Superstar Returns?

Spatial Heterogeneity in Returns to Housing *

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This paper makes the first comprehensive attempt to study within-country heterogeneity of housing returns. We introduce a new city-level data set covering 15 OECD countries over 150 years and show that national housing markets are characterized by systematic spatial variation in housing returns. Total returns in large agglomerations are close to 100 basis points lower per year than in other parts of the same country. The excess returns outside the large cities can be rationalized as a compensation for higher risk, especially higher co-variance with income growth and lower liquidity. Real estate in diversified large agglomerations is comparatively safe.

Keywords: housing markets, household portfolios, asset returns

JEL codes: E21, G11, G52, N90, R21, R31

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1 Introduction

Residential real estate is the most important asset in household portfolios, the main collateral of bank lending, and plays a central role in current macroeconomic models of aggregate fluctuations in which asset structure and household borrowing interact with business cycle fluctuations and monetary policy (Mian and Sufi, 2011; Kaplan, Moll, and Violante, 2018; Berger et al., 2018; Cloyne, Ferreira, and Surico, 2020). While housing markets were a side show for a long time, they are now at the center of a research agenda that studies the consequences of household portfolios for financial stability, the transmission of shocks, and the dynamics of the wealth distribution (Mian, Sufi, and Trebbi, 2015; Favilukis, Ludvigson, and Van Nieuwerburgh, 2017; Kuhn, Schularick, and Steins, 2020; Kaplan, Mitman, and Violante, 2020; Greenwald et al., 2021). While it is understood that portfolio heterogeneity gives rise to varying asset class exposures, we aim to show in this paper that large return differences exist *within* the same asset class of residential real estate. The source of return heterogeneity is location. Using newly assembled long-run data for 15 economies, we demonstrate that there are systematic differences in risk profiles and asset returns between housing in large agglomerations and other parts of the same country.

The "housing market" is a collection of markets that differ by many attributes (Glaeser et al., 2014; Piazzesi, Schneider, and Stroebel, 2020). Households typically do not hold geographically diversified claims on housing portfolios, but individual properties in specific locations (Levy, 2021). The local nature of housing markets suggests that studying its geographical heterogeneity is key to better understand its effects on macroeconomic fluctuations (Piazzesi and Schneider, 2016). But so far we know very little about the spatial distribution of housing market risk and return.

Due to the absence of high quality data sets research on housing markets evolved slowly (Piazzesi, 2018). For this paper, we built an extensive new city-level data set covering cities in 15 OECD countries and their hinterlands over the past 150 years. For the construction of the data set, we could partly draw on existing historical research. In most cases, however, we had to hand-collect house price and rent series from yearbooks or primary sources such as newspapers, tax records, and notary archives. We complement this data set with two granular data sets covering returns for the cross-section of cities in the U.S. and in Germany. For the U.S., we combine the data set constructed by Gyourko, Mayer, and Sinai (2013) with data from the American Community Survey for the 2010-2018 period. For Germany, we hand-collected a data set on housing returns covering 127 small and large German cities.

These new sources allow us to establish a new and robust stylised fact: Over the long-run, there exists systematic variation in total returns on residential real estate between large cities and other parts of the same country: large agglomerations have witnessed lower total returns on housing. An investment in large cities comes with a negative return premium of about 100 basis points per annum. These return differences are a robust feature of the data across countries and time periods, and statistically highly significant. An annual negative return premium of around 1 percentage point accumulates to substantial return differences in the long run.

While housing prices in large cities grew faster in many cases than in the rest of the country (Gyourko, Mayer, and Sinai, 2013), rental returns were typically consistently lower so that taking rental returns into account reverses the spatial distribution of housing returns. The negative spatial correlation between capital gains and rental returns has recently also been documented by Demers and Eisfeldt (2021), but we can show, for the first time, that the differences in rental returns are larger and more persistent than the differences in capital gains, leading to higher long-run returns. This key finding meshes with recent studies showing that more expensive neighborhoods within the same city have had lower total returns than cheaper ones over the last decade (Demers and Eisfeldt, 2021; Morawakage et al., 2022).

The second part of the paper shows that the spatial distribution of returns matches the spatial distribution of risk and liquidity in housing markets. In particular, we show that the covariance of income growth and returns, idiosyncratic price risk and liquidity risk are positively correlated with returns across space. Our core finding regarding the lower returns in large agglomerations can thus be rationalized in a parsimonious rational expectations equilibrium of the housing market: higher returns outside the cities are a compensation for higher risk. Suppose that everything that makes large cities special – the diversified economy, the large market, the amenities, the international linkages – also makes it a safer place as an investment. The present value of future housing services will be subject to less risk so that buyers are willing to pay a higher price and accept a lower return for housing investments. For remote locations to attract capital, they have to offer higher returns.

Our analysis in the second part supports this risk-based interpretation of the (negative) premium on large city real estate. On the one hand, the co-variance between housing returns and income growth is lower in large cities. Between 1950 and 2018, the co-variance between U.S. MSA-level income growth and MSA-level housing returns has been significantly larger in smaller MSAs. On the other hand, households typically do not hold diversified housing portfolios and, therefore, are also exposed to idiosyncratic risk. We show that idiosyncratic housing risk is considerably higher outside the large cities. Using U.S. transaction-level data from Corelogic, we find that the idiosyncratic component of housing risk decreases with MSA size. As liquidity is low, home owners in thinner markets face a greater risk of not realizing the local market return at the point of sale. Real estate search engine data confirm a significant increase of housing market liquidity with city size. Recent work by Giacoletti (2021), Sagi (2021) and Kotova and Zhang (2019) also points to a close relationship between idiosyncratic risk and housing market liquidity.

We perform various robustness checks to back-up our key results. We use different rental yield benchmarks, study sub-periods, the effects of rent regulations, and vary the definitions of large cities. *First*, as our core finding is driven by differences in rent returns, we rebuild our main data set using independent, country specific, current day rental yield benchmarks. The overall results remain very similar. *Second*, although we are interested in long-run returns, we want to make sure that they are not driven by specific time periods. We separate the early historical parts of the sample, and also split the sample period in 1990. The same patterns can be found in the historical period as well as during the last three decades. *Third*, we divide our data set into different rent regulation and tax regimes. It turns out that our results are not driven by periods with strict rent controls or with different taxation of capital gains or rents. *Last*, we explored different definitions of cities, and experimented with different size cut-offs in different eras. Once more, none of this altered the new stylized facts that this paper uncovers: lower long-run returns in large agglomerations.

Previous literature: Our work contributes to a number of distinct research fields. The paper builds on and extends research on asset returns in housing markets (Lustig and Van Nieuwerburgh, 2005; Piazzesi, Schneider, and Tuzel, 2007; Piazzesi, 2018). It adds a new disaggregated perspective to the research on returns on national housing portfolios (Jordà et al., 2019) and brings an international comparative perspective to individual papers on housing returns in individual regions (Eichholtz et al., 2020; Keely and Lyons, 2020; Mian, Sufi, and Trebbi, 2015).

Our paper also speaks to the urban economics literature by bringing together house price data with rental yields, housing returns and measures of local housing market risk. While the existing literature has focused on the spatial distribution of economic activity (Glaeser, 2010) and implications for house prices (Gyourko, Mayer, and Sinai, 2013; Hilber and Vermeulen, 2016; Saiz, 2010), we point to another consequence of agglomeration: Other than having higher productivity and wage levels (Ahlfeldt and Pietrostefani, 2019), less concentrated labour markets (Desmet and Rossi-Hansberg, 2013), higher elasticities of urban costs (Combes, Duranton, and Gobillon, 2019) and more diversified industry compositions (Duranton and Puga, 2000), large cities also feature less housing risk.

This paper is also part of a nascent literature on the risk-return relation in housing markets (Case, Cotter, and Gabriel, 2011; Han, 2013; Peng and Thibodeau, 2017; Sagi, 2021; Giacoletti, 2021; Demers and Eisfeldt, 2021), and complements recent work by Hilber and Mense (2021) as it points to persistent differences in price-rent ratios between cities. Our results mirror findings from the literature on stock returns (Fama and French, 1995), especially with respect to growth vs. value stocks. Large agglomerations are similar to growth stocks, which have higher capital gains but lower dividend (rental) yields. On the other hand, smaller cities are more comparable to value stocks, which are defined by having higher dividend (rental) yields, but smaller capital gains. Analogous to our case, there is evidence that value stocks have higher total returns than growth stocks (Fama and French, 1992; Jegadeesh and Titman, 1993).

We also contribute to the literature on the role of housing for portfolio choice (Flavin and Yamashita, 2002; Cocco, 2005; Chetty, Sándor, and Szeidl, 2017; Martınez-Toledano, 2020; Gomes, Haliassos, and Ramadorai, 2021) by showing that households' exposure to housing risk is determined by the location of their residential property. Finally, we speak to the rapidly growing literature on the drivers of return heterogeneity across the wealth distribution (Gabaix et al., 2016; Benhabib and Bisin, 2018; Bach, Calvet, and Sodini, 2020; Kuhn, Schularick, and Steins, 2020), by showing that location is driving large and persistent return differences within the most important asset class, real estate (Fagereng et al., 2020).

The paper is organized as follows. The following section describes our new long-run data set and provides an overview of the series constructed (see also the detailed documentation in the Data Appendix). In the third section, we describe the novel stylized facts emerging from our data set and compare city-level and national housing returns. We establish our key finding that total returns are lower in large cities. The following section introduces two granular data sets for the U.S. and Germany and studies housing returns over the entire city-size distribution in both countries. In section five, we turn to the differences in housing risk as an explanation for the return differences. We show that housing risk is lower in large cities, both in terms of co-variance risk between excess returns and local income as well as due to smaller idiosyncratic shocks in more liquid markets. The last section concludes.

2 Spatial heterogeneity in housing returns: a new long-run data set

This section introduces our new historical city-level data set. The data cover 27 cities over the long run: London, New York, Paris, Berlin, Tokyo, Hamburg, Naples, Barcelona, Madrid, Amsterdam, Milan, Melbourne, Sydney, Copenhagen, Rome, Cologne, Frankfurt, Turin, Stockholm, Oslo, Toronto, Zurich, Gothenburg, Basel, Bern, Helsinki, and Vancouver. The city-level data set contains house prices and rents as well as rental yields for every city. In the following, we briefly discuss the criteria we employed for the choice of cities and the methods used to construct the series. Details on sources for each city can be found in the Data Appendix.

2.1 City sample

We focused our data collection on the largest cities within 15 developed countries. For each country, we define the largest cities in terms of 1900 population and include cities with a population share of more than 1% in 1900. To the extent possible, we also aimed to cover at least 10% of the 1900 country population in order to analyze a relevant share of the countries' housing markets. Selecting cities based on the population in 1900, instead of using current population, circumvents the problem of survivorship bias. A detailed discussion of city choice by country is provided in the Data Appendix. Urban systems evolve over time and so do the boundaries of cities. Over time, all cities and local housing markets grow either through incorporation of more and more suburbs or through the creation of metropolitan regions. We follow the administrative definitions in our sources which makes our city definition consistent *within* country. City definitions are mostly identical for the rental and ownership markets.

The sample is summarized in Table 1. Data coverage of price and rent data is shown in columns 5 and 6. The sample starts in 1870, but some gaps remain. We have 7 decades of data for all cities and a balanced panel for the post-1950 period. Column 3 shows the cities' share of the country population in 1900 and column 4 the aggregated share of country population in 1900 that is covered by our sample cities.

2.2 Sources and methodology

This section briefly describes the sources of the data and the construction of the total return series. For all cities in our sample, we construct annual house price indices, rent indices and calculate total housing return series.

2.2.1 House price and rent indices

Whenever possible and of sufficient quality, we use house price and rent indices from existing research. An example is the return series for Amsterdam described in Eichholtz et al. (2020). In most cases, however, house price and rent indices are not readily available or the quality is insufficient. To construct the series, we first used data from a broad range of secondary sources such as city yearbooks, but in many cases we had to hand-collect new data from diverse primary sources. These consisted of newspapers, tax records, notaries, archives of real estate agents, and diverse other archival data. About half of the series are newly constructed.

The criteria to select appropriate sources mainly depended on data representativeness and availability. Whenever we had multiple choices, we used the source which provided the best

Table 1: *City choice and data coverage*

City	Pop1900	Share pop	Country	House prices	Rents
London	6480	0.157	0.157	1895–2018	1870–2018
New York	4242	0.056	0.056	1920–2018	1914–2018
Paris	3330	0.082	0.082	1870–2018	1870–2018
Berlin	2707	0.048	0.078	1870–2018	1870–2018
Tokyo	1497	0.034	0.034	1950–2018	1950–2018
Hamburg	895	0.016	0.078	1870–2018	1870–2018
Naples	563	0.017	0.054	1950–2018	1950–2018
Barcelona	552	0.030	0.059	1950–2018	1947–2018
Madrid	539	0.029	0.059	1950–2018	1947–2018
Amsterdam	510	0.099	0.099	1870–2018	1870–2018
Milan	491	0.015	0.054	1950–2018	1950–2018
Melbourne	485	0.130	0.257	1880–2018	1901–2018
Sydney	478	0.128	0.257	1880–2018	1901–2018
Copenhagen	462	0.180	0.180	1938–2018	1885–2018
Rome	438	0.013	0.054	1950–2018	1950–2018
Cologne*	437	0.008	0.078	1902–2018	1890–2018
Frankfurt*	350	0.006	0.078	1897–2018	1895–2018
Turin	330	0.010	0.054	1950–2018	1950–2018
Stockholm	300	0.059	0.084	1875–2018	1894–2018
Oslo	227	0.102	0.102	1870–2018	1892–2018
Toronto	205	0.038	0.050	1900–2018	1921–2018
Zurich	150	0.045	0.098	1905–2018	1890–2018
Gothenburg	130	0.025	0.084	1875–2018	1914–2018
Basel	109	0.033	0.098	1912–2018	1889–2018
Helsinki	97	0.037	0.037	1946–2018	1946–2018
Vancouver*	69	0.013	0.050	1950–2018	1950–2018
Bern	64	0.019	0.098	1912–2018	1890–2018

Note: Column 2 shows city-level population in 1900 in 1000 inhabitants. Column 3 describes the share of each city's population of total country population in 1900. Column 4 states the cumulative share from all cities in a respective country in our data set. Columns 5 and 6 describe data coverage from earliest to latest year of price and rent indices. For some cities there are gaps in the data coverage because of missing data, e.g. during periods of war and hyperinflation. City-level population data is taken from Reba, Reitsma, and Seto (2016) and country-level population from Jordà, Schularick, and Taylor (2017). For Cologne and Frankfurt, city-level population was below 1% of country population in 1900. However, the German Empire in 1900 had a considerably different area compared to Germany today. In 1950, the population in both Frankfurt and Cologne was above 1% of Germany's total population. The estimate for Vancouver is taken as the sum of Burrard and Vancouver city from the Canadian population census from 1901. Burrard became officially part of Vancouver in 1904.

coverage and the most details. The case of London provides an illustration where we could partly rely on data from previous research but had to close a large gap after World War II. The existing house price series cover the years before 1946 and after 1969. To connect the series, we hand-collected asking prices from real estate advertisement sections in newspapers. We focused on sales ads that provided enough information to build quality-adjusted indices.

