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# Housing segregation in Chinese major cities: A K-nearest neighbor analysis of longitudinal big data

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A R T I C L E I N F O

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A B S T R A C T

Most studies on residential segregation in China have primarily relied on decennial population census data, which lacks the granularity and timeliness needed to capture segregation dynamics with higher frequency. Drawing on georeferenced housing market transaction data between 2012 and 2023 in Shanghai and Beijing, and employing fine-grained spatial segregation analysis techniques, including k-nearest neighbor approaches ($k-$NN) and modifiable grids, we find that housing segregation by price and size increased between 2012 and 2018, followed by a decline thereafter, particularly in the larger-sized and higher-priced market segments. While segregation levels are generally comparable between the two cities, Shanghai exhibits higher segregation for the top 20 % of apartments, while Beijing shows greater segregation for the bottom 20 %. Segregation is highest for prices, followed by rents, with housing size showing the lowest segregation. Expanding the analysis to 11 major Chinese cities, we suggest that high and rising housing prices are associated with increasing segregation, particularly in cities with lower initial segregation. Methodologically, this paper demonstrates that leveraging big transaction and listing data, alongside utilizing fine-grained spatial analysis, can advance our understanding of urban inequalities.

## 1. Introduction

Residential segregation has long been recognized as a significant marker of socio-economic inequality in urban areas and is closely linked to a wide range of social and health outcomes (Carter & Zimmerman, 2022; Krysan & Crowder, 2017). Traditionally, socio-economic residential segregation has been measured through proxies such as income, occupation, hukou, and housing tenure (Lu et al., 2023; Shen & Xiao, 2020; Van Ham et al., 2020), helping to explain how different social groups are distributed across neighborhoods. However, as Owens (2019) argues, residential outcomes are shaped not only by the socio-economic characteristics of households but also by the features of the housing they can access. Housing type, cost, and location play a critical role in shaping spatial inequality, influencing where people live and how neighborhoods evolve.

Housing segregation can be defined as the uneven distribution of housing units across urban space based on characteristics such as price, size, type, or tenure. Unlike traditional population segregation studies, housing segregation focuses on the spatial arrangement of housing units, reflecting the spatial inequality of urban housing resources. This segregation can be more than a mere reflection of socio-economic disparities; it is a dynamic mechanism that both mirrors and reinforces social stratification. By constraining different social groups' access to urban resources and opportunities, housing segregation profoundly impacts residents' quality of life, social mobility, and overall urban well-being.

Moreover, housing segregation provides an important lens through which to view wealth and income segregation. While rents are closely tied to income (Davis & Ortalo-Magné, 2011), housing prices reflect housing wealth, which is particularly significant in China, where 70 % of household wealth is tied to property (Xie & Jin, 2015). Recent research has further demonstrated that housing wealth dynamics may reinforce existing income inequalities, as lower-income households experience disproportionately smaller increases in housing wealth compared to their higher-income counterparts (Long et al., 2025). Therefore, examining housing segregation adds a crucial dimension to understanding socio-economic segregation in rapidly changing urban environments.

Chinese first-tier cities experienced an unprecedented boom in housing and rental prices during the first two decades of this century, followed by a significant downturn (Hodges, 2024). However, this boom

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and bust were not uniform across neighborhoods, with some neighborhoods experiencing much steeper increases or declines than others (Wang et al., 2018). The uneven fluctuations in housing prices and rents raise important questions about how these changes have reshaped socio-economic segregation in Chinese cities.

In urban China, segregation across large administrative neighborhoods (*juweihui*) was found to increase before 2010 (Shen & Xiao, 2020), but has stagnated over the recent decade despite the housing price boom (Song et al., 2021). Most studies on residential segregation in China rely on decennial census data, which lacks the granularity and high frequency needed to capture short-term segregation dynamics. In contrast, housing transactions and rental advertisement data offer several key advantages. First, they are more accessible and regularly updated, providing real-time insights into housing market trends. Second, these datasets are highly granular and georeferenced, allowing for more precise analyses at fine geographic scales. Third, the ability to track recent fluctuations in housing prices and rents enables researchers to better understand current trends. Finally, such data are widely available across cities and countries, facilitating standardized comparisons of segregation levels over time and across locations. Methodologically, the georeferencing of this data allows for more detailed segregation measures, moving beyond the coarse administrative boundaries of traditional studies and enabling a more nuanced understanding of how segregation evolves within and between cities.

This paper therefore proposes to investigate housing segregation in Shanghai and Beijing, using 1.6 million secondhand housing transaction records from 2012 to 2023, 2.6 million transacted new units since 2006 and about 40,000 rental advertisements from 2024. These datasets are sourced from a Secondhand Housing Big Data Platform and a real estate service platform in China called Lianjia.[1] Using the k-nearest neighbor (k-NN) approach (Östh et al., 2015), along with a small-scale grid-level method for robustness, we find that housing segregation significantly increased in lower-priced market segments up until 2018, after which it stagnated or even declined. Segregation levels are generally comparable between the two cities; however, in Shanghai, the top-20 % priced apartments are more segregated, while in Beijing, the bottom-20 % priced apartments experience greater segregation. Housing segregation is particularly high at the extremes of the distributions, with the bottom-20 % and top-20 % priced and sized apartments driving segregation most. Segregation levels are highest in terms of secondhand and new housing transaction prices, followed by rental prices and lowest for housing sizes. A multivariate analysis suggests that rising house prices are associated with higher levels of segregation and increases in segregation over time. This paper contributes to segregation studies by introducing an innovative combination of data and methods for studying housing segregation in contexts where detailed and high-frequency data are often scarce. By utilizing large-scale real estate transaction data and applying the k-nearest method to address common spatial analysis challenges, this study enhances both the accuracy and timeliness of segregation measurement and allows for standardized comparisons across various urban settings.

The paper is organized as follows. After a review of the relevant literature, we present a detailed description of the real estate data and spatial methods. We then provide the cross-sectional and longitudinal results for both cities. In the discussion, we connect our quantitative findings to the broader context of urban housing in China. Finally, the conclusion underscores the potential of applying our methodological approach to future research and to studies in other countries.

[1] Lianjia is one of the largest and most trusted property platforms in China offering a wide range of housing-related services, including up-to-date rental listings. However, since rental listings on Lianjia are not archived, only snapshot data from April 2024 was used for this study.

## 2. Literature review

While housing segregation may not have received as much attention in research, there is a substantial body of literature dedicated to examining residential segregation. Residential segregation refers to the extent to which two or more groups live separately in different parts of the urban environment (Massey & Denton, 1988), often segregated by racial or ethnic identity (Wu et al., 2023), age (Milias & Psyllidis, 2022), or by socio-economic indicators such as occupation (Van Ham et al., 2020), income (Zhang et al., 2021), or educational attainment (Musterd et al., 2017). In China, the existing literature on residential segregation predominantly relies on neighborhood-level decennial census data and investigates segregation based on various socio-economic dimensions including income, occupation, hukou status, tenure, and education (He et al., 2022; Li & Wu, 2008; Lu et al., 2023; Shen & Xiao, 2020). These studies have generally reported traditionally low levels of socio-economic segregation in large Chinese cities, with an increasing trend toward Western levels in the late 2000s (Pan et al., 2021; Shen & Xiao, 2020). However, there has been limited research that examines how socio-economic segregation has evolved since the 2010s, primarily due to challenges related to data availability.

Remarkably, housing—humanity's most essential living space—has been under-researched in the field of residential segregation, both in China and globally. Housing choices not only reflect individuals' economic and social resources, knowledge of available options, preferences, and demographic characteristics (Owens, 2019) but also exacerbate income and wealth disparities by influencing access to education, social networks, job opportunities, and exposure to crime in different residential areas (Dwyer, 2014). Additionally, as housing space is directly tied to residents' quality of life and well-being (Foye, 2017; Li et al., 2023), housing space segregation may reflect unequal living conditions and reinforce psychological stress and socio-economic inequality. Housing segregation also limits social mobility by restricting lower-income households' ability to move into wealthier areas that offer better educational and professional opportunities (Baker et al., 2016). This 'lock-in' effect, reinforced by the entrenched ideologies of 'asset-based welfare,' deepens socio-economic divides and perpetuates inequality across generations (Arundel, 2017). Consequently, housing segregation may not only mirror existing socio-economic disparities but also perpetuate them, contributing to intergenerational inequality (Cui et al., 2020).

