4 The clustering pattern of Chinese house price dynamics

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Abstract: This paper investigates the clustering pattern of house price dynamics in 34 major cities in China over the period 2005–2016. Hierarchical agglomerative clustering is implemented based on a distribution-based dissimilarity measure, the Kullback-Leibler divergence, which measures the similarity between house price appreciation trajectories. The clustering procedure reveals a broad two-cluster structure: one relatively homogeneous slow-growing market cluster and one red-hot market cluster which, however, has a higher degree of within-cluster heterogeneity. The two-cluster partition also indicates a geographical pattern that separates out Eastern China. However, this clustering pattern is mainly shaped by the market structure in the recent period after 2014. Prior to 2014, and especially before 2010, the interurban housing market in China could be considered a homogenous market in terms of house price changes.

Keywords: House price dynamics, housing market divergence, hierarchical clustering, Kullback-Leibler divergence, China

§ 4.1 Introduction

After decades of rapid growth in house prices, the Chinese housing market has begun to cool down since 2014, when Chinese economic growth also began to slow. This has caused widespread worries about the prospects of the Chinese economy given the important economic role of the real estate sector. To stabilize the housing market and achieve the economic growth targets, the central and local governments chose to actively engage in the housing market through policy interventions. Then, after the second half of 2015, the housing markets in some cities heated up again while other cities' housing markets remained stagnant. For example, as of June 2016, house prices in Beijing had increased 20 percent compared to June 2015, whereas house prices in Kunming, the capital of a Western province, are nearly stable.

Facing the great divergence in house price dynamics between cities, the government regulation has to resort to diverging, local-oriented policy tools, the design of which heavily depends on our clear understanding about the segmentation of interurban housing market. What is the segregation pattern of the Chinese housing markets? Is the housing market divergence a new phenomenon or a long-established pattern? Does geography play a role in fragmenting the housing markets? This paper attempts to shed light on these questions by conducting classification analysis on city-level housing markets in China. By means of cluster analysis, the divergent housing market structure can be well described by a few homogeneous clusters, within which the markets are very similar to each other but the differences between clusters are significant.

A key element in classifying real estate markets is the similarity criterion. The delineation of intra-city housing submarkets, for example, can be based on the similarity in housing attributes and/or the similarity in shadow prices of those attributes (e.g., Goodman and Thibodeau, 1998; Watkins, 2001; Bhattacharjee et al., 2016). In the case of classifying the interurban real estate market, a large amount of studies have been based on the similarity in market performance, like the dynamics of property rent or price (e.g.,Hamelink et al., 2000; Jackson, 2002). This paper follows the paradigm of market performance approach. However, unlike the previous literature that use distance measures to represent similarities, I introduce a distribution-based dissimilarity measure, the Kullback-Leibler (*KL*) divergence (Kullback, 1968; Kullback and Leibler, 1951), which reflects the structural difference between Data Generating Processes (DGP) that generate the house price dynamics of different cities.

This paper then applies the hierarchical clustering method to 34 major cities' housing markets in China over the period 2005–2016, aiming to investigate the cross-market divergence pattern. The temporal stability of divergence pattern is also examined by performing the cluster analysis on sub-periods. In general, these cities can be broadly grouped into two clusters, one cluster containing relatively homogeneous slow-growth markets and the other containing red-hot markets in Eastern China, which have a much higher degree of heterogeneity. That is, the latter cluster can be further partitioned into sub-clusters. Such a clustering pattern is mainly shaped by the market structure in the recent period after 2014. Throughout the sample period, the Chinese interurban housing market has experienced significant structural changes, particularly in the later years; it has shifted from a homogenous market structure to a divergent one. Besides, this paper also examines whether the geographical demarcation and city-tier division schemes, which are frequently referred to when defining homogenous housing market groups in practice, are consistent with the divergence pattern of housing markets.

While the literature on homogeneous grouping of commercial property markets is extensive, very few studies focus on the cluster analysis of housing markets. Some exceptions are Abraham et al. (1994) on grouping U.S. metropolitan housing markets and Hepşen and Vatansever (2012) on clustering Turkish housing markets. Dong et al. (2015) and Guo et al. (2012) also made attempts to partition the Chinese city-level housing markets into few homogeneous clusters. However, both of the studies are subject to a relatively short period with no more than five years and thus fail to examine the temporal evolution of the segmentation structure. In this regard, the current paper greatly contributes to the understanding of the evolutionary divergence pattern of Chinese housing markets.

The remainder of this paper is organised as follows. Section 4.2 briefly reviews the literature on the clustering of housing markets. The dissimilarity measure and clustering method are described in Section 4.3, followed by an introduction to the data and some stylized facts in Section 4.4. Section 4.5 reports the clustering results, tests the structural changes and discusses the findings. Finally, a short summary is provided in Section 4.6.

§ 4.2 Previous literature

The intra-city and inter-urban real estate market is likely fragmented due to market imperfections. Defining and identifying intra-city housing submarkets thus has various advantages. It can significantly improve the prediction power of house price models, help lenders and investors to better price the risk associated with financing homeownership, and reduce the search cost for housing consumers (Goodman and Thibodeau, 2007). Similarly, the cluster analysis of interurban real estate market also brings considerable benefits. This section mainly reviews the studies on classifying the interurban real estate market.

One benefit of homogenous grouping of real estate markets across cities is aiding in real estate portfolio diversification. The grouping strategy has initially been to conform to the geographical regions created for administrative purposes, such as the U.S. eight-region system used by the Bureau of Economic Analysis (BEA)[1]. However, Malizia and Simons (1991), using the standard deviation of demand-side indicators (employment, for example) as the criterion of homogeneity within categories, found that this eight-region system does not perform well.This calls for a classification scheme based on the characteristics of property markets rather than solely on regional proximity.

Using the time series data of real estate market characteristics, many studies, mostly on commercial real estate markets, employ clustering methods to perform the

1 The eight regions are New England, Mideast, Great Lakes, Plains, Southeast, Southwest, Rocky Mountains and Far West.

classification analysis, based on some similarity measures, such as Euclidean distance and correlation coefficient. Goetzmann and Wachter (1995) looked into the segmentation structure of 21 metropolitan U.S. office markets based on effective rents and the structure of 22 markets based on vacancy data. In line with the suggestion of Malizia and Simons (1991), the *K*-means clustering revealed bicoastal relationships among cities; that is, some east and west coast cities tend to be clustered together regardless of the great distances between them. The resulting clustering pattern in the paper is then tested by a bootstrap procedure. Outside the U.S., Jackson (2002) applied the hierarchical clustering method to the retail property markets of 60 towns and cities in Great Britain and identified seven homogeneous groups based on average retail rental value growth.

Hoesli et al. (1997) applied various clustering techniques to 156 retail, office and industrial markets in the UK, attempting to reveal the extent to which property markets are grouped by property type or by area. Property type is found to be the dominant factor in determining different market behaviours; it is overlaid by the geographical factor, which emphasises the role of London. A later study (Hamelink et al. 2000) extends the work of Hoesli et al. (1997) by testing more property type/ region combinations, such as the 3 property types × 3 super-regions combination and the 3 property types × 13 standard regions combination[2]. The results confirmed the findings of Hoesli et al. (1997), revealing a strong property-type dimension and a weak broad geographical dimension.