Whenever micro-data was available, we relied on repeat-sales or hedonic regression methods. For instance, for Frankfurt we built a hedonic house price index from 1960-2018 using transaction level data from public sources and their archives. Whenever micro-level data was not available, we used data disaggregated by housing types and location inside a city to construct stratification indices.

Regarding the construction of rent indices, we primarily rely on rent indices from statistical agencies. Examples are rent indices that were constructed by city statistical offices for (city-level) CPI data. These mainly use repeated rents methodology. In other cases, when we were able to collect micro-level data, we relied on hedonic methods. For example, for the city of Oslo, we constructed a hedonic rent index for the period between 1950 and 1970 from newspaper rental advertisements. In other cases, we constructed stratification indices whenever possible, mainly relying on statistical publications. For example, in the case of Stockholm we used average rent by size of dwelling to construct a chained stratification rent index. We benchmark our rent indices with rents surveyed in housing censuses. Historically, such censuses were taken roughly every ten years and typically covered all rental units, providing a precise picture of the universal level of rents in a specific city.

All price and rent indices are deflated using country-level CPI data from Jordà, Schularick, and Taylor (2017). For details on source and index construction by city please refer to the Data Appendix. The resulting series cover a representative city-level housing portfolio that approximates the behavior of the value weighted housing market within a city.[1]

2.2.2 Housing return series

We use house price and rent indices to construct housing returns series. As is well known, a house delivers two types of returns. First, the price of a house can change and this generates a capital gain (or loss). Secondly, a house delivers a consumption stream in form of housing

[1] In Appendix A we compare hedonic house price indices for different market segments for Cologne. We show that over a period of 30 years, trends for all residential market segments have been similar.

services. These can be sold to receive a cash flow by renting out the house. Alternatively, they can be consumed; in this case the owner receives the replication value as a cash-flow. Total returns on housing can be computed as:

$$\text{Total return}_t = \underbrace{\frac{P_t - P_{t-1}}{P_{t-1}}}_{\textbf{Capital gain}} + \underbrace{\frac{R_t(1-c)}{P_{t-1}}}_{\textbf{Net rent return}}, \tag{1}$$

where P_t is the house price at time t, R_t is the gross rent payment at time t and c are the total net operating costs as a share of R_t, which we describe in more detail below. Following this equation, the construction of city-wide (real) capital gains is straightforward using our house price indices. To construct rent return series, we estimated rent-price ratios, which we adjusted to nominal house price growth in the following manner: $Rent\ return = \frac{R_t}{P_t} * \frac{HPI_t^{nom}}{HPI_{t-1}^{nom}}$.

Rent-price ratio estimates are constructed following the rent-price approach used in Jordà et al. (2019) and Brounen et al. (2013). To do so, we first use benchmark rent-price ratios for the end of our sample period in 2018. We again follow Jordà et al. (2019) and use benchmarks calculated from realized net operating income yields of real estate investors. These were provided by *MSCI* that collect data from a variety of real estate investors for large cities around the world. Yields are defined net of total operating costs, which are composed of maintenance and property taxes as well as other costs. Other costs included are management costs as well as cost of vacancies, letting and rent review fees, ground rents and bad debt write-offs. Finally, we use our rent and price indices to calculate rent-price ratios over time:

$$\frac{RI_{t+1}}{HPI_{t+1}} = \left(\frac{RI_{t+1}/RI_t}{HPI_{t+1}/HPI_t}\right)\frac{RI_t}{HPI_t}. \tag{2}$$

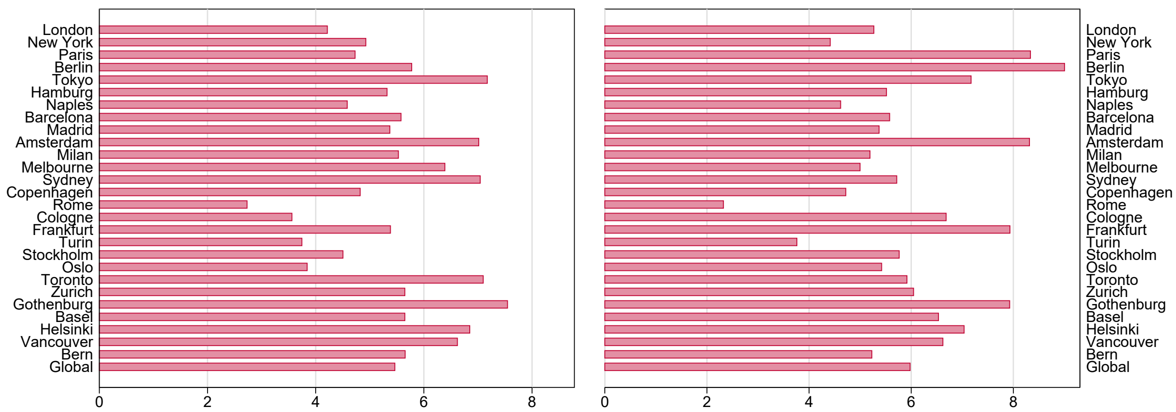
The disadvantage of this methodology is that possible measurement errors accumulate over time due to extrapolation. To account for this, we collected historical rental yield benchmarks to verify our rental yield series. We predominantly relied on secondary sources or newspapers. For all sources, we aimed at collecting rental yield estimates out of rent and price data for the same buildings. All benchmark rent-price ratios are constructed net of depreciation and running costs. If direct estimates for these costs were not available, we instead relied on estimates for depreciation and running costs in percentage of gross rent inside the country in question from Jordà et al. (2019). Whenever the rent-price approach estimates diverge from these historical sources, we adjust the estimates to the historical measures as detailed in the Data Appendix. Another potential bias in our return series could arise from the ratio of net to gross income. Evidence in section III.C of Jordà et al. (2019) and in Figure 3 of Demers and Eisfeldt (2021) shows that the ratio of net to gross stayed relatively constant over time and that there are very small differences across regions over the last 30 years. Additionally, we also do not find systematic differences in the ratio of net to gross income across 22 different U.S. cities both for 2007 and 2020 using MSCI data. The Figure can be found in the Data Appendix.[2]

3 Returns in large cities

In this section, we first establish the main stylized facts on long-run housing returns in large cities. We then proceed to analyze trends in capital gains and rent returns, as well as their contributions to total returns, and compare large cities to the rest of the country.

Figure 1: *City-level real average total housing returns (log points)*

(a) *Full Sample* **(b)** *Post-1950*



Note: The figure shows average real total housing returns in log points for all cities in our main sample. The series have been deflated using the national CPI series from Jordà, Schularick, and Taylor (2017). Panel (a) covers the entire sample for return data in our main data set, which is the subset of years for which rent and house price data (minus 1 year) exist, compare Table 1. Panel (b) shows average housing return data by city starting in 1950.

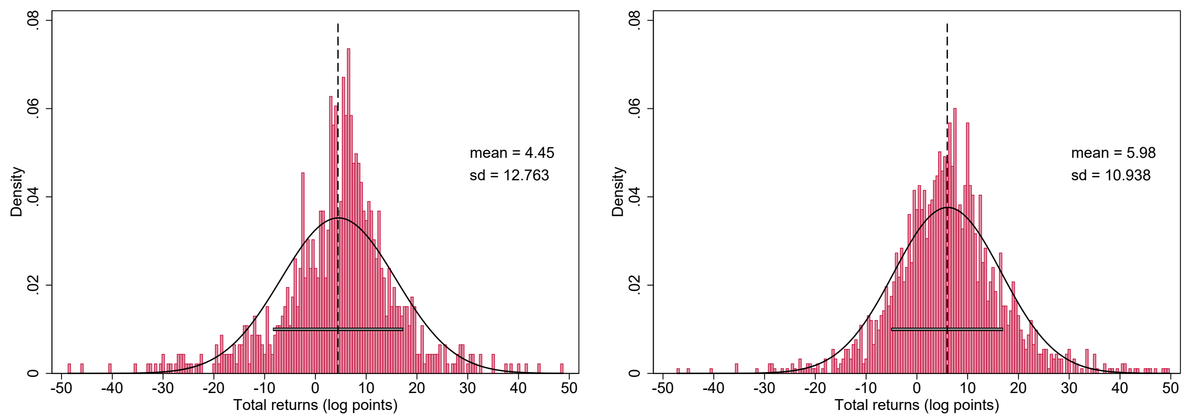
We start with summary statistics on real log housing returns and its components for our new

[2]Throughout the paper we follow the existing literature and measure housing returns in log points instead of percentage points. The main reason is that log returns are time compoundable, whereas percentage returns are not. Moreover, log returns have preferable distributional features and are approximately equal to percentage returns for small numbers. For a full rationalization please refer to the Data Appendix.

data set. The left-hand panel of Figure 1 shows average log housing returns for the full time period and the right-hand panel for the period post 1950.[3] City-level total housing returns have been in the four to six log point range per year, with some differences across the cities in our sample. Toronto, Amsterdam, Gothenburg, Tokyo and Sydney are the cities with the highest long-run returns. The panel on the right shows that housing returns have been higher in the post 1950 period and reached about 6 log points.

Figure 2: *Distribution of annual real housing returns (log points)*

(a) *Pre-1950* **(b)** *Post-1950*



Note: The figure shows the distribution of annual total housing returns in log points for all cities in our main sample. The series have been deflated using the national CPI series from Jordà, Schularick, and Taylor (2017). Panel (a) covers the entire sample of cities until 1950, compare 1. Panel (b) covers the entire sample of cities after 1950.

Figure 2 plots the distribution of annual log real housing returns for the pre- and post-1950 period. While housing returns were on average lower in the pre-1950 period, they also displayed a higher standard deviation than in the post-1950 period, apparent in a thicker left-tail in the pre-1950 period. This does not come as a surprise, considering that this period featured two World Wars, the Great Depression and large variations in housing policies. Post-1950 large city returns were close to 2 percentage points higher with a lower standard deviation.

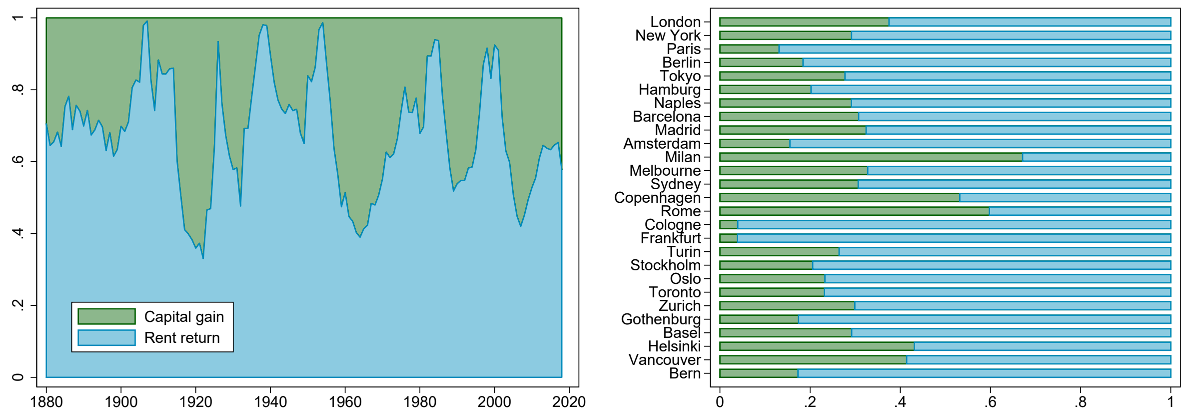
Rent returns represent approximately 67% of total housing returns over the last 150 years.

[3] A table with summary statistics by city in log points, including standard deviations, can be found in the Data Appendix. Additionally, we also included a table with average percentage point (simple) returns for comparison to other literature.

Panel (a) of Figure 3 shows that, although the relative share of rent returns has been quite volatile over time, it has remained by and large the main contributor to total housing returns. In fact, for all cities in our sample, with the exception of Milan, rent returns represent more than 50% of total housing returns in the long-run. This result is in line with the findings in Jordà et al. (2019) and Demers and Eisfeldt (2021).

Figure 3: *Share of log total returns, 1870-2018*

(a) *Full sample* **(b)** *By city*



Note: Panel (a): The displayed series are 10-year lagged moving averages, e.g. the share of capital gains for the year 2010 is the average share of capital gains between 2000 and 2010. All cities get an equal weight. This panel shows the share of log capital gains and log rent returns in the sum of both. In the few cases when moving average log capital gains have been negative, we take the absolute value of the moving average log capital gains instead. Panel (b): Average share of log real capital gains and log rent returns by city for the whole period for which we have data for the city.

3.1 Large agglomerations vs. national housing markets

In the next step, we merge our city-level data set with national housing returns from Jordà et al. (2019) in order to compare returns in the large cities to those in the rest of the country. Jordà et al. (2019) compiled data on capital gains, rent returns and total housing returns for nationally diversified housing portfolios that represent the weighted sum of housing markets within a specific country. We extended their data to 2018 using country-level house price and rent indices from national statistical agencies and substituted house price series for Japan after 2008 and for Sweden after 1952, because series with better methodology and coverage became available. For details see the Data Appendix.

The national housing portfolios include the large cities in our sample. For transparency and comparability reasons, we will still compare the large city returns to the national series from that study. But we also calculate returns of a "rest of the country" portfolio as the weighted average of the housing returns in the other locations in the country. National returns can be expressed as:

$$National\ return_t \ = \ w_{t-1} * Large\ city\ return_t \ + \ (1 - w_{t-1}) * RoC\ return_t, \qquad (3)$$

where w is the relative weight of the large city in the respective national housing series. Using equation 3 and our large cities return series, we can approximate the housing returns in the rest of the country (*RoC return*) by subtracting the large cities in our data set from the national series. As data on market capitalization are lacking, we use population shares as portfolio weights to construct return series for the rest of the country (excluding the large cities). All city-level and national population data for this calculation are taken from United Nations (2018). Due to higher housing prices in large cities, using population weighting will give a smaller weight to the large cities than a market capitalization weighted index. As such, the rest of the country returns that we back-out from national series likely mark a lower bound.

In some cases, the geographical coverage of the national housing series is too narrow in the pre-World War II era to allow a meaningful comparison between the large cities and the rest of the country. In the Data Appendix we included a table, which details the geographical coverage of the national house price series by country. For the comparison between large city returns and the rest of the country, we will therefore focus on the 70-year period between 1950-2018 for which the national housing series have a wide enough geographical coverage. This being said, the overall results are very similar when we study returns over the entire sample period (see Appendix B.2).

To guide the reader through the results, we start with Paris as an example. Our data show that an investor who bought an apartment in Paris in 1950 realized an average yearly capital gain of 4.85 log points over the period until 2018. The annual rent return in Paris was 3.66 log points on average, resulting in a healthy total annual return of 8.33 log points. This means, for instance, that investments in Parisian residential real estate beat investments in the French equity market by a substantial margin, even on an unleveraged basis.