The study of housing segregation is particularly pertinent in China for several reasons. First, housing wealth constitutes the largest asset for Chinese households (Xie & Jin, 2015). Thus, housing segregation offers a valuable lens through which to examine the broader landscape of wealth segregation in China, particularly in the absence of geo-referenced wealth data. Second, in Chinese culture and traditions, the home is not only a place to live but a symbol of well-being and social status (Huang, 2004). For example, homeownership is often considered a prerequisite for marriage (Huang et al., 2021; Jin et al., 2022), making housing segregation a more pronounced indicator of socio-economic stratification in China than in many other nations. Third, housing in China is closely tied to access to various social benefits, including education, healthcare, and employment opportunities (Li et al., 2024). Policies such as school district zoning play a pivotal role in determining access to educational resources and opportunities for students residing within specific residential boundaries (Wen et al., 2017). Consequently, housing segregation is not only a driver of educational inequality but also a significant barrier to broader social mobility (Cui, 2020). Lastly, over the past two decades, China's real estate market has undergone considerable fluctuations. Rapid urbanization, large-scale housing development, speculative investments, and a recent market downturn, coupled with uneven resource distribution across cities, have led to considerable variations in housing prices (Wang et al., 2018). These dynamics have reshaped housing segregation patterns, making China a compelling case for examining the evolution of housing segregation and its broader socio-economic implications.

Despite the scarcity of research, a number of studies have delved into housing segregation. Li and Wu (2008), utilizing the 2000 population census data, examined the spatial distribution of housing tenure in Shanghai, revealing that residential segregation is predominantly tenure-based rather than socioeconomic. Similarly, Lu et al. (2023) analyzed the 2010 census data to investigate the distribution of commodity and work unit housing in Shanghai, assessing their correlation with neighborhood socioeconomic status and amenities. These studies underscore the significant role of housing in shaping residential and socio-economic segregation. Nevertheless, such analyses are constrained to the residential committee (juwei[2]) level—the smallest census tract—limiting the geographical scale of segregation studies. Moreover, while housing tenure is an important aspect, other housing characteristics such as price, rent, and size can offer a more comprehensive reflection of segregation patterns. For instance, Li et al. (2023) observed that different housing submarkets exhibit unique attributes, such as spatial area and rent levels, leading to varying degrees of residential satisfaction and social exclusion. Yet, due to the limited data availability, analyses of housing segregation based on these dimensions remain rare.

Owens (2019) presented pioneering evidence on the extent of housing segregation by type and cost across multiple geographic scales within major metropolitan areas, underscoring the pivotal role of housing in the analysis of residential segregation. Her findings reveal an increase in housing segregation by unit type, while noting a decline in segregation by cost across most metropolitan regions, albeit with notable regional and temporal variations. These results underscore the complexity of housing segregation as a multi-dimensional phenomenon that requires analysis across a spectrum of housing characteristics and geographic scales, with an emphasis on comparative studies across different regions and time frames.

Song et al. (2021) advanced the study of housing segregation in China by leveraging real estate transaction data from the China Real Estate Price Platform. Their research shed light on the distinct patterns of housing price segregation in Nanjing and Hangzhou from 2009 to 2018, broadening the understanding of residential segregation beyond traditional socio-economic indicators. However, while Song et al. (2021) aimed to address multi-scalar residential segregation, their analysis is predominantly focused on housing price segregation at different geographic scales, such as tracts, blocks, and grids. This specific focus on housing prices does not fully capture the complexity of housing segregation.

A salient point of critique is that property transactions are confined to homeownership. In China's first-tier cities, characterized by exorbitant housing costs, homeownership is largely accessible only to wealthier segments of society. A significant portion of the population resides in rental properties, and their segregation is better captured by rental prices rather than housing transaction data. Additionally, rental prices often more accurately represent the living conditions of a dwelling than sale prices. For instance, certain "aged, deteriorated, and small properties" (*laopoxiao*) may command high market prices due to their prime urban locations or proximity to sought-after schools, despite offering substandard living conditions (Pan et al., 2021). Therefore, a comprehensive assessment of housing segregation requires the consideration of multiple factors beyond just housing prices.

Our research addresses key gaps in the literature by leveraging web-scraped housing transaction data (2012–2024) and rental listing data (2024), providing both longitudinal and cross-sectional data. These geographically referenced data enable granular analysis of segregation. We examine housing characteristics, such as rent, transaction price and size. Additionally, we introduce the k-NN method for measuring segregation, which transcends administrative boundaries and allows for cross-city comparisons. The robustness of our findings is further validated using variable grid sizes sensitive to small-scale segregation.

## 3. Data and methods

Data were web-scraped from the Secondhand Housing Big Data Platform (https://ershoufangdata.com), which aggregates secondhand housing transaction data from major real estate brokerage platforms in China, such as Lianjia and Woaiwojia. This platform covers transactions across 11 major Chinese cities. Our in-depth analysis focused on Beijing (2012−2023) and Shanghai (2015–2023), with additional statistics on all new housing units transacted (starting in the late 2000s) from CREIS Data (https://www.cih-index.com), a leading dataset provider.

To validate the representativeness of our transaction data, we conduct coverage analysis for both markets and comprehensive price pattern comparisons for secondhand housing. For newly built housing, our dataset provides comprehensive coverage of all new residential developments in both cities (2.6 million since 2006). For secondhand housing, after cleaning the data by removing outliers (prices above 300,000 yuan/sqm or below 500, sizes below 5 sqm) and duplicates (uniquely identified by residential complex, transaction date, and size), our dataset comprises 1.6 million transacted units, representing approximately 50 % coverage in Beijing and 20 % in Shanghai.

To verify the representativeness of our secondhand housing sample, we conduct two sets of comparisons with CREIS data (see Appendix A1). First, compared with full transaction records, our sample closely tracks the market-wide median prices in both cities. Second, when compared with listing prices, our sample prices follow the same trend and are generally 5–10 % lower than CREIS figures, which is consistent with typical transaction data pattern as listed prices tend to be higher than final transaction prices. The comprehensive coverage of new housing and substantial market coverage of secondhand housing, together with the consistency in both trend and absolute values across these comparisons, indicate that our sample effectively represents the full spectrum of housing prices across different market segments in both cities. Yet, to what extent the transaction data are representative of the entire building stock is a different question, as online housing data may not evenly represent all market segments (Boeing, 2019).

Beijing and Shanghai were selected as China's two largest first-tier cities, with distinct characteristics that make for an interesting comparison. Beijing, as the political center, and Shanghai, as the economic hub of China, operate under different governing philosophies. The local governments in these cities have varying degrees of liberalism and corresponding housing policies, which makes the comparison of housing segregation particularly insightful. While recent studies have predominantly focused on second-tier cities, such as Nanjing and Hangzhou (Song et al., 2021), the contrasting philosophies and policies between Beijing and Shanghai offer a fresh perspective on how these dynamics influence housing segregation, an area that has been largely unexplored in existing research. Additionally, we web-scraped one rental housing listing snapshot in April 2024 for analyzing segregation based on rents (as past rental offers are not archived). The data were obtained using R scripts for web-scraping, then cleaned and organized into a dataset including information on price, size, neighborhood location, and geo-references. To streamline computations, geo-references were converted to the WGS 84 geographic coordinate system (and using the CGCS2000 3° Gauss-Krüger zone projection for mapping), and records with missing essential information were excluded. This process results in 396,000 secondhand transactions in Shanghai and 1.2 million in Beijing, 1.7 million and 928,000 new housing transactions, respectively, while the number of rental listings from 2024 amounted to 20,000 for each city. To ensure robustness, we incorporated supplementary data from nine additional cities—including Shenzhen, Guangzhou, and Tianjin—representing a total of 2.6 million secondhand transactions since 2014. This additional data was used for robustness checks, as the

[2] A juwei accommodates on average 4200 individuals in Shanghai (Lu et al., 2023).

application of the k-NN method was constrained by lower transaction volumes in certain years, limiting coverage. This larger number of city-years also enables us to estimate panel regressions, including country, year and quintile fixed effects, of house price levels and changes on segregation levels and changes, using robust standard errors. We include several city-level control variables obtained from local statistical yearbooks: GDP growth to capture economic conditions, log population to account for city size effects, and the migrant share to control for demographic composition. To address potential endogeneity concerns, these control variables are introduced with their first lag, although we acknowledge that this approach does not establish causal identification.