Compared to the large body of literature on the homogeneous clustering of commercial real estate markets, clustering analyses of housing markets are relatively limited, with a few notable exceptions. Abraham et al. (1994) identified three meaningful homogeneous clusters: an East Coast group, a West Coast group and a central U.S. group. More recently, Hepşen and Vatansever (2012) applied hierarchical clustering method to 71 Turkish metropolitan housing markets and revealed three clusters with different rental return levels. Using a combination of wavelet analysis and expert experience, Guo et al. (2012) first divided the time series of house prices indexes of 70 Chinses cities over the period 2005 - 2010 into a few distinct sub-periods. The DBSCAN clustering algorithm was then applied and partitioned these markets into 6 clusters and 5 un-clustered markets based on the characteristics of each sub-period. With a two-stage clustering procedure, Dong et al. (2015) divided the housing markets of 283 cities in China into three clusters and thirteen sub-clusters. The first stage of classification is based on the similarity in demand and supply fundamentals and the second state further divides the clusters formed in stage one according to the similarity

2 The three super-regions are London, the South (the rest of the South East, East Anglia, and the South West) and the North (East Midlands, West Midlands, Wales, North West, Yorkshire and Humberside, the North, and Scotland). In the 13 cases, London is further divided.

of market performance (housing sale value and house prices).

Besides, van Dijk et al. (2011), using a latent-class panel time series model, divided the Dutch regional housing markets into two clusters according to criterion whether the markets can be modelled by a common house price model. This classification logic is based on the similarity in structural parameters of the regional house price model, which is different from the previous inter-market classification studies but in line with most studies on identifying the intra-city submarkets. Owing to the lack of continuous time series data on housing market fundamentals in a long period, this paper follows the traditional wisdom and performs the cluster analysis based on the house price appreciation trajectories.

§ 4.3 The Kullback-Leibler discrepancy measure and clustering method

§ 4.3.1 The Kullback-Leibler divergence between two housing markets

To assign a local housing market into a corresponding cluster based on its house price growth pattern, a measure that reflects the difference between two house price appreciation series is needed, such as the Euclidean distance. This paper introduces the Kullback-Leibler (KL) divergence (Kullback and Leibler 1951; Kullback 1968), which measures the 'distance' between two probability distributions. Suppose that two house price growth series, say $y_{p,t}$ and $y_{q,t}$ $(t = 1, 2, \cdots, T)$, are generated by probability density functions (pdf) $P(t)$ and $Q(t)$, respectively. Then, the structural dissimilarity between housing markets p and q can be reflected by the discrepancy between the house price distributions of $P(t)$ and $Q(t)$. The Kullback-Leibler divergence is a measure that calculates the divergence of distribution $Q(t)$ from the distribution $P(t)$ and follows the form

$$KL\,(P; Q) = \int \ln \frac{P(t)}{Q(t)} P(t) dt. \tag{1}$$

Note that KL divergence is not symmetric, that is $KL(P; Q) \neq KL(Q; P)$. For ease of classification, a symmetric measure, known as J divergence (Kullback 1968), is defined as

$$JKL(P; Q) = KL(P; Q) + KL(Q; P). \tag{2}$$

This measure has all the properties of a distance measure except triangular inequality and has been widely used in cluster analysis (e.g.,Kakizawa et al. 1998; Bengtsson and Cavanaugh 2008)[3].

Assume that the house price appreciation of a city i, $y_{i,t}$, is generated from an $AR(P)$

3 The triangular inequality of JKL divergence means that $JKL\,(P, Q) \leq JKL\,(P, R) + JKL\,(R, Q)$

process

$$y_{i,t} = c_i + \phi_{1,i} y_{i,t-1} + \phi_{2,i} y_{i,t-2} + \cdots + \phi_{p,i} y_{i,t-p} + \epsilon_{i,t} \tag{3}$$

where c_i is the average growth rate of city i and reflects the long-run growth trend driven by city-specific characteristics such as population, income growth and so forth, $\epsilon_{i,t} \sim N\left(0, \sigma_i^2\right)$ is the independent and identically distributed Gaussian error. In total, $\theta_i = \left(c_i, \phi_{1,i}, \phi_{2,i}, \cdots, \phi_{p,i}, \sigma_i^2\right)'$ is the parameter vector to be estimated in the model. Conditional on the first p observations, the joint probability density function for the house price appreciation in city i becomes

$$\begin{aligned} f\left(y_{i,T}, \cdots, y_{i,p+1} | y_{i,p}, \cdots, y_{i,1}; \theta_i\right) = \prod_{t=p+1}^{T} & \frac{1}{\sqrt{2\pi\sigma_i^2}} \\ & \exp\left(-\frac{\left(y_{i,t} - c_i - \phi_{1,i} y_{i,t-1} - \cdots - \phi_{p,i} y_{i,t-p}\right)^2}{2\sigma_i^2}\right). \end{aligned} \tag{4}$$

By maximizing the natural logarithm of likelihood function (4), one obtains the conditional maximum likelihood estimators (MLE) for θ, which are identical to the ordinary least squares (OLS) estimators of Equation (3). In compact fashion, Equation (4) can be expressed as

$$f\left(y_{i,T}, \cdots, y_{i,p+1} | y_{i,p}, \cdots, y_{i,1}; \theta_i\right) = \left(2\pi\sigma_i^2\right)^{-\frac{T-p}{2}} \exp\left(-\frac{\left(y_i - X_i\beta_i\right)'\left(y_i - X_i\beta_i\right)}{2\sigma_i^2}\right) \tag{5}$$

where $y_i = \left(y_{i,p+1}, \cdots, y_{i,T}\right)'$, $X_i = \left(\left(1, 1, \cdots, 1\right)', \left(y_{i,p}, \cdots, y_{i,T-1}\right)', \left(y_{i,p-1}, \cdots, y_{i,T-2}\right)', \cdots, \left(y_{i,1}, \cdots, y_{i,T-p}\right)'\right)$, and $\beta_i = \left(c_i, \phi_{1,i}, \phi_{2,i}, \cdots \phi_{,p,i}\right)'$.

Now one has another city's house price appreciation series, $y_{j,t}$, generated by the parameter vector θ_j conditional on the observations $\{y_{j,1}, \cdots, y_{j,p}\}$. According to Equation (1), the KL divergence between the two cities' housing markets will be:

$$KL(y_i; y_j) = \int_{y_{p+1}, \cdots y_T} \log \frac{f\left(y_T, \cdots, y_{p+1} | y_{i,p}, \cdots, y_{i,1}; \theta_i\right)}{f\left(y_T, \cdots, y_{p+1} | y_{j,p}, \cdots, y_{j,1}; \theta_j\right)} f\left(y_T, \cdots, y_{p+1} | y_{i,p}, \cdots, y_{i,1}; \theta_i\right) dy. \tag{6}$$

Substituting Equation (5) into Equation (6), one obtains the computational form of the KL divergence:

$$\begin{aligned} KL(y_i; y_j) &= \frac{T-p}{2}\left(\log\frac{\sigma_j^2}{\sigma_i^2} + \frac{\sigma_i^2}{\sigma_j^2} - 1\right) + \frac{\left(X_i\beta_i - X_j\beta_j\right)'\left(X_i\beta_i - X_j\beta_j\right)}{2\sigma_j^2} \\ KL(y_j; y_i) &= \frac{T-p}{2}\left(\log\frac{\sigma_i^2}{\sigma_j^2} + \frac{\sigma_j^2}{\sigma_i^2} - 1\right) + \frac{\left(X_j\beta_j - X_i\beta_i\right)'\left(X_j\beta_j - X_i\beta_i\right)}{2\sigma_i^2}. \end{aligned} \tag{7}$$

The symmetric measure $JKL(y_i; y_j)$ can be easily obtained by summing up the term $KL(y_i; y_j)$ and $KL(y_j; y_i)$, and this symmetric measure will be used for the cluster analysis in the next step.