How does this investment return compare to the rest of France? An investment in the French national housing portfolio over the same 70-year period saw annual capital appreciation of 4.48 log points, somewhat lower than Paris. As Paris is a substantial part of the French national portfolio, the difference must be driven by other regions in France, in which house prices have risen about half a percentage point less per year than in Paris. However, the picture changes when we bring in rent returns, which were substantially higher in the rest of the country (5.06 vs. 3.66) and more than offset Paris' advantage with respect to capital gains. Total housing returns were 9.15 per annum for the rest of France and thus about 85 basis points per year higher than in Paris. Despite higher capital appreciation, Paris underperformed the rest of France with respect to total returns on housing investment.

Figure 4: *Average differences in city-level and national returns (log points), 1950-2018*

Note: This graph shows the mean difference in log capital gains (Panel (a)), log rent returns (Panel (b)) and log total returns (Panel (c)) between the city-level and the respective national portfolio by city. The period covered is 1950 to 2018, except for German cities, Tokyo and Toronto, because the national data only starts in 1963, 1960 and 1957 respectively.

In Figure 4, we broaden the perspective to all 27 large cities in the sample and compare them to their national real estate markets. Figure 4 shows differences in capital gains (left), rent returns (middle) and total housing returns (right) between 1950 and 2018 for each city relative to the national returns.[4] A general pattern can be easily discerned. Just like in the French case,

[4] Appendix Table 9 presents the numbers including standard errors of paired t-tests.

capital gains are higher in nearly all large cities. The only major exception is Tokyo – a city that experienced a severe real estate crisis in the early 1990s. Real house prices in Tokyo were still only one third of their 1990 level in 2018, while house prices in other parts of the country stand at 65% of the 1990 level. Rent returns are generally much lower in the big agglomerations, and overall returns are lower.[5]

Table 2: *City-level and national yearly housing returns (log points), 1950-2018*

	27 large cities				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.25	1.82	0.43* (0.23)	1.64	0.61** (0.26)
Rent return	3.55	4.94	-1.39*** (0.04)	5.21	-1.65*** (0.05)
Total return	5.72	6.68	-0.95*** (0.23)	6.76	-1.04*** (0.26)
N	1767				
	Only largest city/country				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.45	2.12	0.33 (0.30)	1.99	0.46 (0.34)
Rent return	3.53	5.17	-1.63*** (0.06)	5.41	-1.88*** (0.07)
Total return	5.89	7.18	-1.29*** (0.30)	7.30	-1.41*** (0.34)
N	1061				

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. Rest of country (RoC) returns are calculated as national housing portfolio returns share after taking out the returns of the 27 national large cities. We use previous year population shares as weights of the portfolio share of our cities, such that the estimate should be interpreted a lower bound. The upper panel shows the results averaged over all 27 cities in our main data set. The lower panel shows the results only for the cities, which had the largest population in their respective countries in 1950 in our data. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

[5]The main exception is (West) Berlin. As data for East Berlin is missing between 1945 and 1990, the Berlin portfolio covers only West Berlin after World War II. The higher housing return in West Berlin might, however, not be surprising when considering the unique history of the city. Prior to the fall of the Berlin Wall and the reunification of Germany in 1990, Berlin was not only heavily supply constrained, but also potentially a very risky place to invest in taking the political tensions between the Soviet Union and the West into account. Additionally, the reunification of Germany itself could be regarded as a very large positive shock to (West) Berlin potentially keeping housing returns off equilibrium for several years. The other outliers are much smaller and typically featured exceptionally high capital gains compared to the respective national index. These, in turn, might be driven by large positive shocks to the city development. The main example is Basel, which had a rapidly growing economy since World War II and now is the region with the highest GDP per capita in Switzerland. Within Switzerland, the Canton Basel-Stadt (Nuts-2 region) had by far the largest GDP per capita in 2018, which was nearly twice as high as that of the Canton Zurich, (source: Federal Statistical Office Switzerland, Table je-e-04.02.06.03, published 21.01.2021).

Table 2 formalizes the analysis of different large city/national housing portfolio definitions, together with paired t-tests for the equality of means between city and national housing portfolios: the table shows capital gains, rent returns and total returns at the large city-level (Column 1) and for the national housing portfolios as defined in Jordà et al. (2019) (Column 2). Column (4) shows the population-weighted return for the rest of country (excluding the large cities), as defined above. The lower panel narrows the large city definition to the single largest city in each country (New York, London, Paris, etc.), providing an even stronger large city vs. rest of country comparison.[6]

At 2.25 log points capital gains have been about 43 basis points higher in the 27 large cities than in the national portfolio, and 61 basis points higher than in the rest of the country. Rent returns, in contrast, have been lower in the large cities with a difference of 1.39 or 1.65 log points, depending on the comparison portfolio. The higher rent returns outside the large cities more than compensate for the lower rate of capital appreciation. Our overall benchmark estimate is that in the long-run total returns in the large cities were 95-100 basis points lower per year than in the national portfolio and rest of the country.

The lower panel of Table 2 focuses only on the largest city within each country (measured by 1950 population). For this sample, the average difference between the city-level and the rest of the country grows to 1.41 log points per year. The average total return of the national housing portfolio is around 7% per annum so that large city returns are about 15% lower.

While Demers and Eisfeldt (2021) also show that cities with higher capital gains have lower rental returns, they do not show that the spatial difference in rental returns are larger than the ones in capital gains. Finally, our results are also in line with the existing evidence that more expensive neighborhoods have had lower total housing returns than cheaper neighborhoods in the last decade (Demers and Eisfeldt, 2021; Morawakage et al., 2022).

3.2 Further tests

Capital gains are higher in large cities, but they are more than offset by lower rent returns, resulting in lower overall returns. In the following, we will subject this core finding to a number

[6] We use the largest city per country within our data set. This implies that Toronto is included although Montreal was the largest city in 1950, because housing data for Montreal is missing.

of additional tests. First, we use alternative rental yield benchmarks. Secondly, we show that our results hold in the historical period as well as in more recent decades. Finally, we study the potential role of rent regulations. Moreover, a discussion of the effect of taxation can be found in Appendix C where we show that differences in real estate taxation do not affect our results.

Alternative rental yield benchmarks: The data used to calculate rent returns is assembled by professional real estate investors. They are based on rental yield benchmarks net of maintenance, management and other costs. As our core finding rests on the differences in rent returns between large cities and the rest of the economy, we recalculate returns with alternative rental yield benchmarks taken from country-specific sources or from the user driven online database Numbeo.com. The alternative estimates potentially provide a broader coverage of the housing market but might be less precise.

Table 3: *City-level and national yearly housing returns (log points), 1950-2018*

	Alternative Benchmarks					
	27 large cities			Only largest city/country		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.25	1.82	0.43* (0.23)	2.57	2.13	0.45 (0.29)
Rent return	3.32	4.94	-1.62*** (0.04)	3.42	5.20	-1.78*** (0.06)
Total return	5.50	6.68	-1.18*** (0.23)	5.90	7.22	-1.32*** (0.29)
N	1767			1004		
	Standard Benchmarks					
	Until 1990			Post 1990		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.67	2.21	0.46 (0.37)	1.69	1.31	0.38* (0.22)
Rent return	3.73	5.37	-1.63*** (0.07)	3.31	4.36	-1.06*** (0.04)
Total return	6.31	7.47	-1.16*** (0.37)	4.94	5.62	-0.68*** (0.22)
N	1011			756		

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The upper panel shows the results averaged using alternative rental yield benchmarks from country specific sources. The left-hand side shows the results averaged over all cities in our main data set. The right-hand side shows the results for the cities, which had the largest population in their respective countries in 1950. The lower panel shows the results using the standard benchmarks from MSCI for the years from 1950 to 1990 and from 1991 to 2018. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

The upper panel of Table 3 shows the results with alternative rent return data. If anything, the alternative data accentuate the differences in rent returns and suggests that the differences between market segments within cities do not play a major role. In the Data Appendix we show the summary statistics of our main data set and individual city returns with the alternative rental yield benchmarks. The differences are minor.

Subperiods: Driven by limited data availability, most of the recent literature on housing returns focused on developments in the last two or three decades. A natural question to ask is whether our results also hold for the most recent period that saw a particularly pronounced increase in real estate prices (Knoll, Schularick, and Steger, 2017) as well as the emergence of global superstar cities.

For a first test, we split our sample period in 1990. The lower panel of Table 3 shows the results for the 27 large cities relative to the national index. Our key results also hold for the most recent period: large city returns have also been significantly lower in the post 1990 era. The same is true for the largest city in each country. Additionally, Appendix Table B.3 presents moving averages over the entire time period.

Rent regulations: Could stricter rent regulations in large cities account for the lower rent returns compared to the rest of the country? To start with, from an asset pricing perspective, rent regulations should not by themselves have an effect on housing returns since they only regulate the cash-flow received from the asset. As the price of an asset is determined by the discounted value of future expected cash-flows, we would expect house prices to adapt to different cash-flows, such that rent-price ratios will be unaffected. Rent controls could, however, influence expectations about future rents, which could affect house prices and current returns.

As an empirical test for the effects of rent controls on returns, we use the rent control index from the *Rental Market Index (ReMaIn) Database*. The database compiled by Kholodilin (2020) uses rent legislation since 1914 in 64 countries to create standardized indices measuring the existence and intensity of rent control, tenant protection and housing rationing. The results in Table 12 in Appendix B.4 confirm that, independently of rent control regimes, capital gains are higher and rent returns lower in the large cities compared to the national average. The absolute difference between large cities and the national returns is even slightly higher in stricter rent control regimes.

4 Housing returns over the city-size distribution

In this section, we study housing returns across the entire cross-section of cities within two countries, the U.S. and Germany. The choice of these countries allows us to analyze two national real estate markets that belong to two different "housing regimes" (Kohl, 2017): U.S. cities are dominated by owner-occupied, single-family dwellings with light rent regulation but comparatively strong home ownership subsidies. The German housing market is characterized by tenant-occupied, multi-storied buildings and a soft rent-control regime without much home ownership support (Kholodilin and Kohl, 2021). In typologies of housing regimes (Schwartz and Seabrooke, 2008), these two countries often end up on opposite sides and are seen as representative for different approaches in housing policy (Kemeny, 1995).

We use two different data sets that cover the complete size distribution of cities. The approach and the methodology are the same within data sets. The central question is whether the findings from the long-run comparison of large cities with other parts of the country apply more broadly across the entire city-size distribution.

4.1 U.S. superstars redux

For the US, we rely on the data set compiled by Gyourko, Mayer, and Sinai (2013), to which we add two additional observations for 2010 and 2018 from the *American Community Survey* (ACS).[7] Their original data cover the near-universe of MSAs from 1950 to 2000 at decadal frequency from the *Census on Housing and Population*. Gyourko, Mayer, and Sinai (2013) find large differences in house price appreciation across metropolitan areas over a period of 50 years.

Due to the decadal frequency of the data, we calculate total housing returns as averages of capital gains and rental yields over 10-year periods. Moreover, we use rental yields instead of

[7]To make the data comparable, we build MSA level aggregates using the official borders from 1990, as done by Gyourko, Mayer, and Sinai (2013). All our results stay virtually the same when we restrict our analysis to the original data set covering only the years until 2000 and, if anything, become stronger if we restrict the sample to only MSAs with a full county coverage in 2010 and 2018. Results are available on request. All the data is on MSA-level, but to simplify we still refer to them as "cities" here. For details about data construction please refer to the Data Appendix and Gyourko, Mayer, and Sinai (2013).

rent returns, because the decadal data does not allow us to precisely calculate rent returns. Rental yields are the inverse of the price-rent ratios calculated by Gyourko, Mayer, and Sinai (2013) and adjusted downwards for maintenance costs and depreciation. We assume that one third of gross rents is spent on these costs across all locations.

We define the largest cities as being the largest five percent of sampled MSAs in terms of 1950 population. Choosing the largest 5% as the cutoff allows us to focus on exceptionally large and economically important cities. The size of these cities will be far from the mass point of cities, as the city size distribution is approximately a Pareto distribution.[8] In the following, we compare these top-5% of cities to all other MSAs in the data set and, secondly, to the smallest 5% of MSAs. But our overall results do not depend on these cutoffs.

Table 4: *Difference in housing returns (log points) for 316 US MSAs, 1950-2018*

Sample	Capital gain	Rental yield	Total return	N
Large vs rest	0.13 (0.21)	-0.67*** (0.16)	-0.52*** (0.15)	2184
Large vs small	-0.20 (0.25)	-0.63*** (0.20)	-0.80*** (0.20)	217
GMS superst. vs rest	0.53*** (0.13)	-0.68*** (0.11)	-0.17* (0.10)	1936
GMS superst. vs small	0.44** (0.19)	-0.55*** (0.18)	-0.13 (0.18)	347

Note: The table shows differences in housing returns between large cities and the rest of the sample or small cities. It covers 316 MSAs on decadal frequency between 1950 and 2010 and additionally the year 2018. Differences are measured as coefficients in a random effects panel regression of the dependent variable (log capital gain, log rental yield and log total housing return respectively) on a large city dummy and year fixed effects. Standard errors (in parenthesis) are clustered at the MSA-level. Large cities are defined as being at or above the 95th percentile of the MSA population distribution in 1950 from census data. The second row shows the same, but comparing large cities only to small cities, which are defined as being at or below the 5th percentile of the MSA population distribution in 1950. The third row compares the superstar cities defined in Gyourko, Mayer, and Sinai (2013) to the other MSAs. In this comparison, we reduced the sample to the 279 MSAs included in the original analysis of the aforementioned authors. Note that we use rental yields instead of rent returns, because using decadal data rent returns cannot accurately be calculated. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$

Table 4 presents by now familiar patterns. Rental yields are considerably lower in large cities compared to all other cities or to small cities. The absolute difference in total returns is estimated between 50 and 80 basis points per year and hence somewhat smaller than in the international sample. This can be expected as we include more large cities.

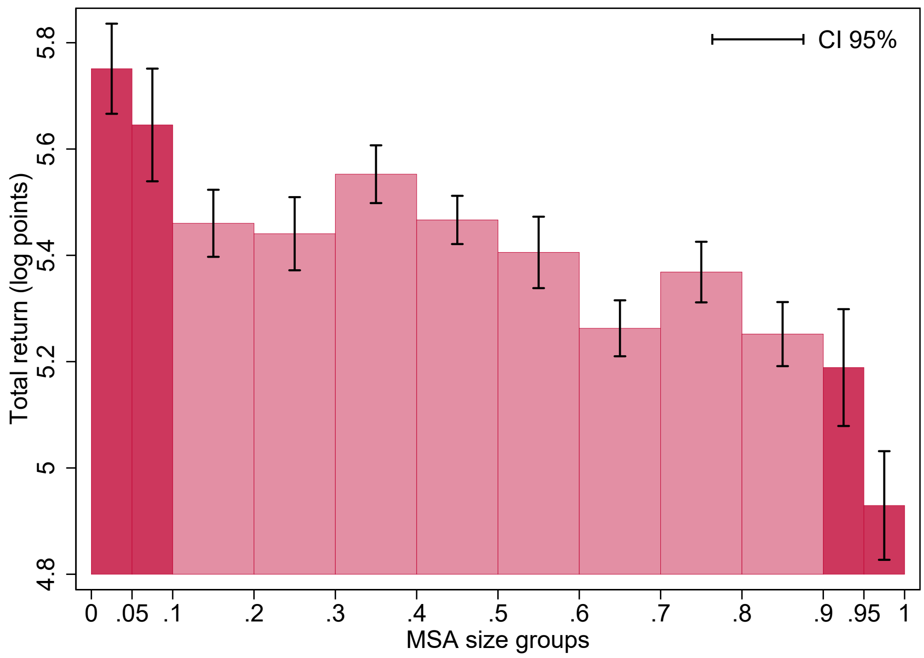
The third row shows the comparison of the "superstar" cities as defined in Gyourko, Mayer,

[8] See e.g. Eeckhout (2004) or Duranton (2007).

and Sinai (2013) with the rest of the city distribution,[9] but extended to 2018. Using this city sample, the difference in capital gains is significantly positive. This is not surprising, because the authors sample their superstar cities based on exceptionally high house price growth. For these cities too the difference in rental yields is significantly negative and larger in absolute values than the difference in capital gains.