In this study, we mainly use the dissimilarity index of segregation to measure the intra-urban dispersion of prices, rents, and square meter sizes of apartments. This index is one of the most widely used measures of segregation, which accounts for the uneven distribution of a minority population across different neighborhoods compared to a majority population (Massey & Denton, 1988). We adapt this measure by shifting the unit of analysis from population to housing units, incorporating variables such as prices, rents, and housing-size characteristics. As the dissimilarity index requires categorical rather than continuous variables, following good practice in inequality research (Milanovic, 2011), we categorize housing into year- and city-specific quintiles along the distribution of prices, rents and size. Specifically, this classification ranges from the bottom 20 % of properties with the lowest price per square meter and rents to the highest, and from the smallest 20 % of apartments by size to the largest.

In the second step, we examine how unevenly the apartments within these quintile groups are distributed across neighborhoods in the two cities. If, for instance, the bottom 20 % of the cheapest apartments are evenly distributed throughout the city, the dissimilarity index would be 0; conversely, if all the cheapest apartments are concentrated in a single neighborhood, the index would be 1 (or 100 %), which is traditionally interpreted as "100% of apartments would need to relocate to achieve an equal urban housing distribution." This application of the segregation measure to housing suggests that, due to the relative immobility of housing compared to a migrating population, housing segregation may be more persistent and resistant to change (Owens, 2019).

The third step involves selecting the geographical unit of analysis. Cities are traditionally divided into administrative areas, which often carry a cultural meaning and may therefore represent important cultural boundaries. The administrative division has its limitations due to the lack of geographic standardization both within and across cities. The widely-used dissimilarity index has long been criticized for not accounting for the spatial arrangement of census tracts, particularly in relation to the checkerboard problem and the Modifiable Areal Unit Problem (MAUP) (Reardon & O'Sullivan, 2004). In theory, these issues could be resolved by including the precise locations of individuals and their proximity to one another in residential space (Reardon & O'Sullivan, 2004), which is mostly impossible in practice. The dissimilarity index, while initially developed for use with fixed geographical units, can be adapted for use in individualized neighborhoods by treating each person's neighborhood as equivalent to a fixed unit (Malmberg et al., 2018). This approach becomes particularly relevant when working with geo-referenced house price and rent data, allowing for the calculation of two alternative segregation measures: 1) using k-nearest neighboring around every individual, for robustness, 2) using grids of varying side length.

We employ the k-nearest neighbor (k-NN) approach to measure housing segregation. The k-NN method computes individualized neighborhoods for each housing unit based on the shortest distance between two points on a WGS84 ellipsoid. We choose k-NN over alternative spatial approaches (xiaoqu-average analysis or grid-based analysis in Appendix A4) because it offers distinct advantages for cross-city comparative analysis. While fixed-distance methods (including both buffer and grid-based approaches) require specifying a spatial radius that may not be appropriate across different urban contexts, k-NN's use of a consistent number of neighbors (k) provides a more variable approach, more sensitive to the local context without creating artificial grids. Intuitively, if a resident was to compare their home price or size, they would look at their k-nearest observable offers on the market in the neighborhood for comparison instead of using a coarsely defined grid. While grid-level data has been applied in segregation studies (Song et al., 2021; Wong et al., 1999), the k-nearest-neighbor approach, which requires geo-referenced individual register data, is much rarer (Andersson et al., 2018; Östh et al., 2015; Rogne et al., 2020) and, to our knowledge, has not yet been applied to the study of housing segregation.

The unweighted k-NN approach offers higher spatial resolution than grid-based methods because it operates directly at the individual housing unit level, creating unique, overlapping neighborhoods for each observation. In contrast, grid-based approaches aggregate all units within the same cell, potentially masking within-cell variations. Even with our smallest grid size (0.01 degrees, approximately 1 km), all housing units within the same cell are treated identically, while k-NN can detect segregation patterns at much finer scales based on the actual spatial distribution of individual units.

When interpreting segregation measures under k-NN, while the spatial extent of these k neighbors varies with local density (see Appendix A2), the comparison basis (k neighbors) remains consistent. This ensures that each unit's segregation measure is based on the same number of comparison units, regardless of location. The dissimilarity index equals zero when the proportion of each housing quintile in every unit's k-nearest neighbors matches the overall proportions, and equals one when there is complete segregation.

To ensure our findings are robust, we test different k values (50, 100, 200) and complement our analysis with two alternative specifications: traditional administrative unit (xiaoqu or district) level analysis and a grid-based approach with varying sizes (see Appendix A4). The consistency of results across these different spatial specifications validates our methodological choice.

While the formula for computing the grid-level index simply starts from the usual dissimilarity index (Duncan & Duncan, 1955), we draw on Malmberg et al. (2018) in adapting the formula to the k-NN approach, where the denominators are adapted to hold the interpretation and meaning of the dissimilarity index D constant:

$$D = \frac{1}{2}\sum_{i=1}^{S}\left|\frac{q_i}{Q} - \frac{r_i}{R}\right|$$

where $i$ represents an individual housing unit; $S$ denotes the entire set of housing units; $q_i$ is the proportion of one certain housing quintile (either price, size or rent) in the individualized neighborhood of $i$; $Q$ is the sum of all $q_i$; $r_i$ is the proportion of other housing quintiles in the individualized neighborhood of $i$; and $R$ is the sum of all $r_i$. As alternative measure, Appendix A5 also shows segregation based on the information theory index.

## 4. Results

### 4.1. Housing market dynamics

Fig. 1 illustrates house price trends across quintiles for both new and secondhand properties in Beijing and Shanghai. Both cities exhibit a significant upward trajectory in housing prices over time, with a particularly pronounced surge between 2015 and 2017. In Beijing's secondhand market, the median house price increased by 70 % during this period. From 2017 to 2023, prices in the lower three quintiles decreased, while higher-end properties continued to show an overall upward trend. The new housing market in Beijing showed similar temporal trends but at consistently lower price levels across all quintiles. This price differential exists despite new properties typically offering better construction quality, primarily reflecting the less central locations of new developments and their relative distance from established

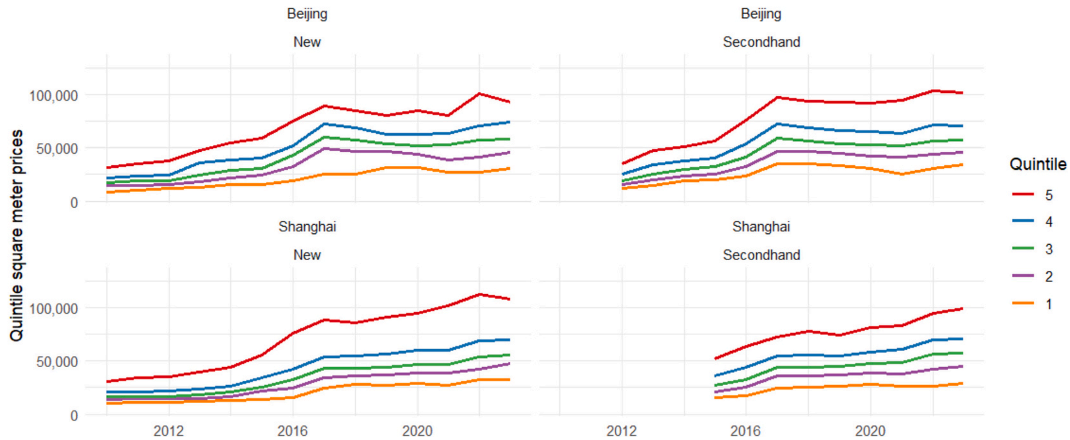


**Fig. 1.** Quintile square-meter-prices over time in Beijing and Shanghai.

amenities and quality schools.

In contrast, Shanghai's secondhand median house prices rose by approximately 50 % between 2015 and 2017, reflecting a somewhat more moderate increase compared to Beijing. After a modest decline from 2017 to 2019, Shanghai experienced a significant price surge from 2019 to 2022, with the median price rising by around 30 %, substantially outpacing Beijing during the same period. From 2017 to 2023, prices in the second to fifth quintiles in Shanghai continued to increase, in contrast to the trends observed in Beijing. Shanghai's new housing market exhibited parallel price movements but, similar to Beijing, maintained lower price levels compared to secondhand properties.

