	(0.154)		(0.180)	(0.181)
Mean of dependent variable	-2.761	-2.761	-2.761	-2.761	-2.761	-2.761
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0440	0.341	0.562			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.00100	0.980	0.0220

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the middle-skilled share on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

These findings could mask the effect of city size on polarization that has been documented in previous literature and confirmed in Section 2.2. Nonetheless, the results in column (2) show that, when I control for initial CZ size, the relationship between price growth and the change in the middle-skilled share remains negative, albeit becomes somewhat smaller in magnitude. That is, greater polarization is not just a feature of big cities story but also a feature of expensive cities. Surely, large cities experienced faster price growth. But regardless of city size, the places where prices increased more have seen stronger polarization. As shown in column (3), additionally controlling for manufacturing share, female share, college share, foreign-born share, and Census region effects does not affect the relationship between price growth and the decline in the middle-skilled share.

Instrumental variables. OLS estimates of β_1 are likely biased due to the omitted variable bias and reverse causality, as price changes may depend on changes in skill shares.[5] Thus, I instrument for changes in prices, price-rent, and price-wage ratios using variables that represent local geographic features relevant for housing supply. The instrumental variable (IV) consists of (1) the share of land unavailable for construction for each CZ from Lutz and Sand (2019), and (2) the great-circle distance of the population centroid of the CZ from the nearest coast (excluding the coasts of internal water bodies, such as the Great Lakes).[6] The correlation between the two variables at the CZ level is 0.02.

Both instruments have been used in prior literature.[7] They are solely determined by geography and are not affected by labor or housing market outcomes. At the same time, housing supply is more constrained in CZs where land available for construction is scarce and where the proximity to the coast may impose additional constraints on development. Thus, such CZs are likely to experience greater increases in prices in response to housing demand shocks. Moreover, while these geographic constraints may affect local job polarization and income distribution, they are most likely to do so via housing and land prices and not other channels. Table 3 presents the results of first-stage regressions of the instrumental variable on changes in the price index, price-rent ratio,

and −24.3%), and price-wage ratios by 25.8% (9.7% and 36.1%). The coefficient values suggest that a CZ at the 75th percentile of price changes would experience a $1.17 = 0.99 \times (4.02 - 2.84)$ larger decline in the middle-skilled share than a CZ at the 25th percentile. A CZ at the 75th percentile of price-rent ratio changes would have a $2.62 = 12.24 \times (0.457 - 0.243)$ larger decline, while a CZ at the 75th percentile of price-wage ratio changes would experience a $1.02 = 3.861 \times (0.361 - 0.097)$ larger decline. For comparison, the mean change in the middle-skilled share across the 465 CZs is −2.761 percentage points, while the 25th and the 75th percentiles are −5.555 and 0.229 percentage points, respectively.

[5]For instance, a large share of high earners in a given city may drive up house prices via housing investment demand or by supporting restrictive land use regulations.

[6]The distance to coast was computed using the data from the Pacific Islands Ocean Observing System.

[7]A more widely used measure of land unavailability is Saiz (2010). The benefit of using Lutz and Sand (2019) is that it provides data at the county level for nearly all U.S. counties, which I aggregate to the CZ level, whereas Saiz (2010) provides data at the metropolitan area level.

Table 3: First-stage regressions

	(1) Log price chg.	(2) Log p/r chg.	(3) Log p/w chg.
Land unavailability	0.00313***	0.00184**	0.00365***
	(0.000528)	(0.000771)	(0.000421)
Distance to coast	-0.000124***	-0.000108**	-0.000114***
	(0.0000361)	(0.0000461)	(0.0000316)
R-squared	0.127	0.0350	0.231

The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Columns (1), (2), and (3) report the coefficients from regressions of the change in housing prices, price-rent indices, and price-wage indices, respectively, on land unavailability and distance to coast. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

and price-wage ratio. They show that the CZs with less land available for development and lower distance to the coast have experienced larger growth in housing prices.

IV results. In columns (4)–(6) of Table 2, I present the results of the two-stage least squares (2SLS) estimation. The coefficients on changes in prices, price-rent ratios, and price-wage ratios remain negative and significant. This suggests that polarization and price growth may not be simply negatively related, but that stronger price growth may lead to more polarization. At the same time, in a few specifications (regressions with price-rent ratios) the instruments are relatively weak, as can be seen from low first-stage F-statistics. Nonetheless, the p-values of the Hansen overidentification test suggest that the exclusion restriction of the instrument is satisfied in most, though not all, specifications.

Note that in all specifications, the 2SLS coefficients are larger than the OLS coefficients. There are at least two possible reasons. First, there may be important variables that are correlated with the change in the middle-skilled share and that were omitted from OLS regressions. Second, there may be strong reverse causality. In particular, if larger reductions in the fraction of middle-skilled workers lead to lower price growth due to lower demand for housing, OLS coefficients could be attenuated.

For these reasons, this evidence should be viewed as suggestive and not definitive. Nonetheless, the relationship between price growth and the fall in the middle-skilled share is strong and, in most cases, independent from city size and other CZ characteristics. In Appendix Section C.1, I show that this relationship is also robust to different thresholds used to split employment into low-, middle-, and high-skilled groups, and using two separate time intervals: 1980–2000 and 2000–2019. I also study the relationship between changes in low- and high-skilled shares and provide evidence that locations where prices grew more also had a greater increase in low- and high-skilled shares.

2.3.2 House Prices and Income Inequality

Job polarization is mechanically related to changes in income inequality, as a larger number of individuals in the tails of the income distribution may lead to a greater dispersion of income. Hence, if cities with faster growth in housing prices experienced more pronounced polarization, we should expect that they also had a larger increase in income inequality. To study this hypothesis, I estimate a relationship between changes in prices and income inequality similar to the one in (1):

$$\Delta I_i = \beta_0 + \beta_1 \Delta Q_i + \beta_2 \ln N_{i,1980} + \beta_3 \mathcal{X}_{i,1980} + \varepsilon_i. \tag{2}$$

where ΔI_i is the difference in the variance of log annual wages between 1980 and 2019.

OLS results. Column (1) in Table 4 shows that there is a statistically significant positive relationship between the growth in housing copsts and the increase in the variance of log wages.[8] Doubling of prices is associated with a 2.3 point increase in 100× the variance of log wages, whereas doubling of the price-rent and price-wage ratio are associated with 12.5 and 6.1 point increase.[9] The strength of the relationship falls in magnitude when I control for initial CZ size (column 2) and include additional regressors (column 3), but it remains statistically significant, with the exception of the regression with price-wage ratios. As in the case of polarization, these results mean that rising house prices is a separate channel that is related to larger increases in inequality, regardless of city size.

IV results. In columns (4)–(6) of Table 4, I estimate the relationship between prices and inequality using the 2SLS estimation and the same instrument as for polarization. The coefficients on price growth remain positive and significant in all specifications. These findings suggest that there may be a causal relationship between price growth and changes in income inequality at the CZ level. At the same time, one should bear in mind that in several specifications instruments are weak, although in most specifications the exclusion restriction is satisfied based on the values of the Hansen's test. And, as in the case of polarization, IV coefficients are somewhat larger than OLS coefficients, likely for the same

[8]These findings are related to Moretti (2013) who shows that metropolitan statistical areas (MSAs) where the share of college graduates grew the most in 1980–2000 also had faster increases in the college wage gap.

[9]To put these results in perspective, note that between 1980 and 2019 prices changed by 351% on average (with 284% and 402% at the 25th and the 75th percentiles, respectively), price-rent ratios by −34.8% (−45.7% and −24.3%), and price-wage ratios by 25.8% (9.7% and 36.1%). The coefficient values suggest that a CZ at the 75th percentile of price changes would experience a $2.71 = 2.3 \times (4.02 - 2.84)$ larger increase in 100× the variance of log wages than a CZ at the 25th percentile. A CZ at the 75th percentile of price-rent ratio changes would have a $2.68 = 12.52 \times (0.457 - 0.243)$ larger increase, while a CZ at the 75th percentile of price-wage ratio changes would experience a $1.61 = 6.084 \times (0.361 - 0.097)$ larger increase. For comparison, the mean growth of 100× the variance of log wages across the 465 CZs is over 10 points, while the 25th and the 75th percentiles are 6.77 and 12.65 points, respectively.

Table 4: Change in income inequality and house price growth

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	2.300***	1.706***	1.319***	2.891***	1.659***	2.941**
	(0.266)	(0.201)	(0.240)	(0.538)	(0.493)	(1.206)
Log initial population		2.433***	1.753***		2.442***	1.875***
		(0.144)	(0.179)		(0.171)	(0.202)
Mean of dependent variable	10.01	10.01	10.01	10.01	10.01	10.01
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.234	0.532	0.601			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0	0.517	0.769

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	12.52***	5.218***	3.723***	27.29***	12.81**	22.65*
	(1.605)	(1.357)	(1.439)	(6.954)	(5.501)	(13.56)
Log initial population		2.416***	1.555***		1.885***	1.052**
		(0.166)	(0.194)		(0.404)	(0.436)
Mean of dependent variable	10.01	10.01	10.01	10.01	10.01	10.01
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.192	0.436	0.571			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0	0.0360	0.276

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	6.084***	4.680***	1.426	9.183***	5.727***	9.412**
	(1.496)	(0.947)	(1.107)	(2.548)	(1.985)	(4.027)
Log initial population		2.687***	1.678***		2.666***	1.814***
		(0.157)	(0.191)		(0.159)	(0.205)
Mean of dependent variable	10.01	10.01	10.01	10.01	10.01	10.01
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0750	0.454	0.566			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0	0.450	0.761

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the variance of log annual wages on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

reasons as outlined in Section 2.3.1.

These results point to a strong relationship between rising prices and income inequality at the city level that operates regardless of the city size. Appendix Section C.2 shows that these findings are robust to measuring inequality using the Gini coefficient, using hourly income, and adjusting income for the effects of gender, race, industry, occupation, education, and age, and using two separate time intervals: 1980–2000 and 2000–2019.

2.3.3 Discussion: OLS vs. IV Results

The evidence from 2SLS regressions suggests that there may be a causal link from price growth to polarization and the growth in inequality. However, the evidence from OLS regressions is no less important. It underscores the relationship between price growth, polarization, and inequality that is independent from city size. In the model presented below in Section 3, the relationship runs both ways. On the one hand, higher prices push out the middle-skilled and result in more polarization and inequality. On the other hand, changes in local skill distribution and especially larger share of high-skilled workers in more polarized locations affects prices via housing demand.

2.4 Interstate Migration

A natural mechanism that may link polarization and changes in inequality to changes in house prices is migration. If households in the middle of the income distribution are more sensitive to differences in house prices, they will be more likely to migrate out of expensive locations and these locations should experience greater polarization and inequality.

In order to study the effect of being in a certain position in the income distribution on the probability of moving to a different state for housing-related reasons, I split households into five quintiles by income in the location of origin and estimate:

$$\mathbb{M}_{h,ij,t+1} = \delta_1 + \delta_2 \ln\left(\frac{Q_{it}}{Q_{jt}}\right) + \sum_{q=1}^{5} \delta_3^q \mathbb{I}_{h,it}^q + \sum_{q=1}^{5} \delta_4^q \ln\left(\frac{Q_{it}}{Q_{jt}}\right) \times \mathbb{I}_{h,it}^q$$
$$+ \delta_5 \ln\left(1 + D_{ij}\right) + \boldsymbol{\delta}_6 \mathcal{X}_{h,ij,t+1} + \varphi_i + \varphi_j + \varphi_{t+1} + \varepsilon_{h,ij,t+1}. \quad (3)$$

In this specification, $\mathbb{M}_{h,ij,t+1}$ is equal to 1 if household h moved for housing-related reasons from state i to state $j \neq i$ between years t and $t+1$, and to 0 if the household moved for another reason or did not move. $Q_{i,t}$ is a measure of housing prices, either the house price index, the price-wage ratio, or the price-rent ratio. Variable $\mathbb{I}_{h,it}^q$ indicates whether household h belonged to the q-th quintile by household income in state i and year t. D_{ij}

is the great-circle distance between population-weighted centroids of states i and j. $\mathcal{X}$ is a set of controls which include information about gender, race, household composition, education, and age. Finally, parameters φ_i, φ_j, and φ_t are origin, destination, and year fixed effects, respectively. Since specification (3) includes income and housing cost variables in the year prior to the observed new state of residence and because none of the control variables are likely to be affected by the decision to migrate, all right-hand side variables are plausibly exogenous.[10] I estimate the model using a logit regression.

The main coefficients of interest are those on the interaction variable between the income quintile and the ratio of housing costs, δ_4^q. They measure how much more likely a household is to move for housing-related reasons from a less affordable to a more affordable U.S. state depending on their position in the income distribution.

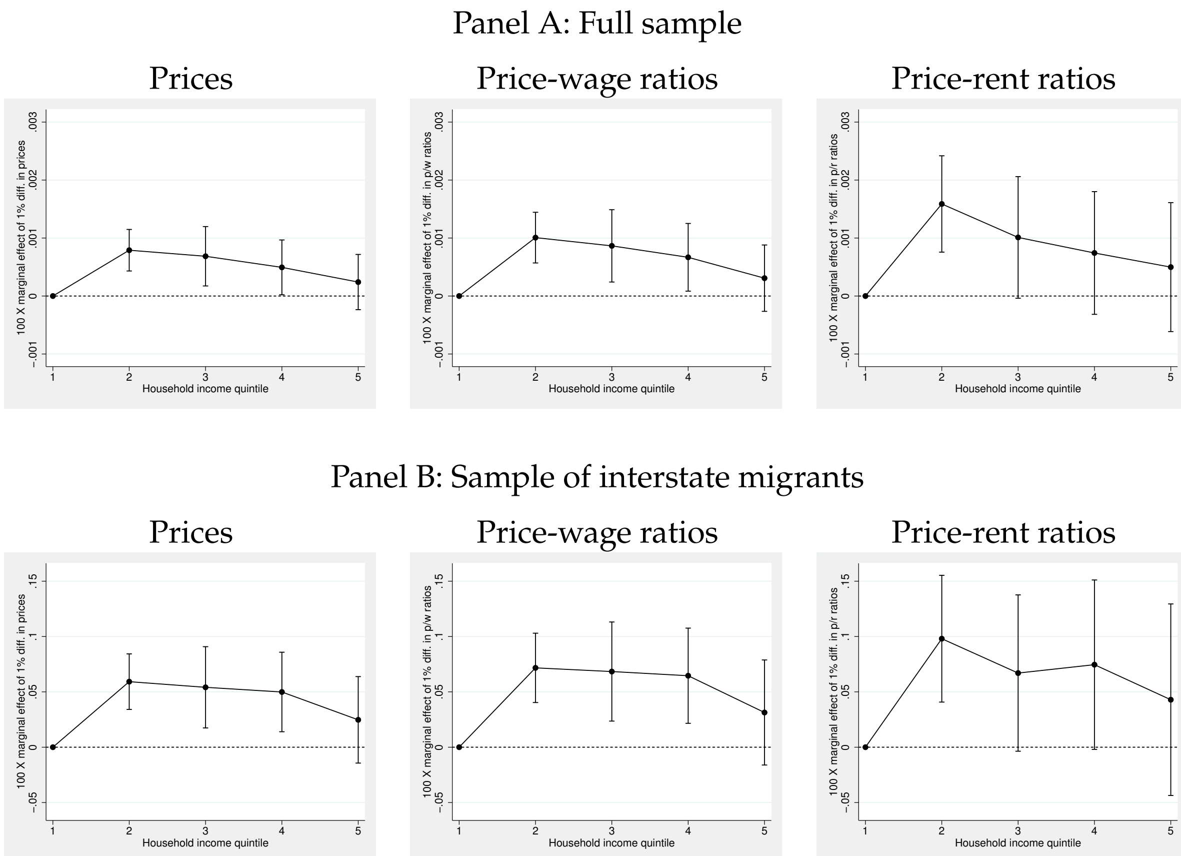
Results. Panel A of Figure 1 plots the marginal effects associated with δ_4^q for each quintile q relative to the first quintile. The marginal effects represent the percentage point change in the probability of moving for housing-related reasons in response to a 1% increase in prices, price-wage, or price-rent ratios in state i relative to state j. The figure shows that, compared to households in the 1st or the 5th income quintile, those in the 2nd to the 4th quintiles are more likely to move for housing-related reasons from state i to j when state j has lower prices, price-wage, or price-rent ratios. In case of price-rent ratios, the marginal effects have larger standard errors but are quantitatively similar to those for prices and price-wage ratios.[11]

Panel B of Figure 1 focuses on the subsample of interstate migrants. It shows that, even conditional on moving across states, middle-income households are more likely to move for housing-related reasons than low- or high-income households. A doubling of the price index in state i relative to j increases the probability that a household in the 2nd to the 4th quintile moves to state j for housing-related reasons by 5–6 percentage points. Similarly, a doubling of the price-wage ratio raises the moving probability by 6–7 percentage points for households in the middle of the income distribution, whereas a doubling of the price-rent ratio increases it by 7–10 percentage points. Given that the probability of moving for housing-related reasons is 0.12 (the fraction of interstate migrants who moved for housing reasons), these marginal effects imply that a twofold increase in prices and price-wage ratios may increase the probability of a housing-related relocation for middle-income households by about 50%, while a similar increase in the price-rent ratio may increase it by 60% to 80%.

[10] CPS respondents report their income and location in the previous year and location in the current year.

[11] Noise is expected since migration is measured at the state level. In some states, such as New York and California, the differences in housing costs between CZs are large and comparable to cross-state differences.

Figure 1: Marginal effects on migration for housing-related reasons



Note: The figure reports marginal effects from coefficients δ_4^q from regression (3) on the full sample of 1,265,832 observations (panel A) or the sample of 15,815 interstate migrants (panel B). The left plot shows 100× marginal effects on the probability of moving for housing-related reasons of the log ratio of house prices in the location of origin to the prices in the location of destination for each quintile in the household income distribution at the location of origin. The center plot shows the marginal effects of price-wage ratios, and the right plot shows the marginal effects of price-rent ratios. Vertical bars represent the 95% confidence interval. Standard errors of marginal effects are computed using the Delta method. Standard errors of the underlying logit regression are clustered by the state of origin.

In Appendix Section C.3, I show that this relationship is unique to housing-related migration and does not hold for non-housing reasons. I also show that the relationship between migration and prices is especially strong for middle-income households with children. They are likely to require larger houses, and for that reason, their location choices are more sensitive to house prices than the choices of childless households.

2.5 Homeownership Rates

One may conjecture that local changes in house prices should also be correlated with changes in the homeownership rate. It is not clear, however, whether any such relationship should exist. On the one hand, rising prices may deter some households from buying a house. On the other hand, prices may go up precisely because many households are buying. Indeed, Appendix Table F.1 shows that there is no statistically significant relationship between the change in homeownership and the growth in prices, price-rent, and price-wage ratios.

3 Theoretical Framework

In this section, I construct a parsimonious spatial equilibrium model consistent with the evidence presented in the previous section. The model builds on the standard system-of-cities model (Henderson, 1974; Rosen, 1979; Roback, 1982) and only makes two extensions to it: skill heterogeneity and housing tenure choice.

The economy consists of a discrete set $\mathcal{I}$ of cities, indexed by i, and is populated by a measure 1 of households that live for a single period, as well as infinitely-lived real estate managers.[12] A household is endowed with skill s drawn from the distribution $\Phi(s)$, with full support on $(0,1]$ and density function $\phi(s)$. Households supply labor inelastically to firms that produce the final consumption good (the numeraire). I assume that skills are perfect substitutes in production but there are differences in returns to skills across cities. The final good is traded between cities at no cost. Households consume the final good and housing, and housing can be either owned or rented. The economy evolves over time as a sequence of spatial equilibria. Since households live for one period, the time dimension is often irrelevant and the time subscripts are omitted unless required in the context.

3.1 Final Goods Production

In each city, there is a represenative firm that produces the final good using labor as the only input. The production function combines workers of different skills in a perfectly substitutable manner,

$$Y_i = A_i \int_0^1 a(s) N_i(s) \mathrm{d}s. \tag{4}$$

Here A_i represents exogenous labor productivity of city i, $a_i(s)$ is a city-specific strictly increasing continuous function that determines the productivity of a worker with skill s, while $N_i(s)$ is the employment of s-skilled workers in the city.[13] Perfect competition

[12] I use the terms "household" and "worker" interchangeably.

[13] I abstract from possible agglomeration externalities in productivity.

implies that the local wage of a worker with skill s is

$$w_i(s) = A_i a_i(s). \tag{5}$$

3.2 Preferences and Choices

Households consume positive quantities of the final good, c, and housing, h. The demand for housing can be satisfied by either renting or owning a dwelling. Households also derive utility from the amenities of the city they live in, X_i. In addition, each household n has an idiosyncratic preference for city i, denoted by ξ_{ni}. Location preferences are drawn from the Fréchet distribution $F(\xi) = \exp(-\xi^{-\epsilon})$, where $\epsilon > 1$. The utility of worker n who lives in city i is given by $u_{ni}(c, h) = \xi_{ni} v_i(c, h)$, where

$$v_i(c, h) \equiv \left(\frac{c}{1-\gamma}\right)^{1-\gamma} \left(\frac{h}{\gamma}\right)^{\gamma} X_i \tag{6}$$

is the common component of the utility function and $0 < \gamma < 1$. Households make three choices: (1) location, (2) housing tenure, (3) consumption of goods and housing.