Unlike the Euclidean distance which measures the straight-line distance between two sample house price appreciation series, the *JKL* divergence measures the structural difference between two distributions that can generate the sample series. Thus, the *JKL* divergence is considered to be more consistent with the 'true' difference between housing markets.

§ 4.3.2 The clustering method

After obtaining the *KL* divergence matrix across cities, the hierarchical clustering method, particularly the bottom-up agglomerative method, is employed to assign the cities into relatively homogeneous sub-groups. The procedure begins by treating each city as an individual cluster and merging the two cities (say y_i and y_j) that have the lowest dissimilarity, measured by $JKL(y_i; y_j)$, into one cluster C_i. The next step involves updating the dissimilarity between a formed cluster and other clusters (or individual cities) according to linkage criteria. There are several linkage criteria available, and in this paper the widely used *average-linkage* method is employed; that is, the dissimilarity between the two clusters is equal to the average dissimilarity between a city in cluster C_i and a city in cluster C_j. Let N_i and N_j be the number of cities belonging to clusters C_i and C_j, respectively. The dissimilarity between clusters C_i and C_j is defined as $JKL(C_i; C_j) = \sum_{y_i \in C_i} \sum_{y_j \in C_j} JKL(y_i; y_j)/N_i N_j$. By repeating this process, a hierarchical tree linking the nearest neighbours is generated, which is known as a 'dendrogram'. Finally, one can cut the tree at the desired level and obtain the corresponding clusters.

Hierarchical clustering is silent on determining the correct number of clusters. This can be achieved by optimizing some cohesion and separation measures. One widely used example of such measures is the Silhouette statistic (Rousseeuw 1987); the number that can maximize the average Silhouette values is chosen as the correct number of clusters. One drawback of the Silhouette statistic is that it is not well defined for the individual clusters that have only one member, which, according to Figure 4.3, is very likely to happen in this study. This paper uses a heuristic approach to determine the number of clusters: the "elbow" approach.

The elbow approach attempts to find a balance between the increase in within-cluster cohesion and the decrease in data compactness. Within-cluster cohesion is measured by the sum of within-cluster distances $S_w(k) = \sum_{i,j \in C_k}^{k} d_{ij}$ where d_{ij} is the distance measure that can be either Euclidean distance or *JKL* divergence. The smaller the $S_w(k)$ is, the higher the cohesion of a cluster. Compactness is measured by the number of between-cluster city pairs $N_b(k) = \sum_{i=1}^{k-1} \sum_{j=k+1}^{k} n_i n_j$ where n_i is the number of objects in cluster C_i. By this measure, the uneven partition is considered to be more compact than the even partition. When one more cluster is added, the S_w is always decreasing while the N_b is always increasing. The process should stop at cluster k, where continuing to increase N_b cannot offer much of a decrease in S_w. Now, I define statistic $A_k = [S_w(1) - S_w(k)] / N_b(k)$, which means the average cohesion gain of $k$clusters. Note that because the numerator of A_k is exactly the sum of between-cluster relationships, A_k can also be interpreted as the average between-cluster distance. If one plots the A_k on the Y-axis and the number of clusters k on the X-axis, it can be found that from some k onward, the remarkably flattens (see Figure A1, for example). The "elbow" point is deemed to be the appropriate number of clusters. I test the effectiveness of the elbow approach on two data sets exhibited in Charrad et al. (2014), which comprehensively uses 27 indicators presented in the literature to determine the number of natural clusters. The elbow approach turns out to correctly identify the number of clusters as recovered by Charrad et al. (2014).

§ 4.4 Data and stylized facts

§ 4.4.1 House price index and appreciation

This paper analysed the monthly house price dynamics of 34 major cities in China from July 2005 to June 2016 ($T = 132$). These cities cover municipalities directly under the central government, provincial (autonomous regions) capitals and vital economic centres, and hence their price changes attract the majority of public attention. For all of the sample cities, the system of "Price Indices of Newly Constructed Residential Buildings in 35/70 Large- and Medium-sized Cities" (70 Cities Index), which is compiled by the National Bureau of Statistics of China (NBSC), publishes month-over-month house price changes[4]. The series of monthly house price changes in 34 cities will be the main input in the classification analysis. The "35/70 Cities Index" was launched in 1997 and reports, on a quarterly basis, the year-over-year index for 35 major cities. In July 2005, the system was expanded to cover 70 Large- and Medium-sized cities and began to report monthly. Also since 2005, house price changes have been calculated through a so-called "matching approach" (Wu et al. 2014), which can better control for quality changes[5]. The price index compilation strategy was slightly adjusted in January 2011, but this change would not significantly affect the consistency of the house price index. Finally, to provide an intuitive perception of house price dynamics during the sample period, I convert the month-over-month price changes into a fixed-base house price index through the

4 Haikou, the capital of Hainan province, is excluded from our analysis. As a popular tourist resort, Haikou's housing market has some distinct characteristics, and its house price dynamics clearly deviate from the other cities during the sample period.

5 The "matching" model used for the NBSC index is analogous to the repeat sales model. In each month, local statistical authorities collect housing transaction information from different housing complexes. The houses within the same housing complex have similar structural and locational characteristics. Thus, for each housing complex, comparing the average transaction prices of different periods roughly produces a quality-adjusted house price index. The city-level index is the weighted average of all complex-level indexes.

chaining algorithm (reference base = June 2015).

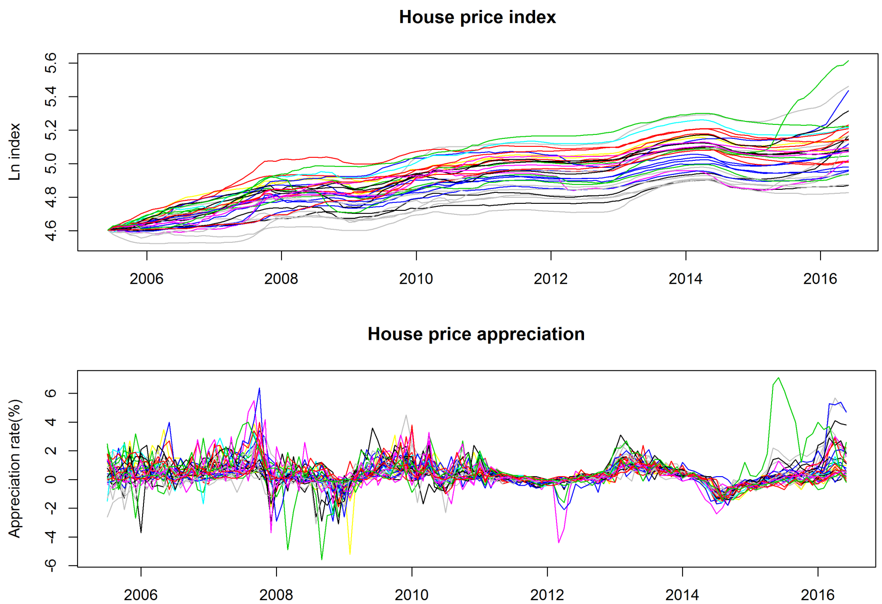

FIGURE 4.1 House price index (ln transformation) and monthly house price appreciation of 34 cities

§ 4.4.2 Stylized facts

The upper panel of Figure 4.1 plots the house price indexes of 34 cities. While a common upward trend can be easily noticed throughout the whole sample period, most of the cities experienced two or three episodes of rising and falling prices. The first common episode of price decreases occurs in approximately 2008-2009, right after the global financial crisis. However, house prices bounced back very quickly and then entered a relatively stable period until 2013. After a national upward trend started in 2013, house prices dropped again in 2014. Recently, particularly after the second half of 2015, house prices in some cities recovered with tremendous price increases. Although a national trend in house prices is noticeable, cities differ from each other in terms of their house price trajectories. For example, some cities obviously have higher growth rates than others.