The two markets demonstrate distinct price formation mechanisms throughout the study period, reflecting their different degrees of government intervention. During 2017–2021, new housing prices remained relatively stable due to strict price controls and supply-side regulations, while secondhand prices showed greater volatility. After 2022, this pattern of divergent price movements continued but in the opposite direction: secondhand prices declined while new house prices remained stable with slight increases.

The quintile distribution of the two most important housing attributes, price per square meter and size, are shown for housing transaction records in Shanghai in 2015, 2018 and 2023 (Fig. 2), which mark the earliest and latest comparable year as well as the housing-price peak of 2018. It becomes evident that distribution based on prices generally follows the well-known center-periphery gradient, with higher-priced units and smaller apartments concentrated in the city center. The geographic distribution of apartments by size, as shown in the lower panel, is much more evenly spread than the price distribution. For instance, top-20 % largest apartments can also be found in more peripheral neighborhoods, whereas top-20 % most expensive apartments are far less common in these areas. The comparison over time shows a spatial expansion of higher-priced apartments from the city core into the semi-peripheral areas, alongside an increase in large apartments in the periphery. Similar trends can be observed for Beijing (Fig. 4). While the overall price-distance gradient pattern is similar for newly constructed vis-à-vis secondhand units, as shown in Appendix A2, two key differences of newly constructed units are that they exhibit less spatial concentration (as evidenced by the more dispersed density contours), but that the majority of units tends to be located in more peripheral areas, typically beyond 30,000 m from the city centers, clustered in complexes of very similar units. The density contour plots reveal that secondhand transactions are heavily concentrated in areas closer to the city centers (within 20 km from Tiananmen Square in Beijing and People's Square in Shanghai). Newly built housing exhibits similar price-distance patterns but with more dispersed distribution concentrated in peripheral developments (See Fig. 3. Fig. 5.)

A similar pattern is seen in the rental market snapshot for both Shanghai and Beijing, based on data web-scraped in April 2024, as shown in Fig. 6, which illustrates the quintile distribution of housing by rent prices per square meter and apartment size. The center-periphery inversion of top rents and top-sized apartments is as clear as in the sales market, with the distribution based on size being more equal than the distribution of rents. However, the peripheral expansion of top-rent apartments seems to be less pronounced than the expansion of top-priced apartments in sales market. The prima facie evidence of this geographic picture may have two counteracting implications for housing segregation: the homogenization of prices in the high-priced city center and the low-priced peripheral suburbs may increase micro-segregation, whereas the growing presence of higher-priced and larger units in the (semi-)periphery may reduce segregation. Which of these tendencies prevails, however, needs to be measured more precisely than eyeballing of maps would allow.

### 4.2. Housing segregation snapshot in 2023

To assess how segregated the individual housing units are, we therefore computed the dissimilarity index for each observation and its 50, 100, and 200 nearest neighbors, counting how many apartments of the different price, rent and sqm quintiles are present in their respective neighborhoods, starting with the snapshot analysis of the latest available year. The median distance for the 100 nearest neighbors is 201 and 288 m in Shanghai and Beijing, respectively (new and secondhand markets combined), with distances naturally increasing with the number of neighbors (or k). We then calculate the dissimilarity indices for the quintile groups based on transaction prices per square meter, rents and apartment sizes. Fig. 7 reveals three stylized facts: *first*, both cities display broadly similar levels and patterns of price- and size-based segregation for most housing market segments, represented by quintiles. Notable differences emerge in specific market segments: for instance, Beijing's bottom 20 % priced housing are more strongly segregated than Shanghai's, whereas Shanghai's top 20 % priced and sized apartments are more segregated than Beijing's. *Second*, both cities show a somewhat U-shaped segregation pattern across the distribution, with the priciest and cheapest apartments being the most segregated. This pattern also broadly holds for the segregation by apartment size. Total housing segregation is therefore particularly driven by the extremes of the distribution. *Third*, confirming the evidence from the map analysis, segregation by apartment size generally shows a lower segregation level than segregation by prices or rents, and there is less variation between the two cities in terms of segregation by size. When ranking segregation by different housing characteristics, price segregation is the highest, followed by rents, with size segregation being the lowest.

These results are robust as to different neighborhood definitions,

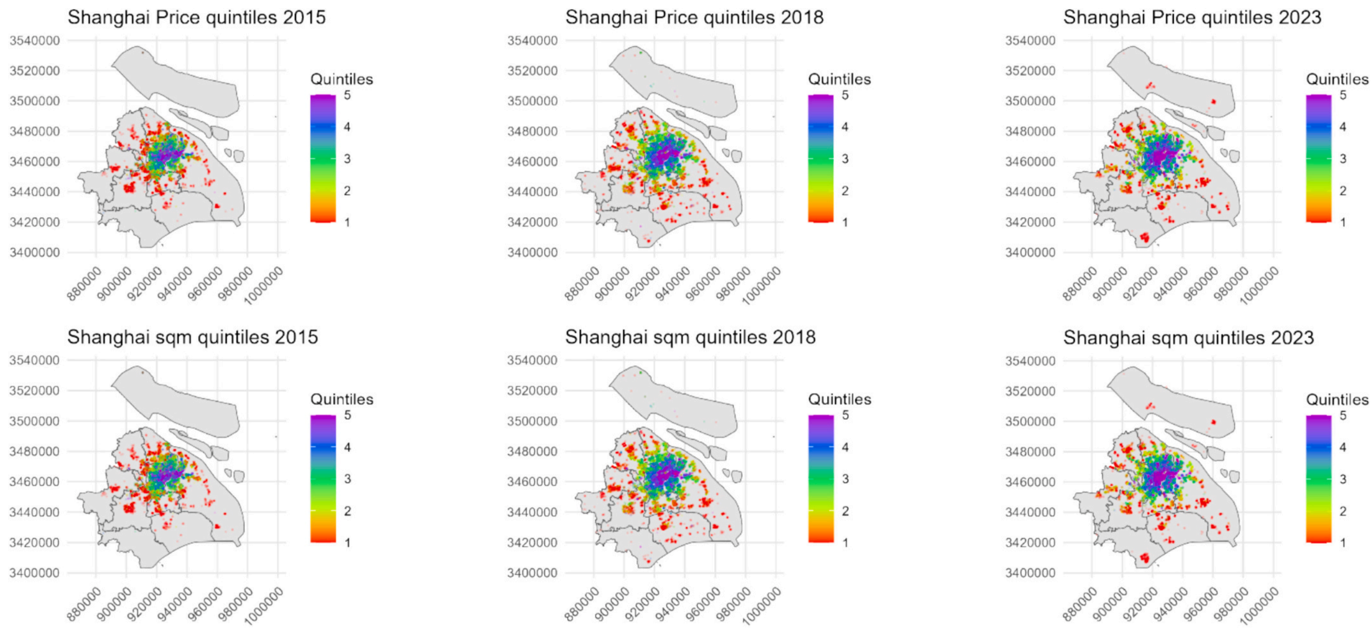


**Fig. 2.** Shanghai secondhand housing transaction distribution over time.
Note: Sqm refers to housing space measured by square meters.