3.2.1 Consumption of Goods and Housing

I now solve the household utility maximization problem, conditional on the tenure choice.

Renters. A household that chooses to rent solves

$$\max_{c,h} v_i(c, h) \quad \text{subject to: } w_i(s) = c + r_i h, \tag{7}$$

where r_i is the rent per square foot in city i. The housing expenditure function is $h = \gamma w_i(s)/r_i$ and the indirect utility function of a renter is

$$v_i^R(w_i(s), r_i) = \frac{w_i(s) X_i}{r_i^{\gamma}}. \tag{8}$$

Homeowners. A household that chooses to own buys a house at the beginning of the period at price p_i and sells it at the end of the period at the same price. Owning a house has a cost δ that represents depreciation, property taxes, mortgage interest payments, etc. Thus, the budget constraint of a homeowner is $w_i(s) + p_i h = c + (1+\delta) p_i h$ which can be simplified as $w_i(s) = c + \delta p_i h$. Besides the budget constraint and the positive consumption constraints, homeowners are subject to two additional constraints. First, owner-occupied houses cannot be smaller than $\bar{h} > 0$. This is the *minimum-size constraint*. Second, a household cannot spend more than a fraction $\lambda < 1$ of their labor earnings on purchasing a house. This is the *payment-to-income (PTI) constraint*. Thus, homeowners solve

$$\max_{c,h} v(c,h) \quad \text{subject to: } w_i(s) = c + \delta p_i h, \tag{9}$$

$$h \geq \bar{h}, \tag{10}$$

$$p_i h \leq \lambda w_i(s). \tag{11}$$

The solution to the homeowner's problem yields the following housing consumption function:

$$h = \begin{cases} \frac{\gamma}{\delta}\frac{w_i(s)}{p_i} & \text{if } \lambda > \frac{\gamma}{\delta} \text{ and } w_i(s) \geq \frac{\delta p_i \bar{h}}{\gamma}, \\ \bar{h} & \text{if } \lambda > \frac{\gamma}{\delta} \text{ and } \delta p_i \bar{h} < w_i(s) < \frac{\delta p_i \bar{h}}{\gamma}, \\ \lambda \frac{w_i(s)}{p_i} & \text{if } \lambda \leq \frac{\gamma}{\delta} \text{ and } w_i(s) \geq \frac{p_i \bar{h}}{\lambda}. \end{cases} \tag{12}$$

This function describes three cases. First, a homeowner's wage may be high enough to spend just a fraction γ/δ of income on housing and be able to afford a house at least as large as $\bar{h}$. Second, the wage may be relatively low and buying even the minimum-size house requires spending a fraction of income greater than γ/δ. These two cases occur when the PTI constraint is not binding. Third, if the PTI constraint is binding, households spend a fraction λ of income on housing. Note that households cannot spend more than a fraction λ of their income on housing. The only household who buys a house of size $\bar{h}$ is the one whose income is equal to $p_i \bar{h}/\lambda$, and this situation is already captured by the third case. These three cases result in the following indirect utility function:

$$v_i^O(w_i(s), p_i) = \begin{cases} \frac{w_i(s)}{\delta p_i^{\gamma}} \left(\frac{\delta - \gamma}{1-\gamma}\right)^{1-\gamma} X_i & \text{if } \lambda > \frac{\gamma}{\delta} \text{ and } w_i(s) \geq \frac{\delta p_i \bar{h}}{\gamma}, \\ \left(\frac{w_i(s) - \delta p_i \bar{h}}{1-\gamma}\right)^{1-\gamma} \left(\frac{\bar{h}}{\gamma}\right)^{\gamma} X_i & \text{if } \lambda > \frac{\gamma}{\delta} \text{ and } \delta p_i \bar{h} < w_i(s) < \frac{\delta p_i \bar{h}}{\gamma}, \\ \frac{w_i(s)}{p_i^{\gamma}} \left(\frac{1-\delta\lambda}{1-\gamma}\right)^{1-\gamma} \left(\frac{\lambda}{\gamma}\right)^{\gamma} X_i & \text{if } \lambda \leq \frac{\gamma}{\delta} \text{ and } w_i(s) \geq \frac{p_i \bar{h}}{\lambda}, \\ -\infty & \text{otherwise.} \end{cases} \tag{13}$$

In the last case the wage is so low that even if the household spends all of their income on housing, they would not be able to afford the minimum-size property.

3.2.2 Housing Tenure Choice

Indirect utility functions (8) and (13) result in different utility levels for the same wage, depending on the housing tenure choice. A worker with skill s in city i chooses to rent if it yields higher utility and to own otherwise. Hence, the indirect utility function of such a worker is

$$v_i\left(w_i(s), p_i, r_i\right) \equiv \max\left\{v_i^O\left(w_i(s), p_i\right), v_i^R\left(w_i(s), r_i\right)\right\}. \tag{14}$$

The next two results characterize tenure choice. Lemma 1 provides conditions for homeownership to be an optimal choice for some households. If any of these conditions does not hold, all city residents will rent. Lemma 2 describes who owns and who rents.

Lemma 1 (**necessary and sufficient conditions for homeownership**). Homeownership with housing consumption $h > \bar{h}$ is the optimal tenure choice for some households in city i if and only if the minimal house size is sufficiently small,

$$\bar{h} < \min\left\{\frac{\gamma}{\delta}, \lambda\right\} \frac{w_i(s=1)}{p_i}, \tag{15}$$

and the price-rent ratio is sufficiently low,

$$\frac{p_i}{r_i} \leq \begin{cases} \left(\frac{\delta-\gamma}{1-\gamma}\right)^{\frac{1-\gamma}{\gamma}} \frac{1}{\delta^{1/\gamma}} & \text{if } \lambda > \frac{\gamma}{\delta}, \\ \left(\frac{1-\delta\lambda}{1-\gamma}\right)^{\frac{1-\gamma}{\gamma}} \frac{\lambda}{\gamma} & \text{if } \lambda \leq \frac{\gamma}{\delta}. \end{cases} \tag{16}$$

Proof. See Appendix Section A.1 □

Lemma 2 (**skill thresholds for homeownership**). Let the conditions (15) and (16) hold. Then:

(a) there exists a unique skill threshold $s_i^* \in (0,1)$ such that all workers in city i with skill $s < s_i^*$ choose to rent, and all those with skill $s \geq s_i^*$ choose to buy;

(b) there exists a unique skill threshold $s_i^{**} \in [s_i^*, 1)$ such that all workers with skill $s > s_i^{**}$ choose to buy a house larger than the minimum size $\bar{h}$;

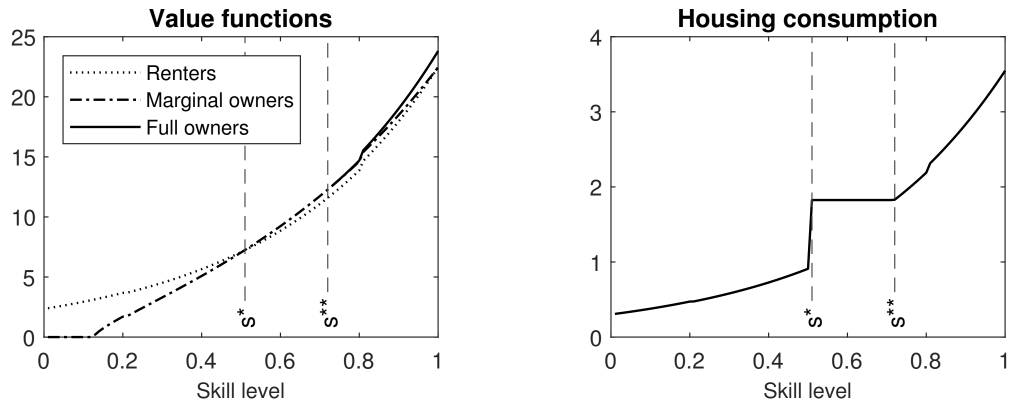
(c) skill thresholds s_i^* and s_i^{**} are decreasing in local labor productivity, A_i.

Proof. See Appendix Section A.2 □

The previous two results stress the fact that the decision to own a home depends on the price-rent ratio (Lemma 1) and the price-wage ratio (Lemma 2). The lower these ratios are, the more households will choose to buy instead of renting.

Lemma 2 also indicates that there are two types of homeowners. First, there are owners whose income is large enough that they can afford to purchase a house larger than $\bar{h}$ without spending more than a fraction γ/δ of their income. I call them "full owners." Second, there are owners whose income is relatively low and they must spend a fraction greater than γ/δ on buying a house. Nonetheless, their utility of owning exceeds the utility of renting and they find it optimal to buy a house of size $\bar{h}$. I dub these homeowners as

Figure 2: Tenure choice and housing consumption



Notes: The left panel shows utility levels for each skill level implied by value functions of renters, marginal owners, and full owners. Note that full ownership is not a feasible choice for $s < s^{**}$; hence, the value of a full owner is only shown for $s \geq s^{**}$. The right panel shows housing consumption for each skill level. Both panels display skill thresholds for marginal ownership (s^*) and full ownership (s^{**}).

"marginal owners." Note that marginal owners only exist if the PTI constraint is not binding. If it is binding, full owners are already spending the maximum allowed share of income on housing and no one can spend a share higher than λ in order to buy a house of minimum size. In this case the two ownership thresholds coincide, i.e., $s_i^* = s_i^{**}$.

Figure 2 demonstrates an example of tenure choice and housing consumption when the PTI constraint binds. In this example, the value of renting exceeds the value of owning for all skill levels below $s^* = 0.51$. At this skill level and above, the value of a owning is higher but households with skills below $s^{**} = 0.72$ can only afford to buy a minimum-size house. Housing consumption jumps at s^* and remains constant up to s^{**}. Starting from s^{**}, it is optimal to buy a house larger than $\bar{h}$. Thus, in this example workers with skill $s \in (0, 0.51)$ are renters, those with $s \in [0.51, 0.72)$ are marginal owners, and workers with $s \in [0.72, 1]$ are full owners.

The reason why households prefer to own is purely financial: ownership reduces the cost of housing consumption. Given that the model is static, many other reasons why households prefer to own (e.g., wealth accumulation or risk insurance) are absent.[14]

3.2.3 Location Choice

Each worker n chooses city i that maximizes her utility. The location choice problem is characterized by

$$\max_i \left\{ \xi_{ni} v_i \left(w_i(s), p_i, r_i \right) \right\}. \tag{17}$$

[14]Some models also allow for explicit "warm glow" utility of ownership.

Since the location preference shocks follow the Fréchet distribution with shape parameter ϵ, the probability that a worker with skill s chooses to live in city i is given by

$$\pi_i(s) = \frac{v_i\left(w_i(s), p_i, r_i\right)^{\epsilon}}{\sum_{j \in \mathcal{I}} v_j\left(w_j(s), p_j, r_j\right)^{\epsilon}}. \tag{18}$$

Thus, a worker is more likely to choose a city that offers high wages, has low prices and rents, and has high amenities. The equilibrium supply of workers with skill s in city i is equal to

$$N_i(s) = \pi_i(s)\phi(s), \tag{19}$$

and the total employment in the city is $N_i \equiv \int_0^1 N_i(s)\mathrm{d}s$.

3.2.4 Relationship Between Location and Tenure Choices

Consider two cities, i and j, and suppose that the skill threshold for homeownership is higher in city i, i.e., $s_i^* > s_j^*$. Then, when choosing city, households with $s \in [s_j^*, s_i^*)$ compare not only wages, housing costs, and amenities, but they also compare between owning a house in city j and renting in city i. The relative probability of choosing city i incorporates the comparison of the two tenure choices and is given by

$$\frac{\pi_i(s)}{\pi_j(s)} = \left[\frac{v_i^R\left(w_i(s), r_i\right)}{v_j^O\left(w_j(s), p_j\right)}\right]^{\epsilon}. \tag{20}$$

Thus, for households whose skills are high enough to buy in city j but insufficient to buy in city i, location choice and tenure choice depend on each other. At the same time, for households with skill levels below s_j^* or above s_i^*, location and tenure choices are independent.[15]

3.2.5 Welfare

The location choice probabilities lead to an expression for welfare.[16] The expected utility of an s-skilled worker prior to making any choices and knowing the value of the location

[15]While my model is static, it has conceptual similarities to Bilal and Rossi-Hansberg (2021). They model location choice as investment in an asset. In my model, location choice is related to housing investment.

[16]The expressions for the location choice probability (18) and expected welfare (21) arise from the properties of the Fréchet distribution and are standard in the literature. Detailed derivations can be found, for example, in the appendix to Monte, Redding, and Rossi-Hansberg (2018).

preference shock is

$$V(s) = \left[\sum_{i \in \mathcal{I}} \left(v_i \left(w_i(s), p_i, r_i \right) \right)^{\epsilon} \right]^{\frac{1}{\epsilon}}. \tag{21}$$

Aggregate welfare is defined as the weighted average of expected utilities for workers of all skill levels,

$$V = \int_0^1 V(s) \mathrm{d}\Phi(s). \tag{22}$$

3.3 Housing Markets

Housing is produced by perfectly competitive developers with technology that uses land L_i and the numeraire good K_i,

$$H_i = \left(\phi_i L_i \right)^{\eta} K_i^{1-\eta}. \tag{23}$$

Land input is augmented by city-specific productivity ϕ_i and the share of land in production is given by η. Each city is endowed with exogenous quantity of land Λ_i owned by absentee landowners. There is no alternative use of land; hence, landowners are willing to sell land at any positive price and developers optimally buy all available land, $L_i = \Lambda_i$.

A part of the housing stock is owned by homeowners, while the remainder is owned by a large number of infinitely lived real estate managers and leased to renters. The managers earn $(1 - \theta)r_{it}$ from leasing housing to renters, where $\theta < 1$ represents the costs of maintaining rental property.[17] I assume that housing stock does not depreciate between periods thanks to maintenance and depreciation payments that are included in ownership cost parameters δ and θ. At the end of the current period t, homeowners sell their houses to the real estate managers at price $p_{i,t}$. At the turn of two periods, the managers own the entire housing stock. Then, at the start of period $t + 1$, new homeowners buy a part of the housing stock from the managers at price $p_{i,t+1}$. In each period, real estate managers earn rental income as well as accrue investment income or incur losses that arise from the difference between $p_{i,t+1}$ and $p_{i,t}$. They spend their rental income on the consumption of the final good. To compensate for the investment income or losses, they save or borrow in the asset market which is external to the economy under study.

Real estate managers discount future periods with factor $\beta < 1$. Rents and prices adjust so that each manager is indifferent between selling a property or keeping it and earning rents perpetually.[18] This implies that in equilibrium, house prices are equal to the

[17]The value of θ may differ from household ownership costs δ. For example, institutional real estate investors do not benefit from mortgage tax deductions but at the same time do not incur many costs that individual homeowners do, such as purchases and maintenance of furniture, upkeep expenses, etc.

[18]If prices were higher than the discounted sum of rents, then managers would sell their properties and

expected discounted sum of rents and that the price-rent ratio is

$$\Omega_{i,t} \equiv \frac{p_{i,t}}{r_{i,t}} = \sum_{\tau=t}^{\infty} \left[\beta(1-\theta)\right]^{\tau-t} \hat{r}_{i,t,\tau}, \tag{24}$$

where $\hat{r}_{i,t,\tau} \equiv \mathrm{E}_t \left[r_{i,\tau}/r_{i,t}\right]$ denotes the real estate managers' expectation about the growth of rents between periods t and τ which I take as exogenous.[19] This implies that, even though prices are endogenous, the ratio between prices and rents is exogenous. Equilibrium house price must clear the market by satisfying

$$\phi\Lambda_i \left(1-\eta\right)^{\frac{1-\eta}{\eta}} p_i^{\frac{1-\eta}{\eta}} = \frac{\gamma}{r_i} \int_0^{s_i^*} w_i(s)N_i(s)\mathrm{d}s + \bar{h} \int_{s_i^*}^{s_i^{**}} N_i(s)\mathrm{d}s + \min\left\{\frac{\gamma}{\delta}, \lambda\right\} \frac{1}{p_i} \int_{s_i^{**}}^{1} w_i(s)N_i(s)\mathrm{d}s, \tag{25}$$

where the left-hand side is housing supply and the right-hand side is the demand.

3.4 Equilibrium

The following definition describes a spatial equilibrium for this model:

Definition 1 (**spatial equilibrium**)**.** Conditional on productivity and amenities in each city, A_i and X_i, the economy-wide distribution of skills, $\Phi(s)$, and the expectations of rent growth, $\{\hat{r}_{i,t,\tau}\}_{\tau=t}^{\infty}$, a *spatial equilibrium* is given by skill-specific local labor supply, $N_i(s)$, rents, r_i, and prices, p_i, such that equations (19), (24), and (25) are satisfied for all i.

3.5 Main Mechanism: Homeownership, Polarization, and Inequality

Even though the nationwide distribution of skills is exogenously given, endogenous location choices determine local distribution of skills and wages in each city.[20] In this section, I discuss how the choice to rent or own shapes the skill distribution within a city.

In order to study labor market polarization analytically, I define low-, middle-, and high-skilled employment shares as follows.

Definition 2 (**skill shares**)**.** Consider arbitrary skill levels s' and s'' that satisfy $s'' > s'$.

the excess supply would reduce prices. Alternatively, if prices were lower than discounted rents, then new entrants would buy properties in order to earn rental income and the excess demand would raise prices.

[19]Because households live for one period, the evolution of the economy over time only matters for determining price-rent ratios, which households take as given. Since all other theoretical results depend on static household decisions, I abstain from discussing causes or consequences of price and rent dynamics.

[20]Wages only depend on a function that is strictly increasing in skills and an exogenous productivity term. Hence, local skill and wage distributions are isomorphic and I use these two terms interchangeably.

Define the *s'-low-skilled share* as the fraction of workers with skills below s' in city i,

$$n_i^L(s') \equiv \frac{1}{N_i}\int_0^{s'} N_i(s)\mathrm{d}s, \tag{26}$$

and the *s''-high-skilled share* as the fraction of workers with skills above s'',

$$n_i^H(s'') \equiv \frac{1}{N_i}\int_{s''}^{1} N_i(s)\mathrm{d}s. \tag{27}$$

The *(s', s'')-middle-skilled share* is given by $n_i^M(s', s'') \equiv 1 - n_i^L(s') - n_i^H(s'')$.

To facilitate analysis, consider a simplified version of the model with two cities, 1 and 2, exogenous housing supply $\bar{H}_i$, and no individual ownership costs, i.e., $\delta = 0$.[21] Furthermore, in order to verify that theoretical results do not depend on local differences in skill returns, assume that the returns to skill are the same in both cities, i.e., $a_1(s) = a_2(s)$.

The following proposition constitutes the central theoretical result of the paper. It demonstrates that cities with higher price-wage and price-rent ratios have a higher low-skilled share and, under an additional condition, also have a larger high-skilled share than cities with lower ratios. This implies that such cities have smaller middle-skilled share, i.e., they exhibit greater employment polarization.

Proposition 1 (larger polarization in cities with higher price-wage and price-rent ratios). Let city 1 have higher price-wage and price-rent ratios, i.e., $p_1/A_1 > p_2/A_2$ and $p_1/r_1 > p_2/r_2$.[22] Consider arbitrary skill levels s' and s'' such that s' is below the level required to own a house in city 2 and s'' is above the level required to own in city 1, i.e., $0 < s' < s_2^*$ and $s_1^* < s'' < 1$. Also, let the conditions of Lemma 1 hold. Then city 1 has a larger s'-low-skilled share, $n_1^L(s') > n_2^L(s')$. Furthermore, if the difference in price-rent ratios is bounded by a constant $\mathcal{B} > 1$, i.e., $\frac{p_1/r_1}{p_2/r_2} < \mathcal{B}$, then city 1 has a larger s'-high-skilled share, $n_1^H(s'') > n_2^H(s'')$, and therefore lower (s', s'')-middle-skilled share, $n_1^M(s', s'') > n_2^M(s', s'')$.[23]

Proof. See Appendix Section A.3 □

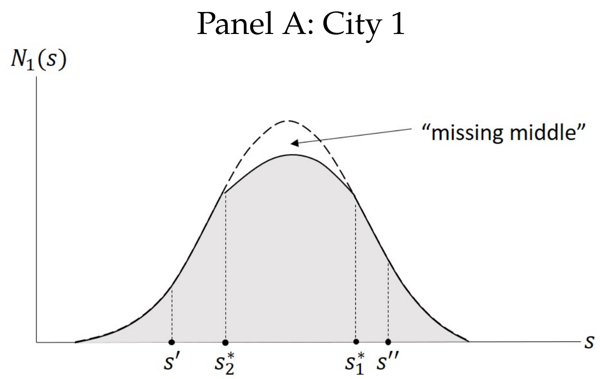
Why do higher price-wage and price-rent ratios in city 1 lead to larger employment polarization there? All households with skill levels below s' cannot afford a house in any city, whereas those with skills above s'' have sufficient income to buy a house in any city. As discussed in Section 3.2.4, location choice of these two groups is independent of

[21]Propositions 1 and 2 derived below will most likely hold with $\delta > 0$ but assuming $\delta = 0$ significantly simplifies the proofs.

