ANNALS OF ECONOMICS AND FINANCE **23-1**, 159–196 (2022)

The Future Evolution of Housing Price-to-Income Ratio in 171 Chinese Cities

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This paper examines the future dynamics of the relative housing price-to-income ratio (RHPIR) in China. We find that the convergence in RHPIR will be more congregated in the non-center cities of city clusters, the cities from the eastern region, with a net outflow of population, and low economic policy uncertainty (EPU). The convergence clubs will emerge in the cities with a net outflow of population and from the central and northeastern regions. The center and the non-center cities of city clusters will converge to parallel affordability paths. We pinpoint the cities with precise ranges of RHPIR that require special attention from the policymakers aiming at convergence in housing affordability.

Key Words: Distribution dynamics; Mobility probability plot; Convergence; Housing price-to-income ratio; Economic policy uncertainty.
JEL Classification Numbers: D39, O18, P25.

1. INTRODUCTION

Housing prices in China have been rapidly rising for the past two decades, especially in the major cities significantly outpacing the corresponding growth in households' disposable income. The importance of the residential real estate market to the Chinese economy and the latter's role as the engine of the world's economic growth are well known. Therefore, China's housing prices have been a popular topic in the empirical literature of the 21st century (e.g., Glaeser et al., 2017; Zhou et al., 2019). Likewise, many studies have investigated Chinese housing affordability (Wu et al., 2012; Fang et al., 2016). However, to the best of our knowledge, virtually no

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1529-7373/2022

attention has been paid to the convergence and transitional dynamics of the housing price-to-income ratio with regards to the four fundamental dimensions: regional and urban agglomeration city-specific location, net migration (population growth), and provincial economic policy uncertainty (EPU).

Our study fills this gap by employing the distribution dynamics analysis (DDA) and the Mobility probability plot (MPP) to investigate the future evolution of China's HPIR concerning these four dimensions. We use a comprehensive sample of 171 Chinese cities[1] located throughout China's vast territory. Therefore, unlike most of the studies that use a sample of 35 (or fewer) major cities (e.g., Chow et al., 2016; Dong et al., 2017), our findings apply to the whole of China. Besides, we employ a novel provincial-level, multi-media sourced EPU index, which can be easily replicated and used in future studies. Thus, we deliver novel and practical contributions to the empirical literature.

The main findings of this paper show that the transitional dynamics and the convergence of the HPIR in the long-run vary across cities grouped by the above-mentioned dimensions. First, the convergence value of the relative housing price-to-income ratio (RHPIR)[2] in the center (non-center) cities of city clusters are higher (lower) than that of the non-city cluster cities. Second, the convergence of the RHPIR will be more congregated in the cities from the eastern region, the non-center cities of city clusters, with the net outflow of population, and low EPU. Third, we document the emergence of convergence clubs within the cities from the central, western and northeastern regions, and with a net outflow of population. Finally, we pinpoint precise ranges of RHPIR for the cities from the eastern region, center city clusters, with the fastest population growth, and low EPU groups that require special attention from the policymakers aiming at equitable and affordable housing in China.

Given Chinese authorities' plans for a 'long-term multi-policy mechanism' to stabilize the property market (e.g., Kemp et al., 2020), the following policy implications are suggested. First, Chinese policymakers should include the DDA and MPP in periodically exercised forecasts of future HPIR. Second, to make housing more equitable, it is advised to implement dynamically adjusted policies following city-specific situations, instead of formulating a one-size-fits-all policy. Thus, some cities should be subjected

[1]In our sample there are entities ranging from super-large sized cities (e.g., Shanghai) to small-sized cities with a population of 0.2-0.5 million (e.g., Sanmenxia).

[2]Relative HPIR (RHPIR) is a ratio of a city-specific annual HPIR to the average HPIR of 171 cities in the same year. Given the size and the coverage of our data, we treat the sample's annual average HPIR values as a proxy for the national housing affordability average value. Therefore, a City's RHPIR greater (less) than one indicates that this city's HPIR is above (below) the national mean HPIR.

to more expansionary measures, whereas others to tighter measures discouraging speculation. Third, the policymakers should use the supply- and the demand-side measures as a city-specific, coordinated nexus. From a practical perspective, the nationwide, city-specific information about the evolution of the RHPIR in Chinese cities provided in this paper can be useful to housing traders, real estate developers and mortgage lenders in planning their investment decisions in the volatile and unpredictable environment (Chow et al., 2018).

The structure of this paper is organized as follows. Section 2 introduces the related literature on China's housing market. Section 3 provides a discussion of the DDA and its application in this study. Section 4 explains the data preparation procedure, and descriptive statistics for the RHPIR variable, and elaborates on the four dimensions for grouping the cities. Section 5 presents and discusses the empirical results. Section 6 concludes the paper.

2. LITERATURE REVIEW

In a series of reforms ending in 1998, the public housing allocation system has been mostly banned, and Chinese housing transformed into market-driven (Zhou et al., 2019). China's real estate sector is determined by a range of unique institutional and socioeconomic supply- and demand-side factors. Starting with the supply-side factors, China has a unique centrally planned system of land quotas that composes of three parts: "the maximum amount of land to be used for construction, the minimum amount of farmland to be maintained, and an annual quota for the amount of newly added construction land that is transferred from farmland" (Dong, 2016, p. 16). However, Chinese local governments also play a pivotal role when it comes to land supply and distribution. First, they de-facto control the land supply (Li and Song, 2016). Second, they have the autonomy to decide the purpose (commercial or residential) of the converted farmland (Dong, 2016). In addition, the land auction proceeds constitute an important source of local government's income under the current "tax-sharing system" (Fang et al., 2016). On the one hand, they attempt to obtain more fiscal revenues and stimulate the economy by increasing the land supply and housing investment. On the other hand, depending on the circumstances, they might want to restrict the supply to maintain land prices and prevent excessive bubbles in the real estate sector (Fang et al., 2016; Glaeser et al., 2017). Therefore, while the cost of building construction in China is relatively low compared to other counties (Glaeser et al., 2017), land purchase is a high cost for real estate developers. In addition, the state-owned real estate enterprises (SOREEs) which dominate the housing development industry, also contribute to soaring housing prices in China. According to e.g., Wu et al. (2012), SOREEs (or so-called 'land-kings'), tend to pay higher prices for land at auction because of their 'soft budgets' and inside information.

As for the unique demand-side factors, some scholars point out that the rising urban housing prices are driven by China's unprecedented rapid and prolonged economic growth and urbanization; both significantly faster than in other parts of the world (Fang et al., 2016). For instance, from 1978 to 2017, over 600 million Chinese migrated from the countryside to the cities, while the urbanization rate increased from 18% to 58% during the same period (Xiao et al., 2018). Moreover, there is a long-standing belief shared by the Chinese citizens that their government will not allow the collapse of the housing sector, making a residential property a seemingly risk-free and highly profitable investment. This, in turn, fuels speculative demand for housing as well as perpetuates a fear amongst households of missing out on another housing-price rally. Meanwhile, the lack of alternative investment choices for Chinese residents to 'park' their savings further contributes to speculative demand for residential property (Li and Song, 2016; Kemp et al., 2020).

Furthermore, unique social and cultural factors have also led Chinese people to have a keen interest in purchasing the residential property. First, the traditional agricultural culture makes Chinese citizens attach great importance to land and real estate, and the ownership of an urban dwelling is an important symbol of social status in China (Glaeser et al., 2017). Second, purchasing real estate has become a multi-generational joint investment as an important precondition for success in the 'marriage market' in China. This is especially the case for the relatives of 'prospective husbands' in a society with over 30 million 'surplus' men. Therefore, it is commonplace for many middle-aged and elderly people to help their sons or male family members buy a flat, to help them succeed in marriage (Wei and Zhang, 2011).

Largely due to the above-mentioned factors, housing prices and unaffordability in China have been on an upward trajectory (with cyclical regulatory-induced adjustments) for well over two decades. It is worth mentioning that the recent urban homeownership in China is in the 80% - 90% region, while residential property accounts for over 60% of household assets. Moreover, over 20% of urban households own multiple residential properties (Kemp et al., 2020). At the same time the average housing vacancy rate exceeds 21%, while lower-income households and young workers from the biggest cities live in small-size sub-standard dwellings and are labelled as "city-ants" (Zhang, 2015).

Against this backdrop, the last decade is characterised by the central government's efforts to cool down the overheating urban housing and make it more affordable (Li et al., 2020; Zheng et al., 2021). The central government plans to achieve the above-mentioned goals through a so-called 'long-term mechanism', i.e., reforms targeting simultaneously the supply and demand for housing (e.g., Kemp et al., 2020; Li et al, 2020)[3]. In recent years, the key message that "houses are meant for living instead of speculative investment purposes" has been reiterated by the Chinese leader Xi Jinping, government officials, and the People's Bank of China. Despite the recent economic slowdown and Covid-19, the Chinese government continues its efforts to eradicate housing speculation and decrease reliance on real estate investment as China's major growth engine.

However, substantial inter-city heterogeneity in China's housing prices and HPIR (e.g., Fang et al., 2016; Dong et al., 2017) constitute a major challenge to Chinese policymakers. On the one hand, real estate in the first-tier (super-sized) cities like Shanghai, Beijing, and Shenzhen have been appreciating rapidly for decades, making a house purchase virtually impossible for younger citizens and lower-income households. On the other hand, in many lower tiers (medium- and smaller-sized) cities, prices and unaffordability of housing have grown at a slower pace or even decreased (Dong, 2016; Dong et al., 2017; Cheong et al., 2021). This divergent trend is further aggravated by an inadequate (over) supply of housing in the largest (medium and smaller) cities. Summing up, China's vast territory has many cities, and its urban housing is largely heterogeneous (segmentation, polarization, and divergence) in terms of prices and affordability (Zhou et al., 2019).

