Interest rates and the spatial polarization of housing markets *

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Abstract

Rising within-country differences in house values are a much debated trend in the U.S. and internationally. Using new long-run regional data for 15 advanced economies, we first show that standard explanations linking growing price dispersion to rent dispersion are contradicted by an important stylized fact: rent dispersion has increased far less than price dispersion. We then propose a new explanation: a uniform decline in real risk-free interest rates can have heterogeneous spatial effects on house values. Falling real safe rates disproportionately push up prices in large agglomerations where initial rent-price ratios are low, leading to housing market polarization on the national level.

Keywords: House prices, regional housing markets, spatial polarization
JEL codes: G10, G12, G51, R30

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1 Introduction

In 1980, the median home in Scranton, PA, was worth more than half the median home in New York City. By 2018, its value had decreased to one fifth of the New York City home according to U.S. Census data. In the U.S. and internationally, there has been a substantial increase in regional housing price differences since the 1980s (Van Nieuwerburgh and Weill, 2010; Hilber and Mense, 2021). The spatial structure of economic activity has changed considerably across countries in recent decades. A prominent trend is increasing social and spatial polarization among different sub-national housing markets. As housing is the most important asset for most households, the increasing dispersion of housing prices and housing wealth have become the subject of intense public debate.[1]

From an economic point of view, rising price dispersion across segmented housing markets could increase spatial misallocation of labor as productive workers are forced to stay in places where housing is still affordable. For instance, Hsieh and Moretti (2019) estimate that such misallocation slowed down the growth rate of U.S. GDP by one third in past decades. An increase in local housing prices has also been shown to lead to more misallocation of capital (Herkenhoff, Ohanian, and Prescott, 2018), to affect local non-tradable employment (Mian and Sufi, 2014) and demand conditions (Mian and Sufi, 2011; Mian, Rao, and Sufi, 2013; Guren et al., 2020), as well as consumer prices (Stroebel and Vavra, 2019).

Why have housing prices risen more in some locations than in others? In the most parsimonious framework, rental cash flows determine the value of housing assets: the price of a house is equivalent to the discounted expected future rental cash flow it generates (Poterba, 1984). An important implication – and the starting point for most existing explanations of growing housing price dispersion – is that price and rent dispersion should evolve in lockstep. Yet, as we will show, this approach is at odds with an important stylized fact: rent dispersion has increased considerably less than price dispersion in recent decades, both in the U.S. and internationally. Existing studies that model housing price dispersion as a function of growing differences in local rents (e.g. Van Nieuwerburgh and Weill, 2010; Gyourko, Mayer, and Sinai, 2013) typically overestimate changes in rent dispersion by a substantial margin.

We use a novel long-run data set of housing prices and rents for 27 major agglomerations in 15 developed countries as well as long-run data covering the entire cross-section of U.S. MSAs, and show that price–rent ratios in large agglomerations have increased about twice as much as the national average since the 1980s. Moreover, new research

[1]For instance, existing homeowners in high price urban areas have an incentive to restrict urban growth to the detriment of new buyers (Ortalo-Magné and Prat, 2014). The increasing polarization of housing wealth may have also contributed to political polarization at the national level (Adler and Ansell, 2019; Ansell, 2019).

using granular transaction data suggest that the disconnect between rent and price dispersion is not driven by measurement error due to market segmentation between owner-occupied and rental housing (Begley, Loewenstein, and Willen, 2021; Demers and Eisfeldt, 2021).

We propose a novel explanation that allows for increasing dispersion of within-country housing prices despite much smaller increases in rent dispersion, and ultimately even without changes in rents altogether. In essence, we argue that a decline in real risk-free interest rates will have differential effects on housing prices if there is heterogeneity in initial rent–price ratios across housing markets within an economy. U.S. and international data provide ample evidence for such differences in rental yields across regions. Importantly, large agglomerations exhibit systematically lower rent–price ratios than smaller cities and more remote regions (Demers and Eisfeldt, 2021; Hilber and Mense, 2021). Such differences in rent–price ratios can be generated either by spatial heterogeneity in housing risk, or by differences in local rent growth expectations.[2] Empirically, the presence of higher housing risk premia outside the large agglomerations has been demonstrated by Amaral et al. (2021). There is limited evidence on rent growth expectations on the regional level, but realized rent growth does not seem to differ much between the major agglomerations and the national average (Van Nieuwerburgh and Weill, 2010; Amaral et al., 2021). Note, however, that for our proposed mechanism the source of the heterogeneity in initial rent–price ratios is irrelevant.

To rationalize how the well-documented decline in real safe interest rates since the 1980s (Holston, Laubach, and Williams, 2017; Del Negro et al., 2019) has boosted economy-wide housing price dispersion in the presence of initial difference in rent–price ratios, we turn to a spatial version of the Gordon growth model (Gordon, 1962).[3] We integrate heterogeneity in risk premia and rent growth expectations across regions in the present-value equation for housing prices and show that a fall in real discount rates disproportionately affects the valuation of housing in cities in which initial rent–price ratios are low. This is because a fall in discount rates leads to a linear fall in rent–price ratios but a non-linear increase in the price–rent ratio as the inverse function of the rent–price ratio. With lower initial levels in larger agglomerations such as New York City, a fall in economy-wide real safe interest rate leads to stronger increases in the price–rent ratios in these places and to an increase in economy-wide housing price dispersion without concomitant rent dispersion.

In a last step, we calibrate our model to the data and demonstrate that it can generate an increase in prices as well as increasing dispersion of price–rent ratios similar to the

[2]Note that this holds under more general conditions. Using a simple discount rate – cash flow decomposition (Campbell and Shiller, 1988), differences in rent–price ratios are driven by local rent growth expectations or by differences in local housing discount rates.

[3]In Figure 9, we plot the evolution of real safe rates for the U.S. and the world using the estimates from Del Negro et al. (2019). Safe rates display a continuous downward trend since the mid-1980s.

observational data. Quantitatively, a fall of the real discount rate of 1.3 percentage points between 1985 and 2018 generates the rise in real housing prices and their dispersion observed in our sample of 27 large agglomerations. A 1.3 percentage points fall is close to existing estimates that point to a fall in real housing discount rates of around 1 and 1.1 percentage points over a similar period (Bracke, Pinchbeck, and Wyatt, 2018; Kuvshinov and Zimmermann, 2020). Note that the fall in real discount rates was less pronounced than the fall in the real safe rate, as there is evidence that risk-premia increased over this period (Caballero, Farhi, and Gourinchas, 2017).

We are not the first to link the rise in real housing prices to declining real interest rates on the national level (Miles and Monro, 2019; Garriga, Manuelli, and Peralta-Alva, 2019). Yet, to the best of our knowledge, our study is the first to make the point that, in the presence of initial heterogeneity in rent–price ratios, declining real risk-free interest rates can not only explain rising overall real housing prices, but also growing housing price dispersion. Related work by Kroen et al. (2021) for the stock market shows that falling real interest rates contribute to the rise of superstar firms, especially when interest rate levels are low.

The remainder of this paper is organized as follows. The following section examines existing explanations for the increase in housing price dispersion and the evidence suggesting that these explanations are insufficient. Section 2.2 presents new empirical evidence that housing price dispersion has notably increased more than rent dispersion since the 1980s. The subsequent section presents the new mechanism and confirms that it matches the empirical evidence and can generate the excess price dispersion observed in the data. The final section concludes.

2 Polarization of housing markets

Table 1 shows the price ratio between the most expensive and the median city as well as the coefficient of variation of housing prices for cities in the U.S., Sweden, Germany and the UK in 1980 and today. The ratio of the most expensive to the median housing price region, and the change in the coefficient of variation tell a consistent story: in the U.S. and internationally, price dispersion in housing markets has increased substantially since the 1980s. Rising polarization and its causes have attracted considerable attention in the spatial and urban economics literature, e.g., Glaeser and Gyourko (2002); Quigley and Raphael (2005); Glaeser, Gyourko, and Saiz (2008); Saks (2008); Saiz (2010); Van Nieuwerburgh and Weill (2010); Gyourko, Mayer, and Sinai (2013); Favara and Imbs (2015); Hilber and Vermeulen (2016); Been, Ellen, and O'Regan (2018); Oikarinen et al. (2018); Arundel and Hochstenbach (2019); Hilber and Mense (2021); Molloy, Nathanson, and Paciorek (2022); Vanhapelto (2022).