[22]I refer to p_i/A_i as the price-wage ratio, since A_i is a common component of local wages.

[23]The constant $\mathcal{B}$ is defined in the proof of the proposition.

Figure 3: Illustration of Proposition 1



Panel A shows the equilibrium skill distribution in city 1, and panel B shows the distribution in city 2. Workers with skill $s \in [s_2^*, s_1^*)$ can buy a house in city 2 but not in city 1. Some of them–the "missing middle"–choose to locate in city 2 only because they can buy a house there. This increases the s'-low-skilled and the s'-high-skilled employment shares in city 1.

their tenure choice. At the same time, some households with skills between s' and s'' can afford to buy a house in city 2, but not in city 1. Since ownership has financial advantages, workers in this skill interval have an extra reason to live in city 2. This empties out the middle of the income distribution in city 1, thereby resulting in *higher polarization*. The reduction in the number of workers in the middle of the distribution also leads to greater dispersion of income in city 1, i.e., *higher income inequality*. Figure 3 depicts the intuition behind this result.

The next proposition shows that the presence of both renters and owners is crucial to produce differences in polarization across cities. In an economy with renters only or owners only, skill shares would be the same in both cities, regardless of the differences in price-wage or price-rent ratios.

Proposition 2 (**no differences in polarization without heterogeneity in housing tenure**). Consider the following two scenarios:

1. One of the conditions of Lemma 1 is not satisfied in each city. In this case, every household in each city chooses to rent.
2. Both conditions of Lemma 1 are satisfied in each city, and there is no minimum size constraint (i.e., $\bar{h} = 0$). In this case, every household in each city chooses to own.

Then, in each scenario and for any finite and positive price-wage and price-rent ratios in each city, as well as for any values s' and s'' in $(0, 1)$, cities 1 and 2 have the same s'-low-skilled, s''-high-skilled, and (s', s'')-middle-skilled shares.

Proof. See Appendix Section A.4 □

3.5.1 The Role of Minimum Size and PTI Constraints

The main mechanism hinges on the result that households with sufficiently low income are excluded from homeownership. In turn, the inability of low-income households to buy a home depends on two parameters: the minimum size constraint, $\bar{h}$, and the PTI constraint, λ. Note that in the extreme case of $\bar{h} = 0$, the necessary and sufficient conditions for ownership always hold and everyone chooses to buy a house.

How empirically plausible are these two constraints?[24] While it is certainly possible to rent a fraction of a property (e.g., rent a room in a house), fractional ownership of residential units is rare. Moreover, even though there are small-sized properties that one could buy, especially in dense cities such as New York, the parameter $\bar{h}$ would likely depend on the household type (e.g., a large family with children requires a larger minimal size than a single adult). Indeed, empirical evidence previously discussed in Section 2.4 shows that households with children are more responsive to local price differences in their migration decisions, possibly because the smallest housing units available for sale are outside their choice set. Additionally, the minimum-size constraint implies that rental and owner-occupied markets are segmented by size. Size segmentation is a common feature of many models with tenure choice (Davis and Van Nieuwerburgh, 2015). Moreover, as Appendix Figure F.6 demonstrates, the U.S. housing market exhibits strong segmentation by size: rental units tend to be much smaller than owner-occupied units and there is not much overlap in the size distributions of rental and owner-occupied properties. As for the PTI constraint, the vast majority of home purchases in the data are financed through mortgages which are typically conditioned on the borrower's income at the time of origination, although as shown in Greenwald (2018) the constraint may often not bind.

3.5.2 Comparison to Existing Mechanisms

The vast majority of spatial equilibrium models, including those that have previously studied local differences in labor market polarization and inequality (Baum-Snow, Freedman, and Pavan, 2018; Cerina, Dienesch, Moro, and Rendall, 2022; Davis, Mengus, and Michalski, 2020), do not distinguish between renting and owning and cannot produce local differences in low- or high-skilled shares without relying on various features of the production function, such as skill-biased productivity, skill complementarities, or task

[24] The minimum-size constraint is commonly used in quantitative models of homeownership (Davis and Van Nieuwerburgh, 2015; Imrohoroğlu, Matoba, and Tüzel, 2018; Garriga and Hedlund, 2020). The PTI constraint is less common but also used (Kaplan, Mitman, and Violante, 2020). In this paper, it also indirectly plays the role of the loan-to-value constraint, which is more common. However, since the model has only one period, there is no explicit downpayment or loan-to-value requirement.

automation. In contrast, the model in this paper can generate differences in low and high-skilled employment shares across locations using a production function with perfectly substitutable skills and without local differences in returns to skills.

4 Quantitative Model

This section describes the quantitative version of the model that is later used in counterfactual experiments. All model parameters are listed in Table 5.

Time. The model is calibrated separately for 1980, 2000, and 2019. Each calibrated model is treated as a separate stationary spatial equilibrium. All individual-level data used to calibrate the model is taken from individuals aged 25–64. This implies that the single model period is assumed to last 40 years.

Locations. The model has two locations that are constructed to represent two groups of cities: large and small. In order to aggregate 465 CZs into two location groups, I first sort them by the size of their labor force in 2019. Then I assign the 30 largest CZs into the "large" group and the remaining CZs into the "small" group.[25] Splitting the CZs into large and small at the 30th rank, I obtain two roughly equally-sized groups: the employment share of the 30 largest CZs is 49.3%. All CZ group-level empirical moments that are used in the quantitative model (e.g., wages, house prices, rents, etc.) are employment-weighted averages of CZ-level moments.

Economy-wide parameters. The scale parameter of the Fréchet distribution of location preference shocks, ϵ, is taken from Monte, Redding, and Rossi-Hansberg (2018) who estimated it at the county level, and is equal to 3.3. The land share in the developers' production function, η, is set to 0.33, following the estimates of Albouy and Ehrlich (2018).

The PTI constraint, λ, is set as follows. I follow Greenwald (2018) who provides evidence for a PTI constraint of 0.5.[26] However, I need to adjust this number to make it consistent with the model. From the point of view of households, the model period lasts 40 years and the model assumes that houses are bought in the beginning of the period. At the same time, mortgage contracts are typically underwritten for a 30-year period. Therefore, the PTI constraint has to be multiplied by 30 and then by the fraction of income

[25] A CZ is named after the most populous municipality it contains. The 30 largest CZs are: Los Angeles, CA; New York, NY; Chicago, IL; Washington, DC; Houston, TX; Newark, NJ; Philadelphia, PA; Boston, MA; San Francisco, CA; Atlanta, GA; Dallas, TX; Seattle, WA; Detroit, MI; Miami, FL; Phoenix, AZ; Minneapolis, MN; Denver, CO; Bridgeport, CT; San Diego, CA; Tampa, FL; Baltimore, MD; Sacramento, CA; San Jose, CA; Orlando, FL; Fort Worth, TX; St. Louis, MO; Cleveland, OH; Pittsburgh, PA; Austin, TX; and Portland, OR.

[26] Another study by Kaplan, Mitman, and Violante (2020) use a PTI constraint of 0.25. Greenwald (2018) shows that a large fraction of new mortgages exceed this constraint but almost all are below 0.5.

an individual earns in the first year of life cycle (estimated to be 0.0205), which implies $\lambda = 0.5 \times 30 \times 0.0205 = 0.307$. See Appendix Section D.1 for details.

The elasticity of utility with respect to housing consumption, γ, is also the housing expenditure share for renters. To calibrate γ I take the share of income renters spend on shelter using the Consumer Expenditure Survey (CEX) data. This share is 0.209 in 1980, 0.216 in 2000, and 0.269 in 2019.[27] Recall that the expenditure share of full owners is $\min\{\gamma/\delta, \lambda\}$ (see equation 12). According to the CEX data, the share of income owners spend on shelter is 0.137 in 1980, 0.143 in 2000, and 0.166 in 2019.[28] All of these values are much lower than the calibrated value of λ. Therefore, I use these values to recover δ using the calibrated value of γ. This yields $\delta = 1.526$ in 1980, 1.511 in 2000, and 1.621 in 2019. Note that the housing expenditure share of marginal owners may be higher than γ/δ, all the way up to λ. However, in none of the quantitative experiments I describe in the next section the expenditure share will reach λ. In other words, the PTI constraint is never binding.

Location-specific parameters. Local labor productivity, A_{it}, and amenities, X_{it}, are calibrated to match mean hourly wages and employment, respectively, in each location group and year. As can be seen in panel C of Table 5, productivity is higher in large cities, while amenities are about the same in both groups.

The minimum size of an owner-occupied house, $\bar{h}_{it}$, is allowed to vary by location and year and is calibrated to the observed homeownership rate in each CZ group and year. The calibrated value of $\bar{h}_{it}$ grew more slowly in large than in small cities. This is consistent with anecdotal evidence that suggests that the supply of small onwer-occupied units, such as studio condos, may be more abundant in large than in small CZs, as well as the evidence that houses have become larger in recent decades.[29]

For the quantitative model, it is not necessary to separately identify the productivity of developers and land area; hence, I calibrate the product $\phi_{it}\Lambda_{it}$ to the observed price-wage ratio in each CZ group and year. The calibrated level of this product has no interpretation; however, as panel C of Table 5 demonstrates, $\phi_{it}\Lambda_{it}$ is smaller in large CZs and the relative gap in its values between large and small cities has widened between 1980 and 2019. This is consistent with the evidence that housing supply in many large American cities has become more constrained in recent decades (Glaeser and Gyourko, 2018).

[27]These values are close to 0.24 estimated by Davis and Ortalo-Magné (2011), a standard value for renters' expenditure share used in the literature.

[28]Together with housing spending shares of renters, these values are consistent with Davis and Van Nieuwerburgh (2015) who report that, based on the NIPA data, housing accounts for about 17% of household expenditures of owners and renters combined.

[29]https://www.wsj.com/articles/BL-REB-35826

Table 5: Parameters of the quantitative model

Panel A: Economy-wide time-invariant parameters

Parameter	Value
Fréchet elasticity	$\epsilon = 3.3$
Land share	$\eta = 0.33$
PTI constraint	$\lambda = 0.307$

Panel B: Economy-wide time-varying parameters

Parameter	Value		
	1980	2000	2019
Elasticity of utility w.r.t. housing, γ	0.209	0.216	0.269
Homeownership expenses, δ	1.526	1.511	1.621

Panel C: Local time-varying parameters

Parameter	CZ group	Value		
		1980	2000	2019
Productivity, A_{it}	Small	2.53	5.14	7.25
	Large	2.78	5.50	7.91
Amenities, X_{it}	Small	0.51	0.51	0.50
	Large	0.49	0.49	0.50
Min. size, $\bar{h}_{it}$	Small	1.97	2.63	2.82
	Large	2.43	2.15	1.82
Construction productivity X land, $\phi_{it}\Lambda_{it}$	Small	17.5	2.89	0.89
	Large	6.43	0.63	0.12
Price-rent ratio, Ω_{it}	Small	0.62	0.43	0.41
	Large	0.53	0.48	0.50
Middle-skilled wage shifter, $\bar{\omega}_{it}^{M}$	Small	0.96	1.01	1.02
	Large	1.04	0.99	0.98
High-skilled wage shifter, $\bar{\omega}_{it}^{H}$	Small	0.90	0.98	0.99
	Large	1.10	1.02	1.01
Skill dispersion, α_{it}	Small	1.90	2.02	2.11
	Large	1.75	2.14	2.25

Notes: The table summarizes parameters used in the quantitative model. Panel A lists parameters common to all years and locations. Panel B shows parameters that vary over time but are common to all locations. Panel C lists parameters that vary by year and location.

In the model, price-rent ratios are exogenous. Hence, I compute Ω_{it} from the ratio of the estimated hedonic price and rent indices in each CZ group and year. The values of Ω_{it} are discussed below. Since the model period is assumed to last 40 years, I convert monthly rent data into a 40-year equivalent by multiplying annual rents by 12×40.

Skill distribution. In the quantitative model, the skill distribution is discretized into a 100-point grid so that $s \in \{0.01, 0.02, ..., 1\}$. Skill groups are labeled "low," "middle," or "high" and are separated at the 20th and the 80th percentiles of the skill distribution, as described in Section 2.1.[30] In each calibration year, aggregate shares of low-, middle-, and high-skilled workers are taken from the data in order to reflect economy-wide changes in each skill group's employment shares. Furthermore, in order to reproduce the share of each skill group in each CZ group, I introduce adjustment factors that shift relative labor earnings of middle- and high-skilled workers. Thus, labor earnings are $\bar{\omega}_{it}^{M} w_{it}(s)$ for a middle-skilled worker and $\bar{\omega}_{it}^{H} w_{it}(s)$ for a high-skilled worker. As shown in panel C of Table 5, these adjustment factors are close to 1, i.e., they do not distort the distribution of income in any major way. Returns to skill in each year and CZ group are parameterized using the exponential function:

$$a_{it}(s) = e^{\alpha_{it} s}. \tag{28}$$

Parameter α_{it} governs the dispersion of returns to skill and is calibrated separately for each CZ group and year so as to match the observed variance of log hourly wages in each location-year combination. Panel C of Table 5 shows that α_{it} increased much faster in large CZs than in small ones which is consistent with more pronounced SBTC in big cities.

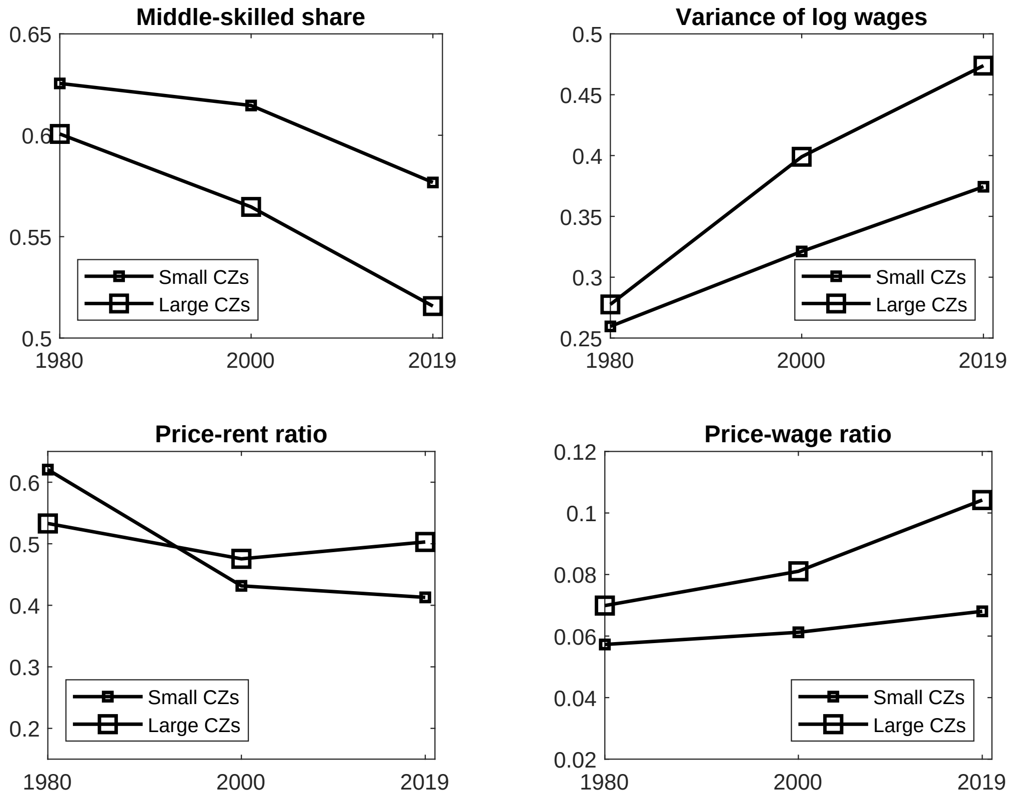
Evolution of polarization and inequality. The top two panels in Figure 4 show the middle-skilled share and the variance of log wages in large and small CZs in the quantitative model. Note that the model reproduces exactly the decline in the middle-skilled share and the rise of the variance of log wages by location and year, since both moments are calibration targets. The figure corroborates the evidence shown in Section 2. In 1980, large cities already had a lower middle-skilled share but the difference between large and small cities was only 2.5 percentage points. Between 1980 and 2019, the middle-skilled share declined in all cities, a result of aggregate labor market polarization, however it fell faster in large cities and the gap between the two groups of cities widened by 3.6 percentage points. Similarly, in 1980 the variance of log wages was nearly the same in both groups of cities: 0.26 in small and 0.28 in large cities.[31] By 2019, it increased much faster in large cities and the gap widened by 0.082, from 0.02 to nearly 0.1.

Evolution of house prices. The bottom two panels in Figure 4 show the evolution of price-rent and price-wage ratios in the two groups of cities. As with polarization and inequality, the model reproduces exactly the two ratios because one of them, the price-rent

[30]That is, low-skilled workers have $s \in [0.01, 0.2]$, the medium-skilled have $s \in (0.2, 0.8]$, and the high-skilled have $s \in (0.8, 1]$.

[31]The variance of log wages in each group of cities is the weighted-average of CZ-specific variances.

Figure 4: Polarization, inequality, and house prices in large and small CZs



Notes: The top two panels plot the middle-skilled share and the variance of log wages in the groups of large and small CZs in the model economy. The bottom two panels plot price-rent and price-wage ratios.

ratio, is a parameter (Ω_{it}), while the price-wage ratio is a calibration target. The price-rent ratio was relatively stable in large cities between 1980 and 2019 but it fell in small cities.[32] At the same time, the price-wage ratio increased much more in large cities. Both indicators imply that purchasing a house became relatively more expensive in large CZs.

Why did prices go up more in large CZs? Table 5 suggests that it was a combination of slower growth in supply and faster growth in demand.[33] The relative land-augmented productivity of developers, $\phi_{it}\Lambda_{it}$, in large CZs fell from 0.37 in 1980 to 0.14 in 2019. At the same time, while overall labor productivity, A_{it}, grew at similar pace in large and small CZs, returns to skill, as represented by α_{it} increased much more in large CZs. This means that large CZs saw a disproportionate increase in high-income households that drove the demand for housing.

[32]Other studies showed that the aggregate price-rent ratio in the U.S. is stable over the long run, though it varies over the business cycle (Davis and Van Nieuwerburgh, 2015; Piazzesi and Schneider, 2016).

[33]This explanation is similar to the explanation proposed by Gyourko, Mayer, and Sinai (2013).

5 Counterfactual Experiments

As discussed above, the most common explanation for greater polarization and rise in inequality in large U.S. cities in the previous literature is skill-biased technical change (SBTC). This paper offers a novel explanation that relies on the interaction between faster house price growth in large cities and the desire to own a house. In this section, I use the quantitative model to compare these two explanations. I find that, while SBTC is a powerful force that accounts for the bulk of disproportionate polarization and inequality in big cities, the interaction of price growth and homeownership significantly amplifies the effect of SBTC on polarization and inequality in large cities.

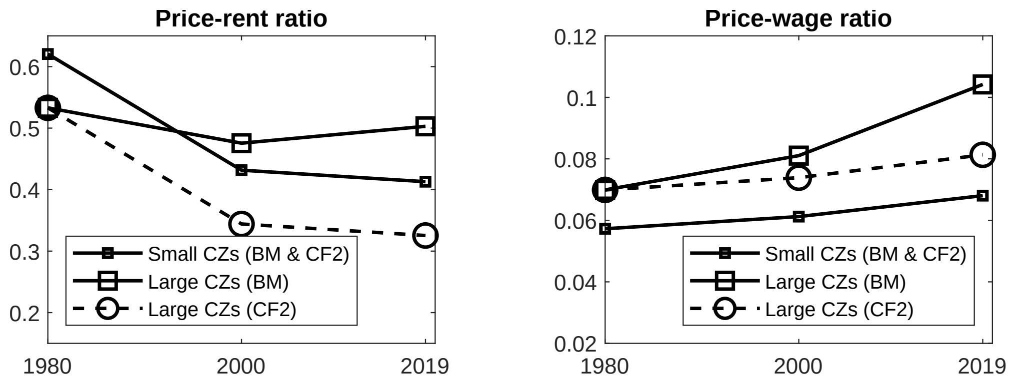
5.1 Counterfactual Experiments

5.1.1 Setup

CF1: No SBTC. There are two sets of parameters that govern returns to skills and that could produce more pronounced SBTC in large cities. First, the middle- and high-skilled wage shifters, $\bar{\omega}_{it}^{M}$ and $\bar{\omega}_{it}^{H}$, that proportionately change wages for all middle- and high-skilled workers. Second, skill dispersion parameters α_{it} which change the elasticity of wages with respect to the skill level. As can be seen in panel C of Table 5, $\bar{\omega}_{it}^{M}$ and $\bar{\omega}_{it}^{H}$ increase in small cities and fall in large ones. This should attract both middle- and high-skilled workers to small CZs and therefore these changes in wage shifters have an ambiguous effect on polarization and inequality. At the same time, α_{it} grows faster in large cities. This should produce greater polarization and inequality in large CZs. As a result, in the quantitative model SBTC is more pronounced in large cities because of differential changes in α_{it} and is somewhat muted by the evolution of $\bar{\omega}_{it}^{M}$ and $\bar{\omega}_{it}^{H}$. To quantify the role of SBTC in driving greater polarization and inequality in large cities, I keep the returns-to-skills parameters $\bar{\omega}_{it}^{M}$, $\bar{\omega}_{it}^{H}$, and α_{it} at their 1980 level and compute counterfactual equilibria for years 2000 and 2019.