Whether there may eventually be a convergence of the urban HPIR in China has become a critical question for Chinese policymakers due to its positive association with wealth equality and 'social harmony' (Piketty, 2014; Zhang, 2015; Cheong et al., 2021). To reach the goal of building a harmonious society, Chinese policymakers must secure housing equality and affordability. Therefore, a long-term convergence in HPIRs across the cities requires the implementation of city-specific differentiated policies (Zhou et al., 2019; Xia et al., 2020). Otherwise, inappropriate one-size-fits-all regulations may have negative long-term consequences[4] i.e., increase the imbalances and promote divergence instead. However, this requires deep knowledge and horizontal comparison of inter-cities HPIR's convergence and transitional dynamics across the whole of China's territory. This study

[3]For example, on the demand side, tightening housing purchase restrictions, introducing the Housing Provident Fund and the shared ownership housing scheme are some of the key policies. On the supply side, the development and promotion of the rental market have been one of the key instruments. For more details on these and other policies see e.g., Li et al. (2020) and Zheng et al. (2021).

[4]For example, non-differentiated (unified) central government expansionary policies of 2008-2010, were the major contributor to a drastic increase in many medium- and smaller-size Chinese cities'HPIR levels from relatively 'healthy' to 'unhealthy' (Dong et al., 2017).

conducts the HPIR's distribution dynamics comparison in a sample of 171 cities grouped by four crucial dimensions.

3. METHODOLOGY

Commonly used parametric approaches of σ-convergence and β-convergence yield a single output value derived from the linear model. Thus, they are not capable of forecasting fully the bi-dimensional distribution e.g., for policy analysis purposes (Cheong and Wu, 2018). Additionally, long-run forecasts based on econometric regressions rely on the selection and extrapolation of explanatory variables which, in turn, are subject to several problems such as endogeneity, omitted variables, outliers[5], multicollinearity, and normality assumptions. It is worth mentioning that both σ-convergence and β-convergence are also criticized as misleading or insufficient tests of convergence (see e.g., Li, 2003; Maasoumi et al., 2007).

In the above backdrop, this study employs the nonparametric distribution dynamics analysis (DDA) first proposed by Quah (1993) to estimate the time-invariant "law of motion" of the distribution, which, in turn, is employed to derive the implied long-run, steady-state equilibrium distribution (Juessen, 2009). The DDA approach can reveal many aspects of the investigated variable that cannot be discovered by traditional econometric methods. Firstly, the DDA can uncover underlying trends (e.g., the persistence and the emergence of convergence clubs) and provide a forecast into the HPIR's future long-term distribution based on historical data. Secondly, it can uncover the transition mechanism and details of the mobility probability for each city's HPIR within the distribution. Due to the above advantages, the DDA has been employed in various economic research on divergence (e.g., Maasoumi et al., 2007; Juessen, 2009; Colavecchio et al., 2011; Cheong et al., 2021).

The DDA approach can be divided into the stochastic kernel approach and the Markov transition matrix analysis. One problem with the latter is that the arbitrary demarcation of the state is associated with the selection of grid values (Cheong et al., 2021). Thus, the former approach is more accurate, as it can avoid arbitrary demarcation completely by employing the stochastic kernel method, which can be understood as an enhancement of the Markov transition matrix analysis with an infinite number of states (Cheong and Wu, 2018). Because of this, we employ the stochastic ker-

[5]For instance, even a single outlier can result in a significant change in the regression line's slope, whereas in the DDA approach there is no slope, instead, we use annual transitions for many cities in each group (subsample). Therefore, the outliers in the DDA method only affect transitions of the outlier, but not the transitions of the remaining entities (cities), thereby eliminating the problem of the outlier associated with the regression analyses.

nel approach, while our estimations use a bivariate kernel shown below in equation (1).

$$\hat{f}(x,y) = \frac{1}{nh_1h_2}\sum_{i=1}^{n} K\left(\frac{x - X_{i,t}}{h_1}, \frac{y - X_{i,t+1}}{h_2}\right) \tag{1}$$

Where n is the number of observations; h_1 and h_2 are the bandwidths, which are calculated based on the approach proposed by Silverman (1986). K is the normal density function and x is a variable representing the relative HPIR (RHPIR)[6] of a city at time t. y is a variable representing the value of RHPIR of this city at time $t+1$, while $X_{i,t}$ is the observed value of the RHPIR of a particular city at time t. Lastly, $X_{i,t+1}$ is the observed value of the RHPIR of that city at time $t+1$. Furthermore, an adaptive kernel approach with flexible bandwidth is used to tackle the potential sparseness of the data which is often a feature of socioeconomic factors characterized by long-tailed distribution (Silverman, 1986; Cheong and Wu, 2018). Besides, this approach ensures that the kernel is not affected by the amount of data available in each region. There are two following steps in this type of adaptive kernel approach. First, we conduct the computation of a pilot estimate. Second, the bandwidth is rescaled again by a factor that reflects the kernel density (Silverman, 1986). Assuming that the evolution is first order and time-invariant, such that the distribution at time $t+\tau$ depends on t only and not on any previous distributions, then the relationship between the distributions at time t and time $t+\tau$ is as follows:

$$f_{t+\tau}(z) = \int_0^\infty g_\tau(z|x) f_t(x) dx \tag{2}$$

Where $f_{t+\tau}(z)$ is the τ-period-ahead density function of z conditional on x. $g_\tau(z|x)$ is the transition probability kernel, which maps the distribution from time t to $t+\tau$, and $f_t(x)$ is the kernel density function of the distribution of the RHPIR at time t (for more details see Juessen, 2009). In this article, annual transitions are employed so that the sample size is sufficiently large such that the estimation results can be prepared and interpreted reliably. The ergodic density function, given that it exists, can be expressed in equation (3) presented below.

$$f_\infty(z) = \int_0^\infty g_\tau(z|x) f_\infty(x) dx \tag{3}$$

Where $f_\infty(z)$ is the ergodic density function when τ is infinite and can provide a forecast of the future evolution of the distribution in the absence of

[6]RHPIR greater (less) than one indicates that this city's HPIR is above (below) the national average HPIR.

structural changes, i.e., the long-run, steady-state equilibrium distribution of the RHPIR. For economic interpretation, it is crucial to point out, that through its construct, $f_{\infty}(z)$ is independent of initial conditions (Juessen, 2009). Based on the above-outlined settings, we can further derive the mobility probability plot (MPP) first proposed by Cheong and Wu (2018), to examine and compare transitional dynamics of HPIR amongst cities with different characteristics. In a nutshell, the MPP tool graphically displays the net probability of city-specific RHPIR moving higher in the distribution in years to come. The net probability of moving higher, in turn,

> (...) is based on the annual transitional dynamics in the sample and computed on the transitional dynamics over the years of the database, and it is calculated by subtracting the sum of probability values of moving downwards within a distribution from the sum of probability values of moving upwards for each state in the transition matrix. (Cheong and Wu, 2018, p.130)

Equation (4) shows how the MPP can be expressed as $p(x)$, which is the net upward mobility probability of the city[7].

$$p(x) = \int_{x}^{\infty} g_{\tau}(z|x)dz - \int_{0}^{x} g_{\tau}(z|x)dz \tag{4}$$

Consequently, the MPP plots the net upward mobility probability against relative HPIR (Cheong and Wu, 2018). The MPP is expressed as a percentage with a range from -100 to 100, such that a positive (negative) value of MPP suggests that the city has a net probability of increasing (decreasing) within the distribution in years to come. Moreover, the MPP method has several advantages over the traditional display tools such as contour maps and three-dimensional plots. First, MPP can provide precise information about the distribution of the probability mass. Second, it can offer enhanced visual representation of the movement of the cities'RHPIR in years to come. Moreover, several MPPs can be superimposed together in a figure, thereby facilitating easier comparison. Finally, the precise mobility probability of the cities'RHPIR can be identified effortlessly just by looking at the relevant MPP (Cheong and Wu, 2018). Summing up, the interpretation of MPP is intuitive and easy to communicate which makes it a powerful tool. Due to the above fortes, the MPP has been recently employed in studies analyzing transitional dynamics of household energy consumption (Shi et al., 2021), consumption upgrading (Yu et al., 2021b), credit rating changes (Lee et al., 2021) or regional housing price disparity (Cheong et al., 2021).

[7]Please refer to Cheong and Wu (2018) for more technical details.

4. DATA SOURCES AND SELECTION OF VARIABLES

4.1. Housing Price to Income Ratio (HPIR)

HPIR is one of the most widely monitored indicators of housing market conditions. It is an intuitive measurement for housing affordability, as income is a fundamental predictor of how much a prospective buyer can afford to pay for a house. For example, Asian Development Bank, OECD, UN-Habitat, and World Bank all routinely employ HPIR in their studies to evaluate housing market conditions (World Bank, 2014). On the one hand, HPIR reflects the ability of residents to buy houses, so it is related to the living standard and welfare level of residents. An excessively high HPIR means it is difficult for residents to purchase housing, often resulting in higher living costs and lower levels of happiness and welfare. Likewise, a divergence (or a very slow convergence) in HPIR can contribute to growing wealth polarization, various socio-spatial stratifications, and social disharmony (e.g., Piketty, 2014; Zhang, 2015; Shen and Xiao, 2019; Cheong et al., 2021). On the other hand, HPIR also reflects the stability of the real estate market, which, in turn, largely affects macroeconomic stability. As such, an excessively high HPIR and convergence to high HPIR may imply speculation in housing stock and housing price bubbles, which may lead to a real estate market crisis. For instance, the bursting of the Japanese (the US) housing bubble of the 1980s (between 2001 and 2006) led to the so-called "lost decade" of the 1990s (US sub-prime mortgage crisis and a global financial crisis). Therefore, HPIR is often used as a summary statistic of over- or under-valuations in the housing market. The HPIR index is also incorporated into other composite indices, such as the UN's urban index and sustainable development index.