Table 1: *Price ratio of most expensive to median city & regional coefficient of variation*

	Ratio (Max/Median)			Coefficient of Variation			
Country	1980	Today	Increase	1980	Today	Increase	N
USA	2.81	8.28	2.9	0.23	0.70	3.1	311
SWE	2.97*	6.14	2.1	0.31*	0.54	1.8	290
DEU	1.45	2.66	1.8	0.20	0.44	2.3	42
UK	3.19*	5.00	1.6	0.31*	0.53	1.7	307

*Note: The table shows the housing price ratio of the most expensive to the median location as well as the coefficient of variation for housing prices in the U.S., Sweden, Germany and the UK in 1980 and today. The units of observation are the following: for the U.S. MSAs, for Sweden and Germany municipalities and for the U.K. local planning authorities. *: The data for Sweden starts in 1981 and for the UK in 1995. Data for today is from 2018 for the U.S. and Germany, from 2020 for the UK and from 2021 for Sweden. The coefficient of variation is defined as the ratio of the standard deviation to the mean, which are both weighted by initial population. Data sources are: U.S.: Housing census (1980) and American Community Survey (2018) (see below); Sweden: Purchase price of one- and two-dwelling buildings by municipality from Statistics Sweden; Germany: Preisspiegel Immobilienverband Deutschland (Amaral et al., 2021); UK: Median house prices for administrative geographies from the Office for National Statistics.*

2.1 Price dispersion in spatial housing models

In the existing literature, increasing price dispersion is typically linked to diverging housing market fundamentals across regions. In spatial housing models, price dispersion derives from the embedded present value equation for housing:

$$P_t^i = \sum_{j=1}^{\infty} \mathbb{E}\left(Rent_{t+j}^i * \left(\frac{1}{1+r_t} \right)^j \right), \tag{1}$$

where P_t^i is the real housing price in city i at time t, $\sum_{j=1}^{\infty} Rent_{t+j}^i$ is the stream of future real rent payments net of costs, and r_t is the real discount rate at time t. Note that we are abstracting from consumption growth in our definition of r.[4] The equation directly links current local housing prices and current and future local rents. Changes in economic fundamentals, such as wages, affect local demand for housing services and thereby rents and housing prices.

For instance, Van Nieuwerburgh and Weill (2010) construct a spatial, dynamic equilibrium model in the tradition of Rosen (1979) and Roback (1982) for the distribution of metropolitan areas in the U.S. These metropolitan areas are hit by idiosyncratic and persistent productivity shocks. Households with heterogeneous abilities move freely across

[4]Note that equation 1 can be derived from a simple consumption based asset-pricing model where investors derive utility from current and future consumption, by setting $\frac{1}{1+r_t} = \beta \frac{u'(c_{t+1})}{u'(c_t)}$, where β is the discount factor of the investor and u' its marginal utility with respect to consumption (Cochrane, 2005). To simplify, we will abstract from the influence of consumption growth on r and simply refer to r as the real discount rate.

metropolitan areas in reaction to these shocks. Housing supply is limited by supply regulations, meaning that rents will adjust to compensate for regional wage differences. This, in turn, determines housing prices. The authors calibrate productivity shocks to match the increase in the observed regional wage dispersion between metropolitan areas from 1975 to 2007. The model matches the increase in housing price dispersion observed in the data. However, as the authors note, it also produces an increase in rent dispersion three times larger than observed empirically.

In another well-known paper, Gyourko, Mayer, and Sinai (2013) develop a two-location model to show that increasing national demand generated by population growth affects regions differently, depending on local housing supply elasticities. Under the assumption that people prefer to live in supply-constrained cities, the model predicts that in response to increasing national demand, supply-constrained cities will experience a stronger rental increase than unconstrained cities. This increase in rents passes through to housing prices via the present-value equation. The authors call the cities that display a combination of low supply elasticities and strong housing price growth "superstar cities". The paper does not explicitly study the model predictions for rents, but in Appendix A, we use the paper's data and show that prices in superstar cities increased considerably more than rents.

A partial exception to the assumption that growing housing price dispersion is a function of increasing rent dispersion is Hilber and Mense (2021). The authors use regional data for the U.K. from 1997 to 2018 and start from the empirical observation that prices have increased much more in the "superstar" city London than rents, i.e., the price–rent ratio has surged in London compared to the rest of the country. They explain this with serially correlated housing demand shocks that induce heterogeneous rent growth expectations. However, the paper is chiefly concerned with cyclical fluctuations and the proposed mechanism generates transitory divergence in price–rent ratios between regions. Over longer horizons, housing demand shocks mean-revert so that rents and prices move in lockstep (Piazzesi and Schneider, 2016).

2.2 Empirical evidence on price and rent dispersion

Explanations focused on rent dispersion as the source of increasing price dispersion are at odds with one important stylized fact in the data: price dispersion has increased much more than rent dispersion. Evidence for such divergent trends has not only been exposed in the U.K. data discussed above (Hilber and Mense, 2021), but also in recent U.S. data (Demers and Eisfeldt, 2021; Molloy, Nathanson, and Paciorek, 2022).

Concerns that measurement error could be responsible for the apparent divergence between rent and price growth do not appear convincing in the light of recent studies with micro data. In principle, market segmentation could lead to selection bias if rental data are typically taken from lower quality segments of the housing market while prices mainly come from higher-quality segments (Glaeser and Gyourko, 2007). However, Begley, Loewenstein, and Willen (2021) study micro-data from Corelogic on prices and rents for the same property to estimate price–rent ratios, thereby avoiding selection bias. They show that the price variation in owner- and renter-occupied housing markets are closely correlated. If anything, renter-occupied prices have risen more than owner-occupied prices. Demers and Eisfeldt (2021) also use micro-data from the American Housing Survey to build rent–price ratios for 15 different U.S. cities from 1985 to 2020. Relying on hedonic models and non-parametric methods, they show that rent–price ratios fell most strongly in "expensive" cities.

In the following, we systematize the available evidence for price and rental dispersion using two comprehensive data sets that have recently become available (Amaral et al., 2021). One is a long-run cross country data set; the other covers the entire cross-section of regions in the U.S.. Both data sets show that dispersion in housing prices increased substantially more than dispersion in rents since the 1980s.

The first data set covers housing price series, rent series, and rent–price ratios for 27 agglomerations in 15 OECD countries over the past century. The major agglomerations are defined as the largest cities within each country in terms of 1900 population statistics, including cities like London, New York, Paris, Berlin and Tokyo. We merge the city-level series with nation-wide housing data from Jordà et al. (2019).

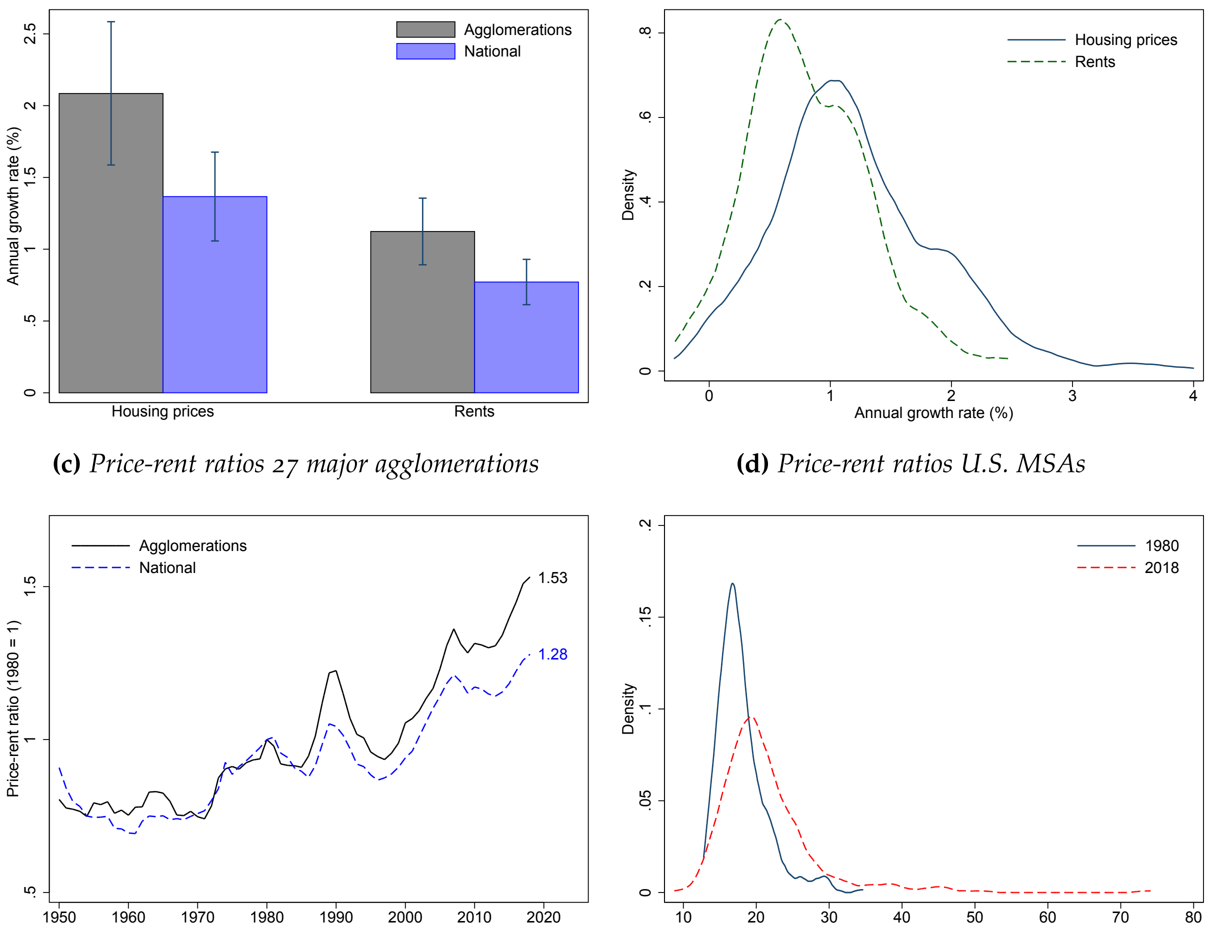
The second covers the entire cross-section of 316 MSAs in the U.S. It comprises housing prices, rents and price–rent ratios with decadal frequency from housing censuses. It is based on the data in Gyourko, Mayer, and Sinai (2013), but extended to 2018 using the American Community Survey.