CF2: Same $\Delta p/w$, $\Delta p/r$. To study the importance of higher growth of price-rent and price-wage ratios in large cities, I run a counterfactual experiment in which both price-rent and price-wage ratios in large cities change as much as they did in small cities between 1980 and 2019. To fix price-rent ratios it is sufficient to adjust Ω_{it}, the exogenous parameter that corresponds to the price-rent ratio. However, since both prices and wages are endogenous, in order to fix price-wage ratios I need to adjust a parameter that either lowers prices or increases wages in large CZs in such a way that the price-wage ratio evolves as it did in small CZs. To this end, I reduce prices by adjusting the combined

Figure 5: Price-rent and price-wage ratios in counterfactual experiments



Notes: The left panel of the figure shows the evolution of price-rent ratios in small and large CZs in the benchmark (BM) and counterfactual (CF2) economies. The left panel of the figure shows the evolution of price-wage ratios.

developers' productivity and land supply, $\phi_{it}\Lambda_{it}$.[34] Note that in this counterfactual I allow for SBTC, i.e., $\bar{\omega}_{it}^{M}$, $\bar{\omega}_{it}^{H}$, and α_{it} change over time as they do in the benchmark economy. Figure 5 illustrates the evolution of price-rent and price-wage ratios in these counterfactual experiments, and shows that both price-rent and price-wage ratios in large CZs are much lower in the counterfactuals than in the benchmark economy, while the ratios remain the same in small CZs.

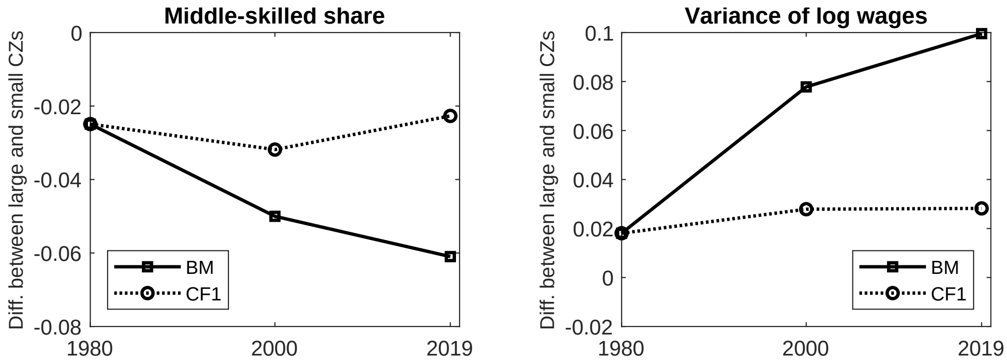
5.1.2 SBTC vs Rising Prices

Panel A of Figure 6 reports the results of CF1 where the returns to skill did not change since 1980. It shows that if skill returns remained constant, we would not see much of a difference in polarization and increase in inequality between large and small CZs in both 2000 and 2019. That is, greater SBTC in large cities accounts for most of the excess polarization and rise in income inequality in large cities. Panel B of Figure 6 shows the results of CF2 where price-wage and price-rent ratios in large CZs evolved exactly as they did in small CZs. In this scenario, there is much less difference in the decline in the middle-skilled share between the CZ groups and also slower increase in the difference in inequality, even when SBTC is in full force. The effect of changes in price-rent and price-wage ratios is much more pronounced in the 2000–2019 period than in 1980–2000. This is because, as Panel B of Figure 4 showed, the divergence of price-rent and price-wage

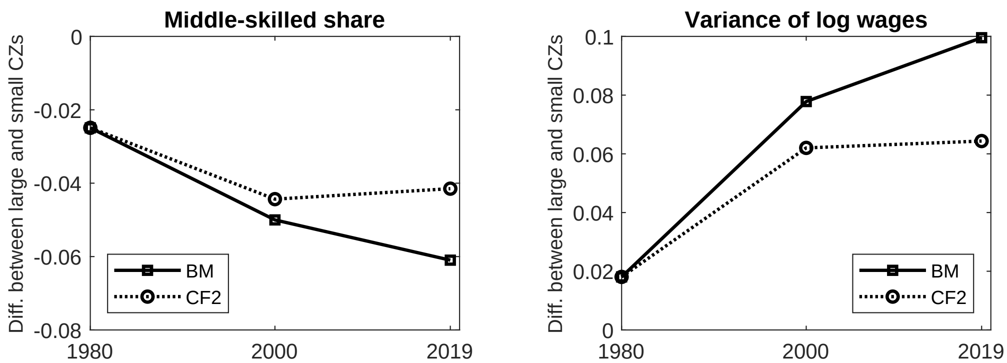
[34]Another possibility is to increase wages, e.g., by raising local productivity A_i. But wage increases capitalize in house prices. In my numerical experiments, wage changes did not have a noticeable effect on the price-wage ratio and I was not able to obtain the same price-wage ratio growth in large CZs as in small CZs by only recalibrating local productivity.

Figure 6: Counterfactual Results

Panel A: Role of SBTC (CF1)



Panel B: Role of Price-Rent and Price-Wage Ratios (CF2)



Notes: The left figure in panel A shows the difference between the share of middle-skilled employment in large CZs and the share in small CZs in the benchmark economy (solid line) and in CF1 (dotted line). The right figure shows the difference between the variance of log wages in large CZs and the variance in small CZs for the benchmark and the counterfactual economies. Panel B shows results for the evolution of the middle-skilled share and the variance of log wages in the benchmark and CF2.

ratios between large and small CZs accelerated since 2000.

Table 6 compares the effects of the two counterfactual experiments on polarization and inequality. The table shows that in the benchmark economy the difference between the middle-skilled share in large CZs and the share in small CZs grew by 3.6 percentage points from 1980 to 2019, and that the difference in the variance of log wages went up by 0.082, as previously reported in Section 4. Next, it shows that SBTC accounts for over 100% of the increase in the gap in the middle-skilled share and 88% of the gap in income inequality. This is consistent with the findings of the previous literature discussed earlier. Baum-Snow, Freedman, and Pavan (2018) find that SBTC accounts for about 80% of the excess rise of inequality in large cities, while Cerina, Dienesch, Moro, and Rendall (2022) find that 67% of the excess job polarization in big cities is due to SBTC. The table also shows

Table 6: Counterfactual changes

	Benchmark	CF1: No SBTC	CF2: Same $\Delta p/w$, $\Delta p/r$
Δ middle-skilled share in large CZs, 1980–2019	0.036	-0.002	0.017
difference explained, %		106	54
Δ variance of log wages in large CZs, 1980–2019	0.081	0.010	0.046
difference explained, %		88	43

Notes: The table shows differences in middle-skilled share and variance of log wages between large and small CZs in the benchmark economy and the two counterfactual economies.

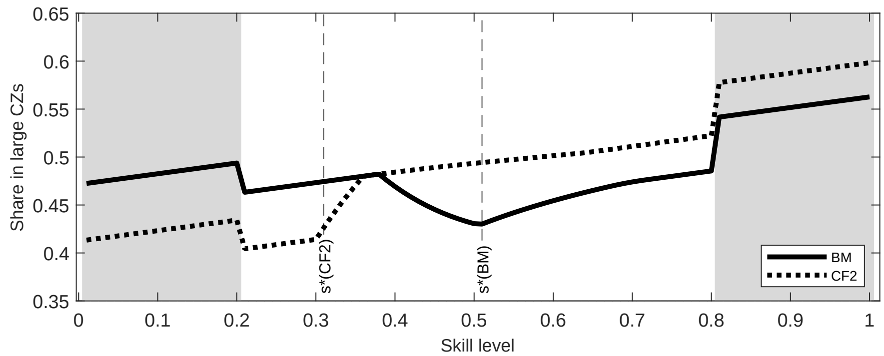
that disproportionately rising price-wage and price-rent ratios in large CZs account for 54% of the increase in the middle-skilled gap and 43% of the growth in the gap in the variance of log wages, even though CF2 incorporates SBTC.

These results mean that, while SBTC is a primary determinant of the rising gap in polarization and inequality between large and small CZs, its effect depends on and is significantly amplified by faster price growth in big cities. Without this amplification mechanism, the effects of SBTC would be about 1/2 smaller. One could argue that larger price-wage and price-rent ratio growth in big CZs is merely a consequence of SBTC and cannot be studied as a separate channel. However, note that I study the growth of prices *relative* to wages and rents. In a simpler spatial equilibrium model without tenure choice and distinction between prices and rents, price-rent ratios would not change simply because they are not defined. Price-wage ratios could change, but this would not differentially affect workers across the skill distribution because they would not be making the choice to rent or own. A model without tenure choice would still be able to account for most of the increase in inequality and polarization in large cities via the SBTC channel; however, in such model the skill-returns parameters would have to change by more because changes in housing parameters would not play any role.

To understand better how the middle class is squeezed out of large CZs due to higher price-rent and price-wage ratios, it is useful to look at the distribution of skills in the benchmark and counterfactual economies in Figure 7. The figure shows that in the benchmark economy, the middle of the skill distribution was underrepresented (for most skill levels between 0.2 and 0.8 the solid line is below the dotted line). Moreover, the share of middle-skilled workers in large CZs was declining between skill levels 0.2 to 0.5 and increasing between skill levels 0.5 to 0.8.[35] This is because the equilibrium skill

[35]The skill distributions have jumps at $s = 0.2$ and $s = 0.8$, since these thresholds separate low-, middle- and high-skilled groups of workers, and shifters $\bar{\omega}_{it}^{M}$ and $\bar{\omega}_{it}^{H}$ are calibrated to match local fractions of these groups in the data.

Figure 7: Skill distribution in large CZs



Notes: This figure shows the fraction of workers of each skill level that resides in large CZs in the benchmark economy (solid line) and the counterfactual economy (dashed-dotted line). Vertical lines show the skill thresholds for homeownership in both economies.

threshold for owning a house in large CZs, s^*, is equal to 0.51. In the counterfactual, the skill threshold fell to 0.31. This explains a steep increase in the share of workers in large CZs starting from $s = 0.31$, and a larger overall share of the middle-skilled in big cities.

5.1.3 Other Results

Table 7 demonstrates several other counterfactual results. Lowering price-rent ratios in large cities makes homeownership a much more attractive choice, so that aggregate homeownership rate jumps from 61.2% to nearly 70%. When both price-rent and price-wage ratios change in large CZs as they did in small CZs, large CZs become more affordable and some households move there. This increases their employment share by nearly 1 percentage point. Rising employment in large CZs also leads to aggregate gains in output, because large cities are more productive, and welfare.[36] These improvements in housing affordability and productivity yield a 3.1% welfare gain for an average worker.[37] However, these gains are not equally distributed.

Who wins and who loses from lower growth in price-rent and price-wage ratios in large CZs? Figure 8 plots welfare gains by skill level. In the counterfactual economy, the skill threshold for homeownership in large CZs falls to $s^* = 0.31$ from 0.51 in the benchmark. Those who are not skilled enough to buy a house even in the counterfactual,

[36] Herkenhoff, Ohanian, and Prescott (2018), Hsieh and Moretti (2019), Parkhomenko (2020), and Duranton and Puga (2022) also find sizable aggregate productivity gains from lowering housing costs in the most productive locations and the resulting relocation of workers there.

[37] Welfare gains are computed as consumption-equivalent percentage changes of the expression in equation (22). Real estate managers are excluded from welfare calculations. Since counterfactuals involve adjusting housing supply or price-rent ratios, welfare effects do not take into account the impact of having to build more housing or making other changes that alter local relationships between rents and prices.

Table 7: Counterfactual changes

	Benchmark	CF2: Same $\Delta p/w$, $\Delta p/r$
Homeownership rate, %	61.2	69.9
Employment in large CZs, %	49.1	50.0
Output	100	100.6
Welfare	100	103.1

Notes: The table shows the values of several variables of interest in the benchmark economy calibrated to 2019 and the counterfactual economy.

i.e., those with $s < 0.31$, are worse off because rents in large CZs go up.[38] However, the new homeowners close to this threshold are worse off too. In the benchmark economy they were renters. In the counterfactual, they find it optimal to buy because rents go up but they are marginal owners and have to spend a relatively large share of income on housing. Workers with $s \geq 0.34$ are better off. The largest welfare gains accrue to those in the middle of the skill distribution. Households with skills between around 0.4 and 0.51 benefit greatly because not only they switch from renting to owning but also, since they are far from the homeownership threshold, they spend a smaller share of income on housing. Households with skills between 0.51 and 0.65 benefit a little more than those with higher skills because, even though the own their homes in both benchmark and counterfactual economies, they were close to the ownership threshold in the benchmark and had to spend a lot on housing.

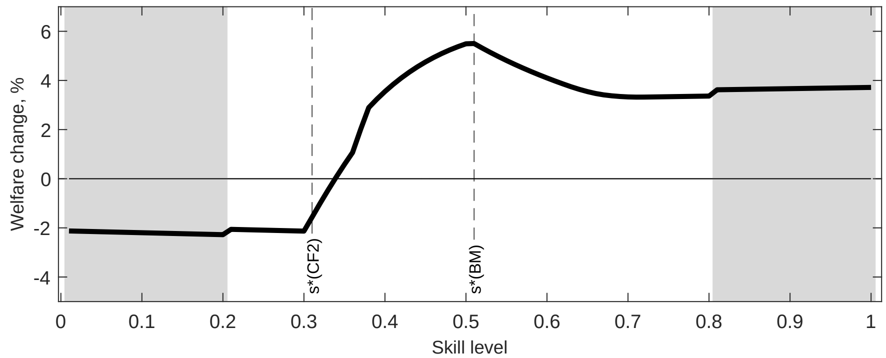
These results suggest that middle-skilled workers, especially those with skill levels between 0.4 and 0.65, were the largest losers from disproportionately rising price-rent and price-wage ratios in large cities from 1980s. They also suggest that renters at the left of the skill distribution may not have lost out. Since they are shut out from homeownership due to low income, they do not benefit from lower house prices relative to rents or wages.

5.1.4 Additional Results, Robustness, and Sensitivity

In the main counterfactual, I restrict the growth in both price-rent and price-wage ratios in large CZs. In Appendix Section E.1, I look at two alternative counterfactuals where I limit the growth of price-rent ratios or price-wage ratios separately. I find that both explanations are quantitatively important and complement each other. That is, large CZs have become

[38] The decline in price-rent ratios in large CZs is a result of simultaneous fall in prices and growth in rents. The calibrated increase in the combination of land supply and construction productivity is not sufficient to reduce both rents and prices. As a result, while prices in large CZs fall by over 19%, rents jump by 25%. Prices and rents in small CZs fall by about 4% each reflecting lower housing demand.

Figure 8: Welfare gains by skill



Notes: This figure shows welfare gains in the counterfactual scenario relative to the benchmark for workers at each skill level. Vertical lines show the skill thresholds for homeownership in large CZs in both economies.

more polarized and unequal both because prices have grown more than rents, which made big cities especially unattractive for potential homeowners, and because prices have grown more than incomes, which made big cities less attractive for everyone.

The findings presented above do not tell us whether middle-skilled households are increasingly leaving large CZs because prices have grown relative to rents and wages or because, regardless of price changes, it became more difficult to own a house. The equilibrium skill threshold for owning a home, s_i^*, increases from 0.33 to 0.38 in small CZs and from 0.47 to 0.51 in large CZs between 1980 and 2019. To shed light on the importance of the increase in ownership threshold, I run an alternative counterfactual where I recalibrate $\bar{h}_i$ in both locations so as to keep s_i^* constant at the 1980 level in all years, while keeping all other parameters the same as in the benchmark calibration. Panel A of Appendix Figure E.2 shows that keeping s_i^* constant does not have a sizable effect on polarization and the rise of inequality in large CZs. That is, large cities have become disproportionately more polarized and unequal not so much because a large group of workers were shut out from homeownership but because it became much more expensive to buy a house in a large city.

In the main counterfactual, I fix the *difference* in price-rent and price-wage ratios between CZs. An alternative approach would be to fix the *levels* of price-rent and price-wage ratios. Panel B of Appendix Figure E.2 shows that this would make the results smaller but still large and would not change any of the conclusions.

In the quantitative model, I let the housing expenditure share increase over time for both renters and owners in line with the evidence from the CEX data. If the shares remained unchanged, the demand for housing would be weaker and, perhaps, the role of rising prices in polarization and inequality in large cities would be smaller. I run a counterfactual where γ and δ are fixed at their 1980 level but, as Panel C of Appendix Figure E.2 shows, the main counterfactual results are virtually unchanged.

Finally, while shifters $\bar{\omega}_{it}^{M}$ and $\bar{\omega}_{it}^{H}$ help match local shares of low-, middle-, and high-skilled workers, they slightly distort the relationship between skill levels and incomes by generating small jumps at $s = 0.2$ and $s = 0.8$. In Panel D of Appendix Figure E.2, I show that if the model was calibrated without these shifters, the quantitative findings on the role of price-wage and price-rent ratios for polarization and inequality would not change.

5.2 Discussion

5.2.1 Implications for Housing Policies

The findings of counterfactual experiments provide important insights for the understanding of housing policies in the United States. In particular, the results suggest that policies that could increase housing supply in large but unaffordable cities, such as zoning reforms, would not only lead to a more efficient spatial allocation of labor and greater aggregate productivity (Herkenhoff, Ohanian, and Prescott, 2018; Hsieh and Moretti, 2019; Parkhomenko, 2020; Duranton and Puga, 2022) but could also make these cities less economically polarized and unequal. This contrasts with the potential effect of policies that promote homeownership by reducing the relative cost of owning a home but without raising housing supply. Such policies may contribute to the concentration of high-skilled workers in large expensive cities, increase local polarization and inequality, and ironically do not necessarily increase the homeownership rate (Hilber and Turner, 2014; Sommer and Sullivan, 2018). In Appendix Section E.1, I study a counterfactual experiment where price-rent ratios in large CZs are lowered but construction productivity is large CZs is the same as in the main counterfactual. In this experiment, homeownership increases less than in the main counterfactual and an average household's welfare falls.

5.2.2 Possible Extensions

The quantitative model is rather stylized and omits several features that may affect the interaction between homeownership, polarization, and inequality. First, the model is static. A dynamic model would incorporate other reasons why households may prefer to own rather than rent, such as asset appreciation or insurance against labor or housing market risk. It would also allow studying how changes in location choices at different stages of life cycle interact with tenure choices.

Second, labor is the only factor of production and different skills are perfect substitutes. A model that features interactions between labor and other production inputs as well as between different skills could enrich our understanding of the relationship between house prices, job polarization, and income inequality at the local level.[39]

Third, I do not model internal city structure. While in the model the price of housing is the same everywhere in a CZ, in practice, there is large price heterogeneity within CZs. Moreover, just as price and rent dispersion *across* local labor markets has gone up in recent decades (Van Nieuwerburgh and Weill, 2010), *within*-city differences in prices have increased too (Albouy and Zabek, 2016). One reason why modeling internal city structure may be second-order is that the elasticity of substitution between locations within a city is likely to be high, and therefore we should expect that within-city price differences largely offset local amenity differences. However, in the presence of housing market constraints that determine who rents and who owns housing, differences in neighborhood amenities will not only be reflected in prices but also in homeownership rates and therefore may have non-trivial implications for the evolution of inequality and polarization within CZs.

Finally, I assume that households must live and work in the same CZ. However, since 2020 we saw an explosion of remote and hybrid working arrangements that decoupled the choice of residence and the choice of workplace for many workers (Barrero, Bloom, and Davis, 2021). Delventhal and Parkhomenko (2022) build a quantitative spatial equilibrium model with work from home. They find that when remote work become more common high-skilled workers move out of central areas of large cities to take advantage of less frequent commutes and cheaper housing, while low-skilled workers who typically cannot work from home move into central areas. This suggests that in the future where workers are less attached to their workplaces, disproportionate polarization and increase in inequality in big cities may fade out.

6 Conclusions

In this paper, I propose a novel mechanism that helps our understanding why jobs have become more polarized and income distribution more unequal in large and expensive cities. While previous studies emphasized the role of skill-biased technical change and external labor demand shocks, I argue that housing markets play a key role. When local price-wage and price-rent ratios are high, some middle-income households relocate to more affordable cities where they can buy a house. This hollows out the middle of the income distribution in expensive cities, which are typically also large cities, and results in higher polarization there.

[39] At the same time, Baum-Snow, Freedman, and Pavan (2018) find that capital-skill complementarity explains little of the excess growth in income inequality in large cities.