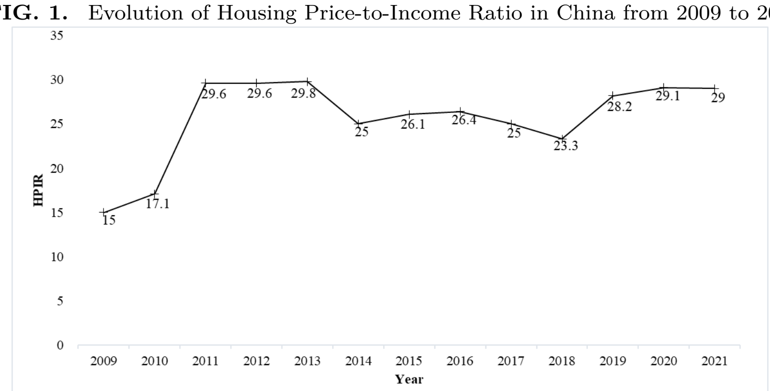
This paper uses the city-level annual HPIR of 171 major Chinese cities. The HPIR is a ratio of housing prices per 100 square meters and disposable income per capita. In conducting stochastic kernel analysis, it is preferable to express the figures as relative values to make the comparison easier[8]. Furthermore, as we focus on the disparity amongst the entities rather than their absolute values, it is better to use relative values which show the difference from the average. Due to that, and to make the housing affordability of different cities comparable, we create the relative HPIR (RHPIR) as follows. First, the national average of HPIR is calculated for each year in the 2002-2016 sample. Second, for each year, the city-specific HPIR score is divided by the national average to compute the RHPIR of each of 171 cities. Consequently, a city's RHPIR greater (smaller) than one indi-

[8]Moreover, if absolute values are used, then for some increasing variables like housing prices (incomes), given that average housing prices (incomes) and absolute housing prices (incomes) of each city increase, if the transition was based on historical absolute value, the forecast could not be higher than the past. Therefore, it is necessary to use relative values when in the sample the variable is increasing over time.

cates that this city's HPIR is above (below) the national average HPIR. Therefore, using nonparametric methods of DDA and MPP, we can investigate cross-sectional distributions of relative housing affordability and their evolution (e.g., convergence, multimodality, and emergence of convergence clubs). However, analysis based on RHPIRs only offers insights on the affordability along the continuum, without information on the actual (absolute) affordability benchmark. Thus, for the whole picture, it is important to have a basic understanding of how the absolute HPIR values have evolved in Chinese cities and in what direction might they move in the future[9].

HPIR values above 5 are considered an indicator of unaffordable housing by supranational organizations (e.g., the United Nations) and in the literature (World Bank, 2014). According to Numbeo, the largest crowd-sourced database specializing in the costs of living, in 2021 China ranked 8$^{\text{th}}$ (out of 109 countries) in terms of the most unaffordable private housing and its HPIR was equal to 29.1 (Numbeo, 2022). Figure 1 shows that between 2009 and 2013, Chinese HPIR doubled from 15.0 to 29.8, while in the following 4 years (2014-2018), it decreased to somewhat lower levels, only to rise again in 2019 and 2020 to 28.2 and 29.1, respectively[10].

FIG. 1. Evolution of Housing Price-to-Income Ratio in China from 2009 to 2021.



Source: Numbeo (2022)

The prioritization of affordable and equitable urban housing by Chinese decision-makers and their impressive track record in handling economic is-

[9]For instance, if the national average HPIR in China declined significantly in years to come, future city-specific relative HPIR above such decreased national average would still be more affordable compared with the same city's current relative HPIR below today's extremely high national average HPIR. We would like to thank the anonymous reviewer for pointing out this important aspect.

[10]This means that during just over two decades Chinese HPIR more than quadrupled from a value of 7.1 in 1998.

sues might suggest that the future path towards affordability and its intercity convergence is just a matter of time. Notwithstanding, the effects of policymakers'efforts are yet to be seen, and thus far, there are no signs of the overall housing situation improving (see Figure 1). Some scholars argue that Chinese urban housing is unlikely to become more affordable given a downward trend in current and expected economic growth coupled with structurally low-interest rates, lack of property tax, alternative investments, and other unique factors outlined in Section 2 (e.g., Rogoff and Yang, 2021). Given the above backdrop and mixed empirical evidence on the house price convergence in China[11], future convergence in HPIR remain uncertain.

Table 1 shows the descriptive statistics of the HPIR by city groups. In terms of the regional grouping, the measures of central location (mean and median) and dispersion (SD and CV) of HPIR in the eastern region are significantly higher than those in the other three regions, which is as expected. Beijing, Shanghai, Guangzhou and Shenzhen (super-sized cities) are far ahead of other cities in terms of housing unaffordability, while all are located in the eastern region. According to the functional positioning of cities, the average (and median) HPIR of the center cities of city clusters is significantly higher than that of the non-center cities of city clusters and non-city cluster cities. This, in turn, is in line with a distinct "center-periphery" feature of the cluster cities. That is, the center cities of Chinese city clusters tend to have the best employment opportunities, and better education and medical resources, thereby attracting labour and students while retaining the elderly, which pushes up the HPIR. Interestingly, the dispersion of HPIR (measured by the CV) is high but similar in the center and non-city cluster cities. On a similar note, we can also observe that cities with the highest population growth rates have the highest HPIRs on average. Lastly, it appears that cities with a higher EPU index (third and fourth quartile) have on average higher (although less dispersed) HPIR than their peers from the first and second quartile EPU groups.

4.2. Cross-sectional Subsampling: The Four Dimensions

The final sample is balanced panel data for the 2002-2016 period and 171 major Chinese cities. Consequently, our sample covers all of China's largest cities, many medium and smaller cities (third-, fourth- and fifth-tier cities) throughout the entire Chinese territory. Timewise, our sample covers most of the recent era; after the implementation of the last round of the

[11]On the one hand, most of the studies document little evidence of convergence (e.g., Zhang and Morley, 2014), the emergence of convergence clubs, that is different growth paths in housing prices (Cai et al., 2022), or even a divergence (Mao, 2016) between and within Chinese regions alike. On the other hand, few studies report the presence of convergence (Chiang, 2014).

TABLE 1.

Descriptive statistics of HPIR variable

HPIR by city groups	Obs.	Mean	Median	S.D.	C.V
Eastern region	600	24.45	21.88	9.237	0.43
Central region	855	17.79	16.90	4.284	0.39
Western region	780	18.38	17.69	4.578	0.38
Northeastern region	330	20.35	19.34	5.323	0.37
The center cities of city clusters	165	30.40	27.04	11.87	0.29
The non-center cities of city clusters	1245	18.61	17.83	4.869	0.29
The non-city cluster cities.	1155	19.69	18.49	5.707	0.27
A negative population growth rate of up to −10%	210	18.74	18.20	4.866	0.26
A population growth rate between −10% and 0%	615	18.27	17.93	3.721	0.26
A population growth rate between 0% and 25%	1395	19.33	18.16	5.523	0.26
A population growth rate above 25%	345	25.48	23.22	10.97	0.25
The lowest (first) EPU quartile	780	18.94	18.62	4.002	0.24
The second EPU quartile	390	17.08	16.02	4.677	0.21
The third and fourth EPU quartiles	1395	21.14	19.18	7.741	0.20

Source: authors'calculation

housing reform in 1998. To investigate the evolution of the urban HPIR in China comprehensively and systematically, we use the following four dimensions (factors) to facilitate grouping the 171 cities into dimension-specific subsamples[12].

Prior literature documents various regional imbalances, polarization, or segmentation in housing prices and affordability due to factors such as uneven economic development, infrastructure, and urban amenities (e.g., Chow et al., 2016; Cai et al., 2022). Quality education, medical care, and employment opportunities are concentrated in the cities located in the eastern region. Accordingly, the demand for urban amenities may be reflected as a premium on housing prices in these cities. Wu et al. (2012) find that the HPIR in China follows different patterns for cities located in different regions. For example, the HPIR rose significantly in the eastern coastal region (Beijing, Shanghai, or Hangzhou), whereas decreased in the central and western regions (e.g., Chengdu, Wuhan, and Xian). Using a sample of 34 major Chinese cities, Chow et al. (2016) forecast that housing prices will converge faster (slower) among the nexus of cities from the northern and southern (eastern and western) provinces. Cheong et al. (2021) find evidence of housing price disparity across China's three main regions is largely determined by intra-regional rather than inter-regional differences. Cai et al. (2022) study regional urban housing prices and document four conver-

[12]For the list of 171 cities classified by the four dimensions please see Table 2 to 5 in the Appendix.

gence clubs largely driven by differences in urban healthcare, changes in population and housing regulations. Against the above backdrop, the first dimension used to group the cities is the geographical location according to the four major regions: eastern, central, western, and northeastern. The eastern, western, central, and northeastern region subsample consists of 40, 52, 57, and 22 cities, respectively.

Zhou et al. (2019) confirm the evidence of spatial heterogeneity in determinants of housing prices as well as in the deviation between the estimated and actual prices. For instance, the net migration factor had a larger positive influence on housing prices in cities located in central and western China (Zhou et al., 2019). The former heterogeneity was observed across the regions, while the latter showed 'spatial agglomeration' across China's three leading city clusters. More specifically, the price deviations were larger in the Yangtze River Delta and Beijing-Tianjin-Hebei urban agglomerations in comparison with the Greater Bay Area (Zhou et al., 2019). The second dimension based on which we split the cities, corresponds to the functional positioning of cities relative to China's urban agglomerations (city clusters). In other words, we divide the 171 cities into three groups according to city cluster classification standards stipulated by the State Council in "the 13th Five-Year Plan" (NDRC, n.d.). Accordingly, we split the cities into three following groups: the center (core) cities of city clusters, the non-center cities of city clusters, and the non-city cluster cities. Since the beginning of the 21st century, the Chinese government has sought to promote regional development and a new advanced form of urbanization by creating city clusters (urban agglomerations) organized around major (center) cities. Such an urbanization plan has two main underlying reasons: an ongoing rural-urban migration and economic slowdown. Our final sample consists of six city clusters. Namely, the three most well-known and leading national-level urban agglomerations: the Yangtze River Delta, the Pearl River Delta, and the Beijing-Tianjin-Hebei city clusters. Another national-level agglomeration in this study is the Chengdu-Chongqing city cluster. Furthermore, we include two regional-level urban agglomerations as follows: Central Plains and Guanzhong Plain.