Thanks to the detailed data, we can also sort all cities into size deciles ordered from smallest to largest MSA. We split the first and last decile again to get a more precise picture of the tails of the distribution. Average log total returns within each bin are plotted in Figure 5, which shows

Figure 5: *Total returns for 316 MSAs (log points) by population size, 1950-2018*



Note: All returns are log returns. Cities are divided into bins based on the size of MSA population in 1950. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half. As the data for American MSAs only exist in decadal steps, we are not able to construct rent returns. Rental yields are, however, used as a decent approximation of rent returns.

that overall housing returns decrease with city size. The relation is not perfectly monotonic across all size bins, but clearly visible overall.[10]

[9]We use the *ever_superstar* variable of the original data set, extended to the years 1960, 2010 and 2018. The authors exclude MSAs that do not meet the population threshold of 50,000 in 1950.

[10]Results for equity markets are similar. The ”big vs small” factor is also not linear across all the size bins and

4.2 German cities

For Germany, we constructed a novel data set for this study that covers 42 (West) German cities between 1974 and 2018 at annual frequency. The data set covers only comparably large cities that correspond to urban municipalities excluding rural hinterlands.[11] We extend the data to 127 (West) German cities from 1992 onward in a data set that covers the near-universe of (West) German cities. We exclude Eastern Germany, because data coverage mostly started later and Eastern German cities might be fundamentally different to West German ones at the beginning of our sample period. The data set is constructed using market reports of the German Real Estate Association and one of its predecessors.[12] These market reports surveyed local real estate agents and collected city-level observations for various market and quality segments. For the period from 1989 onward, the source allows us to directly use annual estimates for rental yields, such that we only have to rely on the rent-price approach discussed above for some years. We provide more information on the data sources and methods in the Data Appendix.

We start with the comparison of large cities and other cities (or the smallest 5% of cities). To do this, we sort cities by their 1975 population.[13] As for the U.S., we define large cities as being at or above the 5% largest of the size distribution. Table 5 confirms an identical pattern

Table 5: *Difference in housing returns (log points) for 42 German cities, 1975-2018*

Sample	Capital gain	Rent returns	Total return	N
Large vs rest	0.47 (0.57)	-0.91*** (0.34)	-0.45* (0.25)	1848
Large vs small	1.03 (0.72)	-1.58*** (0.43)	-0.57* (0.35)	264

Note: The table shows differences in annual housing returns between large cities and the rest of the sample or small cities. It covers 42 major German cities between 1975 and 2018. Differences are measured as coefficients in a random effects panel regression of the dependent variable (log capital gain, log rent return and log total housing return respectively) on a large city dummy and year fixed effects. Standard errors (in parenthesis) are clustered at the city-level. Large cities are defined as being at or above the 95th percentile of the city population distribution in 1975. The second row shows the same, but comparing large cities only to small cities, which are defined as being at or below the 5th percentile of the city population distribution in 1975. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$

is much stronger for the tails of the distribution; compare Fama and French (1993).

[11]The average size of cities covered is approximately 418,000 inhabitants in 1975, with a standard deviation around 414,000 and a minimum of approximately 31,000.

[12]The *Immobilienverband Deutschland (IVD)* and its predecessor *Ring deutscher Makler (RDM)*.

[13]Source: Statistical office of Germany: *Gemeindeverzeichnis, Gebietsstand: 31.12.1975, Statistisches Bundesamt.*

for Germany: Lower total returns in the larger cities. The return gap grows when we compare large to small cities. We also study the more comprehensive housing return data starting in 1992. The results are shown in the Data Appendix.

Using data for the cross-section of cities in both the U.S. and Germany, we have confirmed that the largest cities tend to have lower total housing returns than other housing markets in the same country. In the next section we discuss a framework that rationalizes these findings with differences in risk and present supportive empirical evidence.

5 Housing risk and return

Both in the long-run historical data and for the city-size distribution in the U.S. and Germany we found that: (i) capital gains tend to be higher, (ii) rent returns lower in the big agglomerations, and (iii) the difference in rent returns is larger than the difference in capital gains so that total returns are lower in large cities. In this section we demonstrate that differences in housing risk between large and small cities can account for these findings.

In the following, we will focus on the rational expectations benchmark, but this is not meant to imply that behavioral factors are not important. Recent research has shown that behavioral factors matter in household decision making and home ownership decisions (for instance, Rozsypal and Schlafmann (2020)). In our setting, it is possible that expectations for house price appreciation are systematically too optimistic in large cities, or that investors myopically focus on higher capital gains in the large cities and neglect the rent return component in total housing returns. In Appendix D we use the framework of diagnostic expectations to explore the potential effects of behavioral biases (Bordalo et al., 2019).

In a rational expectation setting, we start with a parsimonious two-city model with housing investments in a large city A and a small city B. We assume that housing risk is lower in the large city A compared to the small city B. In an asset market equilibrium with rational expectations, risk-adjusted total returns need to equalize between cities, such that investors are indifferent between investing in city A or city B:

$$\left(\frac{R^A_{t+1}}{P^A_t} + cg^A_{t+1}\right) * \frac{1}{\delta^A} = \left(\frac{R^B_{t+1}}{P^B_t} + cg^B_{t+1}\right) * \frac{1}{\delta^B}, \tag{4}$$

with P_t^l being the house price at time t in location l, R the rent payment, and $cg^l = \frac{P_{t+1}^l - P_t^l}{P_t^l}$ the capital gain. δ^l is the location-specific discount rate. As housing risk is lower in city A, risk-averse investors will discount future payments in A at a lower rate than in B: $\delta_A < \delta_B \iff \frac{1}{\delta_A} > \frac{1}{\delta_B}$. This holds as long as investors have some degree of risk aversion and implies that, in order to attract investors, risky city B will need to offer higher housing returns than safe city A:

$$\frac{R_{t+1}^A}{P_t^A} + cg_{t+1}^A < \frac{R_{t+1}^B}{P_t^B} + cg_{t+1}^B. \tag{5}$$

For simplicity of exposition, we assume that houses in both cities feature the same expected future rental cash-flow: $R_{t+1}^A = R_{t+1}^B$. Note that the same will hold under the potentially more realistic assumption that future rents are expected to rise faster in the large city.[14] In order for the equilibrium condition (4) to hold, current prices will adjust. Investors will be willing to pay a higher price for the safer rental cash-flow in the large city, because future payments are discounted at a lower rate. Rent returns will be lower in A compared to B:

$$\frac{R_{t+1}^A}{P_t^A} < \frac{R_{t+1}^B}{P_t^B}. \tag{6}$$

This helps rationalize the empirical finding (ii) that rent returns are lower in large cities. In a next step, we can rewrite inequality (5) as:

$$cg_{t+1}^A - cg_{t+1}^B < \frac{R_{t+1}^B}{P_t^B} - \frac{R_{t+1}^A}{P_t^A}, \tag{7}$$

which shows that, in equilibrium, the difference in rent returns between city B and city A will be larger than the difference in capital gains between A and B. This, in turn, would rationalize our third stylized fact that the difference in rent returns in favor of small cities exceeds the difference in capital gains between large and small cities.

While it is clear that the right-hand side of inequality (7) is larger than zero, this does not, however, pin down the difference in capital gains. It could be the case that risky cities have higher capital gains than safer cities or vice versa. Yet the empirical evidence clearly points to higher capital gains in large cities. To rationalize this finding we need to combine

[14]This is because investors will be willing to pay a higher price for a house with the same *current* rental income, which leads to a lower rent return in city A.

the asset market perspective with insights from the urban economics literature. Larger cities have greater supply constraints (Saiz, 2010). National population growth as well as urbanization tendencies increased the demand for housing in cities over the last decades. Highly inelastic housing supply did not meet the surging demand, driving up house prices in the largest cities. A similar mechanism is described in more detail in Gyourko, Mayer, and Sinai (2013). Hilber and Vermeulen (2016) show empirically that more inelastic housing supply causes stronger house price growth in reaction to rising demand. Under the realistic assumption that supply constraints are more binding in large cities, this can also rationalize our empirical finding of higher capital gains in large cities.

In essence, a parsimonious model that features differences in housing risk between large and small cities could account for the key empirical facts established in the previous parts: lower overall returns in large cities despite higher capital gains, driven by lower rent returns. We will now explore the empirical evidence that housing risk is lower in large cities and, if so, what risks investors are compensated for with higher returns outside the large agglomerations.

5.1 Two sources of housing risk

Examining the difference in housing investment risk between cities, we will consider two separate potential sources of risk. On the one hand, housing market returns in small cities could be more correlated with consumption growth providing less consumption insurance. On the other hand, idiosyncratic shocks to property-level housing returns could be larger in more remote locations due to differences in the structure of housing markets. Both types of risk are conceptually independent. We will first give some guidance on the two concepts and discuss how we measure both types of risk. Afterwards, we will turn to the empirical evidence.

In standard asset pricing, risk premia arise as a result of the co-variance between asset returns and marginal utility, where the latter is typically approximated by consumption growth (Cochrane, 2009). In the case of housing, it could be the case that the co-variance of local housing returns and consumption differs across large and small cities. For instance, one could expect that large cities have more diversified economies, less exposure to industry-specific shocks and a weaker co-variance between housing returns and consumption growth. Additionally, the stronger exposure of large cities to foreign or out-of-town investors could decrease the co-variance in these cities, since these investors are typically less concerned with local risk.[15] To test this hypothesis, we approximate consumption growth with local income growth and calculate the co-variance between income growth and excess housing returns.

A second potential source of risk is idiosyncratic housing risk. In the case of housing, there are good reasons to think that idiosyncratic risk is priced. This is because houses are large, indivisible and illiquid assets and most home-buyers are owner-occupiers that own one house in a specific location and not a diversified housing portfolio (Piazzesi and Schneider, 2016; Giacoletti, 2021). As a result, standard assumptions of models of diversified portfolios do not necessarily apply in housing markets and idiosyncratic risk will be priced as Merton (1987) showed. Higher returns in small cities could be a compensation for higher exposure to idiosyncratic risk. To test whether this is in fact true, we calculate the idiosyncratic component of house price risk following the approach pioneered by Giacoletti (2021).

5.2 Co-variance risk

The following holds for a utility-maximizing household that allocates resources between consumption and different investment opportunities:[16]

$$lnE[R_{t+1}] - lnR_f = \gamma Cov\left[ln\left(\frac{C_{t+1}}{C_t}\right), lnR_{t+1} - lnR_f\right], \tag{8}$$

where R_{t+1} is the total return on the asset next period, R_f is the return on the risk-free asset, γ the risk-aversion parameter and $\frac{C_{t+1}}{C_t}$ is consumption growth. In other words, an asset that has a greater co-movement with consumption features a higher risk and, therefore, risk averse agents ($\gamma > 0$) request a higher excess return. Unfortunately, to the best of our knowledge long-run data on consumption at the regional level does not exist. Instead, we approximate consumption growth with regional income growth. An asset is riskier when it has a higher correlation with future income as it cannot be used to hedge income shocks or amplifies them.

[15] Some recent literature has shown that foreign investors push-up house prices in large international cities like London, New York or Paris, and that their investment decisions are mostly driven by economic factors in their hometowns (Badarinza and Ramadorai, 2018; Cvijanović and Spaenjers, 2021).

[16] Cochrane (2009).

To calculate the co-variance between MSA-level income growth and MSA-level excess housing returns, we turn to U.S. Census data, described above in section 4.1. These data provide a measure of total housing returns and of family income growth over time. It is important to note that the data have decadal frequency. This implies that we compare the correlation of log excess housing returns and log income growth over long time periods.[17]

We first calculate MSA-specific co-variances as: $Cov_s = Cov(R_s - R_f, y_s)$, where R_s is total real log housing return for MSA s, R_f is the risk-free rate approximated by total real log returns on short-term U.S. t-bills and y_s is average real log income growth in MSA s. Hence, $R_s - R_f$ is the excess return on housing in MSA s. We calculate the co-variances for the period between 1950 and 2018.[18] We then test whether these co-variances are smaller in large MSAs. The results are depicted in Table 6 row 1. The co-variances of income and excess housing returns are significantly smaller in large MSAs compared to the rest. The difference in co-variances becomes larger when we compare the largest MSAs to only the smallest ones. Appendix F shows results for the entire distribution of MSAs as well as estimated betas from a consumption based asset pricing model (CCAPM).

In the same spirit, the data allow us to test whether high return MSAs exhibit higher co-variances between housing returns and income, as the CCAPM predicts. In the lower half of Table 6 we sort MSAs by housing returns and compare co-variances for high and low return MSAs. We find evidence that return co-variances with income are lower in low return cities. This being said, the statistical significance is mixed. The results are borderline significant at the 10%-level (*p = 0.105*) only in the last column where we compare the lowest return MSAs (that tend to be the largest MSAs in terms of population) with all other MSAs. As can be seen in the middle column, the mean difference between co-variances in high vs. low return markets is particularly large, but it is not significant in the decadal data that we have at our disposal. Future research will have to rely on new types of data sets with more granular consumption series and

[17]By focusing on the 10-year averages, we are averaging out the cyclical evolution in consumption growth. This is in line with Parker and Julliard (2005), who show that the co-variance between current asset returns and cumulative consumption growth explains the cross-section of expected returns to a much greater extent than the co-variance between the asset's return and contemporaneous consumption growth.

[18]Note that given the decadal frequency of the data, we have overall 7 data points for each variable MSA combination.