The lower panel of Figure 4.1 depicts the house price appreciation rates. The house price growth rates are quite volatile in the first half of the sample period and in the most recent period after 2014, while during the period 2011-2013, house price dynamics are relatively stable. Using the difference of the logarithmic house price index (e.g., $\log(Index_{2016}) - \log(Index_{2016})$), I calculate the total house price appreciation for the sample period, as well as for two subsample periods: July 2005-December 2010 and January 2011-June 2016; the results are shown in Figure 4.2. Shenzhen enjoys the largest price appreciation at 100.80%, followed by Beijing, Xiamen and Guangzhou (all of which are eastern cities). Kunming, Taiyuan and Hohhot (either central or western cities) have the lowest price appreciation (below 30%) during the last decade[6]. It seems that geographical proximity is a meaningful way to divide the national housing market. For the vast majority of cities, especially those that have lower house price appreciation during the sample period, housing returns are mainly accumulated during the first 5 to 6 years. A few of the most developed cities, such as Shenzhen, Guangzhou, Shanghai and Nanjing, are the exceptions; their price appreciation in the second half of the period overwhelmingly surpasses their price growth in the first period. The two distinct patterns of house price dynamics also indicate the divergence of interurban housing markets to some extent.

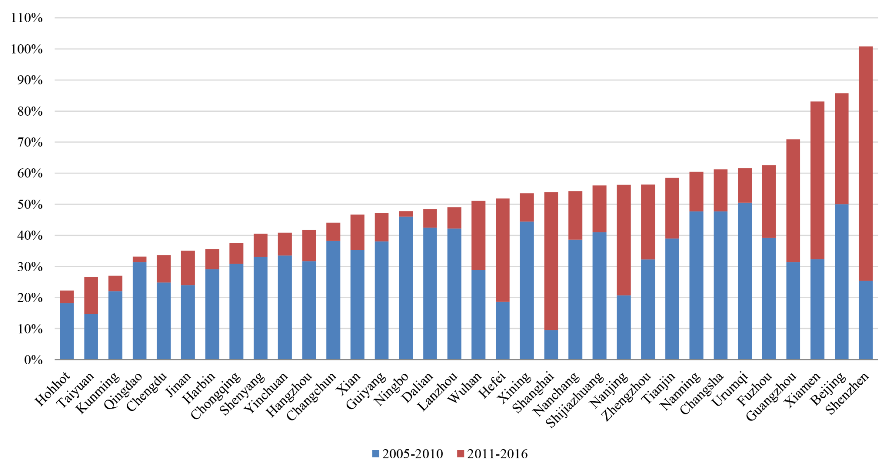

FIGURE 4.2 House price appreciation for 34 cities

§ 4.5 Results

§ 4.5.1 *JKL* divergence vs Euclidean distance

6 The "70 Cities Index" has been largely criticized for underestimating price growth. See, for example, Wu et al. (2014). However, this is the only accessible public house price index that can provide consistent information for a large number of cities over a relatively long time period.

To ensure that the Kullback-Leibler divergence accurately measures the difference between housing markets, one has to first choose the appropriate order p for the $AR(p)$ process in Equation (3). The selection of orders is based on both Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). With setting the maximum lag order to 12. The BIC prefers no more than 3 lags for all of the house price appreciation series. The AIC criterion presents a similar pattern, but in quite a few cities more than 3 lags have been chosen. While both AIC and BIC suggest several choices of optimal order, one should choose a sufficiently large order to remove the serial correlation in residuals. In this regard, $AR(3)$ specification performs quite well for the vast majority of the house price appreciation series. Thus, the $AR(3)$ process is chosen as the data generating process[7].

TABLE 4.1 Descriptive statistics of *JKL* divergence and Euclidean distance

	Min	1st quartile	Median	3rd quartile	Max	Mean	Standard deviation	Coefficient of variance
JKL	25.755	111.310	167.108	276.226	1502.533	221.542	173.214	0.783
Euclidean	4.798	8.773	10.301	12.147	21.714	10.792	3.049	0.283

Notes: There are 561 city pairs in total.

Aside from the *JKL* divergence matrix, the Euclidean distance matrix is also calculated and will serve as the benchmark in the following analysis. The descriptive statistics of *JKL* divergence and Euclidean distances are presented in Table 4.1. The average *JKL* divergence of 561 city pairs is 221.54, with a standard deviation of 173.21; for Euclidean distance, the two statistics are 10.79 and 3.05. As indicated by the coefficient of variation (CV), the *JKL* divergence (CV = 0.78) is distributed in a much more dispersed manner than the distribution of the Euclidean distance, which has a CV of only 0.28. The housing markets difference measured by *JKL* divergence is in line with the difference measured by Euclidean distance to some extent, but the two are not very close; the Pearson's correlation between the two measures is 0.64, while the Spearman's rank correlation is only 0.55. Furthermore, as seen from the quartile statistics, both the distribution of *JKL* divergence and Euclidean distance are right-skewed, but the former is skewed much more severely. Thus, in the majority of the 34 cities, house price dynamics may not be so different from each other. This can be confirmed by the multidimensional scaling (MDS) shown in Figure 4.3.

Figure 4.3 presents some similarities and disparities of the two measures. For example, both separate Shenzhen (indexed by 24) as an "outlier" and identify a few

7 I randomly selected 15 cities out of the sample and reported their *AR(3)* estimation results in the appendix. I also calculated the Kullback-Leibler divergence based on *AR(2)* and *AR(1)* specifications. The results do not differ much from the results based on *AR(3)*. The Pearson correlation between *AR(3) JKL* divergence and *AR(2) JKL* divergence is 0.998, and it is 0.992 with respect to the *AR(1) JKL* divergence.

distinctive cities relatively far away from the main city group that includes the majority of the cities, such as Nanjing(11), Hefei(14) and Xiamen(16). There are certain differences between the two measures, however. The *JKL* divergence suggests that Shanghai(10) is another “outlier”, while this is not prominent in the map of Euclidean distance.

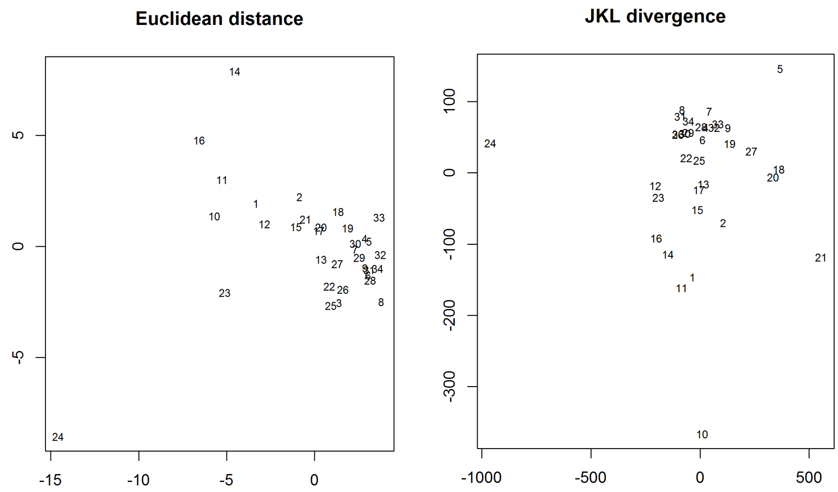

FIGURE 4.3 Multidimensional scaling of Euclidean distance and *JKL* divergence

§ 4.5.2 Classification results

Figure 4.4 plots the dendrograms generated by hierarchical agglomerative clustering method, based on both Euclidean distance and *JKL* divergence. The information hidden in the dendrogram is largely consistent with what one can learn from the Multidimensional scaling (Figure 4.3). A visual check of the dendrograms suggests that there should be one cluster containing most of the cities, a group including only a few cities, and a few individual groups. Furthermore, note that if one wants more clusters ($k > 5$ for instance), the tree of *JKL* divergence might yield better and more meaningful clusters than the Euclidean distance tree, which will produce too many individual groups composed of only one entity[8].