The third dimension is based on the city-specific growth rate of the resident population (net migration). It is estimated that additional 300 million Chinese citizens will migrate from rural to urban areas during the next three decades (Zheng and Saiz, 2016). However, during the last decades, China has also witnessed a substantial urban-urban migration. This has been directed mainly from northern and western to eastern regions and from smaller and medium to large and super-sized cities (e.g., Zhou et al., 2019; Gao and Wang, 2020). In line with the supply-demand model, inward population mobility affects the demand for housing and thus positively correlates with housing prices and unaffordability (e.g., Chow et al., 2016;

Zhou et al., 2019). For example, in their study of the Yangtze River Delta cluster of 25 cities, Zhang et al. (2019) find a large intra-agglomeration migration. Over 70% of the observed migration occurs from the smaller outer cities to the five large core cities (Shanghai, Nanjing, Hangzhou, Suzhou, and Ningbo). This, in turn, is associated with a divergent trend in housing prices between these five core cities and the rest of the cities (Zhang et al., 2019). Therefore, we use the resident population data for the 171 cities between 2002 and 2016 obtained from the National Bureau of Statistics of China (NBSC) to calculate the average growth rates for each of the cities. Accordingly, we divide the full sample into the following four groups. The first (second) group includes 14 (41) cities with a negative population growth rate of up to −10% (between −10% and 0%). The third (fourth) group consists of 93 (23) cities with a resident population growth rate between 0% and 25% (above 25%). Thus, the cities from the first two and the latter two groups experience a net outflow and a net inflow of population, respectively.

The last dimension is economic policy uncertainty (EPU). China's real estate sector remains highly regulated, while key indicators such as housing prices and affordability remain largely policy-driven (e.g., Wang et al., 2020). Kemp et al. (2020) argue that the cyclical pattern in private housing investment and prices is considerably induced by the Chinese government's varying regulations (expansionary versus contractionary). For example, Huang et al. (2020) find that EPU is positively associated with housing price volatility. Wang et al. (2020) report that high policy uncertainty boosts the effects of other macroeconomic factors on housing prices and volatility in China. Furthermore, Aye (2018) and Chow et al., (2018) establish a causality relationship between EPU and housing market returns in China. It is worth mentioning that these studies use the national level, single-media sourced EPU index developed by Baker et al. (2016) as a proxy for policy uncertainty. This index has been criticized for its shortcomings (e.g., Huang and Luk, 2020; Xia et al., 2020; Yu et al., 2021a). Firstly, Baker et al. (2016) screen the keywords from the South China Morning Post to construct the EPU index. However, the South China Morning Post is an English-language newspaper. Although it can reflect China's EPU to some extent, as a regional (Hong Kong-based) newspaper, it pays more attention to Hong Kong or southern China in the selection of its news content and does not cover the news from other regions of mainland China. Secondly, using data from a single newspaper source is deemed insufficient. Thirdly, Baker et al.'s (2016) EPU index remains at the national level, and as such, does not reflect the imbalances in China's regional development or the impact of highly differentiated provincial economic policies and their implementation on the local urban housing market. Therefore, we develop an extended EPU index at the provincial level, using a broad set of mainland China's daily newspapers instead of the single (Hong Kong-based) newspaper used in Baker et al. (2016). Accordingly, the fourth dimension used to divide 171 cities is based on our novel EPU index constructed as follows.

First, we select 31 major daily newspapers (one in each of 22 provinces, 5 autonomous regions, and 4 municipalities directly under the Chinese central government) as the sources for the provincial news media reports[13]. Second, we employ the following provisions regarding the definition of the EPU index obtained through a keyword search. If at least one economic policy keyword and at least one keyword expressing uncertainty are found, then the news article is considered the target article. Third, we calculate the annual total number of target articles for each of the 31 provinces and divide it by the total number of target articles in the newspapers that contain the keyword "economy" in that year, to obtain the article proportion of the EPU in 31 provinces. Fourth, we standardize the proportion of EPU articles by the standard deviation of each province to obtain the EPU index for 31 provinces in China. Fifth, we re-standardize the above-mentioned standardized data according to the average value of 100. Consequently, we obtain the EPU index of each province in China covering the 2002-2016 period. In the final sixth step, we match the EPU index of each province in China with 171 sampled cities, according to the province code (two-digit) and the city code (four-digit). Based on the above procedure, we can rank the province-specific EPU index of the 171 cities from low to high. This, in turn, enables us to divide the cities into three groups, based on the ranked EPU quartiles. Namely, 52 Cities in the lowest EPU quartile (0-25%) belong to the low EPU group. 26 cities from the second quartile (25-50%) form the middle EPU group. The third group (high EPU) consists of 93 Chinese cities from the third and the fourth quartile (50-100%). Our index constitutes a novel and practical contribution to the literature and can aid future studies on China and economic policy uncertainty.

5. RESULTS AND DISCUSSION

To the best of our knowledge, this paper is the first to investigate the future distribution dynamics of Chinese urban housing relative affordability differentiated by the four dimensions: regional and city cluster-specific location, net migration, and provincial-level EPU. In each dimension, the ergodic distribution, and the mobility probability plot (MPP) tools are used to conduct the analysis. It is important to reiterate that the ergodic distribution represents the implied long-run steady-state distribution of China's RHPIR under the assumption of no changes in transitional dynamics. The

[13]We report the detailed information of newspapers in Table 2 in the Appendix.

horizontal axis of the MPP represents the value of the RHPIR while the upper (lower) part of the vertical axis indicates the probability of an increase (decrease) in the city's RHPIR in the future.

5.1. RHPIR Transitional Dynamics and Regions

The ergodic distributions and the MPPs of 171 major Chinese cities grouped by regions are shown in Figures 2 and 3, respectively. It can be observed from Figure 2 that the major peaks for the RHPIR of cities in all four regions correspond to a value of less than 1 on a horizontal axis. This result implies that in each of the regions many entities will congregate around the lower half of the distribution, i.e., below the national average HPIR. Convergence to a value below the mean implies a long-run, steady-state equilibrium, where few cities with extremely high RHPIRs, coexist with many cities characterized by below the mean HPIRs. Therefore, a high disparity in housing affordability across the cities within the same region is observed. Such evidence is in line with Cheong et al.'s (2021) findings of intra- (inter-) regional heterogeneity being the main (less important) factor behind urban housing price disparity in China. Besides, this is grim news to Chinese policymakers as it might further intensify wealth inequality, social instability, various socio-spatial stratifications, and divergence in intra-regional economic growth (Piketty, 2014; Zhang, 2015; Shen and Xiao, 2019; Cheong et al., 2021). Instead, convergence to the mean value is preferred, i.e., a lower regional disparity in housing affordability.

The above findings could relate to the forecast of ageing and declining trends in the Chinese population during the remaining decades of the twenty-first century (United Nations, 2019b; Vollset et al., 2020)[14]. Such trends would likely lead to an overall long-run decline in the demand for housing purchases, which, in turn, would translate into downward pressure on housing prices in many Chinese cities. However, a small number of cities with the best amenities, education and job opportunities would continue to attract people who "vote with their feet". Moreover, assuming no major change in the Chinese health care/insurance system, the growing numbers of retirees would be reluctant to relocate from those few cities with the best healthcare to the lower-tier cities (Fang et al., 2016). In the above backdrop, inter-generational competition for limited housing stock might occur. Given the above factors, we could expect a divergent trend of long-run increase in both absolute and relative HPIR between the majority of Chinese cities and the few urban "hotspots".

[14]The Chinese population has been forecasted to shrink below 1.1 billion according to United Nations (2019b), while Vollset et al. (2020) have forecasted the Chinese population to decrease by 48% to 732 million between 2017 and 2100. Despite the relaxation of the one-child policy, in 2021, according to NBSC, China's population growth rate has been 0.034%; the lowest since 1960.

It is worth mentioning that Japan has been experiencing similar trends in its population and housing prices/affordability since the 1990s (Hashimoto et al., 2020). Additionally, pessimistic population forecasts loom over two other Southeast Asian countries: South Korea and Thailand (United Nations, 2019a, 2019b). Therefore, the research conclusions of this paper have a certain reference value for the future evolution of RHPIR in those countries. However, due to the uniqueness of the Chinese market (see Section 2) we strongly advise caution with specific policy prescriptions and instead, advocate a cross country (and country-specific) future study on the southeast Asian region.

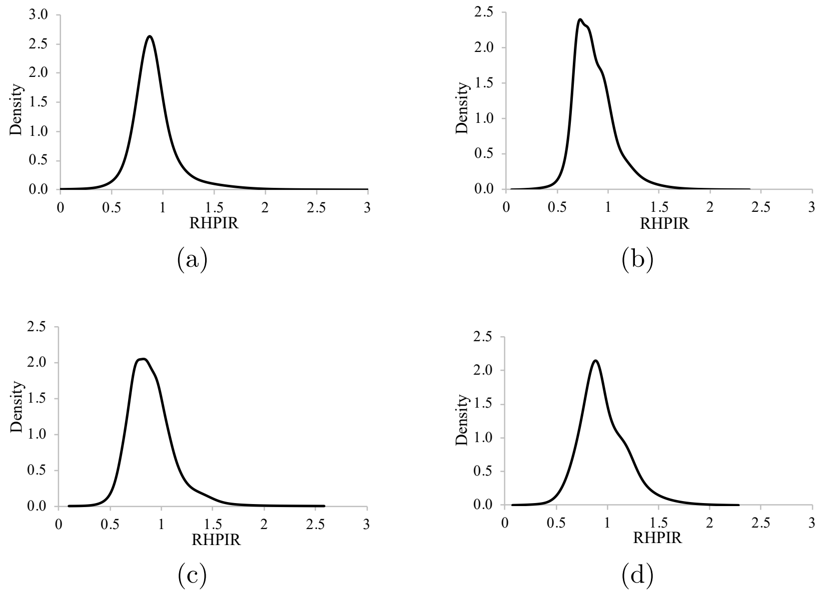
Focusing on the vertical axis of Figure 2 measuring the density of distribution, the height of the peak in panel (a) (the eastern region) corresponds to a value of around 2.6; significantly above the peaks in the other three panels. Furthermore, we can observe one (two) minor peak(s) in the western, northeastern (and central) regions around the values of 1, 1.2 (0.8 and 1), respectively. This, in turn, reflects the emergence of convergence clubs in these three regions meaning different growth paths and conditional convergence is possible in the long run (assuming no changes in transitional dynamics). Summing up, the results suggest the most significant and absolute long-run convergence amongst the eastern region cities.

As for the intuition behind these findings, the eastern region is featured by the highest but relatively more balanced economic development compared to the other three regions. Moreover, many of the eastern region cities have long attracted migration from other regions. From a practical point of view, the economic development in the eastern region has obvious radiation effect. The HPIRs of cities in the eastern region are generally higher (the peak in the eastern region distribution is only slightly below and relatively the nearest to one), and the HPIRs of cities within the region have little difference.