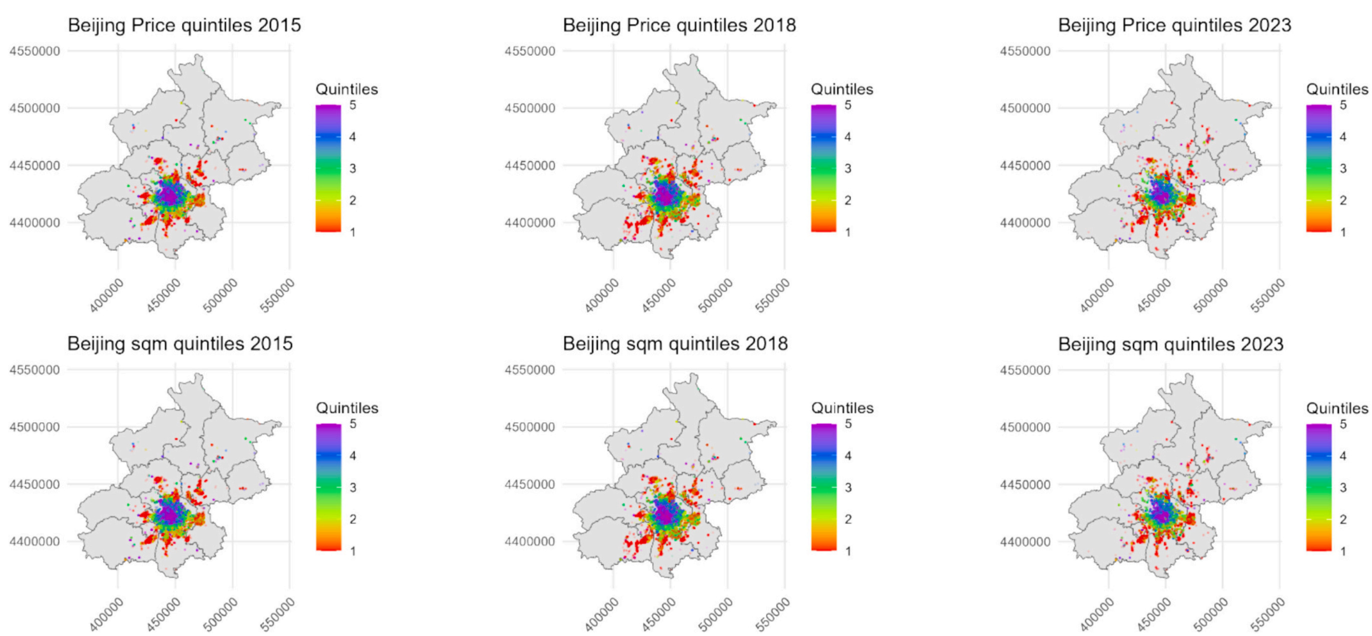


**Fig. 4.** Beijing secondhand housing transaction distribution over time.

ranging from 50 to 200 nearest neighbors. Per definition, smaller neighborhood definitions entail larger segregation levels. The k-NN approach is the spatially most sensitive compared to using administrative area definitions, as it defines individualized neighborhoods for every single housing unit. For additional robustness, we also report the alternative small-scale dissimilarity index computed for each quintile (vs. all other quintiles) and operating for different grid sizes, ranging from 0.01 degrees to 0.2-degree grids. The results, reported in Appendix A4, confirm the three stylized facts above.

### 4.3. *Longitudinal housing segregation trends*

Next, we turn to examine the longitudinal development of housing segregation across different transaction price and size quintiles.[3] Fig. 8

[3] We focus on secondhand rather than new construction prices because the latter's clustering in very few districts makes the estimate of district-level dissimilarity not very reliable. Their k-nearest neighbor-based dissimilarity indices, by contrast, are consistently very high (reaching one), given that most new apartments offered in large complexes are very similar.

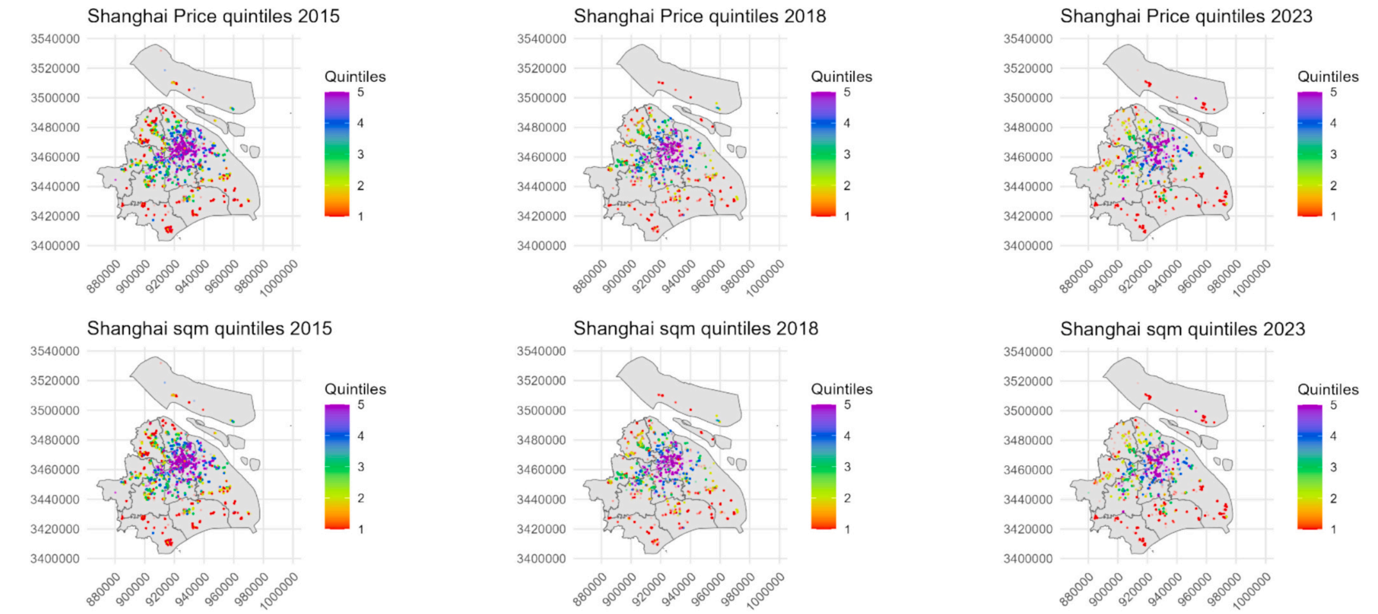


**Fig. 3.** Shanghai newly built housing transactions over time.

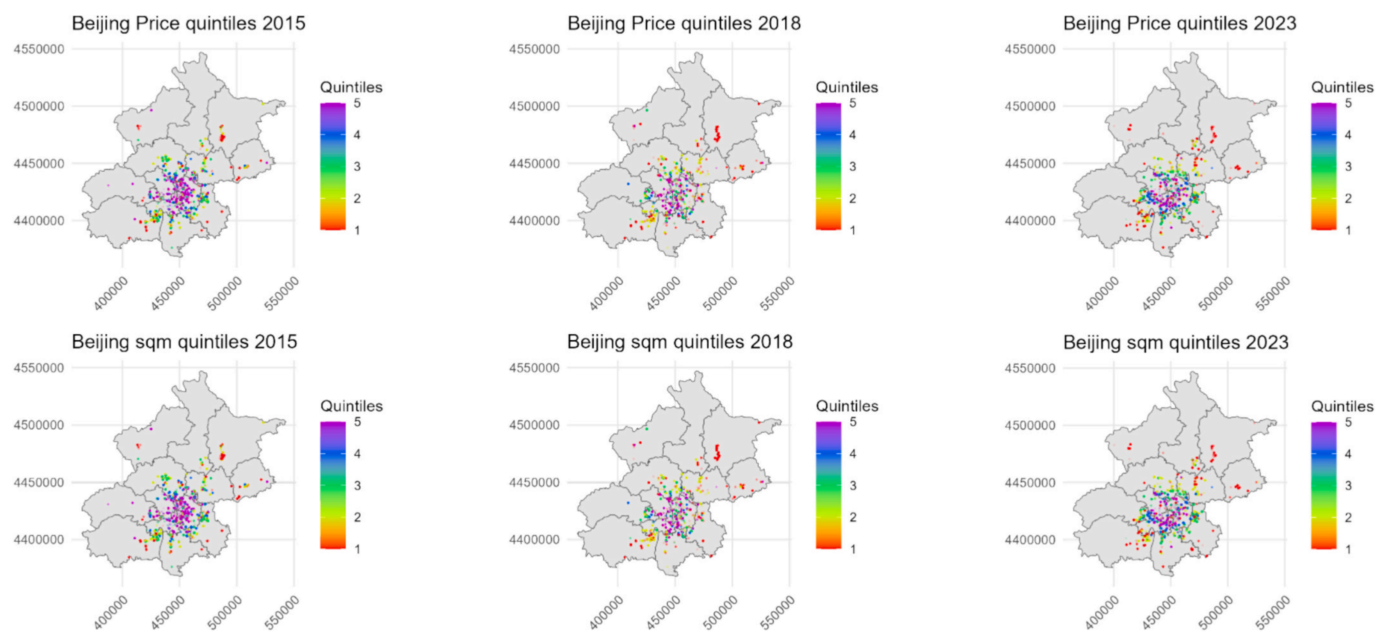


**Fig. 5.** Beijing newly built housing transaction distribution over time.

shows a general upward trend in segregation over time across most housing market segments in both cities until around 2018, after which the trend began to stagnate and even decline. The segregation of cheaper and smaller apartments still remains at higher levels than at the beginning of the reporting period, whereas this pattern holds only for pricier and larger apartments in Shanghai, with declining trends in these market segments for Beijing. Overall, segregation levels across both cities are generally similar, though Shanghai shows higher segregation at the top end of the market, while Beijing is more segregated at the lower end. The U-shaped pattern of segregation along the distribution persists over time, with the top and bottom quintiles being generally more segregated than the middle quintiles. The results hold again for different neighborhood-size definitions and are additionally confirmed by the modifiable grid analysis in Appendix A4.