Table 6: *Differences in co-variances for different MSA sortings, 1950-2018*

Sorting	Large vs rest	Large vs small	Rest vs small
By MSA size	-0.55** (0.273)	-1.94*** (0.573)	-1.49*** (0.496)
By total returns	0.36 (0.416)	0.60 (0.448)	0.27 (0.167)
N	316	31	316

Note: The first row shows differences in the co-variance between income growth and log excess total returns by MSA size. For clarity the differences in co-variances are multiplied by 10,000. Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 1950. Small MSAs are defined as being at or below the 5th percentile of the MSA population distribution in 1950. In column 3 we show the differences between small MSAs and all the rest of MSAs. The second row shows differences in total log housing returns between MSAs with large total housing returns and the rest of the sample or MSAs with smaller total housing returns. MSAs with large returns are defined as being at or above the 95th percentile of the MSA average total log housing returns distribution between 1950 and 2018. MSAs with small returns are defined as being at or below the 5th percentile of the MSA total log housing returns distribution between 1950 and 2018. In column 3 we show the differences between small MSAs and the rest. Differences are measured as coefficients in a cross-sectional regression of the dependent variable (co-variance) on a large MSA dummy (columns 1 and 2) or on a rest MSA dummy (column 3). Robust standard errors in parenthesis. Overall, we use estimates for 316 MSAs between 1950 and 2018. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

higher frequency return data to pin down these differences more firmly. For now, we conclude that the available long-run data for the U.S. suggest that housing risks are higher in small cities as income co-varies more strongly with local housing returns. MSAs with low returns also tend to have smaller co-variances between returns and income growth than others.

5.3 Idiosyncratic house price risk

To test for differences in idiosyncratic risk, we use a combination of transaction-level price data from Corelogic and county-level house price indices from FHFA and Zillow.com for American MSAs over the past three decades. The focus will be on the U.S. because, to the best of our knowledge, equally detailed and micro-level house price transaction data do not exist for other countries.

Importantly, these estimates of idiosyncratic risk build on sales data and mark a lower bound for estimates of the idiosyncratic risk differences between large and small markets. In Appendix H, we demonstrate that in large cities rental markets are substantially more liquid, rental vacancy rates are lower and less volatile, reducing the uncertainty that a landlord faces over his future income stream. Moreover, Sagi (2021) has shown that for commercial real estate markets including income streams is unlikely to affect property-level return variation as.

We estimate idiosyncratic house price risk as the unexplained variation in sales-level capital gains after controlling for: (i) market-level price changes (at the county level), and (ii) common house and transaction characteristics in the following equation:[19]

$$\Delta p_{i,l,t} = \Delta v_{l,t} + BX_i + \sigma_{l,idiosyncratic}\, \varepsilon_{i,t}, \tag{9}$$

where $\Delta v_{l,t}$ is the growth in local county house prices, BX_i is a vector of house and transaction characteristics, which includes zip-code and time fixed effects, and $\sigma_{l,idiosyncratic}\, \varepsilon_{i,t}$ is a sales-specific shock. We measure idiosyncratic risk as the standard deviation of sales specific shocks for properties within a specific MSA. Using data from *Corelogic* on single-family repeat-sales for the period between 1990 and 2020, we can estimate annual idiosyncratic risk in 248 MSAs, covering around 86% of the U.S. population in 1990. We describe the data sources and the methods used to estimate idiosyncratic house price risk in more detail in Appendix E and in the Data Appendix.

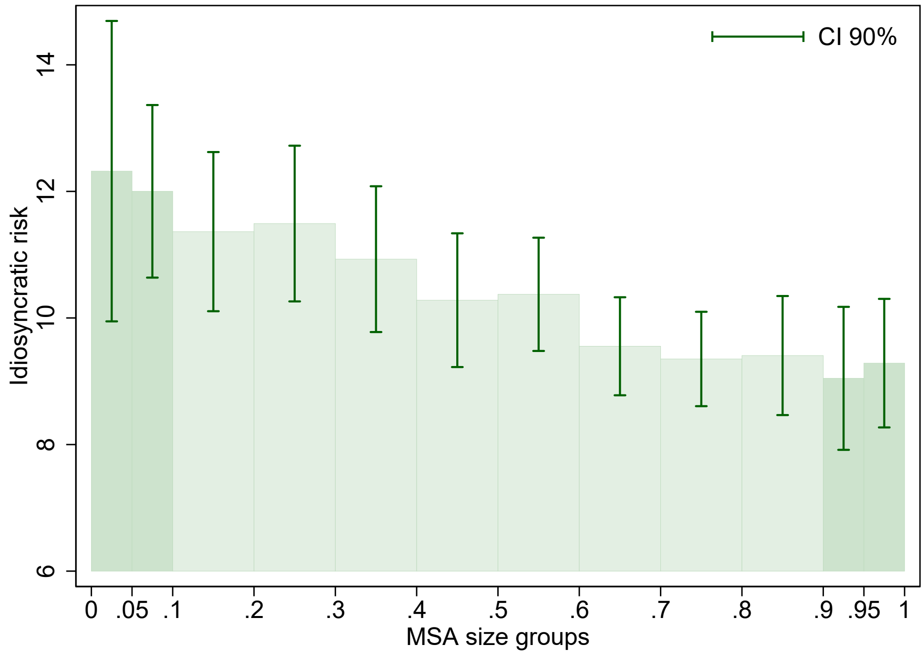
5.3.1 Idiosyncratic risk across space

Figure 6 plots our measure of idiosyncratic house price risk across different MSA-size bins, showing that it decreases substantially with MSA size. Between 1990 and 2020, average idiosyncratic risk in the smallest MSAs was 12.34% of the house sales price, but about 25% lower in the largest MSAs at 9.28%. The measure of idiosyncratic house price risk is orthogonal to local housing market fluctuations and is therefore independent from the co-variance risk that we looked at above.[20] In Appendix E.1 we also look at the distribution of local market housing price volatility in detail. In contrast to idiosyncratic volatility, local market volatility is small and does not differ significantly across MSAs. As such, we focus our discussion here on idiosyncratic volatility.

[19]Giacoletti (2021) studies local market risk at the zip-code level. Our definition of local markets relates to individual counties. The estimates of idiosyncratic risk that we obtain at the MSA level are, however, very similar to the ones we obtain at the zip code level for MSAs for which we have sufficient observations to use both approaches.

[20]Note, that this does not imply that city-wide factors are irrelevant for idiosyncratic housing risk. Realizations of sales-specific shocks are idiosyncratic by nature. But the distribution from which these sales-specific shocks are drawn is arguably the same for similar houses and will be determined by local housing market characteristics.

Figure 6: *Annual idiosyncratic house price risk by MSA size, 1990-2020*



Note: The figure shows average annual idiosyncratic house price risk for different MSA size groups for the period between 1990 and 2020. MSAs are divided into bins based on the size of MSA population in 1990. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half. All series are real and annualized.

5.3.2 Idiosyncratic risk and housing market liquidity

The real estate finance literature has established a close relation between idiosyncratic risk and illiquid markets. Empirical work by Giacoletti (2021) and Sagi (2021) shows that matching frictions in housing markets (i.e. liquidity) drive the magnitude of idiosyncratic risk.[21] A close link between liquidity and idiosyncratic risk has also been shown for other asset classes, e.g. private equity.[22] We would thus expect that MSAs with large idiosyncratic housing price volatility also have very illiquid housing markets. In the next subsection, we test this prediction.

We look at evidence from two liquidity measures across MSAs in the U.S.: time on the

[21] More precisely, they show that the idiosyncratic volatility is mostly realized at the points of sale and re-sale of the property.

[22] Robinson and Sensoy (2016) show that most of the variation in cash-flows is idiosyncratic and Sorensen, Wang, and Yang (2014) demonstrate that idiosyncratic risk (non-systematic risk) faced by private equity investors arises due to its illiquidity. Furthermore, Mueller (2010) and Ewens, Jones, and Rhodes-Kropf (2013) provide empirical evidence that private equity funds with higher idiosyncratic risk also have higher expected returns.

market (TOM) and asking price discount. TOM measures the number of days between the original sale listing of a house and its actual sale. The asking price discount measures the difference between the original asking price and the final transaction price. Intuitively, in more liquid markets sellers will have to wait less time to sell (low TOM) and will be able to sell their properties for a price closer to the original asking price (low discount).

Table 7: *Differences in mean and standard deviation of housing liquidity, US, 2012-2020*

	Asking Price Discount (in p.p.)		
Sample	Mean	S.d. across time	N
Large vs rest	-0.87*** (0.096)	-0.36***(0.016)	62688
Large vs small	-1.50*** (0.184)	-0.75***(0.052)	6336
	Time on the Market (in days)		
Sample	Mean	S.d. across time	N
Large vs rest	-10.90* (6.184)	-4.34***(0.904)	26869
Large vs small	-29.67***(9.918)	-9.89***(1.782)	2716

Note: Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 2010. Small MSAs are defined as being at or below the 5th percentile of the MSA population distribution in 1950. Data on the median number of days on zillow and on the average discount to the asking price from Zillow.com for 277 MSAs for the period between 2012 and 2020. $*: p < 0.1; ** : p < 0.05; *** : p < 0.01$.

We use data from the online real estate marketplace *zillow.com* on median *time on zillow* and median *price cut* for 277 American MSAs for the last decade. Table 7 compares both measures of liquidity in the 5% largest MSAs with the other 95% and the smallest 5% MSAs. In the largest MSAs, sellers take significantly less time to sell on average. Table 7 states that the difference between the largest and the smallest MSAs is around 30 days, compared to an overall mean of 100 days. Not only is mean TOM significantly lower in large cities, but it also fluctuates significantly less over time. Results for the full MSA distribution can be found in Appendix G.

The connection between idiosyncratic risk and housing market liquidity also implies that city-wide shocks – such as the often-cited decline of the car industry in Detroit – influence the distribution of sales-specific shocks. Van Dijk (2019) shows that housing liquidity dries up in declining housing markets. Our data also confirms that idiosyncratic risk in Detroit is far above other MSAs of similar size.[23] Moving beyond U.S. data, in Appendix G we show that in Germany there are, on a per capita basis, more potential sales in larger cities and more potential buyers per sale.

6 Conclusion

In our sample covering 27 cities in 15 countries we uncover a new stylized fact: superstar cities have persistently under-performed smaller, less dynamic cities in terms of housing returns. This result is puzzling given the well-established evidence that large agglomerations have witnessed substantially stronger housing price appreciation than the rest of the country in the last decades. Taking rental returns into account changes our understanding of the performance of housing assets across space. This new stylised fact reveals a second, equally important fact about housing markets: housing investments are significantly less risky in the large agglomerations than in the rest of the country. In fact, these two new stylised facts interact in accordance with the prediction of a standard asset market rational expectations equilibrium: smaller and more risky locations have to offer higher expected housing returns in order to attract new capital. Rationalizing the spatial distribution of housing markets through the lens of an asset market equilibrium also represents, to the best of our knowledge, a novel type of approach, which could be very promising for spatial economics models more generally. Beyond the relevance for spatial economics, the large differences in housing returns across locations also emphasize the need to look more deeply into within asset-class return heterogeneity and its repercussions for wealth inequality dynamics and portfolio choice. We show that the choice between locations is strongly associated with different exposures to housing risk and returns and is, therefore, ultimately, a driver of wealth dynamics. The paper similarly invites more research on the importance of geography and size for the heterogeneity in returns on different assets.

[23]The MSA *Detroit-Warren-Livonia* has an average annualized standard deviation of 13.30 percentage points, by far the largest in the largest size bin, which has an average standard deviation of only 8.35 percentage points and also far above Boston-Cambridge-Quincy (7.40) and Washington-Arlington-Alexandria (6.08), which had a comparable MSA size.

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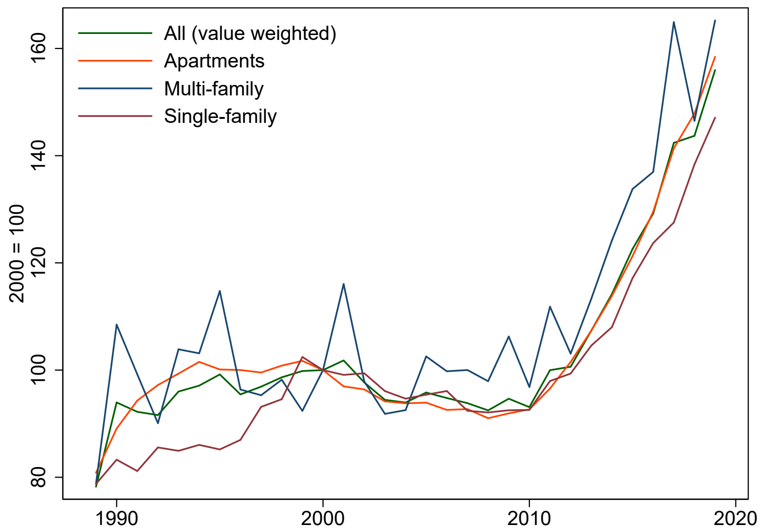
Appendix

A Additional data analyses - Market segmentation

For Cologne, we construct hedonic sub-indices using detailed micro-data between 1989 and 2019. All indices show similar trends. Average yearly house price appreciation differs by 0.217 log points between the complete value-weighted series and the series for single-family houses only. As our rent series might be biased towards apartments in the city center, it is reassuring to see that the value weighted series and the series only for apartments differ only by an average house price appreciation of 0.056 log points between 1989 and 2019.

Figure 7: *Cologne house price indices for different market segments*



Note: Hedonic house price indices for different housing types constructed from transaction level data described in the Data Appendix.

We next use these house price indices for different market segments to calculate housing returns for Cologne.

Table 8: *Yearly housing returns (log points) for Cologne using different hp series, 1990 -2018*

Market segment	Capital gain	Rent return	Total return
All (value weighted)	2.30	4.13	6.16
Apartments	2.24	4.24	6.25
Multi-family	2.47	4.02	6.12
Single-family	2.08	4.16	6.04

Note: Average yearly housing returns for different housing types constructed from transaction level data described in the Data Appendix.

B Additional results for city vs national comparison

B.1 Splitting the sample into Europe and the rest of the world

In this section, we perform our main analysis from section 3.1, but we split our sample into a European sample and a non-European sample. Since our sample has a disproportionate amount of European cities we do this analysis to show that our results are not being driven solely by the European cities in our sample. In practice, this means that the non-European sample includes the United States, Canada, Australia and Japan. We report the results for both samples on Table 10. The Table shows that our results are both present in Europe as well as outside Europe.

B.2 Long-run comparison: Large cities vs. national portfolios

In this section, we repeat our main analysis from section 3.1, but extend the series for selected cities and countries backwards. We select all cities, for which we have long-run series and where the national housing series have a wide geographical coverage, even before 1950. The period before 1950 was characterized by large shocks such as wars and the Great Depression as well as fundamentally different housing policies, which were changing more rapidly and drastically compared to the postwar period. Although this describes a fundamentally different setting compared to today, we want to demonstrate that our results are robust even when including this time period.