Figure 2 delivers insights into the convergence values and long-run distribution of the RHPIR. However, the future and detailed mobility of the RHPIR for 171 cities grouped by the regions is yet to be revealed. The mobility probability plots (MPPs) presented in Figure 3 provide a direct and detailed interpretation of the probability mass for each group of cities.

The horizontal axis of Figure 3 indicates the values of RHPIR, while the vertical axis measures the percentage net upward mobility probability. In the case of the cities from the central, western, and northeastern regions, each of the three MPPs (plot b, c, and d, respectively) has only one intersection with the horizontal axis around a value of 0.85. Moreover, we can observe many intersections among the MPPs of cities from the central, western, and northeastern regions. This implies that the urban RHPIR dynamics in these three regions are not significantly different from each other. In other words, the cities with similar RHPIR values across the cen-

FIG. 2. Ergodic distributions for the RHPIR of 171 cities grouped by the regions.

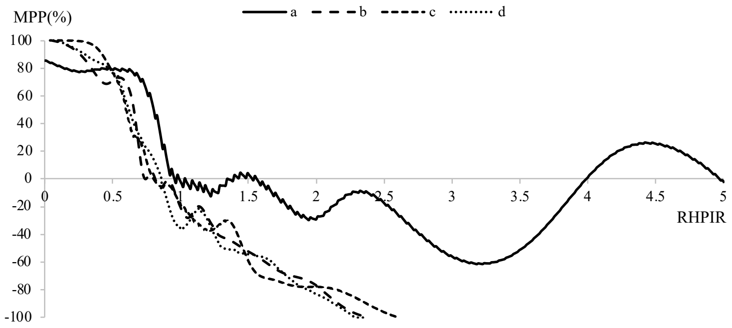


Notes: panels (a), (b), (c), and (d) represent the ergodic distribution for cities in the eastern, central, western, and northeastern regions, respectively.
Source: authors'calculation

tral, western, and northeastern regions have similar net upward mobility probability in the coming years. Furthermore, Plot b, c, and d reach the net upward mobility probability of -100 or a so-called 'development trap' at the range of RHPIR values from 2.2 to 2.5. This is good news for the policymakers as it means that whenever the RHPIR in the cities from these three regions reaches such threshold levels, it will decrease in the following years.

Looking at plot a, we can observe five intersection points at values around 1, 1.3, 1.5, 4, and 5 between the horizontal axis and the MPP of the eastern region cities. This suggests that the cities with above the national average HPIR (from 1.3 to 1.5 and from 4 to 5) are more likely to experience a further upward movement within the distribution in the coming years. Consequently, cities from the eastern region with HPIR within the above ranges of values are the most problematic due to their already relative unaffordable housing with the tendency to increase further in years to come. Thus, the above cities require special attention and should be placed on Chinese policymakers' priority list regarding the goal of equitable hous-

FIG. 3. MPPs for the RHPIR of Chinese 171 cities are grouped by different regions.



Notes: Plot a, b, c and d represent the MPP of cities in the eastern, central, western, and northeastern regions, respectively.
Source: authors'calculation

ing[15]. Furthermore, Figure 3 shows that the MPP of eastern cities plots visibly above the remaining three MPPs at the RHPIR values greater than 0.5. This result implies that except for the entities with very low relative affordability (RHPIR < 0.5), the cities located in the eastern region have a higher (lower) tendency to move upward (downward) within the distribution of 171 Chinese cities in the years to come. This result reflects that the growth rate of future housing prices in the eastern region will exceed the growth rate of residents' income. It can be foreseen that in the future, the eastern region will continue to attract more young people and high-quality talents, thereby promoting future housing prices increases. Such regional differentiation in HPIR's future mobility corroborates with the results of e.g., Wu et al. (2012) showing that housing affordability in major eastern cities worsened, whereas in the central and western cities improved during the 1999-2009 period. Furthermore, this result correlates with Cheong et al.'s (2021) documented evidence of the eastern region having a greater propensity to experience increased growth in urban housing prices relative to the other regions of China.

Summing up, the results from Figures 2 and 3 confirm that the Chinese policymakers aiming at a long-term inter-city convergence in housing affordability, should formulate policies based on the city-specific situation, instead of formulating a one-size-fits-all policy. For instance, the observed

[15]The MPP tool also enables policymakers to rank the entities based on their respective RHPIR and probability of moving upward in the distribution. Consequently, the top of the priority list belongs to the Eastern region cities with RHPIR around a value of 4.5 due to relatively high 20% probability of moving further up in the distribution with their already excessively high HPIR (4.5 times above the national mean).

MPPs imply that, on the one hand, many cities in central, western, and northeastern regions can be subjected to more expansionary measures (e.g., relaxing the household registration system 'hukou'). On the other hand, contractionary measures (e.g., imposing some form of a vacancy tax on the owners and developers) should be considered in many cities in the eastern region with specific HPIR values.

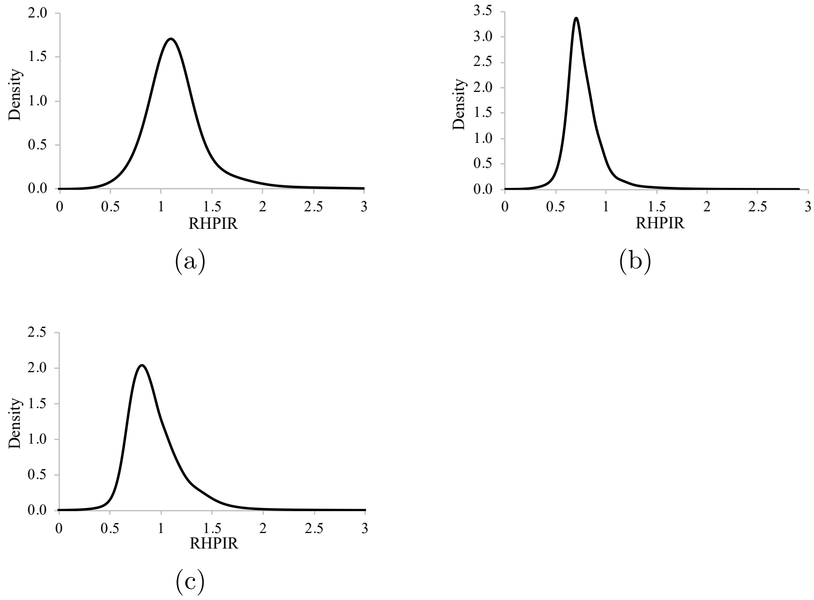
5.2. RHPIR Transitional Dynamics and City Clusters

Studies investigating housing prices within the city clusters document the spatial spillover effect in housing prices from the center (more developed) to non-center (less developed) cities within the city cluster (e.g., Chow et al., 2016; Zhang et al., 2019). Such evidence provides a strong rationale to expect that transitional dynamics and future convergence of the RHPIR may be conditional on the city's positioning relative to Chinese urban agglomerations (city clusters).

Figures 4 and 5 show the ergodic distributions and the MPPs of 171 major Chinese cities divided into three subsamples accordingly. Two important findings can be derived from Figure 4. Firstly, the RHPIR value of the distribution's peak in the center (non-center) cities of city clusters is the highest (the lowest). More specifically, the peak in panel (a), corresponding to 11 core cities of the six major urban agglomerations, has a value of around 1.1, implying that the clusters' center cities will converge above the national mean HPIR in the long-run (under the assumption of no changes in transitional dynamics). Whereas the peaks of ergodic distributions for a group of 83 non-center cluster cities and 77 non-city cluster cities have the approximate values of 0.7 and 0.85, respectively. This, in turn, implies that on average these cities' HPIR will converge in the long-run to values significantly below the national mean. These findings can be interpreted as the outcome of simultaneous 'spread'and 'backwash' forces affecting HPIR's dynamics, with the former effect being smaller than the latter[16]. Overall, we can deduce that the cities grouped by the city clusters are on a converging path to parallel HPIRs. That is, the disparity in housing affordability between the center and non-center cities of city clusters can be a permanent phenomenon. Such findings should be seen as worrisome because long-run housing inequality would contribute to several undesirable phenomena such as income inequality, social instability, socio-spatial stratifications, and divergence in intra-regional economic growth.

[16]The 'spread' and the 'backwash' effects were first introduced in the 'growth pole theory'. In a nutshell, they are the two opposing forces, which in the context of this study determine the direction and the size of the spatial spillover effect in HPIR's dynamics from center to non-center cities of the city clusters. For more on the growth pole theory, the spread and the backwash effect see Chow et al. (2016).

FIG. 4. Ergodic distributions for the RHPIR of 171 cities grouped by locations relative to the city clusters.



Notes: panel (a) denotes the center cities of city clusters, panel (b) denotes the non-center cities of city clusters, and panel (c) represents the non-city cluster cities.
Source: authors'calculation

Secondly, Figure 4 shows that the highest value on the vertical axis of the non-center cities of city clusters (panel (b)) is around 3.3, which is much greater than in the other panels. This result suggests that the distribution of the RHPIR in the non-center cities of city clusters will be substantially more concentrated in the long run, especially in comparison with the core cities of the city clusters.

As for the underlying factors, the center cities of city clusters have more resources to attract (retain) fresh talent inflow (older generation), such as more and better-paid jobs opportunities, high-quality education, infrastructure and superior social security (medical resources). Thus, people are more willing to live, study and work in the center cities of city clusters, which translates into stronger demand for limited housing, thereby making the HPIRs of the clusters' center cities higher than those of other cities today and in the long run alike. A similar trend has been present in Japan since the 1990s (Hashimoto et al., 2020). Moreover, our findings are consistent with the non-center cities of city clusters and the non-city cluster cities, being relatively less attractive and suffering from a brain drain. It appears that the relative HPIR decline in these cities is an irreversible long-run trend.

From the policy perspective, to achieve long-term convergence in housing affordability (around the national mean), the Chinese government should identify the 'spread' and the 'backwash' factors and implement the policies promoting (obstructing) the former (latter). For instance, coordinated economic development, integrated and flexible labour market, improved capital mobility, and transportation infrastructure among the core and non-core cities are the 'spread' factors. On the other hand, e.g., relaxing the 'hukou' registration system and investing in higher quality urban amenities (education, healthcare) in the non-center cities, may reduce the 'backwash' effect. Such targeted, city cluster-specific measures will require effective coordination between the central and local governments as well as among the local governments of the central and non-central cities within the same urban agglomeration.