Figure 1 panel (a) plots the geometric mean of real housing price and rent increases between 1980 and 2018 for the 27 major agglomerations next to the geometric mean of national real housing price and rent increases.[5] The national means are weighted by the number of sample agglomerations in the respective country. The Figure brings two key insights. First, housing prices have grown much more than rents in both the major agglomerations and at national levels. Second, housing prices have grown considerably more in the major agglomerations than the national average. The difference in mean growth rates is as large as 70 basis points per year, which implies that mean growth rates for the agglomerations have been more than 50% higher compared to national housing price growth rates over the past four decades. With only 35 basis points the difference in yearly rent growth rates is considerably lower.

Appendix B presents geometric means of housing price and rent growth rates

[5]We use log growth rates to calculate means and confidence intervals, such that the resulting values can be interpreted as geometric means. This way, mean values show the overall trend during the past 4 decades and are not driven by the volatility of the series.

Figure 1: *Evolution of housing price and rent growth rates and price-rent ratios between 1980 and 2018*



(a) *Annual growth rates 27 major agglomerations*

(b) *Annual growth rates U.S. MSAs*

(c) *Price-rent ratios 27 major agglomerations*

(d) *Price-rent ratios U.S. MSAs*

Note: Panel (a): Geometric mean of annual housing price and rent growth rates of 27 major agglomerations (black) and the respective national averages weighted by the number of sample agglomerations in the respective country. Means and confidence intervals are calculated using log growth rates and transformed back to percentage growth rates afterwards. Panel (b): Kernel density of annualized housing price and rent growth rates between 1980 and 2018 for 316 U.S. MSAs. Panel (c): Index of equally-weighted average increases of price-rent ratios of 27 major agglomerations and average national increases of price-rent ratios weighted by the number of sample agglomerations in the respective country. 1980=1. Panel (d): Kernel density of price-rent ratios of 316 U.S. MSAs in 1980 and 2018 calculated from net rental yields.

between 1980 and 2018 by city, demonstrating that housing prices have grown more than rents in almost all economies. Housing price growth has been higher at the city-level than nationally for virtually all agglomerations in the cross-country data set. This phenomenon is particularly pronounced for the largest agglomerations, like London, New York or Paris.

Figure 1 panel (b) shows kernel densities for the geometric mean of housing price and rent growth rates between 1980 and 2018 by MSA for the full sample of U.S. MSAs. Housing price growth rates have not only been on average higher compared to rent growth rates, but also show more dispersion. The fat right tail of housing price growth rates is particularly striking. As discussed in Gyourko, Mayer, and Sinai (2013) this indicates that a small set of cities had very high yearly housing price growth rates. Importantly, this is not mirrored by rent growth rates.

A necessary condition for our mechanism to hold is that rent–price ratios differ initially by cities. We mapped rent-price ratios for US MSAs in 1980. The resulting Figure 10 in the Appendix visually shows a correlation between city size and the initial rent-price ratios and a clear geographical clustering: the regions with populous urban agglomerations at the coasts already started with considerably lower rent-price ratios in 1980 when compared to the cities in the more rural central regions.[6] Additionally, we show in Figure 3 that this result also holds for our international data set.

Figure 1 panel (c) shows the average increases in price-rent ratios over time for the 27 major agglomerations and on the national level to show the proportion of the housing price dispersion that cannot be accounted for by rent dispersion. Changes in price–rent ratios indicate how much housing prices changed after accounting for changes in rents. From previous observations, price–rent ratios are expected to have increased considerably since 1980. More importantly, the data show that price–rent ratios have increased considerably more in the major agglomerations than the national average. While the gap in price–rent ratios varies over the cycle, a phenomenon that could be explained by the mechanism proposed in Hilber and Mense (2021), it shows a strong persistence over the last decades and seems to be increasing over time. The gap starts to arise during the 1980s and does not exist in the period before. This timing coincides with the fall in the risk free rate.

Figure 1 panel (d) plots the distribution of U.S. MSA-level price–rent ratios in 1980 and 2018, demonstrating not only that the dispersion of price-rent ratios was already substantial in 1980, but also that it increased considerably over the last decades. Again, this phenomenon is particularly strong for the distribution's right tail, where also the major agglomerations like New York are located. As expected, mean price–rent ratios have also increased over time. Still, the coefficient of variation (CV) increased from 0.19 to 0.32.

3 Falling real interest rates and housing price dispersion

This section constructs a parsimonious, spatial asset-pricing model of the housing market to rationalize an increase in housing price dispersion that does not follow from increasing rent dispersion but results from differences in initial rent–price ratios between cities.

[6] Demers and Eisfeldt (2021) also show substantial differences in rent-price ratios for a smaller sample of U.S. MSAs in the 1980s.

We also start from present value equation (1), the only difference being that we allow for differences in real discount rates between cities:

$$P_t^i = \sum_{j=1}^{\infty} \mathbb{E}\left(Rent_{t+j}^i * \left(\frac{1}{1+r_t^i} \right)^j \right). \tag{2}$$

From a theoretical perspective, a combination of local market segmentation and incomplete markets implies that discount rates do not need to equalize between cities.[7] Piazzesi, Schneider, and Stroebel (2020) show that housing markets are locally segmented, using data on online searches to document large differences in housing search behavior across different municipalities in California.[8] Housing markets are also incomplete because housing assets are indivisible, and homeowners are typically non-diversified. The lack of diversification implies limitations to arbitrage precluding discount rates from equalizing (Piazzesi and Schneider, 2016).

Empirically, Amaral et al. (2021) show that over the long run returns have been persistently lower in large cities than in the rest of the country. Differences in housing returns are likely due to differences in housing risk, as housing prices co-vary less with income in larger MSAs and idiosyncratic housing price risk is lower. The assumption that the discount rate differs geographically is further supported by the empirical evidence that landlords concentrate their housing portfolios close to their place of residency, exposing them to local housing market risks (Levy, 2021).

In the following, we assume that discount rates are composed of a risk-free component, that is equal for the entire country and a risk-premium that can differ by the city invested in; $r_t^i = \text{risk-free}_t + \text{risk-premium}_t^i$. To simplify the discussion, we make two additional assumptions: First, we assume that rents in city i are expected at time t to grow at a constant rate g_t^i. Second, we assume that $r_t^i > g_t^i$, such that housing prices are finite. This allows us to rewrite equation (2) as the Gordon (1962) growth valuation formula:

$$P_t^i = \sum_{j=1}^{\infty} \left(Rent_t^i * \left(\frac{1+g_t^i}{1+r_t^i} \right)^j \right) \qquad \Longleftrightarrow \qquad P_t^i = Rent_t^i * \frac{1+g_t^i}{r_t^i - g_t^i}. \tag{3}$$

Following this equation, the rent-price ratio is equal to:

$$\text{Rent-price ratio}_t^i = \frac{Rent_t^i}{P_t^i} = \frac{r_t^i - g_t^i}{1+g_t^i}. \tag{4}$$

We next consider a setting with two cities: agglomeration A and reservation city B. The reservation city can be understood as the average of all other locations within a

[7]Sagi (2021) builds a housing search model, showing that heterogeneity in discount rates is an essential condition to explain the dynamics in real estate prices.

[8]They also demonstrate that differences in housing search between different quality segments within municipalities are less pronounced.

country except the large agglomeration. To compare both cities, we make three additional assumptions. First, as argued in the urban economics literature (Gyourko, Mayer, and Sinai, 2013; Hilber and Mense, 2021) we assume that expected rent growth in the large agglomeration is higher than or equal to the reservation city; $g_t^A \geq g_t^B \;\; \forall t$. Second, as argued above, we assume that risk-premia are lower or equal for housing investments in large agglomerations compared to the reservation city, such that $r_t^A \leq r_t^B \;\; \forall t$. Third, we assume that at least one of the two previous inequalities is strict, such that rent–price ratios are lower in the agglomeration and:

$$r_t^B - g_t^B > r_t^A - g_t^A > 0. \tag{5}$$

From equation (3) we can write the log price difference between cities A and B as:

$$log(P_t^A) - log(P_t^B) = log(Rent_t^A) + log\left(\frac{1+g_t^A}{r_t^A - g_t^A}\right) - log(Rent_t^B) - log\left(\frac{1+g_t^B}{r_t^B - g_t^B}\right). \tag{6}$$

Next we derive the predictions of our model after a fall in the real risk-free rate. We assume that the real risk-free rate decreases by Δ, such that:

$$\begin{aligned} &log(P_t^A) - log(P_t^B) = \\ &\qquad log(Rent_t^A) + log\left(\frac{1+g_t^A}{r_t^A - \Delta - g_t^A}\right) - log(Rent_t^B) - log\left(\frac{1+g_t^B}{r_t^B - \Delta - g_t^B}\right). \end{aligned} \tag{7}$$

If we differentiate with respect to Δ and under the assumptions made above, we get:

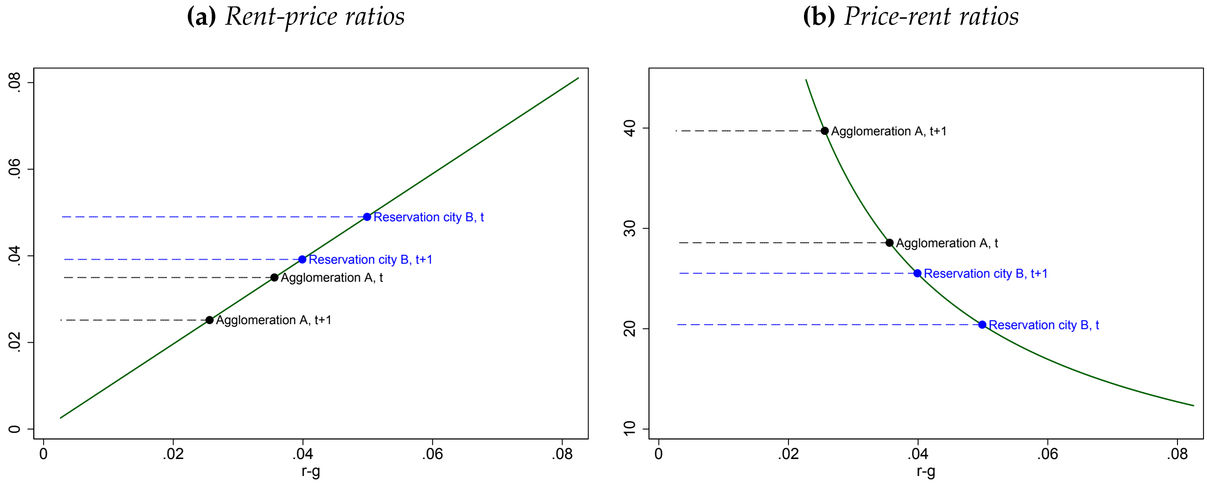
$$\frac{\partial\big(log(P_t^A) - log(P_t^B)\big)}{\partial \Delta} = \frac{1}{r_t^A - \Delta - g_t^A} - \frac{1}{r_t^B - \Delta - g_t^B} \quad > \quad 0.$$

This demonstrates that a uniform fall in real discount rates across both cities, generated by a fall in the real risk-free rate, increases housing price dispersion if rent–price ratios initially differ.

The intuition for this observation is presented in Figure 2. Panel (a) plots the rent–price ratio in the model as a function of $r - g$ for a varying r, wherein the rent–price ratio changes linearly in r. Following equation (5), we assume that $r - g$ is lower in the agglomeration at time t, resulting in a lower rent–price ratio. Next, we assume that between t and $t + 1$ r falls in both cities by one percentage point. This leads to an approximately equal fall in the rent–price ratio in the agglomeration (A) and in the reservation city (B).

Figure 2 panel (b) plots the corresponding price–rent ratio. As the price–rent ratio is the inverse function of the rent–price ratio, when r changes, the price–rent ratio changes in a non-linear fashion. Since the initial price–rent ratio is higher in the

Figure 2: *A fall in discount rates in the model*



Note: Panel (a) plots the rent–price ratio in our model as a function of $r - g$*. To calculate the points, we assumed that* $g = 0.0175$*. Panel (b) shows the corresponding price–rent ratio.*

agglomeration, an equally large fall in r leads to a larger increase in the price–rent ratio in the agglomeration than in the reservation city. Subsequently, the price dispersion between the agglomeration and the reservation city increases when r falls, even when rents are constant in both cities.

3.1 Rent–price ratios in the data

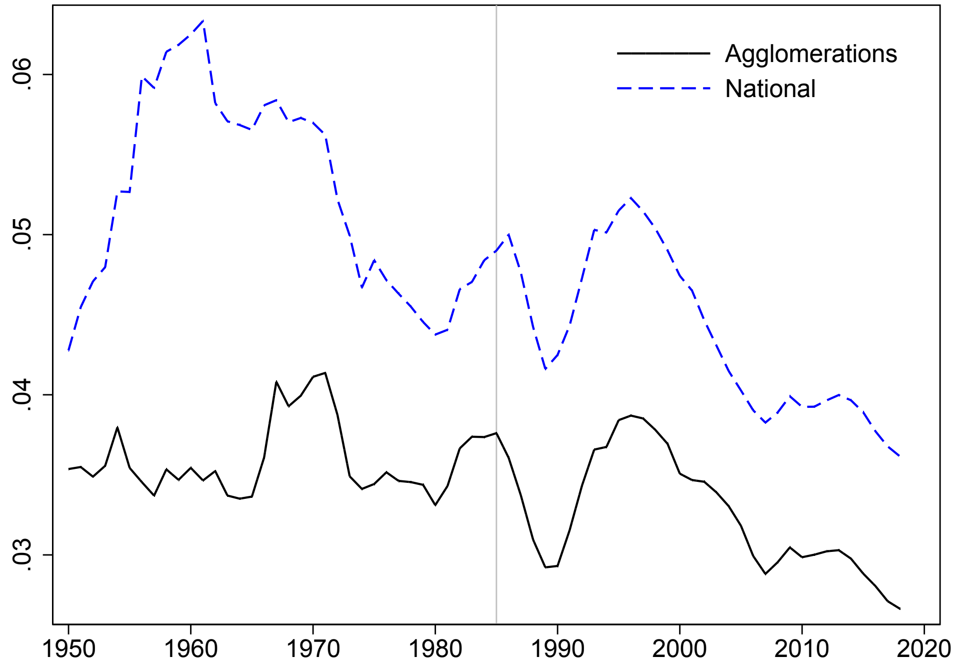
The previous section determined that price dispersion increases in response to a fall in the real risk-free rate if rent–price ratios initially differ. Our model also predicts a parallel fall in rent–price ratios across cities due to a fall in the real risk-free rate.

Figure 3 plots the average rent-price ratios in the 27 major agglomerations and on the national level. Two observations are important. First, rent–price ratios have been lower in the major agglomerations over the entire period since 1950. This evidence validates the assumption regarding the initial differences in rent–price ratios.

Second, the rent–price ratios in the major agglomerations and at the national level have moved in parallel trajectories since 1985 (abstracting from the cyclical variation), suggesting a common downward trend. Rent-price ratios fell by around 1.2 percentage points from 1985 to 2018 in the major agglomerations and at the national level. The equally large fall in rent–price ratios in the major agglomerations and at the national level is equivalent to the parallel fall in rent–price ratios predicted by the model. Note that alternative mechanisms that attempt to explain the increase in price dispersion based on factors that solely affect the major agglomerations, would predict a divergence in rent–price ratios between the major agglomerations and the rest.

We also use the U.S. MSA-level data to compare the full distribution of price–rent

Figure 3: *Rent–price ratios in the data*



Note: The solid black line is the non-weighted average rent–price ratio of 27 major agglomerations. The dashed blue line is the average of the national rent–price ratio weighted by the number of sample agglomerations in the respective country.

ratios in 2018 with our model prediction. While the data align well with our proposed mechanism, there is room for other factors at play such as diverging rent growth expectations between the large agglomerations and the rest of the economy. We discuss this in more detail in Appendix D.

4 Model calibration

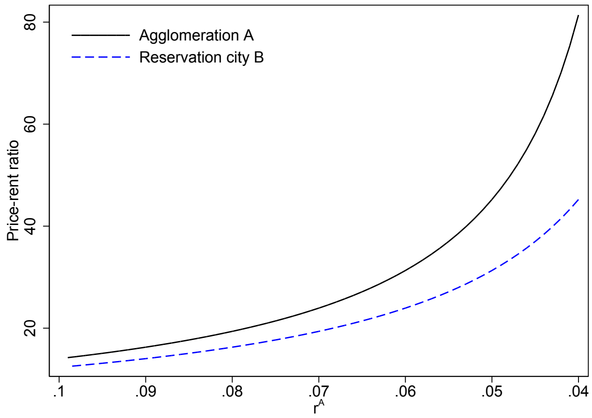
To simulate the increase in price dispersion in response to a fall in r in our model, we calibrate the model to the following values. We set the expected real rent growth in the agglomeration and the reservation city equal to 1.75 %, $g_t^A = g_t^B = 0.0175 \ \forall t$, which is close to long-run real rent growth rates observed in our international data set.[9] Next, we assume that the real discount rate in the agglomeration is 1 percentage point lower than in the reservation city; $r_t^A = r_t^B - 0.01 \ \forall t$. This is equivalent to the difference in total housing returns of around 1 percentage point found in Amaral et al. (2021). For simplification we assume that real rents in the agglomeration and in the reservation city are equal to one in period one, $Rent_1^A = Rent_1^B = 1$.

Figure 4 panel (a) plots the resulting price–rent ratios in the agglomeration and

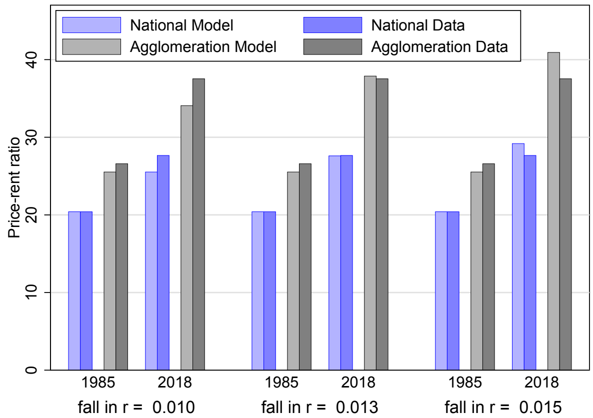
[9]Between 1950 and 2018, rents grew on average by 1.86 % in the 27 major agglomerations and by 1.65 % at the national level.