A severe problem for this analysis is that, for many countries, the geographical coverage of the housing series in Jordà et al. (2019) is limited before World War II. As national statistical

Table 9: *Difference in yearly housing returns (log points) by cities, 1950-2018*

City	Capital gain	Rent return	Total return	N
London	0.83 (0.81)	-1.78*** (0.17)	-0.95 (0.83)	68
New York	0.60 (1.45)	-1.96*** (0.08)	-1.36 (1.43)	68
Paris	0.38 (0.79)	-1.17*** (0.11)	-0.74 (0.78)	68
Berlin	2.99** (1.15)	0.83*** (0.23)	3.65*** (1.16)	56
Tokyo	-1.99 (1.96)	0.77*** (0.24)	-1.10 (1.93)	59
Hamburg	0.21 (0.67)	-0.57*** (0.09)	-0.36 (0.67)	56
Naples	0.14 (1.11)	-0.73*** (0.08)	-0.59 (1.10)	68
Barcelona	-0.66 (1.97)	-0.75*** (0.15)	-1.38 (1.93)	68
Madrid	-0.63 (1.93)	-0.97*** (0.19)	-1.59 (1.90)	68
Amsterdam	0.26 (0.98)	-0.22 (0.15)	0.05 (0.95)	68
Milan	2.23 (1.62)	-2.21*** (0.10)	-0.01 (1.61)	68
Melbourne	0.05 (0.77)	-1.42*** (0.08)	-1.35* (0.76)	68
Sydney	0.39 (0.79)	-1.02*** (0.08)	-0.63 (0.77)	68
Copenhagen	0.88** (0.44)	-3.14*** (0.18)	-2.22*** (0.49)	68
Rome	0.01 (1.15)	-2.93*** (0.08)	-2.88** (1.14)	68
Cologne	0.22 (1.43)	-0.26** (0.11)	-0.05 (1.42)	56
Frankfurt	0.09 (1.65)	-0.25* (0.13)	-0.16 (1.63)	56
Turin	-0.23 (1.09)	-1.23*** (0.07)	-1.44 (1.07)	68
Stockholm	0.04 (0.98)	-2.84*** (0.20)	-2.77*** (0.99)	68
Oslo	-0.11 (0.72)	-3.13*** (0.18)	-3.18*** (0.75)	68
Toronto	0.64 (0.75)	-2.51*** (0.34)	-1.86** (0.85)	62
Zurich	1.19 (1.47)	-0.59*** (0.07)	0.57 (1.44)	68
Gothenburg	0.23 (0.14)	-0.83*** (0.13)	-0.61*** (0.18)	68
Basel	1.51 (1.33)	-0.40*** (0.07)	1.06 (1.32)	68
Helsinki	0.63*** (0.24)	-4.04*** (0.29)	-3.39*** (0.34)	68
Vancouver	1.56 (1.20)	-2.68*** (0.36)	-1.15 (1.26)	62
Bern	0.15 (1.71)	-0.40*** (0.09)	-0.25 (1.68)	68

Note: The table shows the mean difference between city-level and national log housing returns, log capital gains and log rent returns by city. Standard errors (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

agencies were not in existence for most countries, the authors had to rely on housing series from other sources, which often only covered some or even just one large city. As our aim is not to

Table 10: *City-level and national yearly housing returns (log points), 1950-2018*

	Europe				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	2.34	1.86	0.48* (0.27)	1.66	0.68** (0.29)
Rent return	3.54	4.90	-1.36*** (0.05)	5.14	-1.60*** (0.05)
Total return	5.79	6.67	-0.87*** (0.27)	6.72	-0.93*** (0.29)
N	1380				
	Rest of the world				
	Cities	National	Difference	RoC	Cities - RoC
Capital gain	1.94	1.70	0.23 (0.49)	1.54	0.39 (0.59)
Rent return	3.60	5.09	-1.49*** (0.11)	5.44	-1.84*** (0.12)
Total return	5.47	6.71	-1.24** (0.49)	6.91	-1.43** (0.59)
N	387				

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

compare our large cities to other (or in fact often the same) large cities, we exclude all countries before 1950 that have a geographical coverage of house price or rent series of only a very small number of large cities. After matching with our city-level data, this leaves us, before 1950, with Germany starting 1925,[24] Norway starting 1891, the United Kingdom starting 1930[25] and the United States starting 1920.[26]

The results adding the large cities within these countries before 1950 are depicted in Table

[24]We start in 1925 to exclude the period of German hyperinflation, for which measurement of real house price and rent development is subject to very high uncertainty and data is missing for some cities. Moreover, national data for Germany is missing during and in the aftermath of World War II (1939-1962).

[25]We have to exclude World War II (1939-1946) because national data is missing.

[26]We needed to exclude a considerable number of countries because of narrow geographical house price coverage. From the remaining countries we exclude Italy, France and Switzerland, because the rent series before World War II only cover Milan, Paris and Zurich, respectively. Additionally, we exclude Australia because rent return series for the national Australian portfolio are subject to significant uncertainty before 1950, as can be seen in the Online Appendix of Jordà et al. (2019), and are moreover implausible compared to the housing series for Sydney and Melbourne from Stapledon (2012); Stapledon (2007), which we use in our main data set. Housing return series start one year later, such that we are able to calculate capital gains with the wide coverage for all included countries. We provide a table with a precise description of the geographical coverage of the national series in the Data Appendix.

Table 11: *City-level and national yearly housing returns (log points), long-run*

	27 large cities			Only largest city/country		
	Cities	National	Difference	Cities	National	Difference
Capital gain	2.15	1.72	0.43* (0.24)	2.39	1.98	0.41 (0.30)
Rent return	3.61	5.11	-1.50*** (0.04)	3.69	5.39	-1.70*** (0.06)
Total return	5.67	6.75	-1.08*** (0.24)	5.98	7.27	-1.29*** (0.30)
N	1920			1039		

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. All 27 large cities are included after 1950. Before 1950, we add Berlin, Hamburg, Cologne, Frankfurt (all after 1925), Oslo (after 1891), London (after 1930) and New York (after 1920). The left-hand panel shows the results averaged over all 27 large cities in our main data set. The right-hand panel shows the results only for the cities that had the largest population in their respective countries in 1950 in our data. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

11. For the sample of all 27 large cities, the results become, if anything, even stronger than when only including the data post 1950 in section 3.1. For the sample of only the largest city per country, the results stay virtually unchanged. This demonstrates that our results are not dependent on starting in 1950 and excluding the period featuring larger shocks to the housing market. Of course, as we still include the full sample after 1950, the weight on the observations before 1950 is small. However, if we instead include only the cities within countries with data coverage before 1950, the absolute differences in total housing returns stays virtually unchanged, but is less precisely measured.[27]

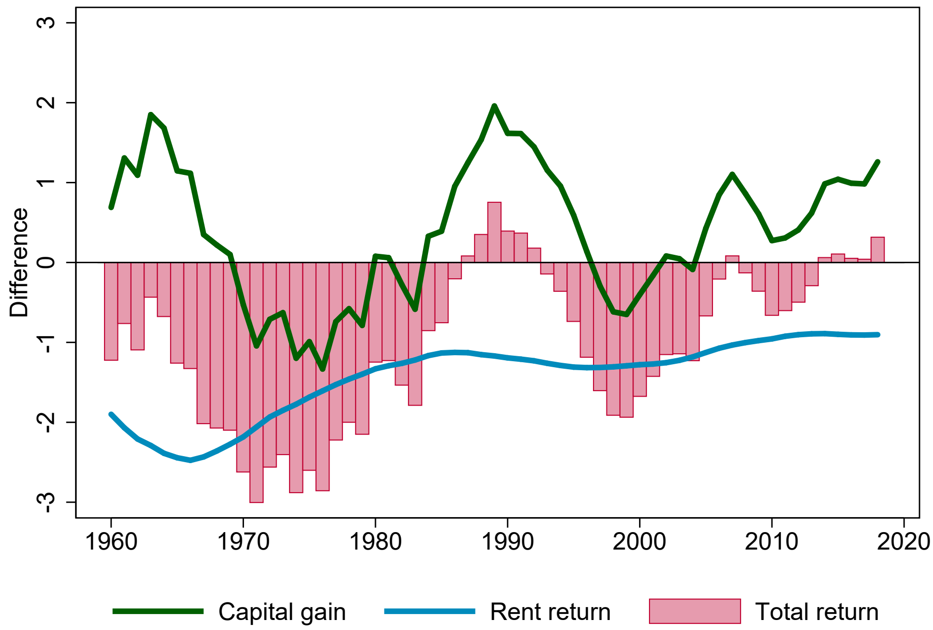
All in all, our main results do not depend on starting our comparison in 1950. Instead, the results become somewhat stronger when we include the time period before 1950 for countries with wider geographical coverage. As the data quality is, however, in general not as good as for the post-war period and large shocks like wars are a source of strong measurement error, we prefer the specification shown in the main text.

[27] The difference in total returns is -0.98** for all large cities in the respective countries and -1.14** for only the largest city per country. As the number of observations is considerably smaller in this specification, the results are, however, less precisely measured. The full results for this comparison are available on request.

B.3 Comparison of housing returns over time

To demonstrate that our main result is not driven by specific time periods, we depict the difference between city-level and national housing portfolios over time. As we want to minimize the effect of housing cycles, we compute 10 year lagged moving averages of this average difference.[28]

Figure 8: *Average differences in city-level and national returns (log points) over time, 1950-2018*



Note: This graph shows 10 year lagged moving averages of the mean difference in log capital gains, log rent returns and log total returns between the city-level and the respective national housing portfolios. The return period covered is 1951 to 2018, such that the moving averages start in 1960, except for the German cities, Tokyo and Toronto, because the national data starts later for these cities.

The outcomes are plotted in Figure 8. It shows that the main result is prevalent over time. The difference in rent returns is stable and negative over the entire time period. The difference in capital gains, in contrast, is more volatile and it is still possible to spot the influence of housing cycles. In consequence, the difference in total returns is also volatile, but negative during most periods.

[28] We rely on the results of Bracke (2013), who shows that the mean duration of complete housing cycles in 19 OECD countries between 1970 and 2010 was around 10 years.

B.4 Rent regulation

Table 12: *Difference in yearly housing returns (log points) by rent regulation, 1950-2018*

Sample	Capital gain	Rent return	Total return	N
Weak rent reg.	0.52* (0.30)	-1.64*** (0.08)	-1.11*** (0.30)	497
Strict rent reg.	0.47 (0.44)	-1.74*** (0.08)	-1.26*** (0.44)	687

Note: The table shows the mean difference between city-level and national log housing returns, log capital gains and log rent returns. Standard errors (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The first row shows the results for weak national rent regulations defined as a rent law index below one third, the second row the results for strict national rent regulation with a rent law index of at least two thirds. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

C Taxes

Taxes associated with real estate have a direct impact on the returns to housing and it is, therefore, important to take them into account when comparing returns across cities. To make this point clearer, consider the housing return equation, where we specifically account for taxes:

$$\text{Total return}_t = \frac{(P_t - P_{t-1})(1-\tau_t^{capital})}{P_{t-1}} + \frac{R_t^{gross}(1-\tau_t^{income}-\tau_t^{property})}{P_{t-1}}, \tag{10}$$

where $\tau_t^{capital}$ is the tax rate on capital gains, τ_t^{income} is tax rate on rental income, $\tau_t^{property}$ is the property tax rate paid by the owner and R_t^{gross} is the rent net of utility and maintenance costs, but not taxes.

If the tax incidence is systematically lower in smaller cities, this - rather than higher pre-tax returns - could explain why we do not find a premium for large cities. For this to be the case, the small-city tax advantage would need to exceed the size of the small city premium.

As mentioned in Section 2 we used data on net operating income yields from MSCI to benchmark our rent return series following the same procedure as in Jordà et al. (2019). MSCI defines the net operating income as being net of property taxes. Therefore, our results with the main data set are not driven by differences in property taxes between large and small cities. Nevertheless, we do not take into account capital gains and rental income taxes in the construction of our series for the main data set. Here we provide suggestive evidence that this omission in the construction of our series is not driving our main results.

C.1 Rental income & capital gains taxes

From Sections 3.1 and 4 we know that the largest cities have higher capital gains, but lower rental returns than the small cities. Therefore, if rental income is taxed considerably more than capital gains, then, post-taxes, the large city negative premium could disappear. Unfortunately, a precise measurement of the effective tax rates is extremely complicated, since these tax classes are often associated with partial or even full exemptions.[29] Nevertheless, we can still explore the fact that in the post-World War II period a great number of the countries in our sample tried to promote home ownership by reducing the tax burden on homeowners. Through the introduction of mortgage interest deduction and the abolition, or considerable decrease, of capital gains and imputed rents taxes, governments tried to incentivize home ownership. Since, throughout this period, rental income continued, in most cases, to be taxed as normal income, this could lead to an effective higher tax burden on rental incomes as compared to capital gains. To test whether this was actually the case we used the series constructed in Kholodilin et al. (2021) to identify the combinations of countries and periods in which capital gains taxes, mortgage interest deductability or imputed rents taxes were effective. We then divided our sample into different sub-samples depending on the degree to which the tax system was effectively incentivizing home ownership or not. More precisely, we created the following three sub-samples: (i) ”not pro homeowner” where only one of the three instruments was in place, (ii) ”medium pro homeowner” where two of the instruments were in place and (iii) ”strong pro homeowner” where all three instruments were in place. We then compared the return differences between the cities in our sample and the respective countries. The results can be seen in Table 13. In all three subsamples, the average returns in the largest cities remain significantly below the returns in the rest of the country.

[29] For example, landlords can deduct a substantial amount of property maintenance costs from the rental income taxes in the US and other countries in our sample. In Germany homeowners are exempted from capital gains taxes if they have owned the property for more than 10 years.

Table 13: *Difference in yearly housing returns (log points), 1950-2018*

Sample	Capital gain	Rent return	Total return	N
Not pro homeowner	0.03 (0.40)	-1.13*** (0.07)	-1.09*** (0.40)	859
Medium pro homeowner	0.90*** (0.31)	-1.66*** (0.06)	-0.76** (0.31)	683
Strong pro homeowner	0.84*** (0.26)	-1.74*** (0.06)	-0.90*** (0.26)	840

Note: The table shows averages of city-level and national log capital gains, log rent returns and log housing returns as well as the difference. National return averages are weighted by the number of cities in the respective country in the sample. Standard errors of differences (in parenthesis) and significance stars are calculated using paired t-tests to test equal means of city-level and national return variables. The left-hand side shows the results averaged over all cities in our main data set. The right-hand side shows the results for the cities, which had the largest population in their respective countries in 1950. $*: p < 0.1; **: p < 0.05; ***: p < 0.01$.

D Housing return expectations

The theory of diagnostic beliefs, as described in Gennaioli and Shleifer (2018), provides a unifying framework, which accounts for the different behavioral biases, i.e. deviations from rational expectations theory, that were documented in the finance and economics literature. It states that people form expectations by extrapolating from past experiences and by overweighting specific representative patterns in the data they observe. Representativeness is defined in the sense of Tversky and Kahneman (1983): ”an attribute is representative of a class ... if the relative frequency of this attribute is much higher in that class than in a relevant reference class”. In other words, some patterns in the data are more salient than others and, therefore, their importance is overvalued. This theory has found empirical support not only in stock return expectations (Bordalo et al., 2019), but also in macroeconomic expectations, such as for consumption or investment (Bordalo et al., 2020). In these cases, forecasters are shown to extrapolate from past trends in the data and to overreact to macroeconomic news. There has not been an explicit attempt to study housing markets from the lens of diagnostic beliefs, but most studies investigating behavioral biases in house price or return expectations find evidence for extrapolation. Expectations of future house price growth are strongly correlated with recent house price appreciation (see e.g. Kuchler and Zafar (2019), De Stefani (2020) or Case, Shiller, and Thompson (2014)), and expectations causally affect future housing investment decisions (see Armona, Fuster, and

Zafar (2018) or Bailey et al. (2018)). Therefore, we will use this framework to organize our discussion on potential biases in housing return expectations.