The elbow plot depicted in Figure A1 suggests a four-cluster solution for classifying the 34 housing markets. In addition to the elbow approach, I also report the average

8 Note that the dendrogram structure definitely relies on the *linkage* method used to calculate the dissimilarity between clusters. Thus, this inference may not hold for the dendrogram generated by other *linkage* methods, such as *complete linkage*.

Silhouette index across all clusters that have more than one member. The Silhouette index ranges from -1 to 1, and a positive larger value toward 1 indicates a better demarcation. In this sense, a two-cluster solution seems to be the best solution for both the Euclidean distance and *JKL* divergence, according to the results of Table A1. However, one should keep in mind that the decision based on the Silhouette index might be not optimal due to the appearance of individual clusters, for which the Silhouette index is not defined. Therefore, I only use the Silhouette index as a robustness check. Given that the average Silhouette value at $k = 4$ is also much larger than the values for any $k > 4$, it is believed that the four-cluster solution is a reasonable choice.

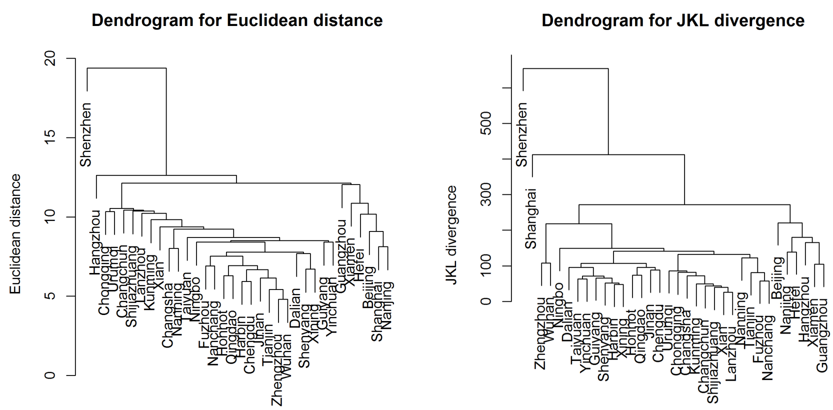

FIGURE 4.4 Dendrogram based on Euclidean distance and *JKL* divergence (average linkage)

The four clusters generated by Euclidean distance and *JKL* divergence, which are shown in Table 4.2, are almost identical with each other. The only difference is that the former separates Hangzhou(12) from Cluster 2 as an independent cluster while the latter separates Shanghai(10). In the following analysis, I mainly focus upon the classification results based on *JKL* divergence. Among the four clusters (see also Figure 4.5), Cluster 1 merges the majority (76%) of the sample cities and is composed mainly of less developed Central, Western and Northeast cities. Cluster 2 is relatively small and includes 6 cities, which are the main centres of the three most developed economic regions in Eastern China: the Pan-Yangtze River Delta (PYRD) containing Nanjing(11), Hangzhou(12) and Hefei(14); the Pan-Pearl River Delta (PPRD) including Guangzhou(23) and Xiamen(16); and the Jing-Jin-Ji Economic Region containing Beijing(1). Moreover, two distinct cities, Shenzhen(24) and Shanghai(10) belonging to the PPRD and PYRD respectively, stand out and form two individual clusters; their house price dynamics are substantially different from each other and from the remaining cities. The four-cluster solution explains the cross-city housing market structure reasonably well. The average distances between the housing markets within Cluster 1 and Cluster 2 are 136.53 and 184.02, respectively, much smaller than the sample average distance (221.54). The extremely low standard deviations of Cluster 1 and Cluster 2 also confirm such findings.

TABLE 4.2 Cluster membership and statistics based on Euclidean distance and *JKL* divergence

	Euclidean distance		*JKL* divergence		
	Membership	Average within distance	Membership	Average within distance	Average monthly growth rate (%)
Cluster 1	2,3,4,5,6,7,8,9,13,15, 17,18,19,20,21,22, 25,26,27,28,29,30, 31,32,33,34	9.10 (1.49)	2,3,4,5,6,7,8,9,13,15, 17,18,19,20,21,22, 25,26,27,28,29,30, 31,32,33,34	136.53 (68.24)	0.35 (0.09)
Cluster 2	1,10,11,14,16,23	10.70 (1.57)	1,11,12,14,16,23	184.02 (45.72)	0.50 (0.13)
Cluster 3	24		24		0.78
Cluster 4	12		10		0.41
Sample		10.79 (3.05)		221.54 (173.21)	0.39 (0.13)

Notes: For the cluster membership, only the ID of the city is presented. Readers can refer to Table B1 for the names of the cities. The numbers in parentheses are the standard deviations. The average within distance is the mean of all city-pair distances within the same cluster. After obtaining the mean monthly growth rate for each city throughout the sample period, the average monthly growth rate reported in the table is the average of mean growth rate across cities in the same cluster.

In a broad sense, the classification results can reduce to a two-cluster solution. One is Cluster 1, which contains mainly slow-growing markets with an average monthly growth rate of 0.35%. The other combines Clusters 2, 3 and 4, which contain markets with relatively higher appreciation rates (see Table 4.2) and are considered to be "red-hot" markets. There is a much higher degree of heterogeneity within these red-hot markets, however. Compared to the difference in house price appreciation rates, the most striking divergence between the two broad groups is that, referring back to Figure 4.2, the red-hot markets experienced tremendous house price appreciation in the second half of the period, whereas house price growth during the first half of the period makes the most important contribution for the cities in Cluster 1. One can also easily identify a spatial pattern in the house price dynamics of cities with red-hot markets located in Eastern China, as well as others that are mainly in the remaining "peripheral" regions.

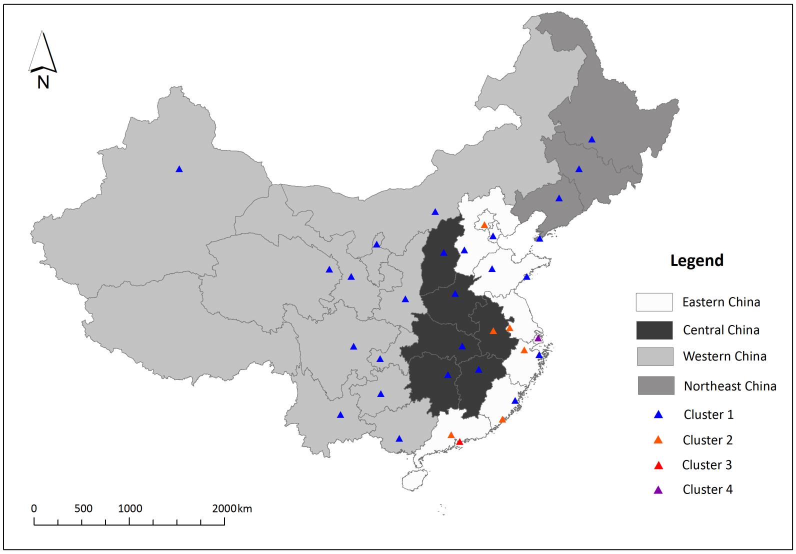

FIGURE 4.5 Spatial distribution of sample cities and their membership based on *JKL* divergence

§ 4.5.3 Do structural changes matter?