Figure 4: *Simulated price-rent ratios in response to a fall in r*

(a) *Price-rent ratios as a function of r_t^A*



(b) *Model predictions vs. data*



Note: Panel (a) shows price–rent ratios for the agglomeration and the reservation city in the model relative to the discount rate in the reservation city. Panel (b) compares the model to the data for different assumed values of the fall in the discount rate r. For both exercises, we assume that $g = 0.0175$ and $r^A = r^B - 0.01$.

reservation cities as a function of r_t^B, demonstrating that the dispersion in price–rent ratios increases when discount rates fall. Although the initial difference between the cities is small for high discount rates, the difference becomes substantial as discount rates become smaller.[10]

The next step is to assess whether our model matches the increasing levels and dispersion of price–rent ratios in the data. This requires estimates for the housing discount rates in 1985 and 2018. The estimated decline in the real risk-free rate ranges from 2.5 to 5 percentage points depending on the estimation method (Del Negro et al., 2019; Rachel and Summers, 2019). At the same time, there is considerable evidence that risk-premia have risen during this period, which partly offsets the effect of the fall in the risk-free rate on housing discount rates (Caballero, Farhi, and Gourinchas, 2017; Kuvshinov and Zimmermann, 2020). To the best of our knowledge, there exist two estimates for the decline in real housing discount rates over this period. Using data on U.K. leaseholds, Bracke, Pinchbeck, and Wyatt (2018) estimate a drop of around 1 percentage point between the 1990s and the 2010s for very long housing discount rates, their results are in line with Giglio, Maggiori, and Stroebel (2015), who also estimate discount rates for the housing market in Singapore.[11] Kuvshinov and Zimmermann (2020) estimate a drop of around 1.1 percentage points between 1985 and 2015 for a sample of developed countries very similar to ours.[12]

Figure 4 panel (b) compares the price–rent ratios predicted by our model to the actual

[10]The same result is demonstrated by Kroen et al. (2021) for stock markets.

[11]Both papers measure discount rates for housing service flows more than 100 years in the future.

[12]Our sample additionally contains Canada and our data sources differ for some specific countries. The details can be found in the Data Appendix of Amaral et al. (2021).

price–rent ratios in the data for the years 1985 and 2018. We represent three scenarios for the fall in real discount rates. On the left, real discount rates fell by 1 p.p., in the middle by 1.3 p.p. and on the right by 1.5 p.p. Overall, the model slightly overshoots the price–rent ratio in the major agglomerations in 1985.[13] This indicates that the difference in risk-premia between the agglomerations and the national average was either smaller than 1 percentage point or the rent-growth expectations have been slightly higher in the major agglomerations.

In the scenario where real discount rates fall by 1 percentage point, our model cannot fully account for the rise in levels and dispersion of the price–rent ratio. It does, however, generate a substantial portion of the increase in levels and dispersion we observe in the data. Assuming a fall in r of 1.5 percentage points instead, our model does overshoot both the level and the dispersion in housing prices we observe in the data. Matching the increase in levels and dispersion in the data requires a fall in discount rates of around 1.3 percentage points.

Our model also matches the increase in levels and dispersion of price–rent ratios if we assume that expected rent growth was 1 p.p. higher in the major agglomerations, keeping discount rates constant across cities, $r^A = r^B$. Given the small difference in observed rent growth and the stable return difference between major agglomerations and the national average, we assert that a constant difference in discount rates is more realistic than a constant difference in expected rent growth. A large-scale simulation of many different combinations of different model variables (Appendix C) demonstrates that falling discount rates robustly lead to increasing housing price dispersion for most realistic value combinations for r and g.

5 Conclusion

In this paper, we present a novel explanation for increasing housing price dispersion that, unlike existing models, does not require a comparable rise in rent dispersion. The key new insight is that a uniform fall in real interest rates can have heterogeneous spatial effects. For realistic values for the fall in real discount rates, the model is able to reproduce the growing dispersion of price–rent ratios observed in the data even in the absence of changes in fundamentals. In light of the central role of rental and housing price dynamics in urban economics, more research is needed to integrate this mechanism into more complex spatial models.[14] An important takeaway of the paper is that increasing polarization of housing prices between "superstar cities" and the rest

[13]Note that the model exactly matches the national price–rent ratio in 1985 by construction, since we back-out the initial average national discount rate from the rent-price ratio in 1985 using our model.

[14]A promising example of this is the dynamic spatial equilibrium model of housing demand and supply in Vanhapelto (2022).

of the country is not just driven by supply-side restrictions, but that interest rates can play a central role not only for the pricing on a national level, but also for the growing dispersion of housing prices. For future research in urban economics this implies to also pay attention to financial factors when thinking about trends in regional housing markets. The findings of this paper potentially also speak to the housing market outlook in the current environment of rising interest rates. All else equal, some of the polarization of housing prices that we could observe over the past decades can be expected to revert if going forward real discount rates rise again.

References

Adler, David and Ben Ansell (June 2019). "Housing and Populism". In: *West European Politics* 43(2), pp. 344–365.

Amaral, Francisco et al. (2021). "Superstar Returns". In: *FRB of New York Staff Report*(999).

Ansell, Ben (May 2019). "The Politics of Housing". In: *Annual Review of Political Science* 22(1), pp. 165–185.

Arundel, Rowan and Cody Hochstenbach (2019). "Divided Access and the Spatial Polarization of Housing Wealth". In: *Urban Geography*, pp. 1–27.

Been, Vicki, Ingrid Gould Ellen, and Katherine O'Regan (Dec. 2018). "Supply Skepticism: Housing Supply and Affordability". In: *Housing Policy Debate* 29(1), pp. 25–40.

Begley, Jaclene, Lara Loewenstein, and Paul S. Willen (2021). "The Rent-price Ratio during the 2000s Housing Boom and Bust: Measurement and Implications." In: *Work in progress*.

Blanchard, Olivier J. and Lawrence F Katz (1992). "Regional evolutions". In: *Brookings Papers on Economic Activity, Economic Studies Program, The Brookings Institution* 23(1).

Bracke, Philippe, Edward W Pinchbeck, and James Wyatt (2018). "The Time Value of Housing: Historical Evidence on Discount Rates". In: *The Economic Journal* 128(613), pp. 1820–1843.

Caballero, Ricardo J., Emmanuel Farhi, and Pierre-Olivier Gourinchas (May 2017). "Rents, Technical Change, and Risk Premia Accounting for Secular Trends in Interest Rates, Returns on Capital, Earning Yields, and Factor Shares". In: *American Economic Review* 107(5), pp. 614–620.

Campbell, John Y. and Robert J. Shiller (July 1988). "The Dividend-Price Ratio and Expectations of Future Dividends and Discount Factors". In: *Review of Financial Studies* 1(3), pp. 195–228.

Cochrane, John H. (2005). *Asset Pricing*. Princeton University Press.

Del Negro, Marco et al. (May 2019). "Global Trends in Interest Rates". In: *Journal of International Economics* 118, pp. 248–262.

Demers, Andrew and Andrea L. Eisfeldt (May 2021). "Total Returns to Single-Family Rentals". In: *Real Estate Economics*.

Favara, Giovanni and Jean Imbs (Mar. 2015). "Credit Supply and the Price of Housing". In: *American Economic Review* 105(3), pp. 958–992.

Garriga, Carlos, Rodolfo Manuelli, and Adrian Peralta-Alva (June 2019). "A Macroeconomic Model of Price Swings in the Housing Market". In: *American Economic Review* 109(6), pp. 2036–2072.

Giglio, Stefano, Matteo Maggiori, and Johannes Stroebel (2015). "Very Long-Run Discount Rates". In: *The Quarterly Journal of Economics* 130(1), pp. 1–53.

Glaeser, Edward and Joseph Gyourko (Mar. 2002). *The Impact of Zoning on Housing Affordability*. Tech. rep.

Glaeser, Edward and Joseph Gyourko (2007). "Arbitrage in Housing Markets". In.

Glaeser, Edward, Joseph Gyourko, and Albert Saiz (Sept. 2008). "Housing Supply and Housing Bubbles". In: *Journal of Urban Economics* 64(2), pp. 198–217.

Gordon, Myron J (1962). "The savings investment and valuation of a corporation". In: *The Review of Economics and Statistics*, pp. 37–51.

Guren, Adam M et al. (Apr. 2020). "Housing Wealth Effects: The Long View". In: *The Review of Economic Studies* 88(2), pp. 669–707.

Gyourko, Joseph, Christopher Mayer, and Todd Sinai (Nov. 2013). "Superstar Cities". In: *American Economic Journal: Economic Policy* 5(4), pp. 167–199.

Herkenhoff, Kyle F, Lee E Ohanian, and Edward C Prescott (2018). "Tarnishing the golden and empire states: Land-use restrictions and the US economic slowdown". In: *Journal of Monetary Economics* 93, pp. 89–109.

Hilber, Christian and Andreas Mense (2021). "Why Have House Prices Risen so Much More than Rents in Superstar Cities?" In.

Hilber, Christian and Wouter Vermeulen (June 2016). "The Impact of Supply Constraints on House Prices in England". In: *The Economic Journal* 126(591), pp. 358–405.

Holston, Kathryn, Thomas Laubach, and John C Williams (2017). "Measuring the Natural Rate of Interest: International Trends and Determinants". In: *Journal of International Economics* 108, S59–S75.

Hsieh, Chang-Tai and Enrico Moretti (Apr. 2019). "Housing Constraints and Spatial Misallocation". In: *American Economic Journal: Macroeconomics* 11(2), pp. 1–39.