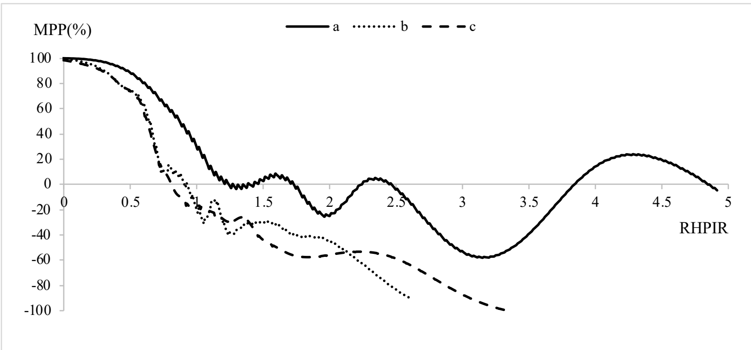
It is worth mentioning that despite unique supply and demand factors, the economy and housing market of China have experienced marketization, privatization, and liberalization similar to post-communist Central and Eastern European countries. Moreover, same as China, these transitional economies have been experiencing increasing unaffordability and differentiation (ageing and shrinking) in their housing stocks (populations)[17] (e.g., Pichler-Milanovich, 2001; Wei et al., 2020). Thus, our findings have a certain reference value and can contribute to the understanding of future HPIR patterns and differentiation in post-communist transitional countries.

It can be observed from Figure 5 that the lowest-value intersection between the horizontal axis and the MPP of the clusters'center cities (plot a) is around 1.3. That is above the national mean and significantly higher than the other two MPPs (both of which have values of less than one). Besides, plot a intersects the horizontal axis at six points with RHPIR values of around 1.5, 1.75, 2.25, 2.5, 3,8, and 4.8. This result suggests that core cities in the city clusters with RHPIR between 1.5-1.75, 2.25-2.5, and 3.8-4.8 are more likely to move further up within the distribution. That is, their housing unaffordability relative to other Chinese cities is likely to increase further in the future. Therefore, the center cities of city clusters with the above range of RHPIR merit a place in the policy priority list. Additionally, this observation is in line with the differences among the ergodic distributions from Figure 4 and as such, offers additional support to the differentiated policies suggested in the previous paragraphs.

[17]Eighteen Central and Eastern European nations are projected to have an even greater decline in their population than China between 2019 and 2050 (United Nations, 2019b).

Moreover, looking at Figure 5, we can observe many intersections between the non-center and the non-city cluster cities' MPPs. That means that on average, the future dynamics of the RHPIR in these two groups of cities are not expected to be significantly different. However, the MPP of 11 center cities from six major urban agglomerations in the sample has a vividly different pattern. More specifically, along its entire length, plot a is positioned significantly above the other two MPPs. This, in turn, suggests that compared to the remaining cities, city clusters' core cities exhibit a significantly higher (lower) tendency to move upward (downward) in years to come within the national distribution. This result is essentially consistent with that reflected in Figure 4 and intuitively corroborates the superior charm and attraction of the center cities of city clusters in comparison with the surrounding cities, especially in the central and western regions. Summing up, the results presented in Figures 4 and 5 carry important policy implications, i.e., without city-specific coordinated policies, the polarization in terms of housing affordability between the central cities of city clusters and other Chinese cities will be a long-run (even more severe) phenomenon.

FIG. 5. MPPs for the RHPIR of 171 cities in China grouped by locations relative to the city clusters.

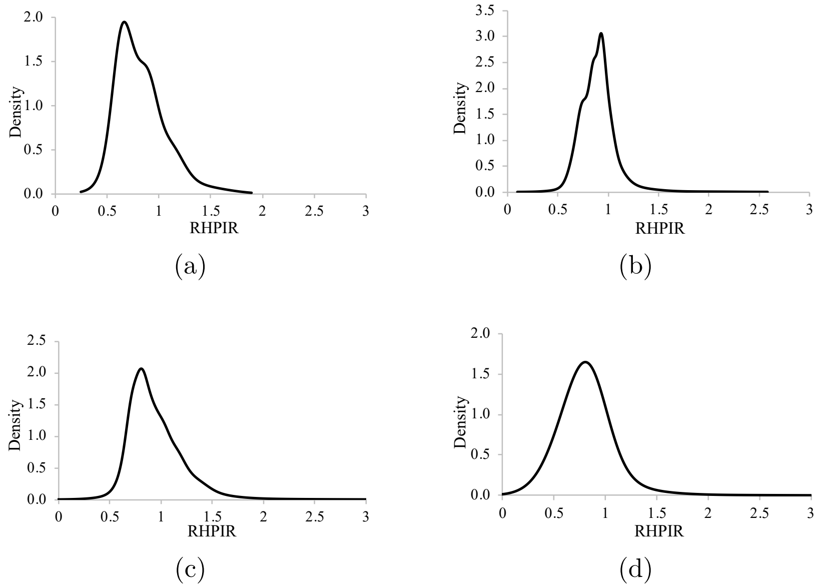


Notes: plot a denotes the center cities of city clusters, plot b denotes the non-center cities of city clusters, and plot c represents the non-city cluster cities.
Source: authors'calculation

5.3. RHPIR Transitional Dynamics and Population Growth Rates

In recent decades, some Chinese cities have witnessed a large inflow of population, while others experienced zero or negative population growth. There is a consensus in the relevant empirical literature regarding the major role that internal migration plays as a demand-side factor influencing the prices and affordability of urban housing in China (Chow et al., 2016; Zhou et al., 2019). Thus, we use the DDA to examine the transitional dynamics of 171 Chinese cities' relative HPIR taking into consideration city-specific net migration. More specifically, we divide the cities into four subsamples according to their average residential population growth rate for the 2002-2016 period. The ergodic distributions and the MPPs of these four groups of Chinese cities are shown in Figures 6 and 7, respectively.

FIG. 6. Ergodic distributions for the RHPIR of 171 cities grouped by different growth rates of the resident population.

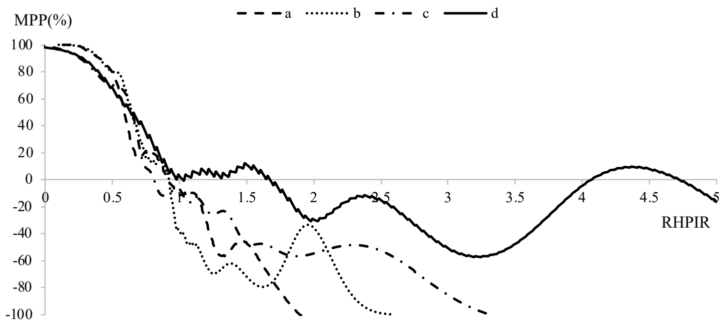


Notes: Panel a (b) denotes the ergodic distribution of cities with a negative population growth rate up to −10% (between −10% and 0). Likewise, panel c (d) represents the ergodic distribution of cities with a population growth rate between 0 and 25% (above 25%).

Source: authors'calculation

Figure 6 indicates that the RHPIR values of the highest peak in two groups of cities with negative population growth are around 0.7 (panel (a)) and 0.9 (panel (b)). Likewise, the highest peaks of the RHPIR in two groups of cities with positive rates of growth are around 0.8 (panel (c)) and 0.85 (panel (d)). This result implies that even though long-run convergence is possible, most of the cities will converge to the lower half (below the national average RHPIR value) of the national distribution. Besides, we can observe additional smaller peaks in the ergodic distribution representing the cities with a net outflow of their population. These peaks, in turn, reflect the emergence of convergence clubs in RHPIR's in the long run, assuming no changes in transitional dynamics. Moreover, the highest value on the vertical axis of the cities with a growth rate between -10% and 0% (see panel (b)) is around 3, i.e., the highest among the four groups. This result implies that in the long-run, if the distribution dynamics remain the same, on average, the RHPIR convergence in this group of cities will be the most significant and the nearest to the national average.

FIG. 7. MPPs for the RHPIR of 171 cities grouped by different growth rates of the resident population.



Notes: Plot a (b) denotes the MPP of cities with a negative population growth rate greater than -10% (between -10% and 0). Likewise, plot c (d) represents the cities with a population growth rate between 0 and 25% (higher than 25%).
Source: authors'calculation

Figure 7 shows two (three) tangency (intersection) points between the horizontal axis and the MPP of the cities with the highest population growth rate (plot d). More specifically, plot d reaches the horizontal axis around the RHPIR value of 1 and 1.3, while intersects with it at the value of 1.7, 4.1, and 4.75. Besides, two obvious peaks can be observed around the values of 1.5 and 2.4, with regards to plot d. Such findings mean that cities with the highest population growth and RHPIR below 1.7 and from 4.1 to 4.75 are more likely to experience a further increase within the distribution in the years to come. This, in turn, implies that especially the cities with population growth above 25% and RHPIR around 1.5 and from 4.1 to 4.75 should be added to the previously outlined policy priority list. Moving on to three other MPPs displayed in Figure 7, the intersection points with the horizontal axis are in the 0.8-0.9 range of RHPIR values, i.e., slightly below the national average. Furthermore, plot a, b, and c, reach the development trap at the RHPIR value of 1.9, 2.5, and 3.3, respectively. This translates to a positive piece of news from the perspective of future relative affordability and convergence in the housing stock. Moreover, we can observe that for the values below 0.9, there are many intersection points among the four mobility plots. This suggests that for the Chinese cities with relatively affordable housing (below-the-average HPIR), future mobility will follow a similar pattern, regardless of the city-specific population growth. By contrast, for the RHPIR values above 0.9, plot d lies significantly above the remaining three MPPs.