Fig. 8 indicates 2018 as a pivotal turning point in both price and size segregation levels. Prior to 2018, segregation levels in both Beijing and Shanghai experienced rapid growth. However, after 2018, segregation across all five quintiles in Beijing either stagnated or declined. For Shanghai, in addition to 2018, the year 2020 also marked a significant turning point. Between 2018 and 2020, segregation levels in the first four quintiles decreased, but after 2020, these levels stabilized and even began to rise again. Notably, the segregation trend for the most expensive 20 % of properties in Shanghai did not exhibit significant changes around 2018. It continued to rise until 2020, after which it started to decline. Interestingly, in Beijing, the segregation level of the top 20 % most expensive properties also showed a marked decline after 2020.

The above detailed findings based on georeferenced data are limited to the two major cities (Fig. 8). For another 9 major cities, we can draw on more years between 2014 and 2022, with more than 10,000 transaction records yearly as a minimum threshold. As this is less than

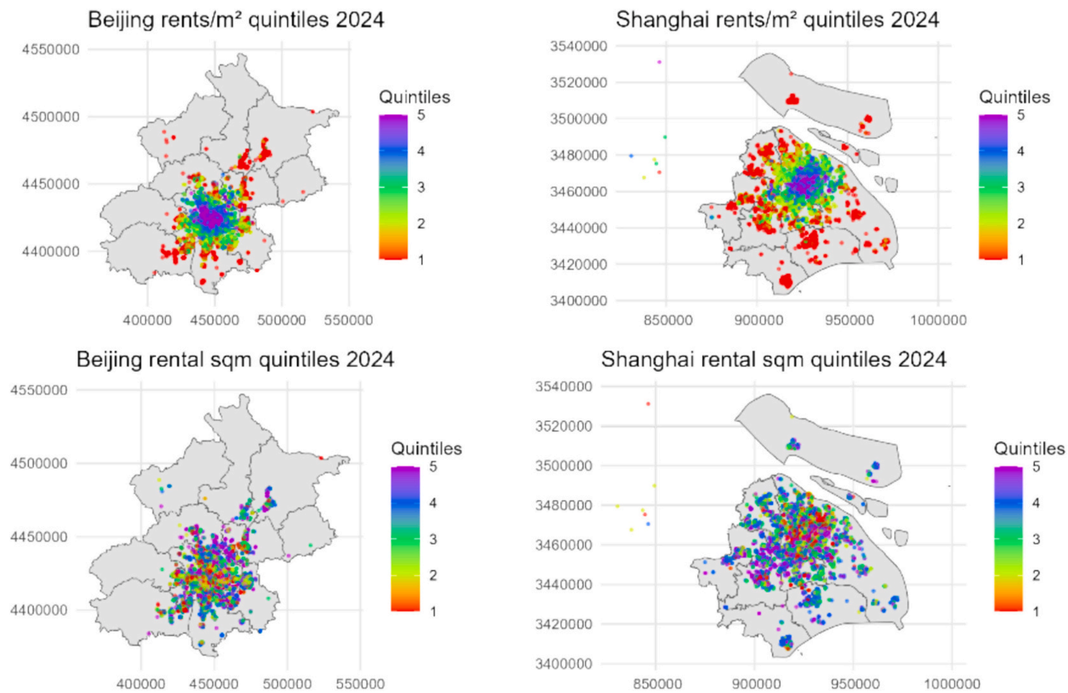


**Fig. 6.** Geographic distribution of rents/m$^2$ and space of rental listings in Beijing/Shanghai 2024.

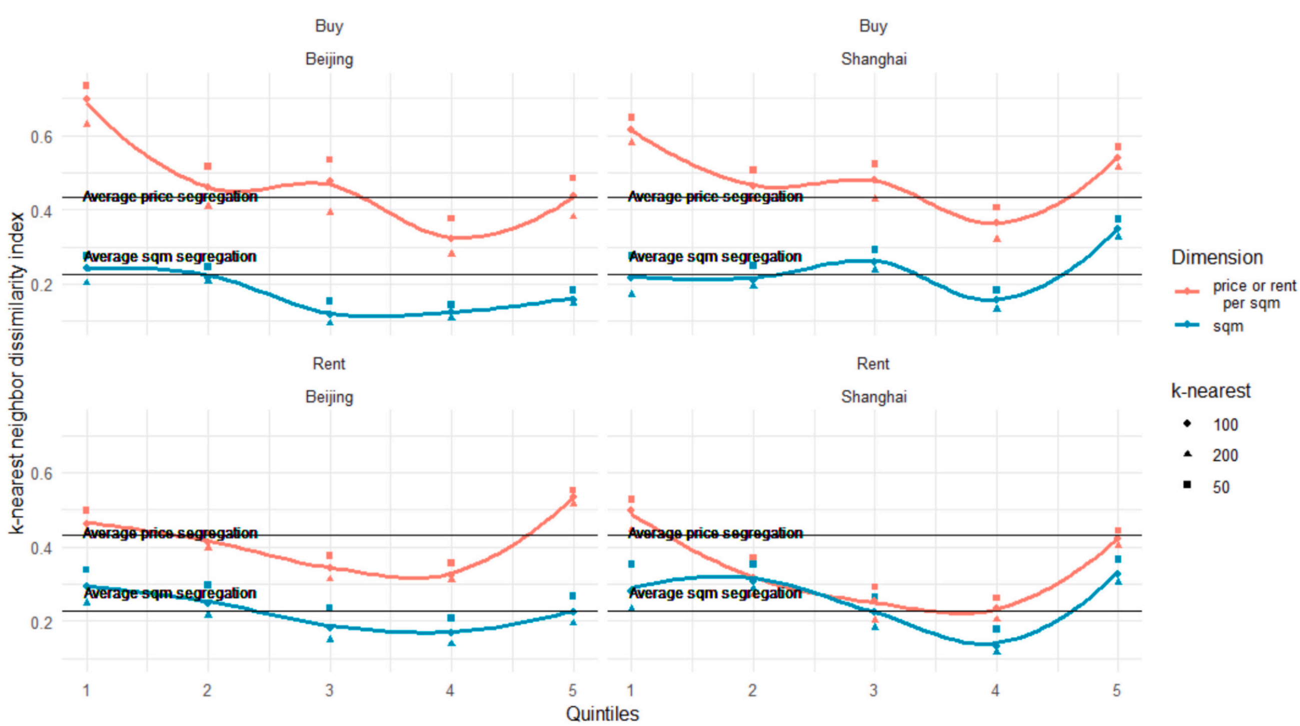


**Fig. 7.** Dissimilarity indices based on 100-nearest neighboring purchase records for secondhand prices and sqm, 2023.

required for a k-nearest analysis, we computed housing segregation indices for the five different price and size quintiles using averages of local districts (*xiaoqu*) as the neighborhood definition. The results found for Shanghai and Beijing are fairly robust (cf. Appendix A4), showing that: 1) price segregation is higher than the apartment-size segregation, 2) both segregations follow a U-shaped curve by quintile, with extremes in the distribution more unequally segregated, and 3) price segregation increased until the late 2010s, followed by stagnation, while size segregation remained relatively flat.