Jordà, Òscar et al. (Apr. 2019). "The Rate of Return on Everything, 1870-2015*". In: *The Quarterly Journal of Economics* 134(3), pp. 1225–1298.

Kroen, Thomas et al. (2021). "Falling Rates and Rising Superstars". In.

Kuvshinov, Dmitry and Kaspar Zimmermann (2020). "The Expected Return on Risky Assets: International Long-run Evidence". In: *SSRN 3546005*.

Levy, Antoine (2021). "Housing Policy with Home-Biased Landlords: Evidence from French Rental Markets". In.

Mian, Atif, Kamalesh Rao, and Amir Sufi (Sept. 2013). "Household Balance Sheets, Consumption, and the Economic Slump*". In: *The Quarterly Journal of Economics* 128(4), pp. 1687–1726.

Mian, Atif and Amir Sufi (Aug. 2011). "House Prices, Home Equity-Based Borrowing, and the US Household Leverage Crisis". In: *American Economic Review* 101(5), pp. 2132–2156.

Mian, Atif and Amir Sufi (Nov. 2014). "What Explains the 2007-2009 Drop in Employment?" In: *Econometrica* 82(6), pp. 2197–2223.

Miles, David Kenneth and Victoria Monro (2019). "UK House Prices and Three Decades of Decline in the Risk-Free Real Interest Rate". In: *SSRN Electronic Journal*.

Molloy, Raven, Charles Nathanson, and Andrew Paciorek (2022). "Housing Supply and Affordability: Evidence from Rents, Housing Consumption and Household Location". In: *Journal of Urban Economics* 129, p. 103427.

Oikarinen, Elias et al. (May 2018). "U.S. Metropolitan House Price Dynamics". In: *Journal of Urban Economics* 105, pp. 54–69.

Ortalo-Magné, François and Andrea Prat (2014). "On the Political Economy of Urban Growth: Homeownership versus Affordability". In: *American Economic Journal: Microeconomics* 6(1), pp. 154–81.

Piazzesi, Monika and Martin Schneider (2016). "Housing and Macroeconomics". In: *Handbook of Macroeconomics*. Elsevier, pp. 1547–1640.

Piazzesi, Monika, Martin Schneider, and Johannes Stroebel (2020). "Segmented housing search". In: *American Economic Review* 110(3), pp. 720–59.

Poterba, James M. (Nov. 1984). "Tax Subsidies to Owner-Occupied Housing: An Asset-Market Approach". In: *The Quarterly Journal of Economics* 99(4), p. 729.

Quigley, John M and Steven Raphael (Apr. 2005). "Regulation and the High Cost of Housing in California". In: *American Economic Review* 95(2), pp. 323–328.

Rachel, Lukasz and Lawrence Summers (Aug. 2019). *On Secular Stagnation in the Industrialized World*. Tech. rep.

Roback, Jennifer (1982). "Wages, Rents, and the Quality of Life". In: *Journal of Political Economy* 90(6), pp. 1257–1278.

Rosen, Sherwin (1979). "Wage-Based Indexes of Urban Quality of Life". In: *Current Issues in Urban Economics*, pp. 74–104.

Sagi, Jacob S (Oct. 2021). "Asset-Level Risk and Return in Real Estate Investments". In: *The Review of Financial Studies* 34(8). Ed. by Stijn Van Nieuwerburgh, pp. 3647–3694.

Saiz, Albert (2010). "The Geographic Determinants of Housing Supply". In: *The Quarterly Journal of Economics* 125(3), pp. 1253–1296.

Saks, Raven (July 2008). "Job Creation and Housing Construction: Constraints on Metropolitan Area Employment Growth". In: *Journal of Urban Economics* 64(1), pp. 178–195.

Stroebel, Johannes and Joseph Vavra (June 2019). "House Prices, Local Demand, and Retail Prices". In: *Journal of Political Economy* 127(3), pp. 1391–1436.

Van Nieuwerburgh, Stijn G and Pierre-Olivier Weill (Aug. 2010). "Why Has House Price Dispersion Gone Up?" In: *Review of Economic Studies* 77(4), pp. 1567–1606.

Vanhapelto, Tuuli (2022). "House Prices and Rents in a Dynamic Spatial Equilibrium". In: *Job Market Paper*.

Online Appendix
"Interest rates and the spatial polarization of housing markets"

Francisco Amaral, Martin Dohmen, Sebastian Kohl, Moritz Schularick

A Superstar cities revisited

A.1 Rent growth

Gyourko, Mayer, and Sinai (2013) derive a set of propositions, that directly imply that superstar cities should have experienced stronger rent growth than the rest of the country. Proposition 1 states that superstar cities have higher rental values than the rest of the country. Proposition 3 states that an increase in aggregate income leads to stronger rental increases in the superstar cities than in the rest.[15] These two propositions are tested in Tables 2 and 3 of the paper, using log house value as the dependent variable. Here, we replicate the analysis focusing on the effects on house value growth and rent growth. Table 2 presents our regression output. There are two primary results. First, the coefficients for rent values are significant and positive, just as the coefficients for house values. Second, the coefficients for rent values are slightly less than half those of house values. This indicates that the effects on rents are much smaller than on prices, which raises the question of whether we can fully explain the strong divergence in prices with the divergence in rents.

Table 2: *Replicating Panel A from Tables 2 and 3 in Gyourko, Mayer, and Sinai (2013)*

	log house value	log rent value	log house value	log rent value
Superstar	0.605	0.291		
	(0.0729)	(0.0377)		
Superstar x Rich			0.394	0.172
			(0.0356)	(0.0193)
N	1116	1116	1116	1116
adj. R^2	0.414	0.308	0.856	0.861

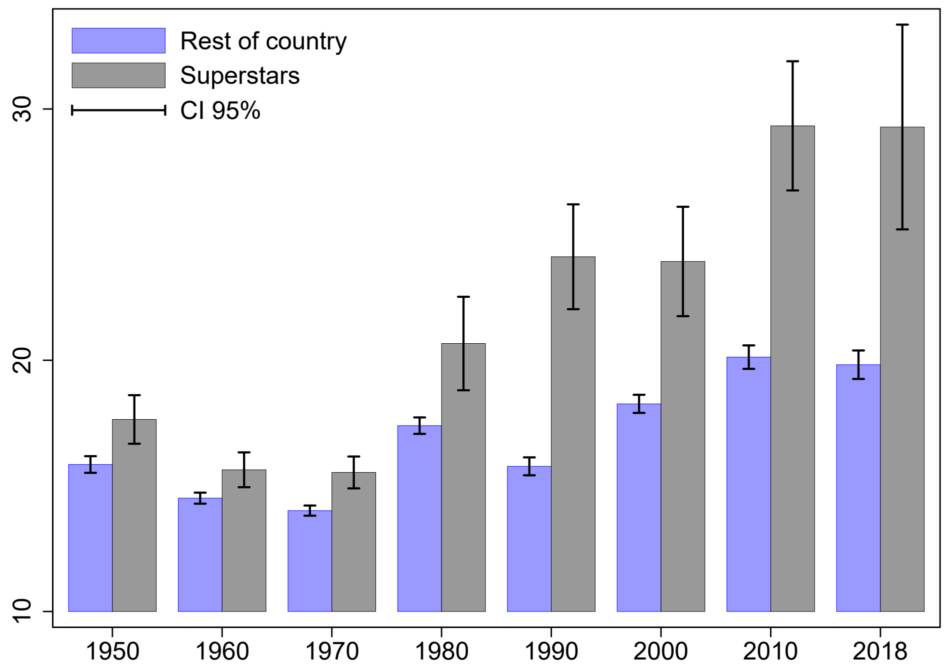
Note: This table replicates Panel A from Tables 2 and 3 in Gyourko, Mayer, and Sinai (2013). In addition to the regression on log house value, we perform the same regression on rent log value. Columns 1 and 2 present the results of a regression of the left hand-side variable on a superstar dummy and year fixed effects. Columns 3 and 4 present the OLS coefficients of a regression on an interaction effect of a superstar dummy and the log number of rich families in the U.S. and time and superstar fixed effects. Standard errors are in parentheses and are clustered at the MSA-level.

[15]Propositions 2 and 4 relate to income growth in the superstar cities.

A.2 Price-rent ratios

In this subsection, we present evidence that the divergence in price-rent ratios between superstar cities and the rest has strongly increased since the 1980s, extending the data set presented in Gyourko, Mayer, and Sinai (2013) to 2010 and 2018. We then use the definition of superstar cities to categorize the cities into superstars group and non-superstars groups, which we call the rest of the country. We estimate an equally weighted average of price–rent ratios for both groups by year. Figure 5 presents the results. The Figure shows that price–rent ratios have been increasing over time in superstar areas and in the rest of the country. However, in the superstar cities, price–rent ratios have increased much more, leading to a growing regional divergence in price–rent ratios.