The classification analysis of the whole period relies on the premise that the housing market structure of a city does not change. In other words, the relationship between any two cities' housing markets is stable throughout the sample period. This assumption may not hold given the evolving conditions of the nascent Chinese housing market. To explore whether structural changes affect previous classification results, I split the sample into subsamples and perform the classification analysis on each subsample. If there is no structural change, the classification results will be highly consistent among the subsamples, as well as with the clusters presented in Table 4.2. Otherwise, some quite different cluster demarcations will be observed.

The house price appreciation trajectories depicted in Figure 4.1 indicate that house price changes among sample cities are quite volatile during the first half of the period and the recent period. Thus, I divide the sample period into three sub-periods: 2005–2010 (66 observations), 2011–2013 (36 observations) and 2014–2016 (30 observations). For each sub-period, the *JKL* divergence is calculated based on an *AR(3)* specification. The average *JKL* distances between cities as well as the associated standard deviations are reported in the last row of Table 4.3. The average distance between housing markets in the period 2014–2016 (196.79) is much larger than the average distance in the first (92.14) and second periods (71.23), indicating a remarkable divergence of housing markets in the recent period. While the overall housing market difference throughout the whole sample is approximately 220, as measured by *JKL* divergence, it can be concluded that the highly divergent market conditions in the third period account for the most important component.

The hierarchical clustering method is then applied to the three subsamples, providing more details about the structural evolution of housing markets. To obtain comparable clusters across the different periods, the dendrograms of these three periods should be cut at a common "height" (divergence threshold). To do this, I first determine the appropriate number of clusters (k) for the 2014–2016 sample, which should be 5 according to Figure A2. This demarcation requires a minimum height (h) approximately 94.87. I then cut the dendrograms of the first and second period at the same height and obtain 3 clusters for both of the periods. According to the elbow plots in Figure A2, the 3-cluster demarcation is not the optimal solution for the first two periods. But only in this way can the demarcation solutions of the three sub-periods be directly compared with each other.

TABLE 4.3 Cluster membership and statistics for different sample periods

	2005-2010		2011-2013		2014-2016		
	$k = 3, h = 94.87$		$k = 3, h = 94.87$		$k = 5, h = 94.87$		
	Membership	Average within distance	Membership	Average within distance	Membership	Average within distance	Average monthly growth rate (%)
Cluster 1	1,2,3,4,5,6, 7,8,9,11,12, 13,14,15,16, 17,18,19,22, 23,24,25,26, 27,28,29,30, 31,32,33,34	72.16 (45.72)	2,3,4,5,6,7, 8,9,11,14, 15,16,17,18, 20,21,22,25, 26,27,28,29, 30,31,32,33, 34	41.66 (24.42)	3,4,5,6,7,8, 9,19,22,25, 26,27,28,29, 30,31,32,33, 34	29.86 (11.96)	-0.12 (0.09)
Cluster 2	20,21	36.37 (20.21)	12,13,19	52.86 (30.65)	2,13,15,17, 18,20,21	52.71 (26.38)	0.21 (0.12)
Cluster 3	10		1,10,23,24	34.67 (11.24)	1,10,12,23	46.41 (24.12)	0.56 (0.27)
Cluster 4					11,14,16	47.65 (16.20)	0.89 (0.16)
Cluster 5					24		1.82
Sample		92.14 (73.90)		71.23 (66.48)		196.79 (275.54)	0.17 (0.46)

Notes: The same notes as Table 4.2.

In both the 2005–2010 period and the 2011–2013 period, one observes highly integrated, homogeneous cross-city housing markets. Most of the cities are classified into the same cluster, with a few exceptions, Shanghai(10) for instance. The most remarkable structural change between these two periods could be that a few developed eastern cities, such as Beijing(1), Shenzhen(24), Guangzhou(23) and Hangzhou(12), began to deviate from the main group during the 2011–2013 period.

When turning to the 2014–2016 period, the interurban housing market diverges much more. House price growth in Shenzhen(24), where the average monthly growth rate is 1.82%, obviously stands out from the other cities. Aside from the red-hot markets that are already separated in the 2011–2013 period (1, 12 and 23 for example), a few more rapid-growth markets with monthly growth rates of 0.89% (Cluster 4), such as Hefei(11), Fuzhou(14) and Xiamen(16), are also isolated from the main group. Furthermore, there is another cluster (Cluster 2) that deviates from the main group but not by much; this group has a relatively low average monthly growth rate (0.21%) and mainly contains some lower-tier centres in Eastern and Central China, such as Ningbo(13), Fuzhou(15), Nanchang(16) and Wuhan(21). Note that a parsimonious three-cluster solution for the 2014–2016 housing markets, which merges Cluster 1 with Cluster 2, and fuses Cluster 3 with Cluster 4, is highly consistent with the classification results based on the whole period (Table 4.2). By grouping Cluster 1 and Cluster 2 in Table 4.3, one obtains precisely Cluster 1 in Table 4.2. Similarly, Cluster 2 in Table 4.2 is almost identical to the combination of Clusters 3 and 4 in Table 4.3.

To summarize the findings, the Chinese interurban housing market in the early periods (2005–2013) can be considered a homogeneous market; only a few markets have distinctive dynamic patterns of house prices. In the recent period (after 2014), the interurban housing market begins to diverge; not only do the markets of the most important centres of the three main economic regions stand out remarkably, the markets of some lower-tier centres are also isolated. Given this sudden structural change, it is not surprising to see that the clustering pattern of the 2014–2016 period almost determines the classification results based on the whole period.

§ 4.5.4 The effectiveness of geographical and economic divisions

The classification results suggest that geography seems to play a role in the homogeneous clustering of the city-level housing markets. In this section, I will test the effectiveness of the traditional geographical demarcation in describing the interurban housing market structure. This classification scheme was introduced by NBSC in 2011 and divides all of China into four regions: Eastern, Central, Western and Northeast China (see Figure 4.5). In addition, I also examine whether the city-tier system of demarcation based on economic factors can produce meaningful groups of housing markets. There are presently several versions of the city-tier division system available, published by different research institutes or real estate agencies. In this paper I refer to the "*China60*" city-tier system compiled by Jones Lang LaSalle (JLL) (JLL 2015), which rates 60 Chinese cities according to a range of economic indicators and classifies these cities into seven different tiers. I make a slight adjustment to the original demarcation of "*China60*" and reduce the seven-tier system to a four city-tier system. A detailed introduction to the geographical and economic demarcation system can be found in Appendix B.

The McClain and Rao (1975) index (MR index for short), which is defined as the ratio of average within-cluster distance to average between-cluster distance, is employed to assess the power of the two demarcation systems in explaining the interurban housing market structure. The smaller the value, the better the classification scheme performs. To evaluate whether the classification systems really make sense and are significantly different from some random allocations, I simulate the distribution of the MR index under the null hypothesis of random division. Specifically, I generate B random partition samples by randomly assigning the sample cities into clusters with the same sizes as those of the "real" partition and calculate the MR index of each sample. Together with the MR index calculated from the "real" partition, one obtains $B + 1$ values in total, and the p-value is the fraction of the measures that are smaller than and equal to the real MR index. Note that the analysis of this section is based on the JKL divergence matrix of the whole sample.