I provide empirical evidence that supports this hypothesis. First, I show that polarization and the rise in income inequality were stronger in CZs where prices, price-rent, and price-rent ratios increased more since 1980, even when controlling for CZ size. Second, I show that middle-income households are more likely than low- and high-income households to move for housing-related reasons to more affordable states. I build a model consistent with this evidence and demonstrate that greater polarization and inequality in locations with high price-wage and price-rent ratios is an equilibrium outcome.

Quantitative exercises corroborate the findings of previous literature that SBTC is an important driver of greater polarization and inequality in big cities. However, the effect of SBTC is significantly amplified by disproportionately high growth or price-rent and price-wage ratios in large cities. Absent amplification in the housing market, the effects of SBTC would be about one-half smaller. These results suggest that policies that constrained housing supply and contributed to high housing costs in many large cities also led to greater polarization and inequality there.

This paper also highlights the benefits of studying location choice and housing tenure choice jointly, as these two choices seem to be interconnected for many households. The vast majority of models with location choice do not have tenure choice, while most models of tenure choice do not have location choice. As this paper shows, a model that combines these two choices goes a long way in explaining differences in economic outcomes across locations.

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A Appendix: Derivations and Proofs

A.1 Proof of Lemma 1

Based on the expression for optimal housing consumption of owners (12), there are homeowners who buy houses larger than the minimum size only if income earned by the most skilled worker ($s = 1$) in the city is high enough. When the PTI constraint does not bind ($\lambda > \gamma/\delta$), the wage of the most skilled worker must satisfy $w_i(s = 1) > \delta p_i \bar{h}/\gamma$. When the PTI constraint binds ($\lambda \leq \gamma/\delta$), the wage of the most skilled worker must satisfy $w_i(s = 1) > p_i \bar{h}/\lambda$. Thus, the necessary condition for homeownership is

$$\bar{h} < \min\left\{\frac{\gamma}{\delta}, \lambda\right\} \frac{w_i(s = 1)}{p_i} \tag{29}$$

However, even if this necessary condition is satisfied, households may find it suboptimal to own houses if prices are too high relative to rents. For a high enough income, ownership is preferred if the indirect utility of owning (13) is greater or equal to the utility of renting (8). In case of a non-binding PTI constraint, we have

$$\frac{w_i(s)}{\delta p_i^{\gamma}} \left(\frac{\delta - \gamma}{1 - \gamma}\right)^{1-\gamma} \geq \frac{w_i(s)}{r_i^{\gamma}}. \tag{30}$$

When the PTI constraint binds, we have

$$\frac{w_i(s)}{p_i^{\gamma}} \left(\frac{1 - \delta\lambda}{1 - \gamma}\right)^{1-\gamma} \left(\frac{\lambda}{\gamma}\right)^{\gamma} \geq \frac{w_i(s)}{r_i^{\gamma}}. \tag{31}$$

These two conditions can be rewritten in terms of the price-rent ratio as

$$\frac{p_i}{r_i} \leq \begin{cases} \left(\frac{\delta-\gamma}{1-\gamma}\right)^{\frac{1-\gamma}{\gamma}} \frac{1}{\delta^{1/\gamma}} & \text{if } \lambda > \frac{\gamma}{\delta}, \\ \left(\frac{1-\delta\lambda}{1-\gamma}\right)^{\frac{1-\gamma}{\gamma}} \frac{\lambda}{\gamma} & \text{if } \lambda \leq \frac{\gamma}{\delta}. \end{cases} \tag{32}$$

A.2 Proof of Lemma 2

Parts (a) and (b)

Case 1: PTI constraint does not bind. First, since $\bar{h} > 0$, there is $s' > 0$ such that $w_i(s') = \delta p_i \bar{h}$. This means that $v_i^O(w_i(s), p_i) = -\infty$ for all $s \leq s'$. At the same time, because renter's housing consumption does not have a minimal level and because $w_i(s) > 0$ for all s, we have $v_i^R(w_i(s), r_i) > 0$ for any $s \leq s'$. Thus, $v_i^R(w_i(s), r_i) > v_i^O(w_i(s), p_i)$ for all $s \leq s'$.

Next, let $v_i^{MO}(w_i(s), p_i)$ be the utility derived from consuming $h = \bar{h}$ units of housing and $v_i^{FO}(w_i(s), p_i)$ be the utility derived from consuming $h \geq \bar{h}$ units (*MO* and *FO* for marginal and full owners). Let s_i^{**} be such that $w_i(s_i^{**}) = \delta p_i \bar{h}/\gamma$. Note that at this skill level it is optimal to switch to become a full owner but still consume $h = \bar{h}$. As a result,

$$v_i^{FO}(w_i(s_i^{**}), p_i) = v_i^{MO}(w_i(s_i^{**}), p_i).$$

Consuming $h > \bar{h}$ when $s < s_i^{**}$ is suboptimal; hence, $v_i^{MO}(w_i(s), p_i) > v_i^{FO}(w_i(s), p_i)$ for all $s \in (s', s_i^{**})$. At the same time, $v_i^{FO}(w_i(s), p_i) > v_i^{MO}(w_i(s), p_i)$ for all $s \in (s_i^{**}, \infty)$ because in this interval $h_i^{FO}(s) > \bar{h}$ and an individual would not maximize lifetime utility by choosing house size $\bar{h}$. Also, since the condition (16) holds, we have $v_i^{FO}(w_i(s_i^{**}), p_i) > v_i^R(w_i(s_i^{**}), r_i)$.

Third, note that the wage threshold for full ownership is higher than the threshold for marginal ownership. As a consequence, since $v_i^{MO}(w_i(s), p_i)$ is a continuous function of s, there exists $s'' < s_i^{**}$ such that $v_i^{MO}(w_i(s''), p_i) > v_i^R(w_i(s''), r_i)$.

Fourth, recall that $\Phi(s)$ has full support on $s \in (0, \infty)$ and that both $v_i^R(w_i(s), r_i)$ and $v_i^{MO}(w_i(s), p_i)$ are continuous functions of s. This means that there exists $s^* \in (s', s'')$ such that that

$$v_i^R(w_i(s_i^*), r_i) = v_i^{MO}(w_i(s_i^*), p_i).$$

Finally, since $s_i^* < s''$ and $s_i^{**} > s''$, we have $s_i^* < s_i^{**}$

Case 2: PTI constraint binds. If the PTI constraint binds, the proof is identical, except that there are no marginal owners and $s_i^* = s_i^{**}$ ■

Part (c). The full-ownership threshold is given by $w_i(s_i^{**}) = \delta p_i \bar{h}/\min\{\gamma/\delta, \lambda\}$. Since, $w_i(s) = A_i a(s)$, the skill threshold s_i^{**} is

$$a(s_i^{**}) = \frac{p_i \bar{h}}{A_i \min\{\gamma/\delta, \lambda\}}. \tag{33}$$

Because $a(s)$ is a strictly increasing function, s_i^{**} is decreasing in A_i.

The marginal-ownership threshold s_i^* is implicitly defined by the equivalence between the value of renting and the value of owning:

$$\Phi = \frac{w_i(s_i^*)}{r_i^\gamma} - \left(\frac{w_i(s_i^*) - \delta p_i \bar{h}}{1-\gamma}\right)^{1-\gamma} \left(\frac{\bar{h}}{\gamma}\right)^\gamma = 0. \tag{34}$$

Using the implicit function theorem, we can determine the relationship between s_i^* and A_i

as $\partial s_i^*/\partial A_i = -\left(\partial\Phi/\partial A_i\right)/\left(\partial\Phi/\partial s_i^*\right)$. We have

$$\frac{\partial\Phi}{\partial A_i} = \frac{a_i(s_i^*)}{r_i^\gamma} - a_i(s_i^*)\left(\frac{1-\gamma}{\gamma}\frac{\bar{h}}{w_i(s_i^*)-\delta p_i\bar{h}}\right)^\gamma, \tag{35}$$

and

$$\frac{\partial\Phi}{\partial s_i^*} = \frac{A_i a_i'(s_i^*)}{r_i^\gamma} - A_i a_i'(s_i^*)\left(\frac{1-\gamma}{\gamma}\frac{\bar{h}}{w_i(s_i^*)-\delta p_i\bar{h}}\right)^\gamma. \tag{36}$$

Therefore,

$$\frac{\partial s_i^*}{\partial A_i} = -\frac{a_i(s_i^*)}{A_i a_i'(s_i^*)}. \tag{37}$$

Since all of the components of the ratio on the right-hand side are positive, $\partial s_i^*/\partial A_i < 0$, i.e., the skill level required to buy a house falls when a city has higher productivity ■

A.3 Proof of Proposition 1

By Lemma 2, higher price-wage ratio in city 1 implies that the skill threshold to become an owner is higher in this city, i.e., $s_1^* > s_2^*$. Define the low-skilled households as those with $s \le s'$ and high-skilled households as those with $s \ge s''$, and let $s' < s_2^*$ and $s'' > s_1^*$. The remainder of households are middle-skilled.

Equilibrium skill shares. Denote $v_i^R(s) \equiv v_i^R\left(w_i(s), r_i\right)$ and $v_i^O(s) \equiv v_i^O\left(w_i(s), p_i\right)$. Optimal location and tenure choices imply that the measure of low-skilled workers in city 1 is

$$\mathcal{L}_1 = \int_0^{s'}\left(1+\left(\frac{v_2^R(s)}{v_1^R(s)}\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s) = \int_0^{s'}\left(1+\left(\frac{A_2X_2}{A_1X_1}\left(\frac{r_1}{r_2}\right)^\gamma\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s) = \frac{1}{1+\mathbf{r}}\mathbf{\Phi}_0^{s'},$$

where $\mathbf{r} \equiv \left(\frac{A_2X_2}{A_1X_1}\left(\frac{r_1}{r_2}\right)^\gamma\right)^\epsilon$ and $\mathbf{\Phi}_0^{s'} \equiv \int_0^{s'}\mathrm{d}\Phi(s)$. Similarly, the number of the high-skilled is given by

$$\mathcal{H}_1 = \int_{s''}^1\left(1+\left(\frac{v_2^O(s)}{v_1^O(s)}\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s) = \frac{1}{1+\mathbf{p}}\mathbf{\Phi}_{s''}^1,$$

where $\mathbf{p} \equiv \left(\frac{A_2X_2}{A_1X_1}\left(\frac{p_1}{p_2}\right)^\gamma\right)^\epsilon$. Finally, the measure of the middle-skilled is

$$\begin{aligned}\mathcal{M}_1 &= \int_{s'}^{s_2^*}\left(1+\left(\frac{v_2^R(s)}{v_1^R(s)}\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s) + \int_{s_2^*}^{s_1^*}\left(1+\left(\frac{v_2^O(s)}{v_1^R(s)}\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s) + \int_{s_1^*}^{s''}\left(1+\left(\frac{v_2^O(s)}{v_1^O(s)}\right)^\epsilon\right)^{-1}\mathrm{d}\Phi(s)\\ &= \frac{1}{1+\mathbf{r}}\mathbf{\Phi}_{s'}^{s_2^*} + \frac{1}{1+\mathbf{q}}\mathbf{\Phi}_{s_2^*}^{s_1^*} + \frac{1}{1+\mathbf{p}}\mathbf{\Phi}_{s_1^*}^{s''},\end{aligned} \tag{38}$$

where $\mathbf{q} \equiv \left(\frac{A_2 X_2}{A_1 X_1}\left(\frac{r_1}{p_2}\right)^{\gamma} \frac{\lambda^{\gamma}}{\gamma^{\gamma}(1-\gamma)^{1-\gamma}}\right)^{\epsilon}$.

In city 2, the number of the low-skilled is

$$\mathcal{L}_2 = \frac{\mathbf{r}}{1+\mathbf{r}} \mathbf{\Phi}_0^{s'}, \tag{39}$$

the number of the high-skilled is

$$\mathcal{H}_2 = \frac{\mathbf{p}}{1+\mathbf{p}} \mathbf{\Phi}_{s''}^{1}, \tag{40}$$

while the number of the middle-skilled households is

$$\mathcal{M}_2 = \frac{\mathbf{r}}{1+\mathbf{r}} \mathbf{\Phi}_{s'}^{s_2^*} + \frac{\mathbf{q}}{1+\mathbf{q}} \mathbf{\Phi}_{s_2^*}^{s_1^*} + \frac{\mathbf{p}}{1+\mathbf{p}} \mathbf{\Phi}_{s_1^*}^{s''}. \tag{41}$$

City 1 has higher s'-low-skilled share. The goal is to show that

$$n_1^L(s') = \frac{\mathcal{L}_1}{\mathcal{L}_1 + \mathcal{M}_1 + \mathcal{H}_1} > n_2^L(s') = \frac{\mathcal{L}_2}{\mathcal{L}_2 + \mathcal{M}_2 + \mathcal{H}_2}, \tag{42}$$

or, equivalently, that

$$\frac{\mathcal{M}_2}{\mathcal{L}_2} + \frac{\mathcal{H}_2}{\mathcal{L}_2} > \frac{\mathcal{M}_1}{\mathcal{L}_1} + \frac{\mathcal{H}_1}{\mathcal{L}_1}. \tag{43}$$

Using the expressions for skill shares derived above, we can rewrite this inequality as

$$\frac{\mathbf{\Phi}_{s'}^{s_2^*}}{\mathbf{\Phi}_0^{s'}} + \frac{\mathbf{q}}{\mathbf{r}} \frac{1+\mathbf{r}}{1+\mathbf{q}} \frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_0^{s'}} + \frac{\mathbf{p}}{\mathbf{r}} \frac{1+\mathbf{r}}{1+\mathbf{p}} \frac{\mathbf{\Phi}_{s_1^*}^{s''}}{\mathbf{\Phi}_0^{s'}} + \frac{\mathbf{p}}{\mathbf{r}} \frac{1+\mathbf{r}}{1+\mathbf{p}} \frac{\mathbf{\Phi}_{s''}^{1}}{\mathbf{\Phi}_0^{s'}} > \frac{\mathbf{\Phi}_{s'}^{s_2^*}}{\mathbf{\Phi}_0^{s'}} + \frac{1+\mathbf{r}}{1+\mathbf{q}} \frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_0^{s'}} + \frac{1+\mathbf{r}}{1+\mathbf{p}} \frac{\mathbf{\Phi}_{s_1^*}^{s''}}{\mathbf{\Phi}_0^{s'}} + \frac{1+\mathbf{r}}{1+\mathbf{p}} \frac{\mathbf{\Phi}_{s''}^{1}}{\mathbf{\Phi}_0^{s'}}. \tag{44}$$

Canceling common terms and combining, this inequality can be simplified to

$$\left(\frac{\mathbf{q}}{\mathbf{r}} - 1\right) \frac{1+\mathbf{r}}{1+\mathbf{q}} \frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_0^{s'}} + \left(\frac{\mathbf{p}}{\mathbf{r}} - 1\right) \frac{1+\mathbf{r}}{1+\mathbf{p}} \left(\frac{\mathbf{\Phi}_{s_1^*}^{s''}}{\mathbf{\Phi}_0^{s'}} + \frac{\mathbf{\Phi}_{s''}^{1}}{\mathbf{\Phi}_0^{s'}}\right) > 0. \tag{45}$$

First, let us examine the ratio $\mathbf{q}/\mathbf{r}$:

$$\frac{\mathbf{q}}{\mathbf{r}} = \frac{\left(\frac{A_2 X_2}{A_1 X_1}\left(\frac{r_1}{p_2}\right)^{\gamma} \frac{\lambda^{\gamma}}{\gamma^{\gamma}(1-\gamma)^{1-\gamma}}\right)^{\epsilon}}{\left(\frac{A_2 X_2}{A_1 X_1}\left(\frac{r_1}{r_2}\right)^{\gamma}\right)^{\epsilon}} = \Lambda^{\epsilon} \left(\frac{p_2}{r_2}\right)^{-\gamma\epsilon}, \tag{46}$$

where $\Lambda \equiv \frac{\lambda^{\gamma}}{\gamma^{\gamma}(1-\gamma)^{1-\gamma}}$. Note that $\mathbf{q}/\mathbf{r} \geq 1$ if and only if $p_2/r_2 \leq \Lambda^{1/\gamma}$. The latter inequality is exactly the same as the condition (16) in Lemma 1 which, I assumed, must hold. Thus,

$\mathbf{q}/\mathbf{r} \geq 1$. Next, let us examine the ratio $\mathbf{p}/\mathbf{r}$:

$$\frac{\mathbf{p}}{\mathbf{r}} = \frac{\left(\frac{A_2X_2}{A_1X_1}\left(\frac{p_1}{p_2}\right)^{\gamma}\right)^{\epsilon}}{\left(\frac{A_2X_2}{A_1X_1}\left(\frac{r_1}{r_2}\right)^{\gamma}\right)^{\epsilon}} = \left(\frac{p_1/r_1}{p_2/r_2}\right)^{\gamma\epsilon}. \tag{47}$$

Since I assumed that the price-rent ratio is higher in city 1, $\mathbf{p}/\mathbf{r} > 1$.

Therefore, since $\mathbf{q}/\mathbf{r} \geq 1$ and $\mathbf{p}/\mathbf{r} > 1$, and because all other object in inequality (45) are positive, the inequality holds. This proves that the low-skilled employment share is higher in city 1 ■

City 1 has higher s''-high-skilled share. The objective is to show that, under certain conditions,

$$n_1^H(s'') = \frac{\mathcal{H}_1}{\mathcal{L}_1 + \mathcal{M}_1 + \mathcal{H}_1} > n_1^H(s'') = \frac{\mathcal{H}_2}{\mathcal{L}_2 + \mathcal{M}_2 + \mathcal{H}_2}, \tag{48}$$

or, equivalently, that

$$\frac{\mathcal{M}_2}{\mathcal{H}_2} + \frac{\mathcal{L}_2}{\mathcal{H}_2} > \frac{\mathcal{M}_1}{\mathcal{H}_1} + \frac{\mathcal{L}_1}{\mathcal{H}_1}. \tag{49}$$

Using the expressions for skill shares derived above, we can rewrite this inequality as

$$\frac{\mathbf{r}}{\mathbf{p}}\frac{1+\mathbf{p}}{1+\mathbf{r}}\frac{\mathbf{\Phi}_{s'}^{s_2^*}}{\mathbf{\Phi}_{s''}^{1}} + \frac{\mathbf{q}}{\mathbf{p}}\frac{1+\mathbf{p}}{1+\mathbf{q}}\frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_{s''}^{1}} + \frac{\mathbf{\Phi}_{s_1^*}^{s''}}{\mathbf{\Phi}_{s''}^{1}} + \frac{\mathbf{r}}{\mathbf{p}}\frac{1+\mathbf{p}}{1+\mathbf{r}}\frac{\mathbf{\Phi}_{0}^{s'}}{\mathbf{\Phi}_{s''}^{1}} > \frac{1+\mathbf{p}}{1+\mathbf{r}}\frac{\mathbf{\Phi}_{s'}^{s_2^*}}{\mathbf{\Phi}_{s''}^{1}} + \frac{1+\mathbf{p}}{1+\mathbf{q}}\frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_{s''}^{1}} + \frac{\mathbf{\Phi}_{s_1^*}^{s''}}{\mathbf{\Phi}_{s''}^{1}} + \frac{1+\mathbf{p}}{1+\mathbf{r}}\frac{\mathbf{\Phi}_{0}^{s'}}{\mathbf{\Phi}_{s''}^{1}}. \tag{50}$$

Canceling common terms and combining, this inequality can be simplified to

$$\left(\frac{\mathbf{r}}{\mathbf{p}} - 1\right)\frac{1+\mathbf{p}}{1+\mathbf{r}}\left(\frac{\mathbf{\Phi}_{s'}^{s_2^*}}{\mathbf{\Phi}_{s''}^{1}} + \frac{\mathbf{\Phi}_{0}^{s'}}{\mathbf{\Phi}_{s''}^{1}}\right) + \left(\frac{\mathbf{q}}{\mathbf{p}} - 1\right)\frac{1+\mathbf{p}}{1+\mathbf{q}}\frac{\mathbf{\Phi}_{s_2^*}^{s_1^*}}{\mathbf{\Phi}_{s''}^{1}} > 0. \tag{51}$$

First, note that because $\mathbf{p}/\mathbf{r} > 1$, as shown above, $\mathbf{r}/\mathbf{p} < 1$. Next, let us examine the ratio $\mathbf{q}/\mathbf{p}$:

$$\frac{\mathbf{q}}{\mathbf{p}} = \frac{\left(\frac{A_2X_2}{A_1X_1}\left(\frac{r_1}{p_2}\right)^{\gamma}\Lambda\right)^{\epsilon}}{\left(\frac{A_2X_2}{A_1X_1}\left(\frac{p_1}{p_2}\right)^{\gamma}\right)^{\epsilon}} = \Lambda^{\epsilon}\left(\frac{p_1}{r_1}\right)^{-\gamma\epsilon}. \tag{52}$$

Note that $\mathbf{q}/\mathbf{p} \geq 1$ if and only if $p_1/r_1 \leq \Lambda^{1/\gamma}$. The latter inequality is exactly the same as the condition (16) in Lemma 1 which, I assumed, must hold. Thus, $\mathbf{q}/\mathbf{p} \geq 1$.