Figure 5: *Price–rent ratios in the U.S., 1950-2018*



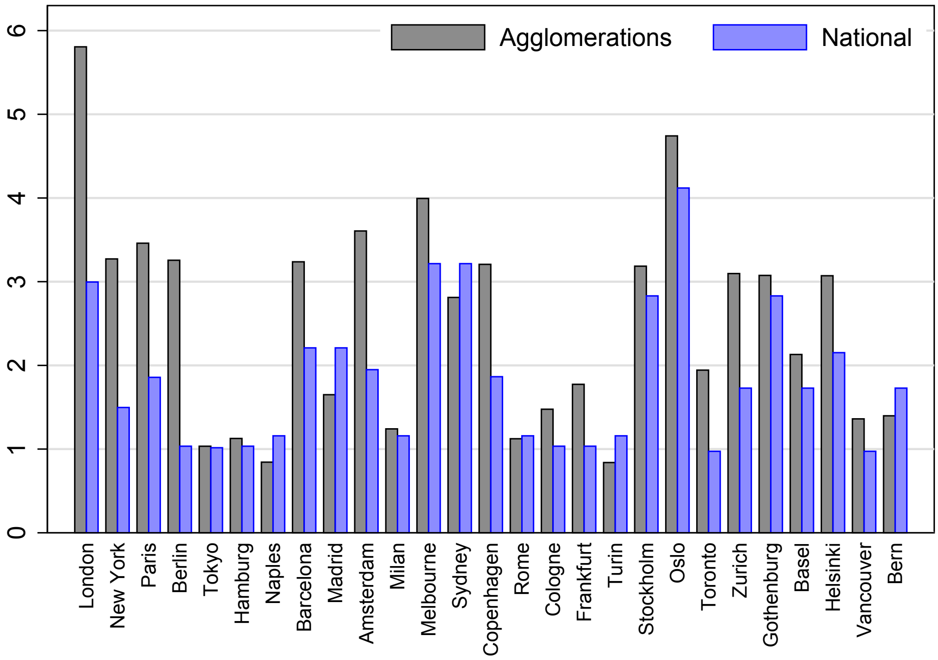
Note: We define superstar cities as cities that were at least once a superstar city between 1950 and 2000 according to the superstar definition in Gyourko, Mayer, and Sinai (2013). We extended the data from Gyourko, Mayer, and Sinai (2013) to 2010 and 2018. Each bar represents an unweighted average by year for the specific group. 95% confidence bands are shown in black.

The model developed by Gyourko, Mayer, and Sinai (2013) predicts that price–rent ratios are higher in superstar cities, but it does not account for the growing gap between superstars and non-superstars over time.

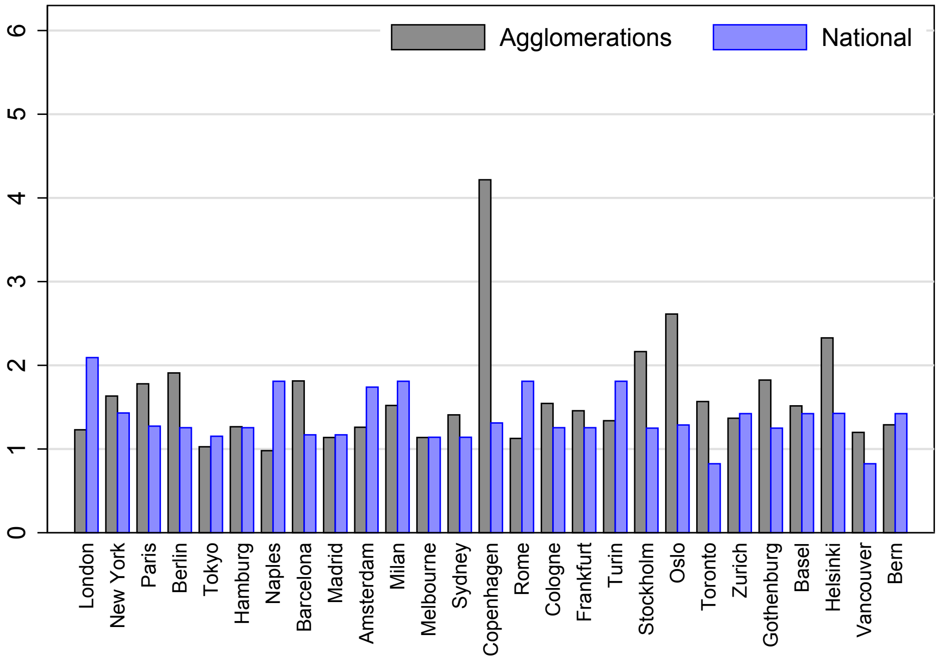
B Price and rent growth rates for 27 major agglomerations

Figure 6: *City-level growth rates for 27 major agglomerations compared to national averages*

(a) *Housing prices*



(b) *Rents*

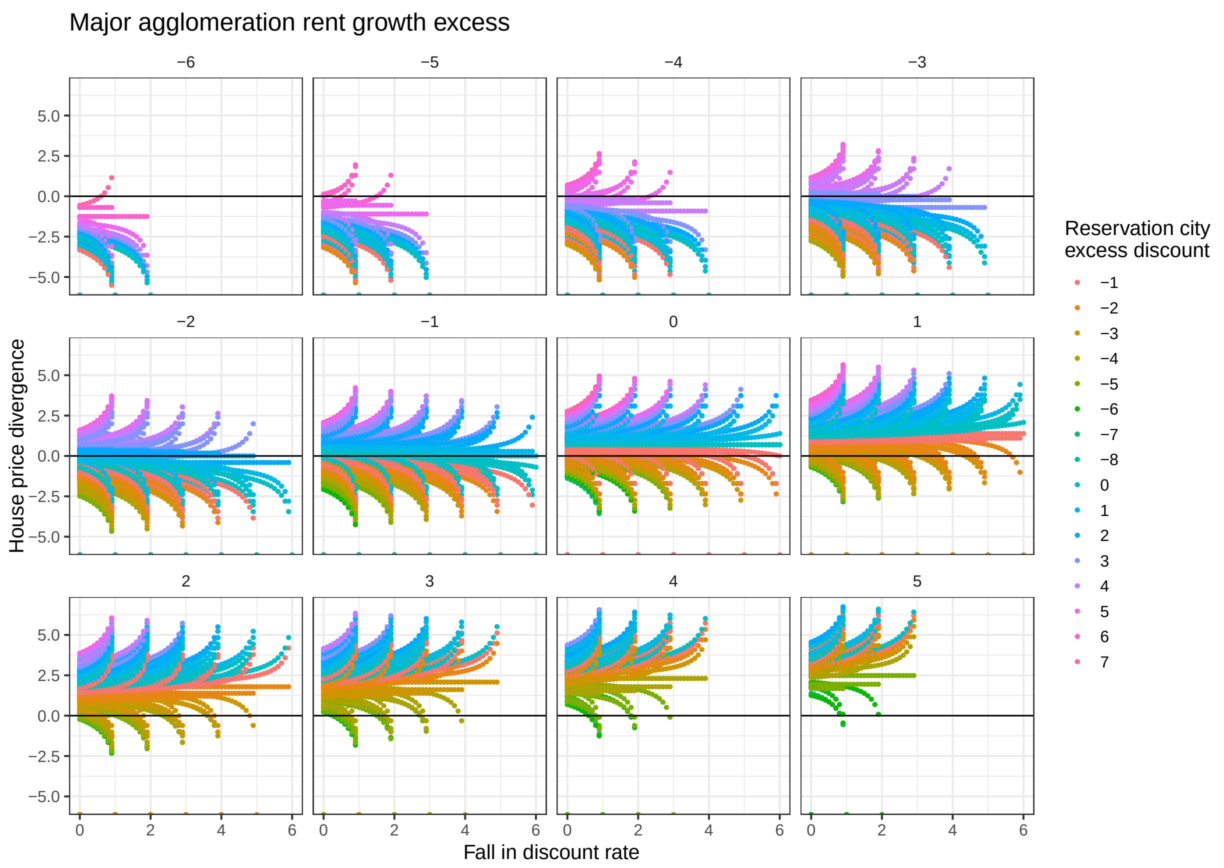


Note: Geometric mean of annual housing price (Panel (a)) and rent (Panel (b)) growth rates by city for 27 major agglomerations (black) and the respective national averages (blue).

C Model simulation of risk–free rate fall on housing price divergence

To examine the scope conditions under which a falling discount rate leads to increasing housing price divergence between the agglomeration and the reservation city, we simulate our asset-pricing model for a range of potential, and not always realistic, values. The result displays the housing price divergence (in log) as a function of falling discount rates (in %) and is broken down for all possible combinations of differences in rent and discount rate growth rates between the agglomeration and reservation city (7). The figure demonstrates that housing price divergence occurs under a majority of calibrations, as long as the agglomeration rent growth excess and the reservation city excess discount rate is sufficiently high.

Figure 7: *Simulation results by excess rent growth of agglomeration*



Note: Facets show the percentage points by which the agglomeration's rent growth exceeds that of the reservation city. Colors indicate the percentage points by which the reservation city's discount rate exceeds that of the agglomeration.