The housing literature (e.g. Gyourko, Mayer, and Sinai (2013)) and section 3.1 have shown that large "superstar" cities have outperformed the rest of their countries in terms of house price appreciation. Moreover, media coverage and the public debate in recent years seem to have focused on the strong house price growth in specific cities, for example concerned about the resulting affordability problems. Recent research by De Stefani (2020) shows peoples' perceptions about the local house price evolution depend on past local price growth. This could potentially explain why homebuyers are more optimistic about the future of the housing markets in large cities than in smaller cities or rural areas and, therefore, willing to pay a higher house price today. In addition, it might be plausible that homebuyers overweight the capital gains component of total returns over the rent return component. We know from section 3 that rent returns represent the majority of housing returns, still most news about the housing market focuses exclusively on the evolution of house prices and not on rent returns.[30]

From the perspective of diagnostic beliefs, capital gains are a good candidate for being a representative heuristic of total housing returns, since they are more salient than rent returns. Combining extrapolation of past house price growth and overweighting of the capital gains component has the potential to explain why housing return expectations could be differentially biased between large cities and the rest of the country. If this bias is persistent over time, this could, in turn, explain why house prices in large cities are elevated and, consequently, housing returns are smaller than in other cities as observed in the data.[31]

For illustration, we take the extreme assumption that discount rates are non-stochastic and equal between cities, such that we can drop them from equation 4. Next, we assume that expectations are formed using past average capital gains and rent returns, but placing a different weight on the capital gain component, such that we can rewrite the equation as:[32]

[30] One reason might be the fact that house price data over time is more readily available than rent data.

[31] There is, however, evidence that the effect of expectations on house prices depends on the level of interest rates (Adam, Pfäuti, and Reinelt, 2020) and might, therefore, not be persistent over time. Periods of low interest rates can lead to larger fluctuations in expectations-driven house price dynamics.

[32] Here we also make the assumption that extrapolation of past house price growth is constant across cities. There is evidence that sentiment plays a larger role is local housing markets with a higher share of less-informed buyers

$$w^P \ast \overline{cap\ gain}^A + \overline{rent\ return}^A = w^P \ast \overline{cap\ gain}^B + \overline{rent\ return}^B, \qquad (11)$$

where w^P is the subjective weight that homebuyers attach to capital gains. We know that capital gains in the large city A have been higher on average than in the small city B, $\overline{cap\ gain}^A > \overline{cap\ gain}^B$. If $w^P > 1$, then the expected returns would increase relatively more in the large city A compared to B. As a result, the expected discounted returns in city A and B could equalize holding discount rates constant across both cities.

Unfortunately, to the best of our knowledge, data on housing return expectations is scarce, let alone on a regional level. Existing surveys mostly focus on house price developments only and are only representative on the national level.[33] Therefore, we are not aware of a direct way to test this hypothesis. However, with a back of the envelope calculation, we are able to approximate the subjective capital gain weight (w^P) that would be necessary for equation 11 to hold in equilibrium over our long-run data. In the comparison between large cities and national housing portfolios in section 3.1, the resulting weight on capital gains would approximately need to be 2.35.[34] This implies that home-buyers would need to attach more than double the weight (or attention) to capital gains than to rent returns, when forming their expectations about future housing returns. Consequently, a substantial behavioral bias would be necessary to explain spatial differences in housing returns without any differences in discount rates.

For homebuyers planning to become owner-occupiers a considerable bias in housing return expectations might, however, be probable. These types of buyers might neither have a reliable estimate of the rent a potential property would be able to earn nor pay much attention to future rent growth. For large-scale (e.g. institutional) real estate investors, in turn, who buy houses or apartments to rent them out, a large behavioral bias seems to be less realistic. Due to their

(Soo, 2018). Nevertheless, there is no clear evidence on the relation between sentiment and expectations.

[33] Although there are some more detailed surveys on housing, e.g. the National Housing Survey from Fannie Mae or the Michigan Survey of Consumers, which contain questions on price and rent expectations, these neither allow approximating rent return expectations directly, as price-rent ratios are missing and questions are not very specific, nor do they feature enough observations to reliably approximate expectations on a city-/MSA-level.

[34] To calculate the weight on capital gains we first transform the log returns from Table 2 into percentage returns, because log returns do not aggregate linearly across return components. By assuming that capital gains weights are constant across cities and countries, we can then simply calculate the necessary weight for the differences to be equal to 0. For our main specification (*Cities vs National*) we calculate a subjective capital gains weight of 2.35.

investment strategy, these types of investors can be assumed to take rent returns into account and not overweight capital gains to a large extent. Still, we observe that large real estate investors are concentrated in the largest cities, although housing returns have been lower in these cities on average. Preqin data show that city size is an important predictor for how many real estate deals and residential housing value changed hands in big deals among institutional investors in Europe in the 2010s.[35] At least for these expert homebuyers, a rational explanation seems to be more likely.

Our main results focus on the mean differences in housing returns between large and small cities over a long time period. Deviations from rational expectations in housing markets found in the literature, e.g. extrapolative expectations, have been established over the housing cycle. In that sense, the theory of diagnostic beliefs is more appropriate to explain the cyclical behavior in housing markets. Since we would expect the biases in beliefs to correct over a sufficiently long time period, we propose an alternative rational explanation for the mean differences in returns.

E Estimation of idiosyncratic risk

In this section we describe in more detail the method we used to estimate idiosyncratic risk. Like we mentioned in section H, we mostly follow the method employed by Giacoletti (2021).

Before analyzing the results, it is important to note that our estimation differs from the one in Giacoletti (2021) in two ways. First, we are not able to explicitly take remodeling expenses into account, as the necessary data is missing. However, as shown by Giacoletti (2021), remodeling expenses mainly affect the mean and not the standard deviation of the sales specific shock, which is our variable of interest. Secondly, we do not explicitly control for physical characteristics of housing, since these are absent from the data we use. Nevertheless, our estimates of idiosyncratic risk for the MSAs in California are very similar to the ones in Giacoletti (2021). Therefore, we do not think that these limitations influence our city-level comparisons.

We define the local market at the county level. To measure house prices at the county level, we build new house price indices from January 1990 to December 2020 combining repeat-sales indices from FHFA, which cover the period between 1990 and 1996, and price indices

[35]Results are available on request.

from Zillow.com, which cover the period after 1996. The FHFA indices are built based on single-family transactions covered by mortgages guaranteed by Fannie Mae or Freddie Mac.[36] The Zillow Home Value Index is based on *zestimates* for single-family houses. *Zestimates* are quality-adjusted house price estimates, constructed using proprietary algorithms that incorporate data on sales and listings prices and other home and transaction characteristics from a variety of sources.[37]. We then aggregate the county level indices to the msa-level using repeat sales transaction weights from the Corelogic data set.

Following Giacoletti (2021) we combine the county level series with the corelogic transaction level data to construct the Local Market Equivalents (LME). LMEs measure the extent to which a specific house re-sale deviates from the value fluctuation of the median house in the same county. They are computed as follows:

$$LME_t = \frac{P^{loc}_{i,t_i} - P_{i,t_i}}{P_{i,t_i}}; \qquad P^{loc}_{i,t_i} = \frac{P_{i,T_i}}{R^{loc}_{t_i,T_i}}, \tag{12}$$

where P_{i,T_i} is the nominal price at which the house was sold, P_{i,t_i} is the price at which the house was initially bought and R^{loc} is the gross capital gain on the local County price index, i.e. $R^{loc}_{t_i,T_i} = \frac{Index_{county_i,T_i}}{Index_{county_i,t_i}}$. P^{loc}_{i,t_i} is then the market-adjusted buying value of the house.

The changes in individual house values can also stem from transaction and house characteristics, which are more prevalent in specific MSAs. Therefore, in a second step, we remove the additional return variation determined by common house and transaction characteristics from the individual house resale value fluctuations. For that purpose we run the following regression:

$$\tilde{lme}_i = \alpha_{s,y} + \alpha_{e,y} + \alpha_{s,m} + \alpha_{e,m} + \alpha_{zip} + \beta_P log(P_{i,t_i}) + BX_i + u_i, \tag{13}$$

where $\tilde{lme}_i = \frac{lme_i}{\sqrt{hp_i}}$ and hp_i is the holding period in years. The rescaling by holding periods follows Sagi (2021) and deals with potential collinearity arising from differences in holding periods across resales. $\alpha_{s,y}$ and $\alpha_{e,y}$ are fixed effects for the year in which the house was bought and sold,$\alpha_{s,m}$ and $\alpha_{e,m}$ are fixed effects for the month in which the house was bought and sold

[36]More details regarding the methodology used to produce the series are described in Bogin, Doerner, and Larson (2018).

[37]More details about the data and methodology can be found in *www.zillow.com*

and α_{zip} is a zip-code fixed effect. $log(P_{i,ti})$ is the log of the price at which the house was bought, which is also a control for other unobservable persistent characteristics. BX_i is a vector of additional transaction characteristics. The vector X_i contains dummies for different holding periods (less than 2 years, between 2 and 3 years, between 3 and 5 years, between 6 and 8 years, between 8 and 10 years and longer than 10 years), it also contains dummies for sales or resales which fit the following descriptions: short sales, bought solely with cash, foreclosures, and bought or sold by institutional investors or real estate developers. [38]

The residuals u_i then capture the unexplained component of returns, which is controlled for systemic price fluctuations and common house and transaction characteristics. We then measure annual idiosyncratic risk as the standard deviation of the residuals within a specific MSA. The standard deviation in measured in terms the original price's %. Since the dependent variable of the regression is scaled by the square root of the holding period we need to rescale the residual as $\hat{e}_i = \hat{u}_i\sqrt{hp_i}$ in order to have the residual associated with the holding period.

We also do a comparison of the standard deviation of the residuals across MSAs. The results can be seen in the second row of Table 14, which can be found in Section E.1. Larger MSAs have a lower idiosyncratic risk than smaller MSAs.

E.1 Distribution of house price growth variation

Table 14: *Total house price growth variation and its decomposition by MSA size, 1990-2020*

	1A	1B	2	3	4	5	6	7	8	9	10A	10B
Local risk	4.96	5.02	5.65	5.14	5.19	5.16	5.46	5.79	5.51	5.09	6.58	6.63
Idiosyncratic risk	12.32	12.00	11.36	11.49	10.93	10.28	10.37	9.55	9.35	9.41	9.05	9.29
Share of idios. risk	0.81	0.83	0.76	0.80	0.78	0.76	0.76	0.72	0.73	0.75	0.64	0.65
Total risk	13.61	13.17	13.11	12.80	12.47	11.86	12.18	11.64	11.18	10.96	11.54	11.63
# Repeat sales	139369	126863	266186	359600	406745	616257	732470	1038956	1532555	3003841	3190250	4779689
# MSAs	13	12	25	25	24	25	25	24	25	25	12	12

Note: All risk measures are yearly and in percentage points of initial prices. MSAs are divided into bins based on the size of MSA population in 1990. The bins go from the smallest MSAs (bin 1A) to the largest MSAs (bin 10B). The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half.

Table 14 shows annual total house price growth variation and its decomposition across the MSA-size distribution for the period between 1990 and 2020. Following Giacoletti (2021), we

[38] For a full description of the methodology please refer to Giacoletti (2021).

define total house price growth variation as the sum of idiosyncratic risk and local house price risk. We measure local house price risk as the standard deviation of the yearly growth of the local house price index. We divide the 248 MSAs into increasing size bins according to their population in 1990. The first row shows that local risk increases slightly with MSA size. This finding might seem counter-intuitive at first glance,[39] but can be explained by the observation that large urban centers tend to have tighter housing supply constraints,[40] which amplify shocks to house prices leading to higher house price index volatility.[41] However, the differences are not statistically significant. Additionally, as shown in the last section, overall house price growth co-varies less with income in the largest MSAs.[42] Conversely, idiosyncratic risk is substantially smaller in the largest cities and clearly decreases with MSA-size.

Next, we look at total house price risk. As idiosyncratic house price risk represents the major share of total house price risk across the entire MSA-size distribution (Row 3), the pattern of idiosyncratic risk across MSAs is reflected in the distribution of total risk. Consequently, Row 4 of Table 14 reveals that total risk also decreases with MSA-size. While the smallest MSAs had on average an annual total house price risk of 13.61% of the sales price of a house between 1990 and 2020, the largest MSAs had a considerably lower total risk of 11.63% relative to the sales price.

F Co-variance risk distribution and MSA-level betas

In this section we show that the co-variance between excess housing returns and income growth decreases almost monotonically across the city-size distribution. Next, we show that also MSA-level housing betas are lower for large cities.

Figure 9 plots the average co-variance between excess housing returns and income growth

[39]This result is, however, not new, but has already been shown for example in Bogin, Doerner, and Larson (2018).

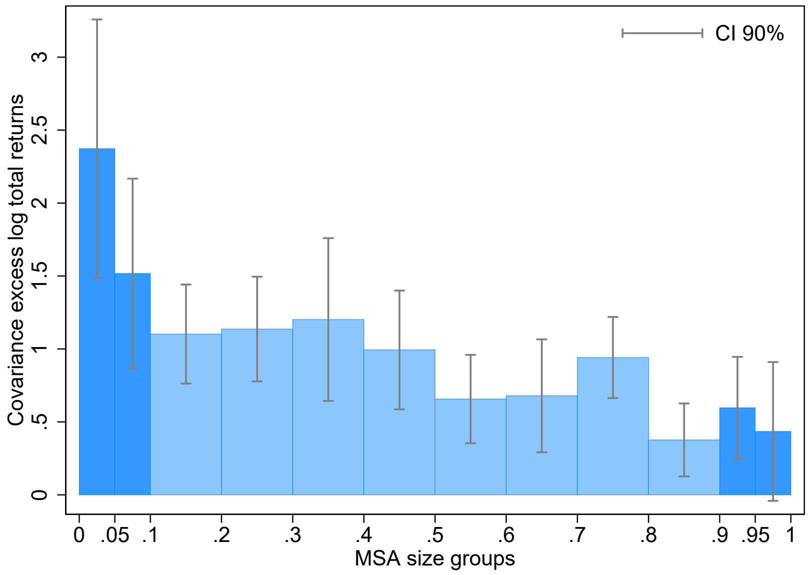
[40]See, for example, Saiz (2010).

[41]See Paciorek (2013) for a theoretical and empirical explanation of the relation between housing supply constraints and house price index volatility.