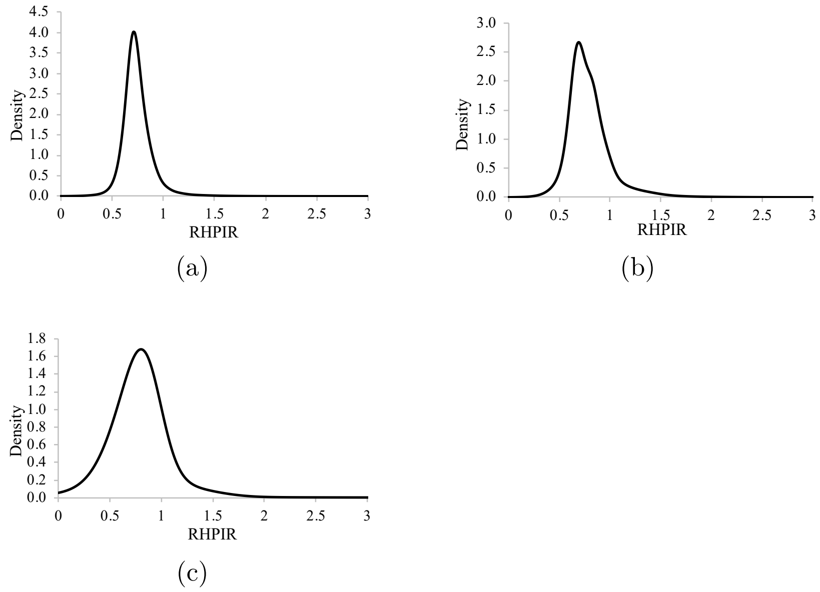
Concluding, our findings suggest that in the cities with population growth rate above 25%, the further rise (fall) in RHPIR will be significantly more (less) likely in the future. This result implies that in ageing and declining population, the net migration (especially younger cohorts) is the decisive factor affecting the demand for housing stock and thus its price and affordability (e.g., Cai et al., 2022). From the policy perspective, the policymakers should augment their forecasting arsenal with periodically computed MPP of nationwide RHPIR and use such output to pinpoint the cities which require special attention, i.e., a place on the policy priority list.

5.4. RHPIR Transitional Dynamics and Economic Policy Uncertainty (EPU)

A growing empirical literature documents that urban housing prices are affected by economic policy uncertainty (EPU) (e.g., Aye, 2018; Chow et al., 2018; Wang et al., 2020). In this study, we develop a novel provincial-level multi-media sourced EPU index and divide the 171 Chinese cities into three groups: low-, middle-, and high-EPU. Figures 8 and 9 show the ergodic distributions and the MPPs of Chinese cities grouped by the EPU levels, respectively.

Two important findings can be inferred from Figure 8. First, cities in the low- and middle-EPU groups will converge to a long-run steady-state equilibrium with the RHPIR value of around 0.7, i.e., significantly below the national average. This signifies that even though HPIR convergence is possible in cities with low and medium EPU, most of the cities will congregate around the lower part of the distribution. Likewise, the cities in the high group of EPU (panel (c)) will converge to the RHPIR value of around 0.8, which is higher and closer to the national average HPIR than the other two groups. Second, the highest value in the ergodic distribution (on the vertical axis) for the low-EPU group is around 4, i.e., significantly higher than the corresponding peak heights in the other two panels. This result shows that in the long run, the convergence of the RHPIR in the cities characterized by low economic policy uncertainty will be relatively the most significant. By contrast, the peak value (on the vertical axis) of the high-EPU group of cities is only 1.7. Consequently, under the assumption of no changes in transitional dynamics, in the long run, the RHPIRs of the cities with high (low) levels of EPU will be the most (the least) dispersed. Thus, our results are congruent with the recent study by Huang et al. (2020) where the EPU had a positive effect on housing price volatility.

FIG. 8. Ergodic distributions for the RHPIR of 171 cities in China grouped by different values of the provincial-level EPU index.



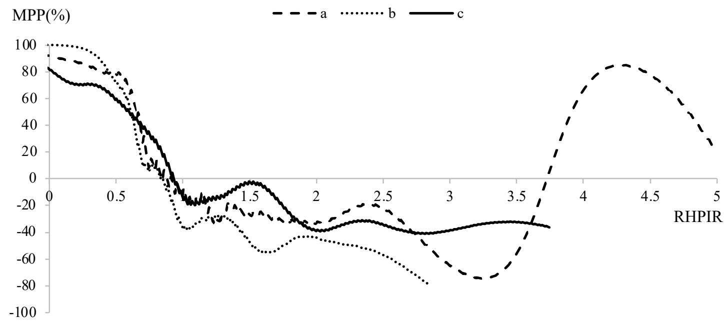
Notes: panel (a), (b), and (c) shows the ergodic distribution for the low-, the middle-, and the high-EPU group of the cites, respectively.
Source: authors'calculation

Moving on to Figure 9, we can observe that MPPs of the middle- and high-EPU (low-EPU) group, lie above the vertical axis for RHPIR values below 0.85 and 0.95 (below 0.85 and from 3.7 to 5), respectively. We can derive two inferences from the above-mentioned observations. First, most (all) of the sampled cities characterized by high and medium EPU and with the RHPIR below (above) the national average are more likely to move upward (downward) within the distribution in years to come[18]. Besides, we can observe that cities within the low-EPU group and RHPIR values equal to one (the national average) have a relatively high 40% probability of moving downward within the distribution in the following years. Second, we can conclude that the low-EPU Chinese cities with RHPIR range of values from 3.7 to 5 are extremely worrisome from the policy perspective

[18]However, it is worth mentioning that plot c approaches the horizontal axis around the RHPIR value of 1.5. This means that cities with high EPU and HPIR of around 1.5 times the national average have high tendency to remain in the same place within the future distribution, i.e., relatively unaffordable in terms of their housing stock.

and should be placed by the policymakers high on their priority list[19]. Moreover, the MPP for the high-EPU group (plot c) is generally less volatile in comparison to two other MPPs. This, in turn, translates to relatively weaker aggregate net mobility of high-EPU cities within the distribution in years to come.

FIG. 9. Mobility probability plots (MPPs) for the RHPIR of 171 cities in China grouped by different values of the provincial-level EPU index.



Notes: Plot a, b, and c represent the low-, middle-, and high-EPU groups of Chinese cities, respectively.
Source: authors'calculation

6. CONCLUSIONS AND IMPLICATIONS

The real estate sector plays a pivotal role in the Chinese economy, households' wealth, and investment. Moreover, due to the strong negative relationship with income inequality, affordable and equitable housing stock is crucial from the perspective of achieving a harmonious society (Piketty, 2014; Zhang, 2015; Shen and Xiao, 2019; Cheong et al., 2021). Thus, the goal of long-term price stability and convergence in housing affordability has ranked very high on the Chinese government's agenda during the last decade. However, achieving it is going to be difficult, because of substantial regional and inter-city heterogeneity in urban housing (Fang et al., 2016; Dong et al., 2017; Cai et al., 2022) reinforced by the forecasts of ageing and shrinking population (United Nations, 2019b; Vollset et al., 2020).

This paper employs balanced panel data of 171 Chinese cities during the 2002-2016 period. Thus, our findings are based on a sample covering urban HPIR data ranging from the super-large-sized to the small-sized

[19]This is particularly the case for the cities with RHPIR value of 4.4, i.e., the cities with severe relative unaffordability of housing and very high net probability (85%) of moving further above the national average in the future.

cities located throughout the entire Chinese territory. This constitutes a major contribution compared with most prior studies limited to 35 (or fewer) largest first- and second-tier cities. We use the distribution dynamics analysis (DDA) and the MPP tool to study the future evolution of the relative HPIR concerning four important dimensions: regional and city clusters-specific location, net migration, and economic policy uncertainty (EPU). To the best of our knowledge, we are the first to investigate Chinese housing affordability from this perspective. Furthermore, we construct a new provincial-level, multi-media sourced EPU index, which can be conveniently used in future studies instead of criticized but commonly used national-level, single-media sourced EPU index developed by Baker et al. (2016). Thus, we deliver novel contributions to the empirical literature.

Our results reveal several important differences in the distribution dynamics of China's urban housing. Firstly, we find that the convergence in RHPIR will be more congregated in the non-center cities of city clusters, the cities from the eastern region, with a net outflow of population, and low economic policy uncertainty (EPU). Secondly, the convergence clubs will emerge in the cities from the central, western and northeastern regions and with a net outflow of population. Thirdly, the center and the non-center cities of city clusters will converge to parallel housing affordability paths.

From the policy angle, the following implications may be drawn and incorporated by the Chinese authorities in their planned 'long-term mechanism' to stabilize the urban housing market. First, the Chinese policymakers should enrich the arsenal of the methodologies used to forecast future trends in the urban HPIR. That is, the DDA and MPP constitute useful augmenting tools worthy of inclusion in the annually or biannually exercised nationwide RHPIR projections. Second, to make the housing stock more equitable, it is advised to implement city-specific policies, rather than formulating a one-size-fits-all policy. Thus, to achieve the inter-city long-term HPIR convergence around the national average, cities projected to have below the national average HPIR in the future should be subjected to more stimulatory measures. On the other hand, the cities from the policy priority list (as pinpointed by the MPP tool) merit urgent contractionary policies. Third, the supply- and the demand-side policies should be considered simultaneously as city-specific regulatory nexus.

From a practical perspective, our findings (and more generally the DDA and MPP methods) can be relevant to housing traders, real estate developers and mortgage lenders in their planned investment decisions by providing them with multidimensional city-specific information about the evolution of the RHPIR. Given that the housing market in China is still volatile and unpredictable (Chow et al., 2018), such insights could be useful to these agents. For instance, cities with RHPIRs significantly above the national average and high positive net upward mobility probabilities can be regarded as having overheated housing markets in the future, thereby informing banks about the potentially high risk of default on local mortgage loans.

It is important to note that although DDA and MPP tools provide valuable insights into the evolution of studied variable distribution, this approach (like any other) has limitations. Firstly, the analytical results must be presented graphically. Secondly, when using DDA techniques, we could not control for other driving underlying factors (e.g., government investment, housing regulations, population age, wage growth, healthcare level etc.) but instead must run the additional analysis for different sub-groups based on these driving factors. Thirdly, the implied ergodic density function relies on a restrictive assumption of no changes in transitional dynamics, i.e., the time-invariant law of motion (Juessen, 2009). Therefore, while we advocate the usefulness of the DDA and MPP tools to the industry practitioners and policymakers, we also advise those tools to be used periodically (annual or biannual basis). Finally, we would like to stress that we are not ascribing any causal relationship in our study, nor denying the influence of a range of factors outside the scope of this paper. We are merely trying to improve the understanding of the existence of HPIR convergence focusing on only four dimensions. Therefore, this paper should be portrayed as a nascent work that calls for further studies on the convergence of urban HPIR in China and other countries. For instance, future China-focused research could undertake comparisons between HPIR's distribution dynamics based on different city-tiers healthcare levels and periods.