With $\mathbf{r}/\mathbf{p} < 1$ and $\mathbf{q}/\mathbf{p} \geq 1$, inequality (51) may not hold. However, note that $\mathbf{r}/\mathbf{p}$ approaches 1 when the difference in price-rent ratios between the two cities shrinks. Hence, it is possible to define a threshold $\mathcal{B} > 1$ such that the expression on the left-hand side of inequality (51) is equal to zero. If the ratio of price-rent ratios is smaller than $\mathcal{B}$, i.e., $\frac{p_1/r_1}{p_2/r_2} < \mathcal{B}$, then inequality (51) holds. In this case, city 1 has a larger high-skilled employment share ■

A.4 Proof of Proposition 2

Scenario 1: all households are renters. If at least one of the conditions of Lemma 1 does not hold, all households choose to rent in each city. As a result, the threshold s_i^* is not defined. Following the same steps as in the proof of Proposition 2 (Section A.3), one can show that the number of low, middle, and high-income workers in city 1 is

$$\mathcal{L}_1 = \frac{1}{1+\mathbf{r}}\mathbf{\Phi}_0^{s'}, \quad \mathcal{M}_1 = \frac{1}{1+\mathbf{r}}\mathbf{\Phi}_{s'}^{s''} \quad \mathcal{H}_1 = \frac{1}{1+\mathbf{r}}\mathbf{\Phi}_{s''}^{1}, \tag{53}$$

where $\mathbf{\Phi}$ and $\mathbf{r}$ were defined in Section A.3, and the latter variable does not depend on the skill level. Similarly, in city 2

$$\mathcal{L}_2 = \frac{\mathbf{r}}{1+\mathbf{r}}\mathbf{\Phi}_0^{s'}, \quad \mathcal{M}_2 = \frac{\mathbf{r}}{1+\mathbf{r}}\mathbf{\Phi}_{s'}^{s''} \quad \mathcal{H}_2 = \frac{\mathbf{r}}{1+\mathbf{r}}\mathbf{\Phi}_{s''}^{1}, \tag{54}$$

Using previous expressions and the fact that $\mathbf{\Phi}_0^{s'} + \mathbf{\Phi}_{s'}^{s''} + \mathbf{\Phi}_{s''}^{1} = 1$, the low-skilled employment share in both city 1 and city 2 is

$$\frac{\mathcal{L}_i}{\mathcal{L}_i + \mathcal{M}_i + \mathcal{H}_i} = \mathbf{\Phi}_0^{s'}, \tag{55}$$

and the high-skilled share in both cities is

$$\frac{\mathcal{H}_i}{\mathcal{L}_i + \mathcal{M}_i + \mathcal{H}_i} = \mathbf{\Phi}_{s''}^{1}. \tag{56}$$

Scenario 2: all households are owners. If both conditions of Lemma 1 are satisfied and the minimum size of an owner-occupied property is zero, $\bar{h} = 0$, then all households in all cities choose to be homeowners. Using the same steps as for Scenario 1 and replacing $\mathbf{r}$ with $\mathbf{p}$, one can show that in this case there are no differences in high or low-skilled employment shares between the two cities.

Therefore, when there are no differences in housing tenure choices within and across cities, both cities have exactly the same low and high-skilled employment shares ■

B Appendix: Data

B.1 Locations

Empirical analysis is done at the level of U.S. states (48 mainland states plus the District of Columbia) and commuting zones (CZs). CZ definitions follow Tolbert and Sizer (1996); there are 741 CZs available for all years used in this study. CZ borders may change over time and, to guarantee comparability over time, I use the crosswalk by Eckert, Gvirtz, Liang, and Peters (2020). To ensure that I have enough observations to compute CZ-level aggregates using micro data, such as wage or house price indices, I only keep CZs with at least 2,000 observations per sample year (for 5% Census/ACS samples, this means keeping CZs with population of about 40,000 or above). This reduces the number of CZs to 465.

B.2 Wage Indices

Wage indices for each state and year are constructed using the Census and the American Community Survey (ACS) for years 1980, 2000, and 2015–2019 (5-year ACS sample).[40]

Sample cleaning. I exclude observations who live in group quarters, are younger than 18 years old, worked less than 26 weeks last year and less than 35 hours last week, work in the government or the military, and had non-positive wage or total income last year. Also excluded are observations with reported annual wage and salary income equivalent to less than half the minimum federal hourly wage.

Wage indices. A CZ-year wage index is calculated as follows. I estimate

$$\ln w_{n,it} = \beta_0 + \boldsymbol{\beta}_1 \mathcal{X}_{n,it} + \varphi_{it} + \varepsilon_{n,it}, \tag{57}$$

where $w_{n,it}$ is the annual wage income of individual n in CZ i and year t, whereas $\mathcal{X}_{n,it}$ is a vector of controls that includes dummies for gender, race, 2-digit industry, 2-digit occupation, college, and 5-year age groups. Parameter φ_{it} is a CZ-year fixed effect. The wage index represents the annual wage after controlling for the observable characteristics listed before and idiosyncratic effects, and is given by $W_{it} \equiv \exp(\beta_0 + \varphi_{it})$.

B.3 Rent and House Price Indices

Hedonic rent and price indices are constructed both at the state and at the CZ level. I use rent and price data from the Census and the ACS.[41]

[40] Tabulated by the IPUMS-USA (Ruggles, Flood, Foster, Goeken, Pacas, Schouweiler, and Sobek, 2021).
[41] See footnote 40.

Sample cleaning. I keep only household heads to ensure that the analysis is conducted at the household level. I exclude observations who live in group quarters; live in farm houses, mobile homes, trailers, boats, tents, etc.; are younger than 18 years old; and live in a dwelling that has no information on the year of construction.

Hedonic rent and price indices. To construct rent and price indices, I use self-reported rents and home values (variables `RENT` and `VALUEH` in the IPUMS-USA).[42] I estimate the following regression,

$$\ln \mathbf{q}_{n,it} = \beta_0 + \boldsymbol{\beta}_1 \mathcal{X}_{n,it} + \varphi_{it} + \varepsilon_{n,it}, \tag{58}$$

where $\mathbf{q}_{n,it} \in \{r_{n,it}, p_{n,it}\}$ is either the rent or the house value reported by household n in state i and year t, while $\mathcal{X}_{n,it}$ is a vector of controls that includes the number of rooms in the dwelling, the number of units in the structure (e.g., single-family detached, 2-family building), and the year of construction. Parameter φ_{it} is a location-year fixed effect. The rent or price index, $\mathbf{Q}_{it} \in \{R_{it}, P_{it}\}$, represents the rent or price after controlling for the observable characteristics listed before and idiosyncratic effects, and is given by $\mathbf{Q}_{it} \equiv \exp(\beta_0 + \varphi_{it})$. In the empirical analysis, I use either the price index, P_{it}, the price-wage index, P_{it}/W_{it}, or the price-rent index, P_{it}/R_{it}.

B.4 Employment Polarization

For the ease of comparison with the literature on labor market polarization, I follow Autor and Dorn (2013) in defining employment polarization. In particular, I use the skill percentile ranking of 3-digit normalized occupations. The percentile ranking was constructed in the aforementioned paper using 1980 wages at the national level. It assigns each occupation into a percentile bin, and a worker who holds an occupation that belongs to bin k is interpreted to be in the k-th percentile of the skill distribution. I compute the skill distribution at the CZ level using the Census and the ACS data.[43] In order to ensure that occupations are comparable between 1980, 2000, and 2015–2019, I use the crosswalk of occupations between 1980 and 2005 from Autor and Dorn (2013) and supplement it by constructing a crosswalk between the 2005 and the 2010 definitions of occupations (2010 definitions are used in the 2019 5-year sample).

[42]Self-reported prices have been widely used in the literature in cases when other measures were not available. Kiel and Zabel (1999) show that, while self-reported prices are 3-8% higher than actual prices, the size of the bias does not depend on observable owners' characteristics and location. Thus, for the purposes of comparison across metro areas, self-reported prices are good proxies for market prices.

[43]Tabulated by the IPUMS-USA (Ruggles, Flood, Foster, Goeken, Pacas, Schouweiler, and Sobek, 2021).

B.5 Income Inequality

I estimate income inequality at the CZ level in 1980, 2000, and 2015–2019 using the wage data from the Census and the ACS.[44] I focus on two measures of inequality: the variance of log wages and the Gini coefficient. Each measure is estimated for either annual or hourly wage income, where wage income can be either the reported monetary income or income adjusted for the effects of gender, race, industry, occupation, education, and age.

Sample cleaning. I exclude observations who live in group quarters, younger than 18 years old, worked less than 26 weeks last year and less than 35 hours last week, work in the government or the military, and had non-positive wage or total income last year. Also excluded are observations with reported annual wage and salary income equivalent to less than half the minimum federal hourly wage.

Adjusted wage income. To construct adjusted wage income, I estimate

$$\ln w_{n,it} = \beta_0 + \boldsymbol{\beta}_{1,t}\mathcal{X}_{n,it} + \varepsilon_{n,it}, \tag{59}$$

where $w_{n,it}$ is the wage income, either annual or hourly, of individual n in commuting zone i and year t. $\mathcal{X}_{n,it}$ is a vector of controls that includes dummies for gender, race, 2-digit industry, 2-digit occupation, college, and 5-year age groups. The adjusted wage income is then given by

$$\tilde{w}_{n,it} \equiv \exp\left(\beta_0 + \varepsilon_{n,it}\right). \tag{60}$$

B.6 Interstate Migration Data

The data on interstate migration comes from the Annual Social and Economic Supplements (ASEC) of the Current Population Survey (CPS). I use the data for years 2001–2019.[45]

Sample cleaning. I first clean the sample by only keeping household heads to ensure that the level of observation is a household. Then I exclude observations in group quarters; younger than 18 years old; those who live in mobile homes, trailers, boats, tents, etc.; government and military employees; those who did not report location of residence last year or resided in a foreign country; those with non-positive or missing total income.

Definition of a migrant. In the cleaned sample, a migrant is defined as a household who reported that his state of residence last year was different from the state of residence at the time of the survey (variable `MIGSTA1` in the IPUMS-CPS).

Imputed migration. Kaplan and Schulhofer-Wohl (2010) show that imputations of

[44] Tabulated by the IPUMS-USA (Ruggles, Flood, Foster, Goeken, Pacas, Schouweiler, and Sobek, 2021).
[45] Tabulated by the IPUMS-CPS (Flood, King, Rodgers, Ruggles, and Warren, 2020).

Table B.1: Summary statistics for interstate migration in the CPS

	Number of households	*Percentage of total*
Full sample	1,265,832	100
Moved between states		
all observations	22,518	1.8
non-imputed observations	15,815	1.2
Reason for moving between states (non-imputed observations)	*Number of households*	*Percentage of interstate migrants*
Job-related	8,097	51.2
Family-related	3,659	23.1
Housing-related	1,920	12.1
Other	2,139	13.5

Notes: The table reports the number of households (i.e., the number of observations in the cleaned sample) in the 2001–2019 CPS by their migration status and the reason for moving.

missing data by the Census Bureau significantly bias estimated interstate migration rates. Thus, I drop observations with imputed migration status using the procedure in the aforementioned paper. In particular, I categorize an observation as having imputed migration status when the migration status of the individual was imputed, when the state of residence last year was imputed, when the migration status was not allocated, or when the migration status was allocated from another household member and the status of that member was imputed or inferred from yet another member whose status was imputed.

Moving reasons. The CPS also asks about the reason for moving (variable `WHYMOVE` in the IPUMS-CPS). In particular, the questionnaire asks what was the "main reason for moving to this house (apartment)." Respondents can choose from 20 distinct reasons which can be grouped into job-related reasons, family-related reasons, housing-related reasons, and other reasons. Housing-related reasons combine the following answers: "wanted to own home, not rent," "wanted new or better housing," "wanted better neighborhood," "for cheaper housing," "other housing reason."[46]

Summary statistics. Table B.1 summarizes the data. It shows that 15,815 non-imputed observations (1.2% of the sample) moved across states. Among these, 1,920 (12.1% of interstate migrants) reported having moved for housing-related reasons.

[46]Even though the answer "wanted to own home, not rent" explicitly indicates that the primary reason for relocation was the desire to become a homeowner, other reasons may also be related with the transition to ownership. For this reason, I focus on all housing-related reasons in the empirical analysis.

B.7 Household Income (For Migration Analysis)

The data on household income for migration analysis comes from the Annual Social and Economic Supplements (ASEC) of the Current Population Survey (CPS).[47]

Sample cleaning. I first clean the sample by only keeping household heads to ensure that the level of observation is a household. Then I exclude observations in group quarters; younger than 18 years old; those who live in mobile homes, trailers, boats, tents, etc.; government and military employees; those who did not report location of residence last year or resided in a foreign country; those with non-positive or missing total income.

Definition of household income. Household income is the total monetary income during the previous calendar year of all adult household members (variable `HHINCOME` in the IPUMS-CPS).

Income distribution at the migration origin. Household income is reported for the previous year. This allows me to understand how the position of a household in the income distribution in the state of origin affects the likelihood of migration.

C Appendix: Additional Empirical Results

C.1 Polarization

In the main text, I investigated the relationship between the growth in housing prices and the change in the *middle*-skilled shares. Tables C.1 and C.2 repeat the analysis in Table 2 but for *low*- and *high*-skilled shares. The OLS results in columns (1)–(3) are mixed. However, columns (4)–(6) show that once the changes in prices, price-rent, and price-wage ratios are instrumented, higher growth in prices leads to larger increase in the low-skilled share. Table C.2 shows that larger price increases are associated with greater increases in the high-skilled share, both in OLS and 2SLS specifications.

Next, I study whether the results in Table 2 are robust to other ways to split employment into low-, middle-, and high-skilled groups. Tables C.3 and C.4 show the results when the groups are split at the 10th and the 90th wage percentiles, and the 33rd and the 67th percentiles. In both tables, the majority of coefficients remain negative and statistically significant, confirming that the results presented in the main text are not the artifact of my choice to split skill groups at the 20th and the 80th wage percentile.

Finally, in Table C.5 I show that the findings in Table 2 are robust to using shorter time intervals. I estimate stacked regressions with two periods: 1980–2000 and 2000–2019.

[47]Tabulated by the IPUMS-CPS (Flood, King, Rodgers, Ruggles, and Warren, 2020).

Coefficients remain negative and significant and, in most cases, have similar magnitude.

C.2 Inequality

In the main text, I investigated the relationship between the growth in housing prices and the change in income inequality, measured as the variance of log annual wages. In Table C.6 I show that the findings presented in the main text hold when inequality is measured as the Gini coefficient of annual wages. In Table C.7 I demonstrate that the results are robust to using hourly, not annual wages. In Table C.8 I show that the results are also robust to using wages adjusted for the effects of gender, race, industry, occupation, education, and age. Finally, in Table C.9 I show that results do not change much when I use shorter time intervals and estimate a stacked regression with two periods, 1980–2000 and 2000–2019, with the exception that OLS coefficients in price-wage ratio regressions become smaller and lose statistical significance.

C.3 Migration

In Figure 1 in the main text I show that middle-income households are more likely to move for housing-related reasons from expensive to affordable states than low- or high-income households. In Figure C.1, I show that this hump-shaped relationship between income and the probability of moving only holds for housing-related migration and not for other migration reasons. Panel A shows that for job-related reasons, the relationship is somewhat U-shaped, though it is not statistically significant at the 95% level in most cases. This suggests that middle-income households may be less likely to move to a more affordable location when their relocation is related to a job. This could occur, for example, when the move is accompanied with a pay rise that compensates for an increase in housing costs. Panels B and C show that there is no statistically significant relationship between the probability of moving for family or other reasons and the income level.

Figure C.2 reports marginal effects from regression (3), separately for households with and without children. It shows that migrant households with children are more responsive to the differences in homeownership costs between the location of origin and the location of destination, and especially so the households in the middle of the income distribution.

Table C.1: Change in the low-skilled share and house price growth

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	-0.296	-0.553***	-0.659***	2.130***	1.935***	2.457**
	(0.185)	(0.181)	(0.193)	(0.539)	(0.597)	(1.087)
Log initial population		1.049***	0.658***		0.541**	0.893***
		(0.141)	(0.158)		(0.217)	(0.223)
Mean of dependent variable	0.245	0.245	0.245	0.245	0.245	0.245
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.00700	0.104	0.550			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.969	0.320	0.250

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	8.191***	6.800***	0.971	19.89***	19.14***	25.06*
	(0.952)	(1.085)	(1.096)	(5.641)	(6.815)	(13.43)
Log initial population		0.460***	0.682***		-0.403	0.0411
		(0.141)	(0.159)		(0.521)	(0.423)
Mean of dependent variable	0.245	0.245	0.245	0.245	0.245	0.245
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.144	0.160	0.535			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.986	0.238	0.798

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	1.384*	0.905	-0.395	7.774***	6.802***	7.916***
	(0.740)	(0.786)	(0.758)	(1.689)	(1.741)	(3.063)
Log initial population		0.918***	0.701***		0.800***	0.842***
		(0.131)	(0.160)		(0.154)	(0.184)
Mean of dependent variable	0.245	0.245	0.245	0.245	0.245	0.245
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.00700	0.0840	0.534			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.409	0.339	0.191

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the low-skilled share on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.2: Change in the high-skilled share and house price growth

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	1.286***	1.075***	1.488***	1.468***	0.987***	2.161***
	(0.169)	(0.169)	(0.209)	(0.384)	(0.382)	(0.831)
Log initial population		0.864***	0.810***		0.882***	0.860***
		(0.131)	(0.145)		(0.152)	(0.159)
Mean of dependent variable	2.516	2.516	2.516	2.516	2.516	2.516
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.163	0.246	0.482			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.00700	0.314	0.0660

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	4.051***	0.986	2.495**	13.84***	6.703	23.34**
	(0.889)	(0.888)	(1.033)	(4.822)	(4.215)	(11.87)
Log initial population		1.014***	0.631***		0.614*	0.0768
		(0.147)	(0.160)		(0.324)	(0.366)
Mean of dependent variable	2.516	2.516	2.516	2.516	2.516	2.516
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0450	0.140	0.384			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.0250	0.0620	0.607

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	2.477***	1.931***	3.671***	4.729***	3.381**	6.971**
	(0.752)	(0.682)	(0.798)	(1.621)	(1.460)	(2.791)
Log initial population		1.044***	0.760***		1.015***	0.816***
		(0.135)	(0.155)		(0.143)	(0.164)
Mean of dependent variable	2.516	2.516	2.516	2.516	2.516	2.516
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0280	0.155	0.410			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.00200	0.288	0.0740

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the high-skilled share on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels. R^2 coefficients, first-stage F-statistics (Kleibergen-Paap) and the p-value for the Hansen overidentification test are shown in the last three rows.