TABLE 4.4 MR indexes of different demarcation schemes

	NBSC 4-region classification	Adjusted NBSC 2-region classification	JLL 4-tier classification	4-cluster classification in Table 4.2
MR index	0.9760	0.7321	0.7021	0.3971
p-value	0.3807	0.0014	0.0006	0.0000

Notes: The p-value is calculated based on 9999 random permutation samples.

The MR index of the four-region NBSC geographical demarcation, shown in Table 4.4, is 0.9760 with the significance p-value of 0.3807, suggesting that this widely used demarcation scheme is not significantly different from random demarcation schemes and thus cannot explain the interurban housing market structure. However, according to the clustering results of Figure 4.5, the cities in Eastern China indeed behave in a distinct fashion. I therefore test a broader geographical classification scheme with Eastern China in one cluster and the remaining regions in the other. As expected, the adjusted NBSC two-region classification system, which has a lower MR value, is more powerful in explaining the interurban housing market structure and rejects the null hypothesis of random partition at the 1% significance level.

Compared to the larger MR values of geographical demarcation schemes, the JLL 4-tier classification scheme based on socio-economic conditions clearly outperforms the division system that is purely based on geography, though there is some correlation between economic development and localities. Although the economic division and the broad East – Remainder geographical division can make sense in classifying the interurban housing markets, they still produce a large amount of "noise" compared to the clustering solutions reported in Table 4.2. This is mainly because the developed cities' housing markets, such as the markets within Eastern China and Tier 1 cities, diverge more among each other than the undeveloped cities do.

§ 4.5.5 Discussion

House price dynamics are driven by shifts in demand factors, such as income, population and credit market conditions, and by changes in supply factors, such as construction costs and regulation constraints; they are sometimes even driven by behavioural factors, such as spillovers. One weakness of the cluster analysis in this paper is that the markets are clustered solely based on the time-series behaviour of house price changes, but the underlying factors that drive the house price behaviour and clustering process are not clear. However, from the existing literature, one can still make some inferences about the driving mechanisms behind these trajectories. A recent study (Fang et al. 2016) of Chinese house price appreciation reveals that the house price appreciation of first-tier cities (Beijing, Shanghai, Guangzhou and Shenzhen) nearly doubles the increases in disposable income, whereas the price growth of second-tier (i.e., most of the remaining cities in this paper) and third-tier cities is strongly in accordance with income growth. Meanwhile, they also report that the urban population living in the four first-tier cities has increased by 46%, while the population of the second-tier cities has increased by 18% and that of third-tier cities has almost remained stable. On the supply side, Li and Chand (2013) state that supply factors, including construction costs and land prices, play a role in determining the house prices of developed provinces in Eastern China. Thus, it can be tentatively concluded that the slow-growing markets in Cluster 1 (Table 4.2) are mainly driven by income growth, while the red-hot markets in Eastern China (Clusters 2, 3 and 4 in Table 4.2) are more influenced by population growth and housing supply. Moreover, another potential weakness of this paper lies in the fact that the cities' house price dynamics are assumed to be independent from each other after accounting for the time-series structure. This is probably not true given the spillover effect between housing markets that is evidenced in a large amount of literature (e.g.,Holly et al. 2011).

The clustering method in this paper attempts to group the markets that have similar growth trajectories, no matter what the underlying structure is. This logic is different from the clustering logic of van Dijk et al. (2011), who tried to group cities that can be described by a common house price model ($\beta_i = \beta_j$). Furthermore, although the markets within the same cluster tend to move synchronously, this cannot guarantee the property of market cointegration as studied in, for example, MacDonald and Taylor (1993).

The classification results show that diversifying the housing portfolio across space and cities indeed brings some benefits, especially in the recent period when the interurban market has been more fragmented. Beyond this, the results can also benefit policy makers in both the central and local governments. Because the Chinese interurban housing market has undergone significant structural changes in the recent period after 2014, national policy guidance – monetary policy, for instance – would no longer be appropriate for the overall divergent market. The central government has already called on the local governments of those red-hot markets, such as Shanghai, Shenzhen and Nanjing, to play a more active role in tailoring local-oriented policy. Aside from these red-hot markets, the markets of some lower-tier centres (Cluster 2 in Table 4.3), such as Ningbo and Wuhan, also need special attention. Of course, considering the changing circumstances of Chinese housing markets, structural changes might be expected in the future, and policy guidance needs to be updated accordingly. However, the housing market clusters presented in this paper can still provide useful policy guidance in the near future. For housing researchers who focus on aggregation levels above the city, grouping markets based on the city-tier system is a better choice than the geographical four-region division. However, a broad geographical demarcation, which emphasises the role of Eastern China, can still make sense to some extent.

§ 4.6 Conclusion

This paper is a response to the lively debate about interurban housing market divergence in China. I investigated the clustering pattern of 34 cities' housing markets according to their house price appreciation trajectories over the period of July 2005 to June 2016. The hierarchical agglomerative clustering method was employed to perform the partition. In particular, I adopted a distribution-based statistic – Kullback-Leibler (*KL*) divergence – to measure the dissimilarity between markets, which can enable inferences about future market discrepancy. Specifically, the KL divergence was calculated based on the assumption that the house price appreciation series is generated by an *AR(3)* process.

As a response to the debate, I found that the interurban housing market is indeed fragmented and can be broadly partitioned into two clusters. One cluster, which is very large, is mainly composed of markets with low house price growth that are mostly located in Central, Western and Northeast China. The other cluster is a combination of the most important centres in Eastern China that have flourishing housing markets. This cluster has a higher degree of heterogeneity and can be further partitioned into smaller groups. However, I noted that the market divergence seems to be a new phenomenon appearing after 2014; before that year, the interurban housing market in China was relatively homogeneous. The classification results of the recent period (2014–2016) also suggest that not only the red-hot markets of major regional centres but also the markets of some lower-tier centres require special attention.

This paper also tested the usefulness of the widely used geographical demarcation and city-tier system in describing the interurban housing market structure. The four-region geographical demarcation scheme created by the National Bureau of Statistics of China plays no role in terms of explaining housing market structure, but a super-region demarcation scheme, namely 'Eastern China – Remaining periphery', makes sense to some extent. The city-tier system based on socio-economic conditions is a superior system in applied housing market analysis. However, it still produces considerable noise due to the large discrepancies among the cities within higher tiers.

Although this analysis offers no conclusions regarding the driving mechanism underlying the clustering pattern, it is inferred from the literature that the slow-growing cluster is likely to be driven by income increases, while the red-hot markets are probably driven by supply factors and population growth. The classification results also aid housing portfolio managers in diversifying their investments, policy makers in tailoring proper policies for specific markets, and regional researchers in aggregating city markets properly. However, one should bear in mind that structural changes in the future may influence the robustness of the clusters.