[42]Moreover, tighter supply constraints imply that house price increases will be higher in reaction to positive demand shocks. As housing supply cannot be decreased easily in all cities, the effect of negative demand shocks will be much more comparable between constrained and unconstrained cities. Tighter supply constraints, therefore, are comparable to an option value for positive demand shocks without bearing a higher risk if demand shocks are negative.

by MSA-size group for the period between 1950 and 2018. We can see that the co-variance is significantly positive for the smallest MSAs, and decreases almost monotonically with MSA-size. For the largest MSAs the estimated co-variance is not significantly different from zero.

Figure 9: *Co-variance between log excess total housing returns and log income growth by MSA size, 1950-2018*



Note: The figure shows the co-variances for different MSA size groups for the period between 1950 and 2018. For clarity the co-variances are multiplied by 10,000 MSAs are divided into bins based on the size of MSA population in 1950. The middle 8 bins cover size deciles 2 to 9. The 4 extreme bins split the smallest and largest deciles in half.

We calculate MSA-specific betas as:

$$\beta_s = \frac{Cov(R_s - R_f, y_s)}{Var(y_s)},$$

where R_s is total real log housing return for MSA s, R_f is total real log return on short-term US t-bills and y_s is average real log income growth in MSA s. We calculate income betas for the period between 1950 and 2018.[43] We then test whether income betas are smaller in large MSAs. The results are depicted in Table 15 column 3. It shows that income betas of total housing returns are indeed significantly smaller in large MSAs compared to the rest. The difference becomes

[43]Note that given the decadal frequency of the data, we have overall 7 data points for each variable MSA combination.

larger when we compare the largest MSAs to only the smallest ones.

Table 15: *Differences in income betas by city size, US, 1950-2018*

Sample	Capital gain	Rental Yield	Total return	N
Large vs rest	-0.23*** (0.036)	-0.24*** (0.018)	-0.29*** (0.033)	2212
Large vs small	-0.57*** (0.079)	-0.35*** (0.032)	-0.66*** (0.073)	217

Note: The table shows differences in income betas for log excess total returns, log excess capital gains and log excess rental yields between large MSAs and the rest of the sample or small MSAs. Differences are measured as coefficients in a cross-sectional regression of the dependent variable (income beta) on a large MSA dummy. Robust standard errors in parenthesis. Large MSAs are defined as being at or above the 95th percentile of the MSA population distribution in 1950. The second row shows the same, but comparing large MSAs only to small MSAs, which are defined as being at or below the 5th percentile of the MSA population distribution in 1950. Overall, we use estimates for 316 MSAs between 1950 and 2018. $* : p < 0.1; ** : p < 0.05; *** : p < 0.01$.

We do the same analysis for the two components of log total returns: log capital gains and log rental yields. We calculate the income betas for each one of the components separately. The results can be found in Table 15 columns 1 and 2, which also show that betas for both components are smaller in the largest cities.

G Additional results on housing liquidity

US: Table 17 and Table 17 show the liquidity measures for the US over the entire city-size distribution.

Table 16: *Cross-sectional differences of time on the market for 277 MSAs, 2012-2020*

	1	2	3	4	5	6	7	8	9	10
mean	114.92	97.31	107.26	98.96	107.84	101.26	93.60	99.61	89.69	85.56
sd	39.37	27.72	29.42	30.54	32.51	27.81	26.55	26.98	24.86	25.69

MSAs are divided into decile bins based on the size of MSA population in 2010. Decile represents the 10% *smallest MSAs. Each bin contains between 27 and 28 MSAs. Data on the median number of days on Zillow from Zillow.com for 277 MSAs for the period between 2012 and 2020.*

Germany: We analyze two liquidity measures for Germany, which are connected to the thickness of the housing market. Using data from the online real estate marketplace *immobilien-scout24.de*, we test whether large cities in Germany have a stronger supply and demand for

Table 17: *Cross-sectional differences of asking price discount in p.p. for 277 MSAs, 2012-2020*

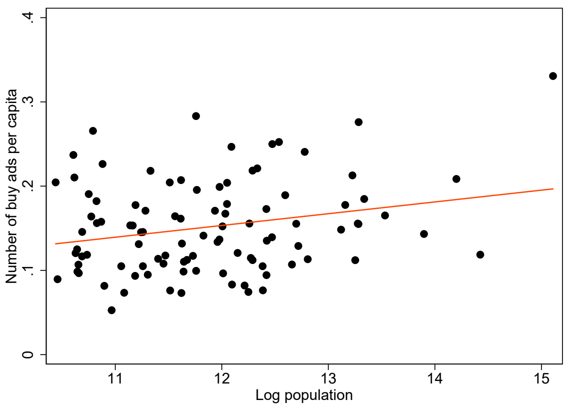
	1	2	3	4	5	6	7	8	9	10
mean	114.92	97.31	107.26	98.96	107.84	101.26	93.60	99.61	89.69	85.56
sd	39.37	27.72	29.42	30.54	32.51	27.81	26.55	26.98	24.86	25.69

MSAs are divided into decile bins based on the size of MSA population in 2010. Decile represents the 10% smallest MSAs. Each bin contains between 27 and 28 MSAs. Data on the average discount to the asking price from Zillow.com for 277 MSAs for the period between 2012 and 2020.

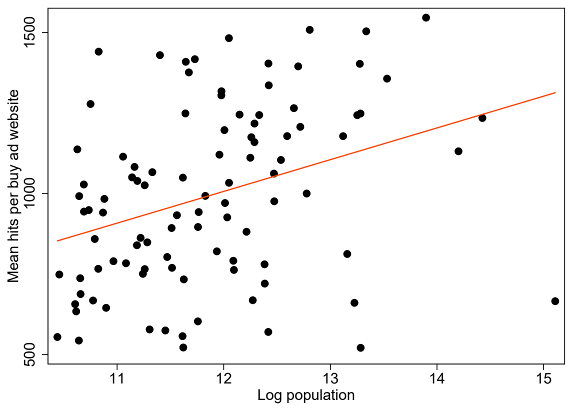
housing. We first look at the supply side by analyzing the number of sales ads posted per capita in each city. The results can be found in panel (a) of Figure 10. It shows that in larger cities there are significantly more ads posted per capita. This indicates that even on a per capita basis, housing supply is larger in large cities. We next quantify demand for housing. To do so, we look at the number of hits per sales ad by city. Figure 10 panel (b) shows that in large cities housing ads receive substantially and significantly more hits, and therefore have more potential buyers, than in small cities. This indicates that, even relative to a higher supply, demand per supplied unit is substantially larger in large cities.

Figure 10: *Thickness of the housing market by city size, Germany*

(a) *Number of ads per capita*



(b) *Mean hits per ad*



Note: The figure shows (a) the number of real estate sales ads per capita and (b) the median clicks per sales ad on city level for 98 German independent city counties (kreisfreie Städte) between 2007 and 2019 by population size in 2015. All data is from the largest German listing website for real estate ImmoScout24. In a regression including year fixed effects, log population is significant at the 1%-level for both panels. For details about the data source please refer to Klick and Schaffner (2020).

The results based on German data are very insightful because they measure liquidity on a per sale or per capita basis. The fact that there are mechanically more sales and inhabitants in larger cities amplifies the effect. Other local housing market characteristics might additionally reinforce the link between larger liquidity and lower risk in large cities. For example, large cities might have more institutionalized housing markets, which further reduce matching frictions and can make better use of the more abundant information from comparison prices.

H Rental yield risk and city size

In this section, we provide evidence on spatial differences in rental yield volatility. Rental yields at the property level are defined as the rental income of a property divided by its potential sales price. Consequently, volatility in rental yields can have two possible sources: changes in rental income or changes in the sales price. Changes in rental yields driven by changes in the sales price are negatively related to changes in capital gains. To see why, consider the following simplified example: Assume a property at time t has a rental yield of 5%. At time $t+1$, its price doubles, but the rental income stays constant. This leads to a capital gain of 100 percentage points in t+1, but its rental yield is reduced to 2.5%, such that total returns only change by 97.5 percentage points. The negative co-variance between rental yields and capital gains at the property level attenuates capital gain volatility, but only to a small extent.[44]

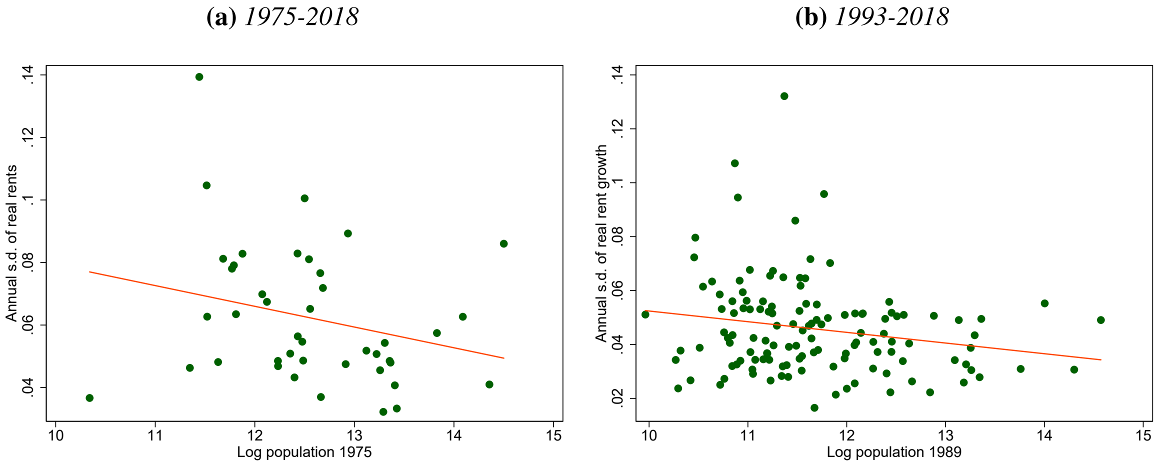
The other source of rental yield volatility are changes in the rental income of a property. We can decompose volatility in rents in a location-wide and an idiosyncratic component. In the remainder of this section we show empirical evidence that suggests that, if anything, both components of rental income risk are lower in large cities.

First, we analyze location-wide rent risk. Unfortunately, there does not exist a data set with long-run annual rent data on city- or MSA-level for the U.S. However, the German data set we use in section 4.2 does feature rent indices for a large cross-section of German cities. We use these data to calculate location-wide rent volatility on city level. Figure 11 plots volatility in annual rent growth by city size. For both samples, one of 42 cities for the period between 1975 and 2018 (left hand side) and the other of 127 cities between 1993 and 2018 (right hand side),

[44] Eichholtz et al. (2020) also find a negative co-variance of rental yields and capital gains empirically.

rent growth volatility is smaller in larger cities.

Figure 11: *Real rent growth volatility and population, Germany*



Note: Standard deviation of real rent growth for 42 German cities between 1975 and 2018 (Panel (a)) and for 127 German cities between 1993 and 2018 (Panel (b)). More details on the data sources can be found in the Data Appendix.

Next, changes in rental vacancies also induce volatility in rental income of a property. One the one hand, for a large-scale investor with a high number of rental units within a city, volatility of city-level vacancy rates add to location-wide rental income risk. On the other hand, for a small property owner with only one rental unit, a higher city-level vacancy rate induces a higher idiosyncratic risk, because it increases the probability that his one unit is vacant. We use data from the American Housing Survey from the period between 1985 and 2020 for 49 MSAs to compare vacancy rates between large and smaller MSAs. The results can be found in Table 18. It shows that the mean as well as the standard deviation of annual rental vacancies is lower in large cities.

Both pieces of evidence suggest that location-wide risk in rental income is smaller in large cities. Regarding idiosyncratic risk, the problem is that, to the best of our knowledge, no data set exists that covers rental income at the property level over a long-enough time period for a cross-section of cities. However, as we argue in section and is shown by Giacoletti (2021), Sagi (2021) and Kotova and Zhang (2019), idiosyncratic risk in capital gains is mainly driven by liquidity in the housing market. As the rental market is not fundamentally different from the

Table 18: *Differences in mean and standard deviation of rental vacancies in p.p., US, 1985-2020*

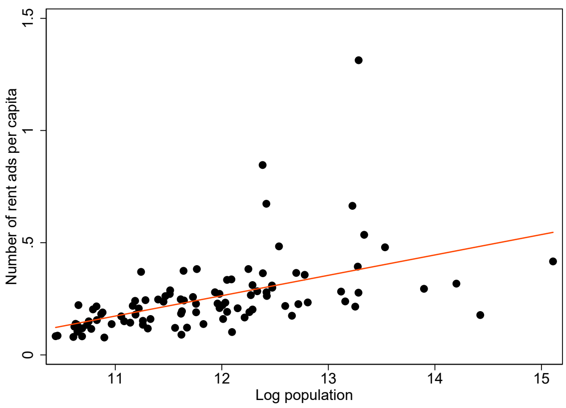
Sample	Mean	N	S.d.	N
Large vs rest	-2.06*(1.093)	1372	-0.73***(0.169)	1372
Large vs small	-1.25 (1.415)	168	-1.06***(0.274)	168

Note: The Table shows the difference in rental vacancy rates between the 5% largest MSAs in terms of 1970 population relative to the other MSAs in the sample (Row 1) and to the 5% smallest MSAs (Row 2). The data covers 49 MSAs for the period between 1985 and 2020 and is collected from the American Housing Survey.

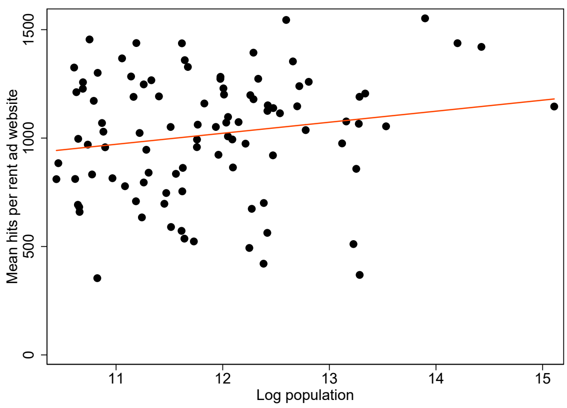
house sales market, we also expect liquidity to play a considerable role for idiosyncratic risk of rental income. Unfortunately, we cannot use the liquidity measures for the US for the rental market that we use for the house sales market. However, we can replicate the two measures we use for liquidity in Germany also for the rental housing market. Figure 12 shows the results, which are, if anything, even stronger then for the house sales market and highly significant. This strengthens the assumption that idiosyncratic rental income risk is, if anything, smaller in large cities.

Figure 12: *Thickness of the rental market by city size, Germany*

(a) *Number of ads per capita*



(b) *Mean hits per ad*



Note: The figure shows the number of rental real estate advertisements per capita (Panel (a)) and the median clicks per rent advertisement (Panel (b)) on city level for 98 German independent city counties (kreisfreie Städte) between 2007 and 2019 by population size in 2015. All data is from the largest German listing website for real estate ImmoScout24. In a regression including year fixed effects, log population is significant at the 1%-level for both panels. For details about the data source please refer to Klick and Schaffner (2020).

To summarize, the evidence presented in this section is only suggestive, because we cannot calculate rental yield volatility at the property level for a cross-section of cities. However, each piece of evidence points at a lower rental yield volatility in large cities compared to smaller ones. This suggests, that, if anything, including rental yields volatility would increase the risk differences between large and small cities.

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