Table C.3: Change in the middle-skilled share and house price growth, 10/90 split

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	-0.332***	0.0108	0.0310	-1.989***	-1.456***	-1.964**
	(0.127)	(0.115)	(0.126)	(0.395)	(0.404)	(0.919)
Log initial population		-1.403***	-1.060***		-1.103***	-1.210***
		(0.110)	(0.129)		(0.156)	(0.163)
Mean of dependent variable	-2.229	-2.229	-2.229	-2.229	-2.229	-2.229
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0120	0.258	0.485			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.0300	0.937	0.264

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	-7.885***	-4.631***	-1.026	-18.69***	-12.70***	-20.11*
	(0.746)	(0.828)	(0.954)	(4.827)	(4.584)	(10.73)
Log initial population		-1.076***	-1.035***		-0.511	-0.528
		(0.109)	(0.130)		(0.350)	(0.330)
Mean of dependent variable	-2.229	-2.229	-2.229	-2.229	-2.229	-2.229
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.190	0.310	0.486			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.0450	0.0570	0.796

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	-1.175*	-0.448	-0.00449	-6.732***	-5.067***	-6.329**
	(0.629)	(0.592)	(0.630)	(1.337)	(1.251)	(2.730)
Log initial population		-1.391***	-1.062***		-1.299***	-1.170***
		(0.104)	(0.130)		(0.124)	(0.142)
Mean of dependent variable	-2.229	-2.229	-2.229	-2.229	-2.229	-2.229
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.00700	0.259	0.485			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.00100	0.933	0.237

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the middle-skilled share on the change in prices, where the middle-skilled group is defined as occupations between the 10th and the 90th wage percentile. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.4: Change in the middle-skilled share and house price growth, 33/67 split

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	-0.621***	-0.325**	-0.837***	-2.345***	-1.864***	-2.244**
	(0.153)	(0.142)	(0.148)	(0.392)	(0.392)	(0.941)
Log initial population		-1.213***	-0.951***		-0.898***	-1.057***
		(0.111)	(0.138)		(0.161)	(0.156)
Mean of dependent variable	2.658	2.658	2.658	2.658	2.658	2.658
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0410	0.220	0.425			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.0120	0.403	0.0440

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	-7.652***	-4.802***	-2.523***	-22.03***	-14.54***	-25.31*
	(0.806)	(0.891)	(0.957)	(5.528)	(4.749)	(13.73)
Log initial population		-0.943***	-0.821***		-0.261	-0.215
		(0.122)	(0.147)		(0.362)	(0.423)
Mean of dependent variable	2.658	2.658	2.658	2.658	2.658	2.658
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.174	0.264	0.396			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.0400	0.00400	0.484

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	-1.936***	-1.282**	-2.505***	-7.956***	-6.438***	-7.250**
	(0.688)	(0.638)	(0.627)	(1.501)	(1.353)	(3.072)
Log initial population		-1.253***	-0.931***		-1.150***	-1.012***
		(0.109)	(0.141)		(0.133)	(0.149)
Mean of dependent variable	2.658	2.658	2.658	2.658	2.658	2.658
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0180	0.218	0.405			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0	0.278	0.0390

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the middle-skilled share on the change in prices, where the middle-skilled group is defined as occupations between the 33rd and the 67th wage percentile. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.5: Change in the middle-skilled share and house price growth, 20-year intervals

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	-1.053***	-0.544**	-1.089***	-7.743***	-6.238***	-9.083***
	(0.278)	(0.243)	(0.248)	(1.343)	(1.331)	(3.460)
Log initial population		-0.977***	-0.844***		-0.677***	-1.007***
		(0.0718)	(0.0934)		(0.118)	(0.168)
Mean of dependent variable	-1.381	-1.381	-1.381	-1.381	-1.381	-1.381
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.324	0.437	0.529			
1st-stage F-statistic				23.69	21.70	5.360
Hansen overid. test, p-value				0.252	0.506	0.238

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	-7.122***	-4.801***	-3.625***	-32.11***	-20.11***	-52.69
	(0.695)	(0.693)	(0.681)	(8.183)	(5.809)	(32.25)
Log initial population		-0.828***	-0.762***		-0.262	0.0372
		(0.0714)	(0.0937)		(0.237)	(0.584)
Mean of dependent variable	-1.381	-1.381	-1.381	-1.381	-1.381	-1.381
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.392	0.466	0.534			
1st-stage F-statistic				7.805	9.309	1.411
Hansen overid. test, p-value				0.0290	0.00200	0.889

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	-2.255***	-1.600***	-1.922***	-14.96***	-12.21***	-16.84***
	(0.594)	(0.565)	(0.560)	(2.390)	(2.190)	(5.754)
Log initial population		-0.988***	-0.851***		-0.868***	-1.084***
		(0.0720)	(0.0940)		(0.0961)	(0.162)
Mean of dependent variable	-1.381	-1.381	-1.381	-1.381	-1.381	-1.381
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.321	0.438	0.525			
1st-stage F-statistic				37.89	36.89	8.728
Hansen overid. test, p-value				0.00600	0.973	0.152

Notes: The table shows the results from regressions for the 1980–2000 and 2000–2019 periods. The number of observations is 930 (465 CZs times 2 periods). All regressions include a dummy for the 2000–2019 period. Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the middle-skilled share on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.6: Change in income inequality and house price growth, Gini coefficient

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	0.794***	0.506***	0.505***	1.746***	1.249***	2.457***
	(0.112)	(0.0905)	(0.107)	(0.280)	(0.273)	(0.781)
Log initial population		1.178***	0.917***		1.026***	1.064***
		(0.0773)	(0.0973)		(0.109)	(0.135)
Mean of dependent variable	6.044	6.044	6.044	6.044	6.044	6.044
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.117	0.409	0.499			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.0110	0.958	0.595

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	6.610***	3.472***	2.331***	16.42***	10.85***	21.79**
	(0.605)	(0.617)	(0.774)	(3.861)	(3.310)	(10.49)
Log initial population		1.038***	0.817***		0.522**	0.300
		(0.0854)	(0.101)		(0.260)	(0.329)
Mean of dependent variable	6.044	6.044	6.044	6.044	6.044	6.044
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.224	0.412	0.488			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.0160	0.0450	0.633

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	2.338***	1.686***	0.754	5.877***	4.345***	7.888***
	(0.618)	(0.438)	(0.563)	(1.173)	(0.995)	(2.392)
Log initial population		1.247***	0.892***		1.194***	1.014***
		(0.0749)	(0.100)		(0.0849)	(0.121)
Mean of dependent variable	6.044	6.044	6.044	6.044	6.044	6.044
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0460	0.388	0.479			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.00100	0.902	0.595

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the Gini coefficient of annual wages on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.7: Change in income inequality and house price growth, hourly wages

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	2.204***	1.657***	1.162***	2.687***	1.527***	2.475**
	(0.231)	(0.182)	(0.212)	(0.492)	(0.445)	(1.095)
Log initial population		2.238***	1.628***		2.265***	1.727***
		(0.130)	(0.161)		(0.155)	(0.182)
Mean of dependent variable	9.536	9.536	9.536	9.536	9.536	9.536
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.252	0.548	0.631			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0	0.336	0.880

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	11.03***	4.116***	3.181**	25.38***	11.11**	19.61
	(1.466)	(1.227)	(1.233)	(6.403)	(4.972)	(12.12)
Log initial population		2.288***	1.456***		1.799***	1.019***
		(0.152)	(0.173)		(0.365)	(0.380)
Mean of dependent variable	9.536	9.536	9.536	9.536	9.536	9.536
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.175	0.432	0.603			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0	0.0220	0.340

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	5.559***	4.258***	0.898	8.468***	5.249***	7.925**
	(1.333)	(0.845)	(0.945)	(2.351)	(1.821)	(3.693)
Log initial population		2.491***	1.556***		2.471***	1.676***
		(0.142)	(0.171)		(0.144)	(0.187)
Mean of dependent variable	9.536	9.536	9.536	9.536	9.536	9.536
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0740	0.456	0.597			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0	0.298	0.870

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the variance of log hourly wages on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.8: Change in income inequality and house price growth, adjusted annual wages

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	1.261***	0.955***	0.639***	1.439***	0.806**	2.184**
	(0.152)	(0.122)	(0.170)	(0.363)	(0.348)	(0.999)
Log initial population		1.253***	0.840***		1.283***	0.956***
		(0.103)	(0.127)		(0.119)	(0.160)
Mean of dependent variable	7.194	7.194	7.194	7.194	7.194	7.194
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.188	0.398	0.468			
1st-stage F-statistic				21.80	22.65	8.165
Hansen overid. test, p-value				0.00300	0.878	0.458

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	6.101***	2.188**	2.689***	13.58***	6.693*	20.47*
	(1.033)	(0.994)	(1.007)	(4.252)	(3.730)	(11.75)
Log initial population		1.295***	0.720***		0.980***	0.247
		(0.130)	(0.138)		(0.281)	(0.354)
Mean of dependent variable	7.194	7.194	7.194	7.194	7.194	7.194
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.122	0.309	0.455			
1st-stage F-statistic				7.920	6.581	2.555
Hansen overid. test, p-value				0.00500	0.244	0.884

Panel C: Price-wage ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	3.119***	2.387***	0.882	4.587***	2.796**	7.021**
	(0.946)	(0.681)	(0.764)	(1.551)	(1.309)	(3.147)
Log initial population		1.400***	0.807***		1.392***	0.911***
		(0.108)	(0.130)		(0.108)	(0.146)
Mean of dependent variable	7.194	7.194	7.194	7.194	7.194	7.194
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0530	0.327	0.447			
1st-stage F-statistic				40.19	40.81	14.19
Hansen overid. test, p-value				0.00100	0.810	0.458

Notes: The table shows the results from first-difference regressions for the 1980–2019 period. The number of observations is 465 (the number of CZs). Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the variance of log annual wages on the change in prices, where wages are adjusted for the effects of gender, race, industry, occupation, education, and age. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

Table C.9: Change in income inequality and house price growth, 20-year intervals

Panel A: Prices

	(1)	(2)	(3)	(4)	(5)	(6)
Price change	2.848***	2.193***	1.756***	6.522***	3.642***	5.196*
	(0.399)	(0.319)	(0.369)	(1.283)	(1.211)	(2.920)
Log initial population		1.257***	1.055***		1.181***	1.125***
		(0.0914)	(0.122)		(0.105)	(0.140)
Mean of dependent variable	5.004	5.004	5.004	5.004	5.004	5.004
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.102	0.282	0.317			
1st-stage F-statistic				23.69	21.70	5.360
Hansen overid. test, p-value				0.00100	0.739	0.378

Panel B: Price-rent ratios

	(1)	(2)	(3)	(4)	(5)	(6)
Price-rent ratio change	7.557***	4.139***	4.094***	23.61***	9.129*	21.74
	(0.969)	(0.816)	(0.897)	(6.896)	(5.034)	(17.72)
Log initial population		1.219***	0.952***		1.035***	0.665**
		(0.0940)	(0.121)		(0.199)	(0.331)
Mean of dependent variable	5.004	5.004	5.004	5.004	5.004	5.004
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0940	0.250	0.309			
1st-stage F-statistic				7.805	9.309	1.411
Hansen overid. test, p-value				0	0.0140	0.208

Panel C: Price-wage ratios

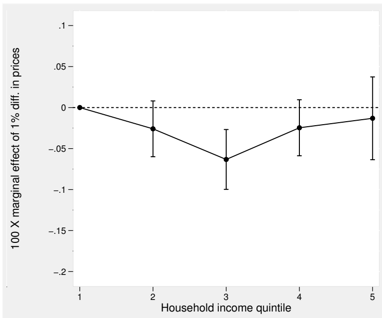
	(1)	(2)	(3)	(4)	(5)	(6)
Price-wage ratio change	1.743*	0.840	-1.074	11.08***	6.884***	9.796*
	(0.895)	(0.761)	(0.810)	(3.040)	(2.611)	(5.804)
Log initial population		1.363***	1.002***		1.295***	1.172***
		(0.0985)	(0.126)		(0.104)	(0.160)
Mean of dependent variable	5.004	5.004	5.004	5.004	5.004	5.004
Model	OLS	OLS	OLS	2SLS	2SLS	2SLS
Additional controls	No	No	Yes	No	No	Yes
R-squared	0.0120	0.228	0.292			
1st-stage F-statistic				37.89	36.89	8.728
Hansen overid. test, p-value				0	0.455	0.411

Notes: The table shows the results from regressions for the 1980–2000 and 2000–2019 periods. The number of observations is 930 (465 CZs times 2 periods). All regressions include a dummy for the 2000–2019 period. Panel A shows results for the house price index, panel B shows results for price-rent ratios, and panel C shows results for price-wage ratios. Column (1) reports the results from the OLS regression of the change in 100× the variance of log annual wages on the change in prices. Column (2) includes initial CZ population as a control. Column (3) adds manufacturing share, female share, college share, foreign-born share, and Census region dummy as additional controls. Columns (4)–(6) report results from 2SLS estimation. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.

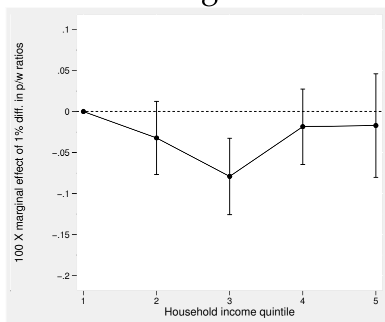
Figure C.1: Marginal effects on migration for non-housing reasons

Panel A: Job-related reasons

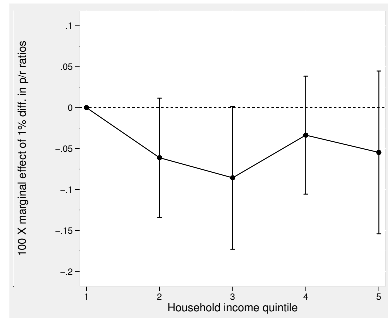
Prices



Price-wage ratios

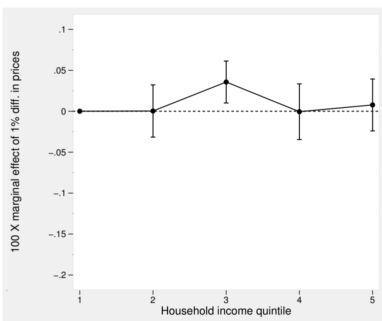


Price-rent ratios

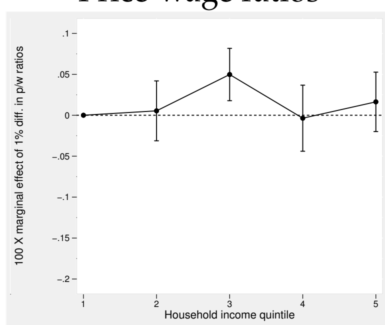


Panel B: Family-related reasons

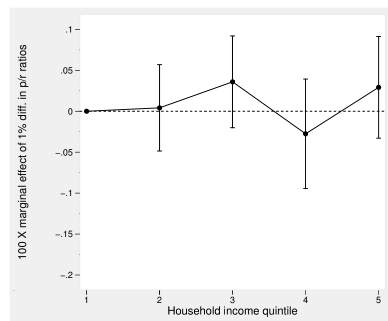
Prices



Price-wage ratios

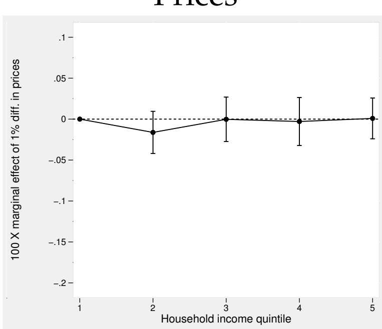


Price-rent ratios

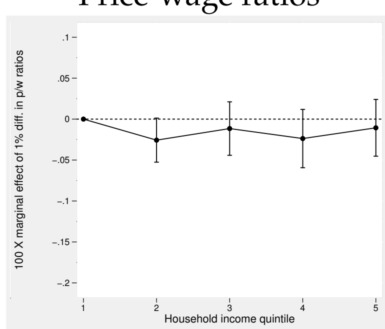


Panel C: Other reasons

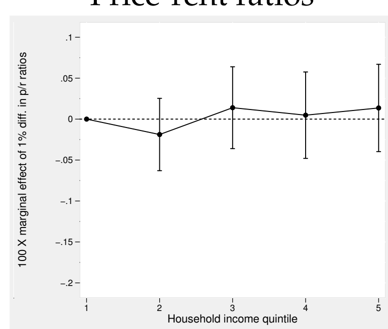
Prices



Price-wage ratios



Price-rent ratios

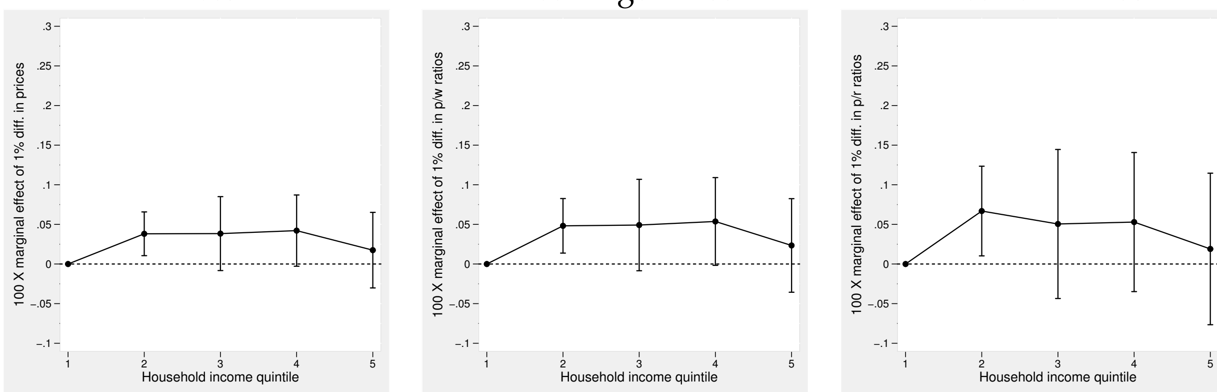


Notes: Panel A shows 100× marginal effects on the probability of moving for job-related reasons. The left plot shows the marginal effect of the log ratio of house prices in the location of origin to the prices in the location of destination for each quintile in the household income distribution at the location of origin. The center plot shows the marginal effects of price-wage ratios, and the right plot shows the marginal effects of price-rent ratios. Panel B shows the results for family-related migration, and panel C shows the results for migration for other reasons. Marginal effects are estimated at the average observation from coefficients δ_4^q from regression (3) on the sample of 15,815 interstate migrants. Vertical bars represent the 95% confidence interval. Standard errors of marginal effects are computed using the Delta method. Standard errors of the underlying logit regression are clustered by the state of origin.

Figure C.2: Marginal effects on migration for housing-related reasons

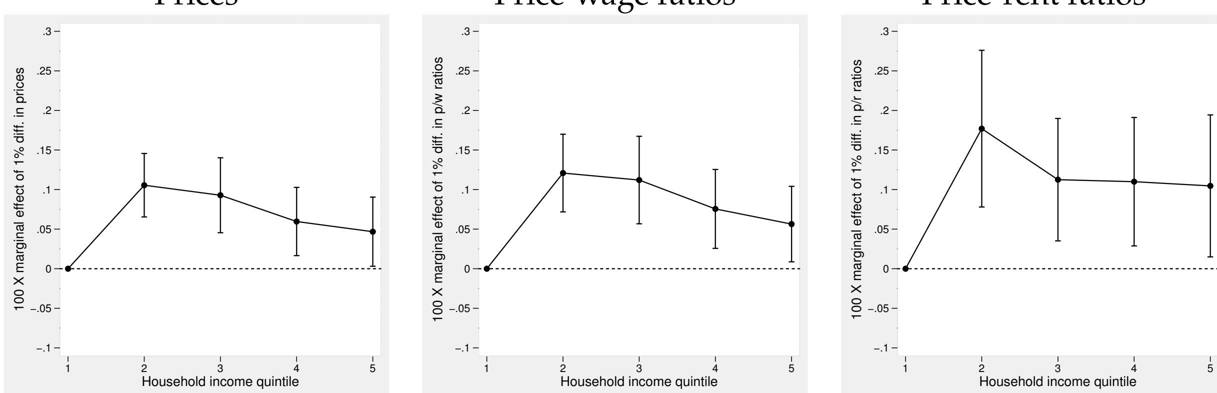
Panel A: Households without children

Prices | Price-wage ratios | Price-rent ratios



Panel B: Households with children

Prices | Price-wage ratios | Price-rent ratios



Notes: The left plot in panel A shows 100× marginal effects on the probability of moving for housing-related reasons of the log ratio of house prices in the location of origin to prices ratio in the location of destination for each quintile in the household income distribution at the location of origin; the relationship is shown for the subsample of households without children. The center and right plots repeat the analysis for price-wage and price-rent ratios. Panel B repeats the exercise for the subsample of households with children. Marginal effects are estimated at the average observation from coefficients δ_4^q from regression (3) on the samples of 9,663 interstate migrants without children or 6,152 migrants with children. Vertical bars represent the 95% confidence interval. Standard errors of marginal effects are computed using the Delta method. Standard errors of the underlying logit regression are clustered by the state of origin.

D Appendix: Calibration

D.1 PTI Constraint

I follow empirical evidence presented in Greenwald (2018) and assume that the payment-to-income (PTI) constraint is 0.5. Recall that the model is calibrated to the data on individuals aged 25–64 (i.e., 40-year interval), while the vast majority of mortgage contracts are underwritten for 30 years. If the model had a 40-year life cycle and households bought houses in the first period, the 0.5 PTI constraint would apply to the first-period income and households would pay off their house before the life cycle ends. Therefore, the value of the PTI constraint must be adjusted in two ways. First, I must incorporate the fact that in the data household income tends to be lower at the beginning of the life cycle. Second, I must take into account the fact that household income streams arrive for 40 years, while mortgage payments last for only 30 years. The adjusted PTI constraint can be written as

$$\lambda = \text{PTI} \times \frac{30w_1}{\sum_{t=1}^{40} w_t} \tag{61}$$

I find that the average annual wage income of an individual in the 25–29 age group constitutes a fraction 0.0205 of the lifetime income from 25 to 64 years old. Therefore, the PTI constraint applicable to the quantitative model is $\lambda = 0.5 \times 30 \times 0.0205 = 0.307$.

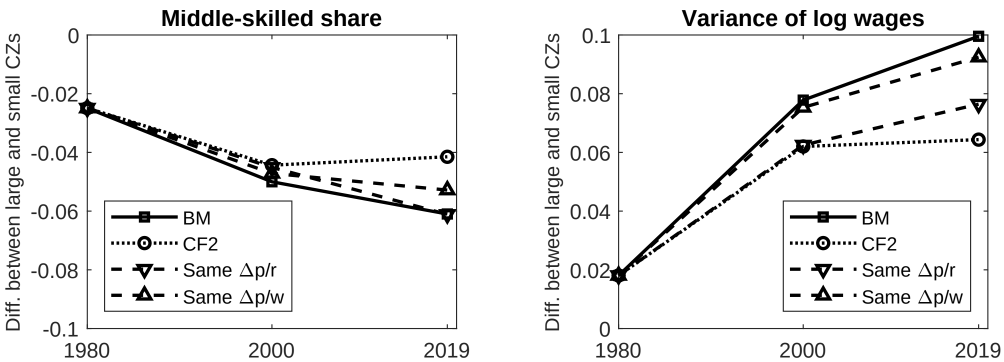
E Appendix: Counterfactuals

E.1 Separating the Effects of Price-Rent and Price-Wage Ratios

In the main counterfactual, I required that both price-rent and price-wage ratios in large CZs change as in small CZs. Here I study changes in price-rent and price-wage ratios one by one. In the first experiment, the price-rent ratio in large CZs evolves as in small CZs (this counterfactual is labeled "same $\Delta p/r$"). This experiment investigates the implications of changes in the relative cost of owning versus renting in each group of CZs. In the second one, the price-wage ratio in large CZs evolves as in small CZs ("same $\Delta p/w$"). This experiment looks at the implications of changes in the affordability of purchasing a house for an average worker in each group of CZs. The results of both exercises are shown in Figure E.1 and Table E.1.