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Appendices

Appendix A.Hierarchical agglomerative clustering

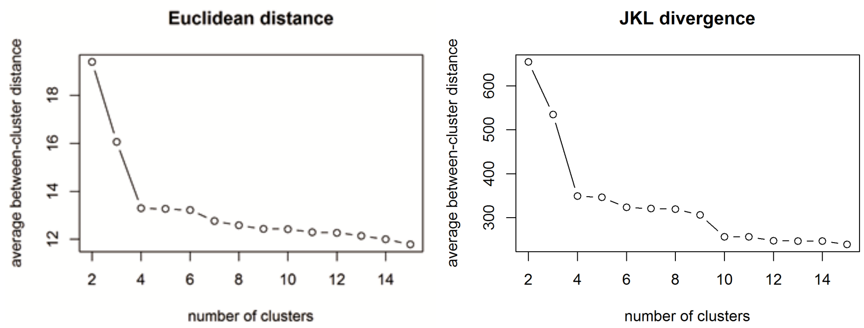

FIGURE A1 The elbow plot for Euclidean distance and *JKL* divergence

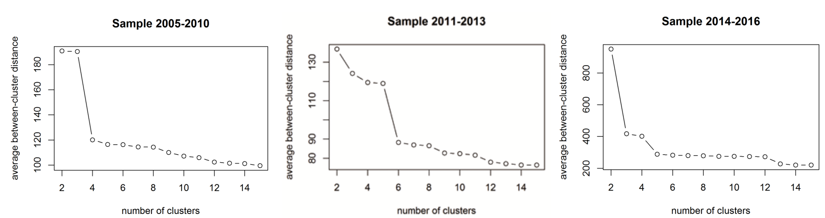

FIGURE A2 The elbow plot for first and second half of the sample period (*JKL* divergence)

TABLE A1 Average Silhouette index for different clusters

	2 clusters	3 clusters	4 clusters	5 clusters	6 clusters	7 clusters	8 clusters	9 clusters
Euclidean	0.4670	0.1966	0.2063	0.2033	0.1875	0.1259	0.1149	0.1144
JKL	0.6287	0.4963	0.4239	0.3469	0.2709	0.2424	0.2093	0.1528

Notes: Since Silhouette statistic is not well defined for the individual groups that have only one member, the average Silhouette indexes are calculated based on the groups that have more than one member.

Appendix B.The geographical and economic division

To better reflect the regional structure of socio-economic conditions, the National Bureau Statistics of China (NBSC) officially divided 32 municipalities, provinces and autonomous regions (excluding Hong Kong and Macao) into four economic regions according to geographical proximity, namely Eastern, Central, Western and Northeast China (see also Figure 4.5) . The Panel A of Table B1 lists the four regions and the cities belonging to them.

The Jones Lang LaSalle (JLL) launched their China Cities Research programme in 2006 and has sequentially published "China30", "China40" and "China50" before the release of "China60" in 2015. The "China60" assesses the relative position of each of 60 cities based on the analysis of a range of economic, business and property indicators and finally allocate the cities to one of the seven tiers: Alpha cities, Tier 1, Tier 1.5, Tier 2, Tier 3 Growth, Tier 3 Emerging and Tier 3 Early Adopter. In this paper, we reduce the seven tiers into four tiers by merging Alpha cities into Tier 1 and by combining Tier 3 Growth, Emerging and Early Adopter into Tier 3 cities. Then the 34 cities, which are all included in the "China60", are assigned into the relative tiers accordingly (see Table B1).

TABLE B1 The list of cities grouped by geographical divisions and by city-tiers

Panel A: Cities grouped by geographical divisions	
Eastern	Beijing (1), Tianjin (2), Shijiazhuang (3), Shanghai (10), Nanjing (11), Hangzhou (12), Ningbo (13), Fuzhou (15), Xiamen (16), Jinan (18), Qingdao (19), Guangzhou (23), Shenzhen (24)
Central	Taiyuan (4), Hefei (14), Nanchang (17), Zhengzhou (20), Wuhan (21), Changsha (22)
Western	Hohhot (5), Nanning (25), Chongqing (26), Chengdu (27), Guiyang (28), Kunming (29), Xian (30), Lanzhou (31), Xining (32), Yinchuan (33), Urumqi (34)
Northeast	Shenyang (6), Dalian (7), Changchun (8), Harbin (9)
Panel B: Cities grouped by tiers	
Tier 1	Beijing (1), Shanghai (10), Guangzhou (23), Shenzhen (24)
Tier 1.5	Tianjin (2), Shenyang (6), Nanjing (11), Hangzhou (12), Wuhan (21), Chongqing (26), Chengdu (27), Xian (30)
Tier 2	Dalian (7), Ningbo (13), Xiamen (16), Jinan (18), Qingdao (19), Zhengzhou (20), Changsha (22)
Tier 3	Shijiazhuang (3), Taiyuan (4), Hohhot (5), Changchun (8), Harbin (9), Hefei (11), Fuzhou (15), Nanchang (17), Nanning (25), Guiyang (28), Kunming (29), Lanzhou (31), Xining (32), Yinchuan (33), Urumqi (34)

Appendix C.The AR(3) estimation

TABLE C1 The AR(3) estimation of selected cities

	Lag 1	Lag 2	Lag 3	Intercept	R-squared	BG test
Tianjin	0.6423***	-0.0355	0.2180**	0.0922*	0.504	8.30**
	(0.088)	(0.105)	(0.093)	(0.052)		
Taiyuan	0.2663***	-0.0502	0.3104***	0.0847	0.179	27.64***
	(0.084)	(0.087)	(0.081)	(0.055)		
Shenyang	0.4988***	0.0611	0.1395	0.0922	0.380	3.33
	(0.089)	(0.098)	(0.087)	(0.057)		
Changchun	0.4762***	0.0576	-0.0414	0.1743**	0.249	26.12***
	(0.089)	(0.097)	(0.085)	(0.075)		
Shanghai	1.0636***	-0.2565*	0.0715	0.0772*	0.801	1.65
	(0.090)	(0.130)	(0.090)	(0.040)		
Ningbo	0.7572***	-0.0572	0.0777	0.0768	0.580	3.00
	(0.089)	(0.111)	(0.089)	(0.051)		
Hefei	0.7352***	0.2850***	-0.1992**	0.0982	0.640	13.24***
	(0.087)	(0.102)	(0.097)	(0.065)		
Nanchang	0.5306***	0.0566	0.1114	0.1336**	0.389	1.01
	(0.089)	(0.100)	(0.089)	(0.061)		
Zhengzhou	0.5888***	0.0147	0.1432	0.1086**	0.447	4.30
	(0.089)	(0.103)	(0.090)	(0.047)		
Changsha	0.5207***	0.2283**	-0.1019	0.1517**	0.418	6.32
	(0.088)	(0.095)	(0.082)	(0.070)		
Guangzhou	0.5805***	0.2104**	-0.0348	0.1422*	0.512	3.81
	(0.089)	(0.102)	(0.091)	(0.080)		
Chengdu	0.5154***	0.2242**	0.0024	0.0686*	0.471	2.07
	(0.089)	(0.096)	(0.088)	(0.041)		
Guiyang	0.5804***	-0.0476	0.0299	0.1588***	0.318	5.89
	(0.089)	(0.103)	(0.089)	(0.061)		
Xian	0.0792	0.2755***	0.2213**	0.1492*	0.179	2.79
	(0.087)	(0.084)	(0.086)	(0.078)		
Yinchuan	0.1882**	0.4658***	0.0623	0.0922*	0.369	1.38
	(0.090)	(0.081)	(0.090)	(0.054)		

Notes: The standard errors are reported in the parentheses. The BG test represents the Breusch-Godfrey test, following the χ_3^2 distribution under the null hypothesis of no serial correlation of order up to 3. ***, ** and * indicate 1%, 5%, 10% significance level, respectively.