### 4.4. *Housing prices and segregation: a panel analysis*

To analyze the factors influencing housing segregation over time, a fixed-effects regression model is estimated, which accounts for both city-specific factors and time-specific influences, using data from 11 cities between 2012 and 2022. We draw on the full sample of cities, years and quintiles to have a sufficient number of observations. Our analysis includes both the absolute levels of segregation and the changes in segregation from year to year (first differences). Additionally, we use log

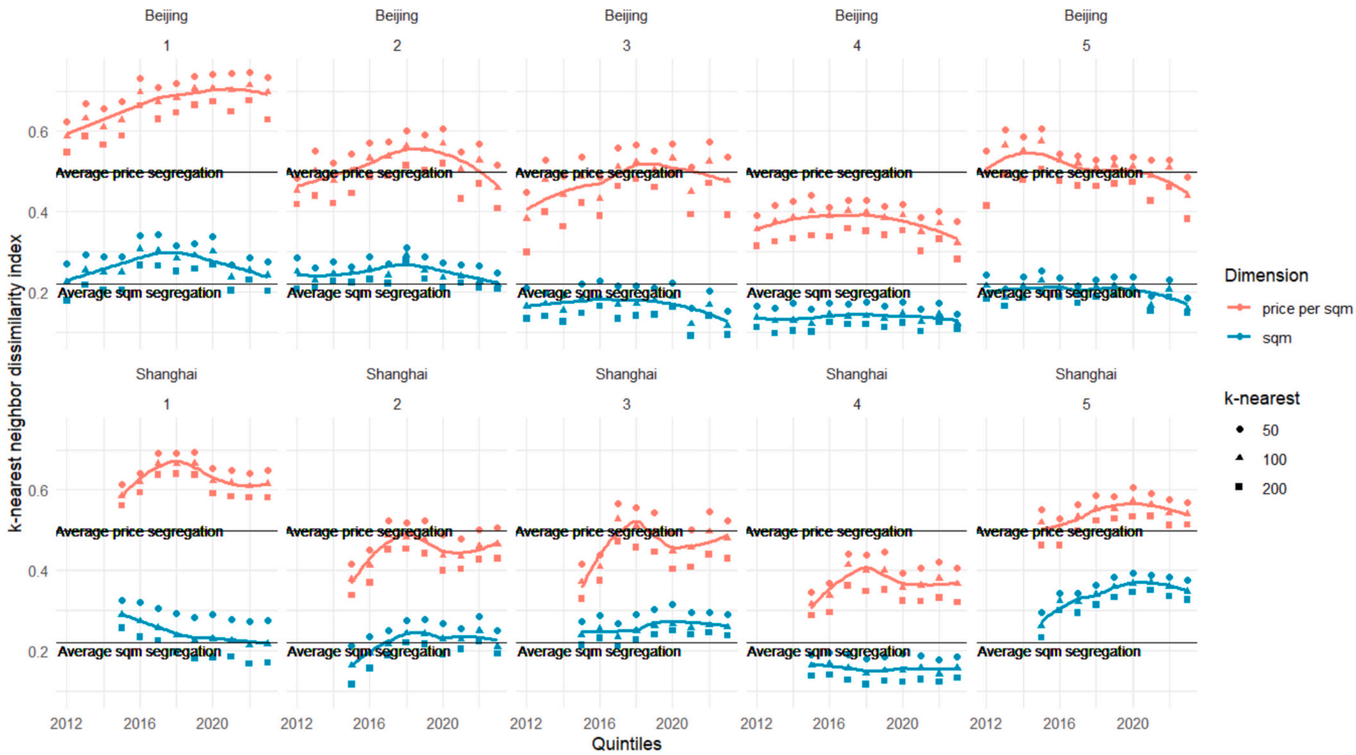


**Fig. 8.** Dissimilarity indices for secondhand transaction prices and sizes for different k's.

price per square meter and price increases as predictors, along with indicators for different price categories (quintiles). The model also controls for the lagged migrant rate, GDP growth, and log population at the city level. See Appendix A6 for a descriptive analysis of the variables used in the regression.

The results are shown in Table 1. In the first model, we find a positive and significant relationship between housing price increases and segregation changes, indicating that accelerating price growth is associated with faster increases in segregation. In the second model, the relationship between price increases and segregation levels is negative, suggesting that higher rates of price growth are associated with lower overall levels of segregation. These seemingly contrasting results reveal different dimensions of the price-segregation relationship: while accelerating price increases lead to faster segregation changes, they are linked to lower absolute levels of segregation. In both models, population, migration and GDP growth in the previous years are not significantly associated with segregation. The results of the third and fourth models indicate that cities with higher housing price levels tend to experience greater increases in and levels of segregation. While the price coefficients are significant statistically and in magnitude, the overall explained variance of the models is very low due to differenced variables.

Overall, the results suggest that accelerating housing prices—both in terms of growth rates and absolute levels—have significant but complex relationships with segregation patterns. However, price dynamics alone may not explain existing segregation levels, pointing to other structural factors that shape the degree of segregation in cities.

**Table 1**
Regression of prices/price-increases on segregation increases and levels.

| | Year-to-year segregation change | Segregation level | Year-to-year segregation change | Segregation level |
|---|---|---|---|---|
| Δ Sqm prices | 0.543* (0.242) | −0.133* (0.058) | | |
| Log Sqm prices | | | 1.363* (0.534) | 0.052 (0.080) |
| Lag Share migrants | 0.374 (0.849) | 0.038 (0.268) | −0.272 (0.843) | −0.114 (0.110) |
| Lag GDP growth | −0.260 (1.192) | −0.233 (0.376) | −0.634 (1.112) | −0.263 (0.335) |
| Lag log population | 0.461 (0.382) | 0.195 (0.221) | −1.032 (0.529) | 0.035 (0.188) |
| Observations | 208 | 208 | 208 | 248 |
| $R^2$ | 0.080 | 0.021 | 0.194 | 0.005 |
| Adjusted $R^2$ | −0.035 | −0.102 | 0.093 | −0.102 |
| F Statistic | 3.993** (df = 4; 184) | 0.964 (df = 4; 184) | 11.062*** (df = 4; 184) | 0.281 (df = 4; 223) |

Notes: $^*p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$; including year, city, quintile fixed effects.

## 5. Discussion

One fundamental difference between housing segregation and traditional socio-economic segregation is that, while people are mobile, houses are not. As a result, the primary mechanisms influencing housing segregation are changes in housing prices, rents, and sizes relative to surrounding properties—essentially, the spatial redistribution of housing units based on these factors. Figs. 2 and 4 illustrated how segregation can increase through the homogenization of wealthier core urban areas, driven by gentrification and the displacement of affordable housing, as well as through the clustering of cheaper apartments in peripheral neighborhoods. Both processes contribute to increased segregation by making neighborhoods more homogeneous and socially stratified. Conversely, the displacement of lower-cost housing into semi-peripheral areas tends to create more diverse, mixed neighborhoods, thereby reducing segregation. This reflects a broader trend of core-periphery polarization in cities. However, this raises the question: What are the indirect mechanisms driving both polarization and mixing? Specifically, what factors contribute to the spatial reconfiguration of housing units? In this section, we will suggest three potential mechanisms –market dynamics, policy interventions, and ideological influences – that may indirectly shape housing segregation patterns.

Since price segregation is significantly more pronounced than rent or space segregation, we will focus on the case of price segregation. However, the factors influencing rent segregation are largely similar. Space segregation is the least prominent because housing size is less directly correlated with spatial characteristics. Even in expensive urban centers, the housing landscape remains diverse, including large luxury apartments, moderately-sized homes for the middle class, and older, deteriorating units (Li, 2023). Therefore, the discussion will primarily center on price segregation.

### 5.1. Supply-demand drivers of housing segregation

Changes in housing prices are primarily driven by supply and demand dynamics. Since we can only calculate annual housing segregation levels, more detailed statistical regression analyses for Beijing and Shanghai are not feasible. Instead, we refer to some key covariates of rising housing segregation from our regression results, along with a more descriptive analysis of historical trends in housing prices, rents, population changes, housing and land supply, and relevant policy documents, with a specific focus on Beijing and Shanghai.

One of the key factors driving the rise in housing segregation in Beijing and Shanghai before 2018 was the rapid surge in housing prices (see Table 1), leading to significant spatial reconfiguration. Between 2011 and 2017, median housing prices more than doubled, with high-end housing in the urban core tripling in value. This resulted in the gentrification and homogenization of central areas, particularly in larger cities, where rising prices displaced lower-income residents, reinforcing socio-economic divides. Owens' (2019) findings similarly observed an increase in housing segregation following the Great Recession due to rising home values. In parallel, peripheral neighborhoods also experienced homogenization, as clusters of cheaper housing created segregated enclaves for lower-income groups. Both processes—gentrification of central areas and the clustering of cheaper housing in peripheral regions—contributed to increasing overall segregation by making neighborhoods more homogeneous.