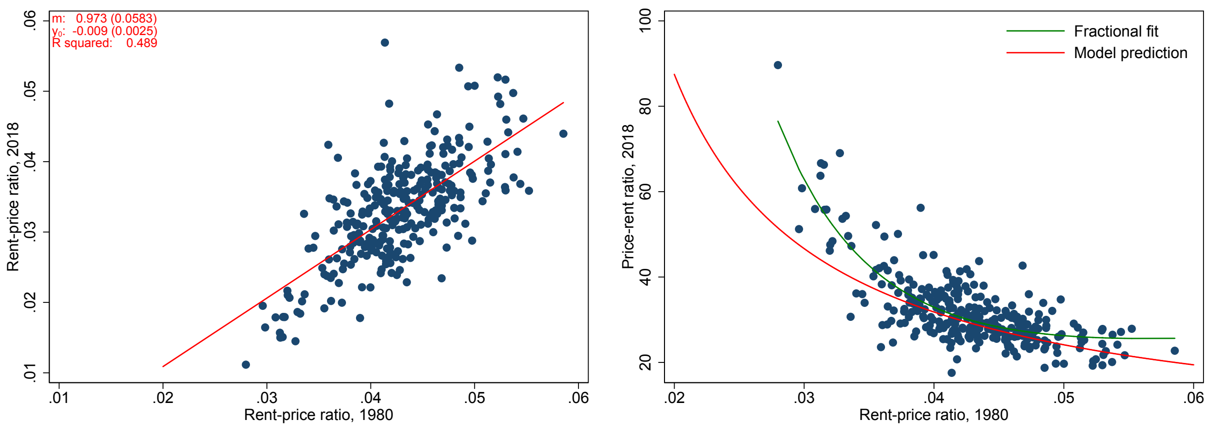
D Model evidence using U.S. MSA-level data

We also use the U.S. MSA-level data from Gyourko, Mayer, and Sinai (2013), which was extended to 2018 in Amaral et al. (2021), to test our mechanism empirically. We want to replicate Figure 3 in the main paper. Our mechanism predicts a one-to-one relation between rental yields in 1980 and in 2018, with a linear shift due to the fall in real discount rates (compare Figure 2 in the main paper). It also predicts a non-linear relation between rental yields in 1980 and price–rent ratios in 2018, with initially lower rental yield MSAs subsequently having disproportionately higher price–rent ratios (compare Figure 3 panel (b) in the main paper). As demonstrated below, these predictions hold to a great extent in the data.

Figure 8 panel (a) plots the rent–price ratios for all MSAs in 2018 relative to the rent–price ratios in 1980. It also shows a linear fit with the resulting regression coefficients. Rent–price ratios in 2018 can indeed be predicted by rent–price ratios in 1980 but have fallen uniformly by approximately 85 basis points. Of course, MSA-level rent–price ratios do not perfectly align with the regression line. This implies that rent–price ratios have also been affected by city–specific shocks. Not all variation in rent–price ratios can be explained by a fall in discount rates alone, however, the linear fit can explain approximately half of the variation in the data.

Figure 8: *Comparison model and U.S. MSA-level data*

(a) *Rent-price ratio 2018* **(b)** *Price-rent ratio 2018*



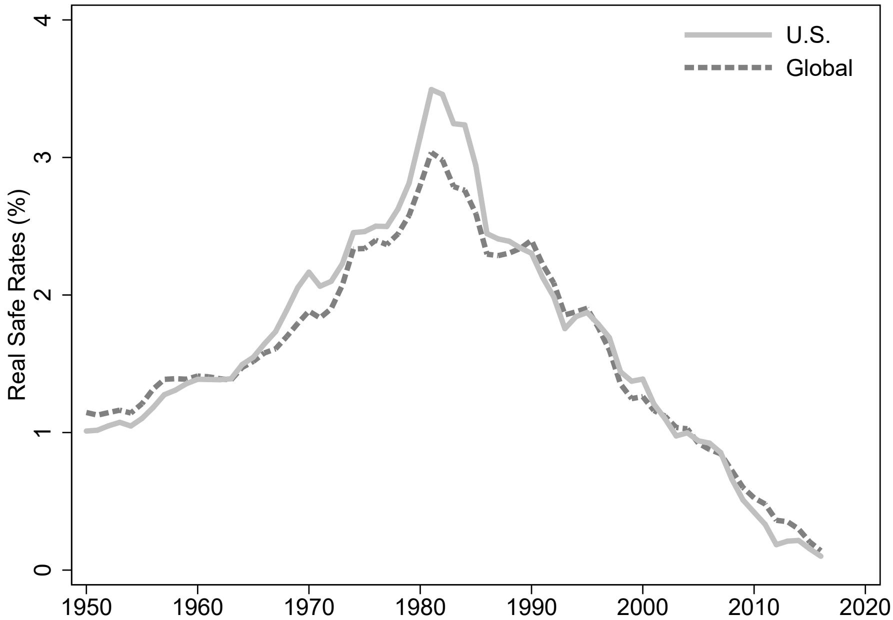
Note: Panel (a) shows the rent–price ratios in 2018 relative to the rent–price ratios in 1980 together with a linear fit and the resulting regression coefficients (standard errors in parentheses). Panel (b) shows the price–rent ratio in 2018 relative to the rent–price ratio in 1980 together with a fractional fit and the predictions of our model resulting from the linear fit in Panel (a). The data is taken from Gyourko, Mayer, and Sinai (2013) and extended by Amaral et al. (2021).

Panel (b) of Figure 8 plots price–rent ratios in 2018, also presenting a fractional fit to the data (green line). The red line depicts the price–rent ratios that the model would predict for 2018, given the rent–price ratio in 1980 and the uniform fall in rent–price ratios estimated in panel (a). Again, the model does not fit the data perfectly, however, it does agree with the overall picture of the data and predicts higher price–rent ratios for cities that already had low rent–price ratios in 1980. The fact that price–rent ratios in cities with the lowest rental yields initially are even higher than predicted by the model leaves some room for alternative explanations. One example would be increasingly more optimistic rent expectations (g) in major agglomerations relative to the rest of the country. Another would be a tightening of supply constraints in major agglomerations.

E Fall in real safe rates

Several papers have documented the long-run decline in real safe rates across OECD economies since the 1980s (Del Negro et al., 2019; Rachel and Summers, 2019; Blanchard and Katz, 1992). Using the estimates from Del Negro et al. (2019), we plot the time-series evolution of ex-ante real safe rates in the U.S. as well as averaged over 15 OECD economies in Figure 9. It is evident that real safe rates have been declining considerably both in the U.S. as well as across the world, since the 1980s.

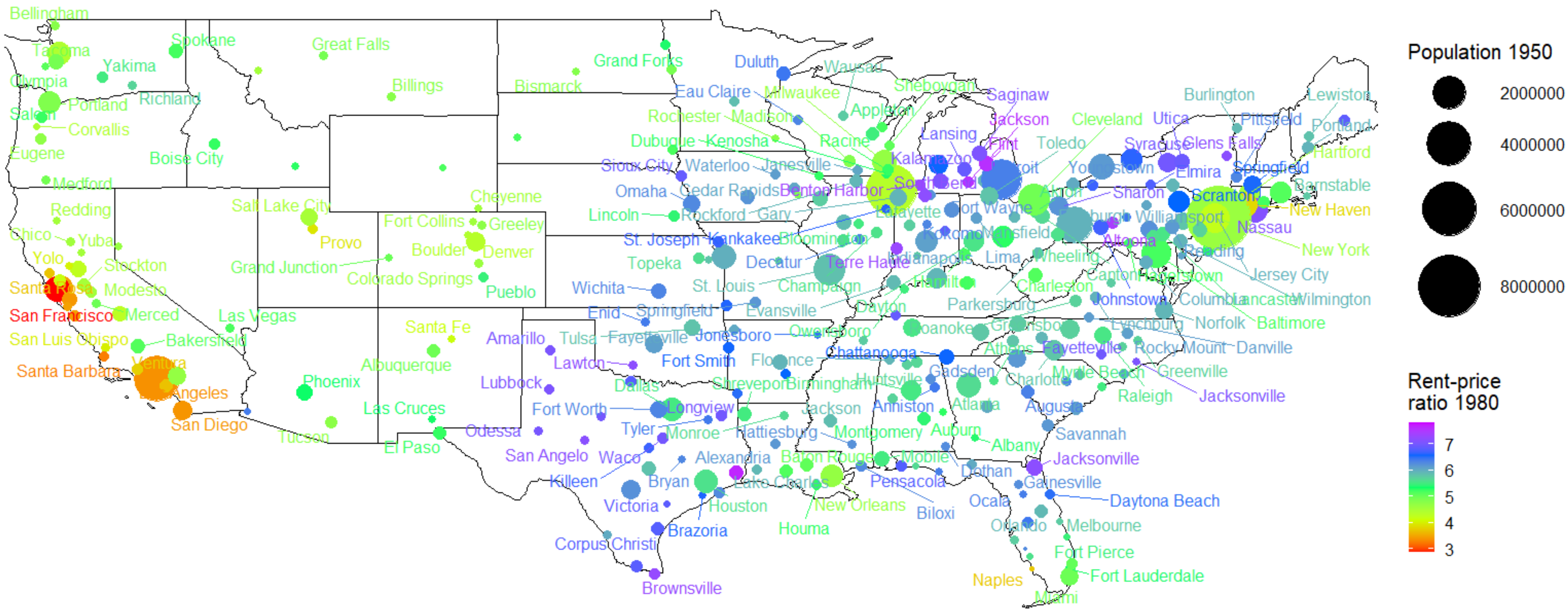
Figure 9: *Global and U.S. Real Safe Rates, 1950-2016*



Note: The Figure plots the posterior median of the trend in global and U.S. real safe rates. The estimates are taken from Del Negro et al. (2019).

Figure 10: *Rent–price ratios in the U.S. 1980*

F USA Rent-price ratios 1980



Note: Data for US MSAs are taken from Gyourko, Mayer, and Sinai (2013) extended for the period 2010 to 2018 with the American Community Survey.