Counterfactual 1: same $\Delta p/r$. In this experiment, the price-rent ratio in large CZs falls as much as it did in small CZs between 1980 and 2019, instead of remaining roughly constant as it did in the data. This leads to greater homeownership in large CZs and

Figure E.1: The importance of rising prices for polarization and inequality



Notes: The left panel of the figure shows the difference between the share of middle-skilled employment in large CZs and the share in small CZs in the benchmark economy (solid line), the main counterfactual (dotted line), the same $\Delta p/r$ counterfactual (dashed line with downward-pointing triangle markers), and the same $\Delta p/w$ counterfactual (dashed line with upward-pointing triangle markers). The right panel shows the difference between the variance of log wages in large CZs and the variance in small CZs for the benchmark and the counterfactual economies.

Table E.1: Counterfactual changes

	Benchmark	CF2: Same $\Delta p/w$, $\Delta p/r$	Same $\Delta p/r$	Same $\Delta p/w$
Homeownership rate, %	61.2	69.9	65.8	65.5
Employment in large CZs, %	49.1	50.0	45.3	54.7
Output	100	100.6	99.8	101.0
Welfare	100	103.1	99.3	104.0

Notes: The table shows the values of several variables of interest in the benchmark economy calibrated to 2019, the main counterfactual, and the two alternative counterfactuals.

greater homeownership overall. However, more pronounced SBTC in large CZs leads to an increase in housing rents, and pushes out low- and middle-skilled renters into small CZs. As a result, the gap in middle-skilled shares between large and small CZs in 2019 does not change much compared to the benchmark economy, although the gap in the variance of log wages falls from 0.1 to about 0.08. Since small cities are less productive, migration to small CZs also results in a slight reduction of aggregate output. In this counterfactual welfare falls by 0.7%.

Counterfactual 2: same $\Delta p/w$. Slowing down the growth of price-wage ratios in large CZs makes supplying housing in large CZs less costly due to higher calibrated values of $\phi_{it}\Lambda_{it}$. This lowers prices and rents, and leads to a higher homeownership rate. As large cities become more affordable, some workers move there, especially those in the middle of the skill distribution. As a consequence, the gap in middle-skilled shares between large and small CZs shrinks and so does the gap in the variance of log wages. Also, because large cities are more productive, aggregate output goes up. Greater housing affordability and higher productivity yield strong welfare gains.

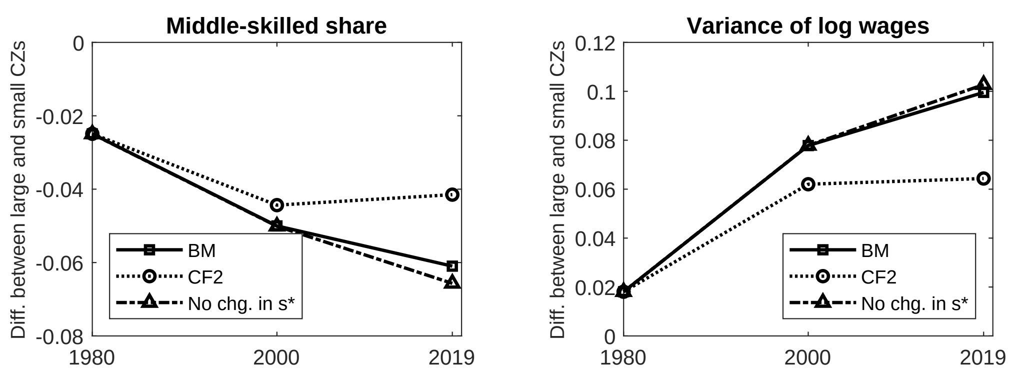
What explains the difference in results between counterfactuals 1 and 2? Lowering price-rent ratios in cities that experienced high growth in housing costs, as in counterfactual 1, makes the *relative* cost of buying a house in large CZs lower. However, without an accompanying increase in housing supply, as in counterfactual 2, both prices and rents go up in response to an influx of affluent homebuyers, and as a result, many low-skilled workers have to relocate to small CZs.

E.2 Additional Results, Robustness, and Sensitivity

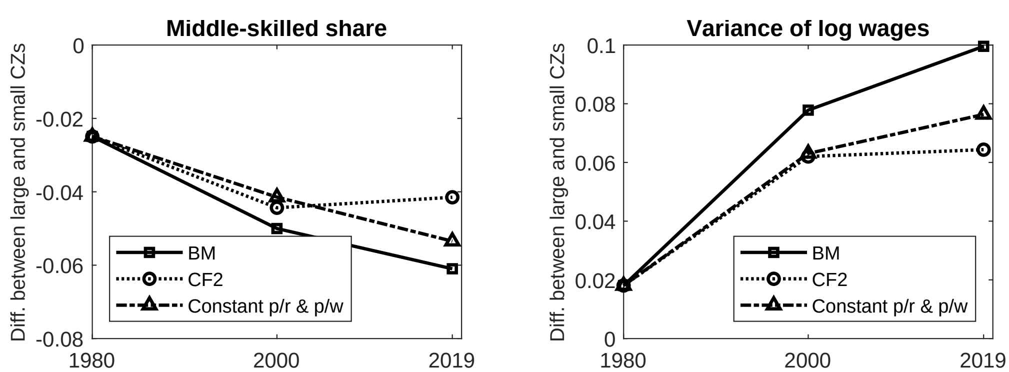
Figure E.2 displays the results of robustness and sensitivity checks described in Section 5.1.4.

Figure E.2: Alternative Counterfactuals

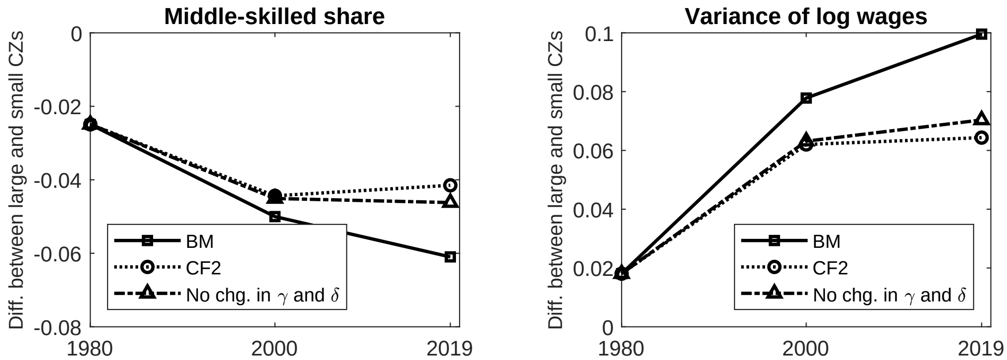
Panel A: fixed ownership thresholds



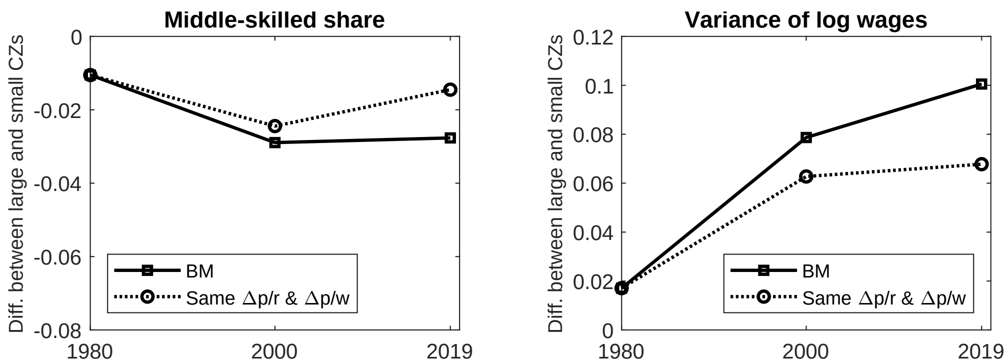
Panel B: fixed levels of price-rent and price-wage ratios



Panel C: fixed expenditure shares



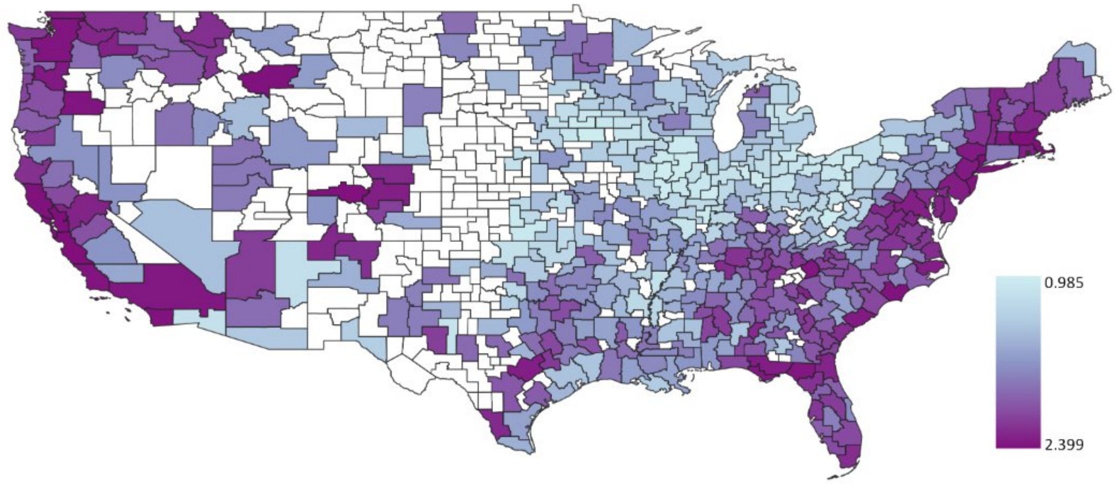
Panel D: no skill group shifters



Notes: Panel A shows the results for the counterfactual where local ownership thresholds, s^* and s^{**}, are constant at the 1980 level. Panel B shows the results for the counterfactual where the local levels of price-rent and price-wage ratios are constant at the 1980 level. Panel C shows the results for the counterfactual where the evolution of price-wage and price-rent ratios is the same in large and small CZs but housing expenditure share parameters, γ and δ, are constant at the 1980 level. Panel D shows the results for the counterfactual where the model was calibrated without skill-group shifters $\bar{\omega}^M_{it}$ and $\bar{\omega}^H_{it}$. In each panel, the left figure shows the difference between the share of middle-skilled employment in large CZs and the share in small CZs in the benchmark economy (solid line), the main counterfactual (dotted line), and the alternative counterfactual. The right figure shows the difference between the variance of log wages in large CZs and the variance in small CZs for the benchmark and the counterfactual economies.

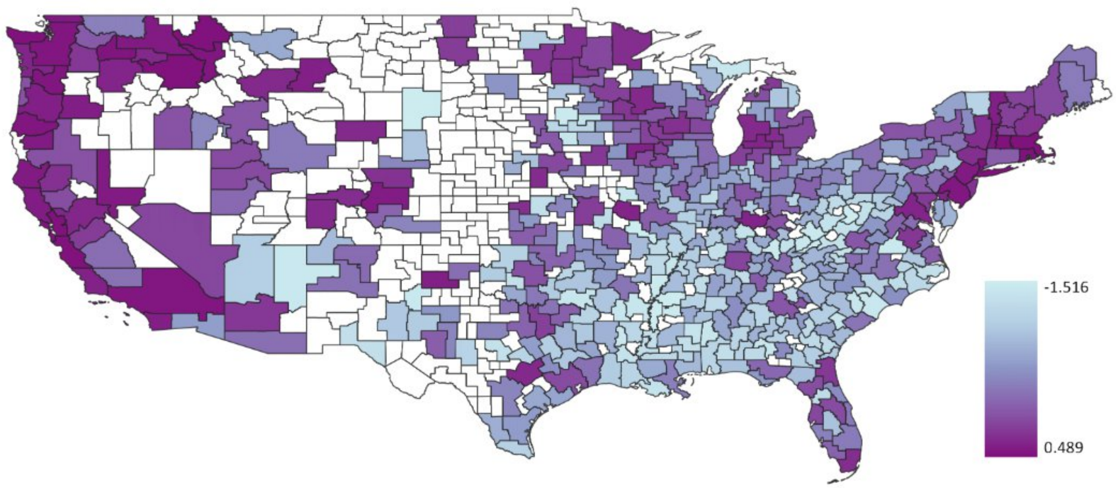
F Appendix: Additional Figures and Tables

Figure F.1: Change in house prices by CZ, 1980–2019



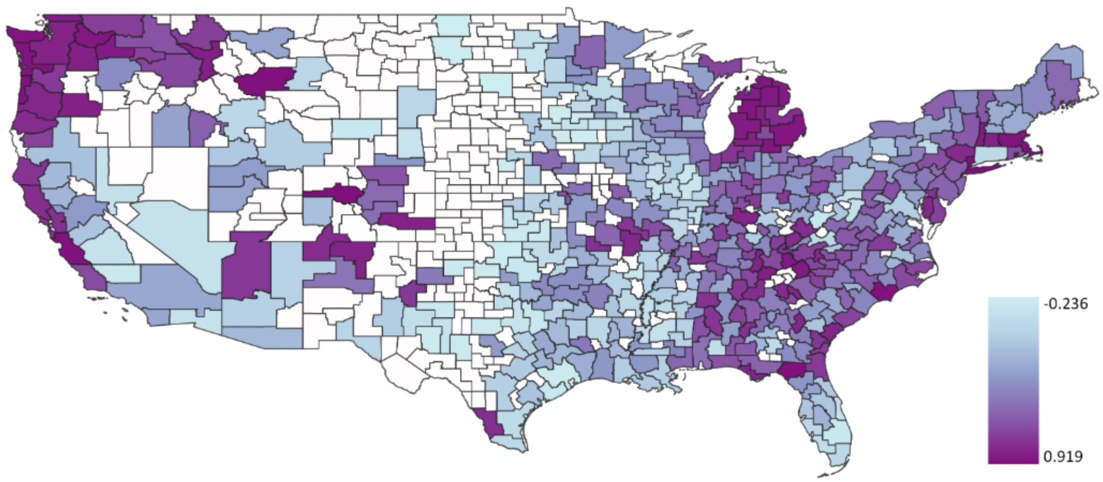
Notes: This map shows log change in the house price index between 1980 and 2019 at the CZ level. Blank areas show CZs with no data available.

Figure F.2: Change in price-rent ratios by CZ, 1980–2019



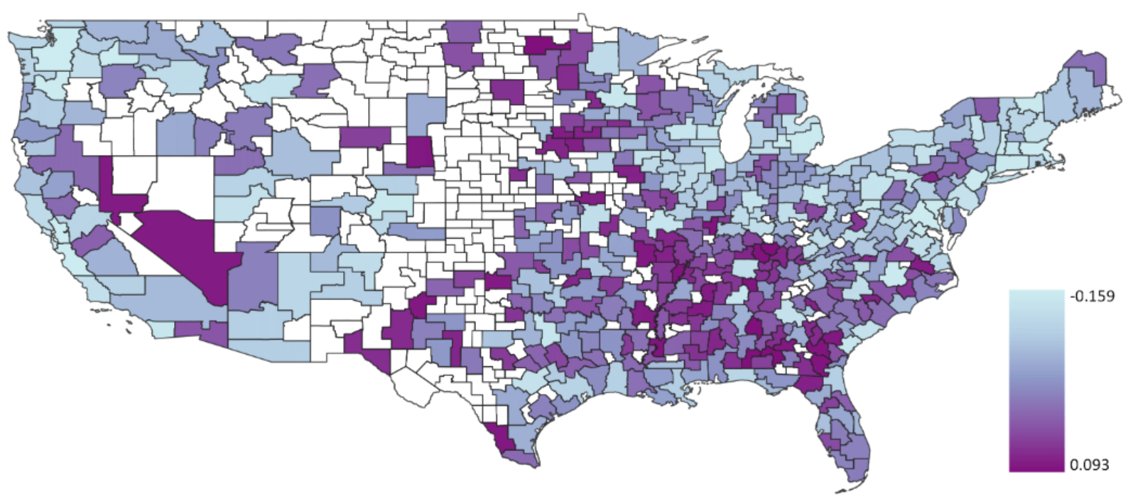
Notes: This map shows log change in the price-rent ratio between 1980 and 2019 at the CZ level. Blank areas show CZs with no data available.

Figure F.3: Change in price-wage ratios by CZ, 1980–2019



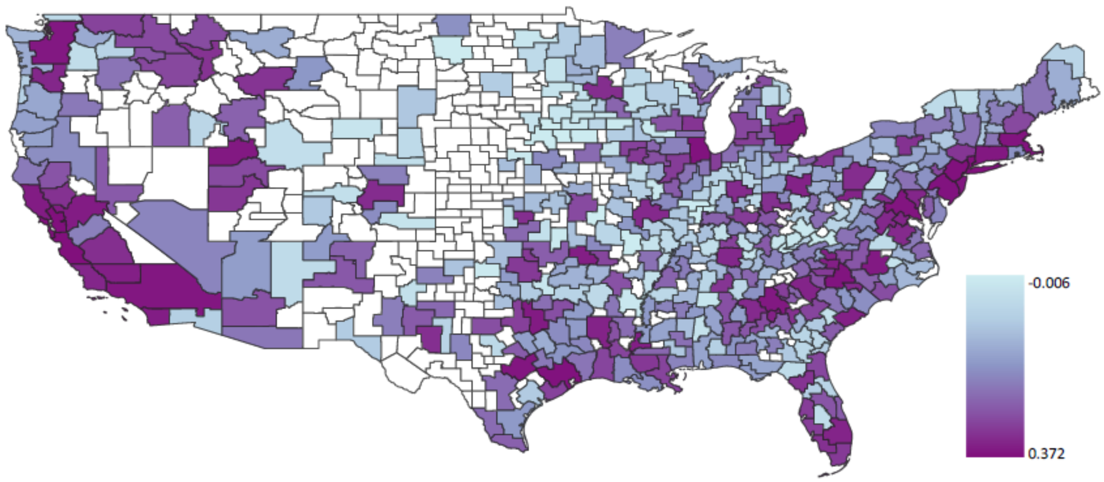
Notes: This map shows log change in the price-wage ratio between 1980 and 2019 at the CZ level. Blank areas show CZs with no data available.

Figure F.4: Change in the middle-skilled share by CZ, 1980–2019



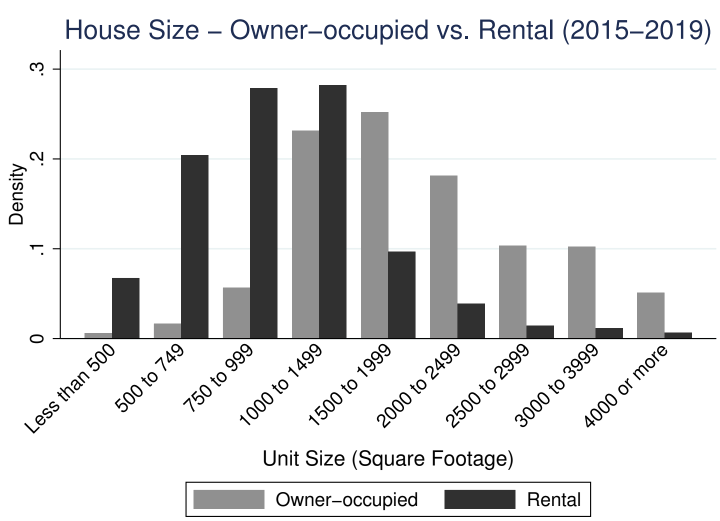
Notes: This map shows log change in the middle-skilled share between 1980 and 2019 at the CZ level. Blank areas show CZs with no data available.

Figure F.5: Change in the variance of log annual wages by CZ, 1980–2019



Notes: This map shows log change in the variance of log annual wages between 1980 and 2019 at the CZ level. Blank areas show CZs with no data available.

Figure F.6: Distribution of sizes of rental and owner-occupied housing units



Notes: This figure shows the distribution of sizes of rental and owner-occupied usings from pooled 2015–2019 American Housing Survey samples.

Table F.1: Relationship between homeownership and housing costs

	(1)	(2)	(3)
Log housing costs change	1.632*	1.041	1.076
	(0.938)	(0.824)	(1.137)
R-squared	0.00900	0.00500	0.00300

Notes: The table shows the results from first-difference OLS regressions for the 1980–2019 period. The number of observations in each regression is 465 (the number of CZs). Column (1) reports the coefficient from a regression of the change in log housing price index on the change in 100× the homeownerhip rate. Columns (2) and (3) report results for price-rent and price-wage ratios, respectively. Robust standard errors are reported in parentheses. *, **, and *** indicate 10%, 5%, and 1% significance levels.