Although segregation declined after 2018 across all quintiles, it began rising again in Shanghai after 2020, whereas in Beijing, it continued to decline. This divergence, driven by rising prices in Shanghai and stagnation in Beijing, underscores the central role of housing prices in shaping segregation. In Beijing, the crowding out of cheaper units into the semi-periphery may have temporarily reduced segregation by creating more mixed neighborhoods, whereas Shanghai's continued price increases reinforced the segregation of affluent areas.

Another potential contributing factor to housing segregation could be the decline in housing and land supply. Since 2011, residential land availability in Beijing and Shanghai has experienced continuous tightening. For instance, the "Beijing 2017 State-Owned Construction Land Supply Plan" explicitly stated that residential land supply in 2017 would decrease by nearly 50 % compared to the previous year. The data further illustrates that between 2014 and 2017, the housing completion area in Beijing contracted significantly, with a reduction of two-thirds. This shrinking supply intensified competition for available housing, especially for properties in prime locations with better infrastructure and services. Higher-income groups, with greater financial flexibility, secured these scarce resources, while middle- and lower-income groups were marginalized and forced into less desirable areas. As developers increasingly prioritized high-end residential projects to maximize profitability, the supply of affordable housing declined, exacerbating the geographic divide between income groups and reinforcing segregation. In the core cities, gentrification continued to drive the homogenization of wealthy neighborhoods, while lower-income groups clustered in increasingly segregated peripheral regions.

Although previous literature suggests that migrant inflows might intensify housing segregation by simply increasing aggregate housing demand (Monkkonen et al., 2017; Monkkonen & Zhang, 2014; Reardon & Bischoff, 2011; Spierenburg et al., 2023), our regression results indicate that the effect of migrant share is not directly significant. This suggests that the influence of migration on segregation does not operate merely through overall demand pressures. Instead, the impact of migrant inflows on housing segregation may be mediated by the unequal competition for spatial resources. For example, when new migrants exhibit a wide socio-economic gap—such as when low-income migrants, restricted by household registration policies or limited financial means, are forced to concentrate in specific areas like urban villages or suburban new districts—the spatial sorting is more pronounced, thereby exacerbating segregation. Conversely, if the socio-economic differences among new migrants are minimal, the resulting spatial clustering and subsequent segregation may not be as severe. This nuanced perspective implies that it is the heterogeneity within the migrant population—rather than the sheer volume of migrants—that plays a crucial role in shaping local segregation patterns.

### 5.2. Policy and political ideology shaping divergent urban trends

While the previous section analyzed common supply-demand factors influencing housing segregation, it's important to note that, despite similar housing price trends in Beijing and Shanghai over the past 20 years, these two cities differ significantly in policy orientation and political priorities. These differences likely shape their local housing systems, leading to distinct patterns of housing segregation.

Shanghai is widely recognized as China's economic hub, while Beijing serves as its political center. This distinction not only reflects historical developments but also embodies the contemporary structure of political power in China. In general, Shanghai is more market-oriented, likely due to its past as a Western concession and its role as a port city. In contrast, as the capital and the seat of the highest authority, Beijing's primary focus may be on maintaining stability. This fundamental difference significantly influences the urban planning, economic strategies, and immigration policies of Shanghai and Beijing.

Due to its high level of marketization, the land market in Shanghai is more competitive than in Beijing. Although Shanghai's geographic area is significantly smaller than Beijing's, its land grant premiums are generally higher. For example, in 2023, Shanghai transacted 72 residential land plots, garnering a total of 220 billion yuan, whereas Beijing only transacted 61 plots, with a total of 174.1 billion yuan. According to research by Monkkonen et al. (2017), more competitive land markets lead to greater neighborhood differentiation, a trend evident in Shanghai's diverse and distinctly segmented residential areas. This competitive environment promotes homogenization in affluent neighborhoods by clustering high-end developments, thus reinforcing segregation.

Differences in immigration policies between the two cities may also play a critical role. Although both cities aim to attract "high-end talent," Beijing appears to be less welcoming toward the so-called "low-end population." This policy approach became particularly evident during the 2017 "low-end population cleanup," following a deadly fire in Xinjian Village. The ensuing 40-day campaign led to mass evictions and the demolition of informal housing structures, disproportionately affecting migrant workers without local household registration (hukou) (Morris, 2022). Morris (2022) argues that by creating smaller, more homogeneous population hubs that can be more easily governed, the likelihood of mass incidents can be reduced, thus ensuring long-term party-state stability. Indeed, we have observed a reduction in segregation in Beijing after 2018, which may be related to the "clearance of low-end population," although there is no direct evidence of this correlation. A number of studies have found that residential segregation can negatively impact social stability (Morenoff et al., 2001; Peterson & Krivo, 2010). For instance, Peterson and Krivo (2010) argue that higher levels of residential segregation contribute to social and economic disadvantages, which in turn lead to higher crime rates in segregated areas.

Furthermore, the structure of the housing market itself plays a crucial role in shaping segregation patterns. Beijing has a notably higher proportion of public housing compared to Shanghai. According to data from the Seventh Population Census in 2020, in Beijing, 5.8 % of households lived in public rental housing, 7 % purchased affordable housing, and 14.2 % acquired former public housing. In contrast, Shanghai's figures were 4 %, 1 %, and 10.8 % respectively. This higher public housing share in Beijing alleviates housing segregation by enhancing housing accessibility and economic diversity. Government provisions of affordable and public rental housing might enable low-income families to afford homes in desirable city areas, reducing housing segregation. This facilitates mixed-income living across various urban districts, increasing socio-economic diversity within communities and leading to a more balanced and inclusive urban structure. The relationship between public housing and segregation has also been confirmed by Monkkonen et al. (2017), who found that cities with low state housing shares, such as Hangzhou, Chengdu, Qingdao, and Taiyuan, exhibit higher segregation indices, suggesting that state housing is crucial for spatial structuring and reducing segregation.

## 6. Conclusion

This study has mapped the trends of housing segregation in Beijing and Shanghai by incorporating key variables such as housing prices, rents, and housing size into the analysis. It provides new insights into the supply-demand dynamics and policy influences shaping urban segregation patterns in China's rapidly evolving cities. Through the use of large-scale real estate transaction data, this research captures a level of detail often missing in previous studies, particularly in contexts where longitudinal and spatially detailed data are scarce.

Two significant methodological contributions are highlighted in this study. First, the use of large-scale real estate data to study housing segregation marks an innovative approach in the Chinese context, where traditional data sources like the decennial census cannot adequately capture the rapid changes in residential segregation. This approach fills a critical gap by offering a real-time, fine-grained analysis of segregation trends. Second, the application of the k-nearest neighbor (k-NN) method successfully addresses the Modifiable Areal Unit Problem (MAUP) and the checkerboard problem, two challenges in measuring segregation accurately. By mitigating these issues, the k-NN method allows for more standardized and comparable assessments of segregation across cities, strengthening the analytical rigor of the study.

A key conclusion of this study is that the overheating of the real estate market, population growth, and market-oriented policies have exacerbated housing segregation. This process is driven by the core-periphery polarization of cities, where the gentrification and homogenization of wealthier core areas displace lower-income residents and the clustering of cheaper housing in peripheral neighborhoods segregates lower-income populations. However, Beijing's migration control policies, though controversial, may have reduced housing segregation, challenging the long-standing assumption that residential segregation has continuously risen since the housing market reforms of the 1990s (Li & Wu, 2008). This suggests that state intervention, even in the form of migration controls, could have a meaningful impact on urban inequality.

The positive correlation between marketization and segregation may stem from the inherent tendency of capitalism to exacerbate inequality. Market-liberal policies that prioritize market efficiency often overlook the socio-spatial divides they create, especially in cities with high real estate demand. This finding calls for a critical reevaluation of these policies and their role in deepening inequality, urging a reflection on how economic growth and social equity can be better balanced in policy-making. The implications of these findings extend beyond the boundaries of Beijing and Shanghai, offering broader insights for cities facing similar issues of rapid urbanization, housing market speculation, and growing socio-economic inequalities.

## CRediT authorship contribution statement

**Sebastian Kohl:** Writing – original draft, Methodology, Visualization, Writing – review & editing. **Bo Li:** Data curation, Writing – original draft, Formal analysis, Software, Writing – review & editing. **Can Cui:** Data curation, Writing – review & editing, Validation.

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## Appendix A. Supplementary data

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