ACKNOWLEDGEMENT

This work was supported by the Beijing Research Center of the thought on socialism with Chinese characteristics for a new era (19LLLJA001), the National Social Science Foundation of China (21BJL011), and the Program for Innovation Research at the Central University of Finance and Economics.

APPENDIX

TABLE 2.

The selection of 31 major newspapers (and the number of corresponding newspaper texts) in each of China's provinces, as well as, in five autonomous regions (AR) and four municipalities directly under the Chinese central government (MDCCG).

Province/ (AR)/ MDCCG	Newspaper	The number of newspaper texts
Beijing (MDCCG)	Beijing Daily	55,370
Tianjin (MDCCG)	Tianjin Daily	33,370
Hebei	Hebei Daily	51,854
Shanxi	Shanxi Daily	70,638
Inner Mongolia (AR)	Inner Mongolia Daily (in Chinese only)	35,098
Liaoning	Liaoning Daily	48,839
Jilin	Jilin Daily	69,689
Heilongjiang	Heilongjiang Daily	46,724
Shanghai (MDCCG)	Jiefang Daily	37,874
Jiangsu	Xinhua Daily	41,213
Zhejiang	Zhejiang Daily	37,215
Anhui	Anhui Daily	26,369
Fujian	Fujian Daily	40,693
Jiangxi	Jiangxi Daily	33,868
Shandong	Dazhong Daily	24,203
Henan	Henan Daily	47,257
Hubei	Hubei Daily	71,167
Hunan	Hunan Daily	37,887
Guangdong	Southern Daily	54,842
Guangxi (AR)	Guangxi Daily	43,432
Hainan	Hainan Daily	4,631
Chongqing (MDCCG)	Chongqing Daily	34,539
Sichuan	Sichuan Daily	48,518
Guizhou	Guizhou Daily	37,622
Yunnan	Yunnan Daily	41,070
Tibet (AR)	Tibet Daily (in Chinese only)	26,294
Shaanxi	Shaanxi Daily	58,054
Gansu	Gansu Daily	65,637
Qinghai	Qinghai Daily	36,729
Ningxia (AR)	Ningxia Daily	29,429
Xinjiang (AR)	Xinjiang Daily (in Chinese only)	25,320

Sources: authors' calculation

TABLE 3.

Eastern region cities
Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Shanghai, Wuxi, Yangcheng, Zhenjiang, Taizhou (Zhejiang), Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou (Jiangsu), Lishui, Jinan, Tsingtao, Guangzhou, Shenzhen, Zhuhai, Shantou, Dongguan, Zhongshan, Chaozhou, Jieyang, Haikou

Central region cities
Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Lüliang, Hefei, Wuhu, Bengbu, Huainan, Maanshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Luan, Bozhou, Chizhou, Xuancheng, Nanchang, Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Xingxiang, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Zhumadian, Yichang, Xiangyang, Ezhou, Jingmen, Huanggang, Changsha, Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiajie, Chenzhou, Huaihua, Loudi

Western region cities
Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Ordos, Hulunbuir, Bayannur, Ulanqab, Nanning, Liuzhou, Beihai, Qinzhou, Chongqing, Chengdu, Zigong, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Yibin, Guangan, Dazhou, Bazhong, Ziyang, Guiyang, Liupanshui, Xian, Tongchuan, Baoji, Xianyang, Weinan, Yanan, Hanzhong, Yulin, Ankang, Shangluo, Lanzhou, Baiyin, Tianshui, Wuwei, Zhangye, Pingliang, Jiuquan, Xining, Yinchuan, Shizuishan, Wuzhong

Northeastern region cities
Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkow, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Changchun, Jilin, Siping, Tonghua, Baishan, Songyuan, Harbin, Jiamusi

Source: NBSC

TABLE 4.

City clusters	**The center cities of City clusters**
Beijing-Tianjin-Hebei city cluster:	Beijing, Tianjin, Baoding, Langfang
Yangtze River Delta city cluster:	Shanghai
Central Plains city cluster:	Zhengzhou
Pearl River Delta city cluster:	Guangzhou, Shenzhen
Chengdu-Chongqing city cluster:	Chongqing, Chengdu
Guanzhong Plain city cluster:	Xian

The non-center cities of city clusters

Wuxi, Yangcheng, Zhenjiang, Taizhou (Zhejiang), Hangzhou, Ningbo, Jiaxing, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou (Jiangsu), Hefei, Wuhu, Bengbu, Maanshan, Huaibei, Tongling, Anqing, Chuzhou, Fuyang, Suzhou, Bozhou, Chizhou, Xuancheng, Nanchang

The non-city cluster cities

Hengshui, Taiyuan, Datong, Yangquan, Shuozhou, Jinzhong, Xinzhou, Lüliang, Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Ordos, Hulunbuir, Bayannur, Ulanqab, Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkow, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Changchun, Jilin, Siping, Tonghua, Baishan, Songyuan, Harbin, Jiamusi, Wenzhou, Quzhou, Lishui, Huainan, Huangshan, Luan, Jinan, Tsingtao, Shaoyang, Zhangjiajie, Chenzhou, Huaihua, Shantou, Chaozhou, Jieyang, Nanning, Liuzhou, Beihai, Qinzhou, Haikou, Guangyuan, Bazhong, Guiyang, Liupanshui, Yanan, Hanzhong, Yulin, Ankang, Lanzhou, Baiyin, Tianshui, Wuwei, Zhangye, Jiuquan, Xining, Yinchuan, Shizuishan, Wuzhong

Source: NBSC

TABLE 5.

Cities with a negative population growth rate below -10%
Ulanqab, Tieling, Chaoyang, Quzhou, Lishui, Anqing, Fuyang, Luan, Shangqiu, Zhumadian, Guangyuan, Guangan, Ziyang, Pingliang

Cities with a population growth rate between -10% and 0%
Chifeng, Hulunbuir, Bayannur, Fushun, Dandong, Jinzhou, Fuxin, Huludao, Jilin, Siping, Tonghua, Baishan, Jiamusi, Yangcheng, Taizhou, Huangshan, Chuzhou, Suzhou, Kaifeng, Anyang, Xuchang, Nanyang, Xiangyang, Zigong, Deyang, Mianyang, Suining, Neijiang, Leshan, Yibin, Dazhou, Liupanshui, Xianyang, Weinan, Hanzhong, Ankang, Shangluo, Baiyin, Tianshui, Wuwei, Zhangye

Cities with a population growth rate between 0% and 25%
Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Lüliang, Hohhot, Wuhai, Tongliao, Shenyang, Dalian, Anshan, Benxi, Yingkow, Liaoyang, Panjin, Changchun, Songyuan, Harbin, Wuxi, Zhenjiang, Ningbo, Wenzhou, Huzhou, Shaoxing, Jinhua, Zhoushan, Taizhou, Bengbu, Huaibei, Bozhou, Chizhou, Xuancheng, Nanchang, Jinan, Tsingtao, Luoyang, Pingdingshan, Xingxiang, Puyang, Luohe, Sanmenxia, Yichang, Ezhou, Changsha, Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiajie, Chenzhou, Huaihua, Loudi, Zhuhai, Shantou, Chaozhou, Jieyang, Nanning, Liuzhou, Beihai, Qinzhou, Chongqing, Chengdu, Luzhou, Nanchong, Bazhong, Xian, Tongchuan, Baoji, Yanan, Yulin, Lanzhou, Jiuquan, Xining, Shizuishan, Wuzhong

Cities with a population growth rate above 25%
Beijing, Tianjin, Taiyuan, Baotou, Ordos, Shanghai, Hangzhou, Jiaxing, Hefei, Wuhu, Huainan, Maanshan, Tongling, Zhengzhou, Jingmen, Huanggang, Guangzhou, Shenzhen, Dongguan, Zhongshan, Haikou, Guiyang, Yinchuan
Source: NBSC

TABLE 6.

Cities from the lowest EPU quartile (0-25%)

Hefei, Wuhu, Bengbu, Huainan, Maanshan, Huaibei, Tongling, Anqing, Huangshan, Chuzhou, Fuyang, Suzhou, Luan, Bozhou, Chizhou, Xuancheng, Zhengzhou, Kaifeng, Luoyang, Pingdingshan, Anyang, Xingxiang, Puyang, Xuchang, Luohe, Sanmenxia, Nanyang, Shangqiu, Zhumadian, Nanning, Liuzhou, Beihai, Qinzhou, Chongqing, Chengdu, Zigong, Luzhou, Deyang, Mianyang, Guangyuan, Suining, Neijiang, Leshan, Nanchong, Yibin, Guangan, Dazhou, Bazhong, Ziyang, Guiyang, Liupanshui, Xining

Cities from the second EPU quartile (25-50%)

Taiyuan, Datong, Yangquan, Changzhi, Jincheng, Shuozhou, Jinzhong, Yuncheng, Xinzhou, Linfen, Lüliang, Nanchang, Changsha, Zhuzhou, Xiangtan, Hengyang, Shaoyang, Yueyang, Changde, Zhangjiajie, Chenzhou, Huaihua, Loudi, Yinchuan, Shizuishan, Wuzhong

Cities from the two highest EPU quartiles (50-100%)

Beijing, Tianjin, Shijiazhuang, Tangshan, Qinhuangdao, Handan, Xingtai, Baoding, Zhangjiakou, Chengde, Cangzhou, Langfang, Hengshui, Hohhot, Baotou, Wuhai, Chifeng, Tongliao, Ordos, Hulunbuir, Bayannur, Ulanqab, Shenyang, Dalian, Anshan, Fushun, Benxi, Dandong, Jinzhou, Yingkow, Fuxin, Liaoyang, Panjin, Tieling, Chaoyang, Huludao, Changchun, Jilin, Siping, Tonghua, Baishan, Songyuan, Harbin, Jiamusi, Shanghai, Wuxi, Yangcheng, Zhenjiang, Taizhou (Zhejiang), Hangzhou, Ningbo, Wenzhou, Jiaxing, Huzhou, Shaoxing, Jinhua, Quzhou, Zhoushan, Taizhou (Jiangsu), Lishui, Jinan, Tsingtao, Yichang, Xiangyang, Ezhou, Jingmen, Huanggang, Guangzhou, Shenzhen, Zhuhai, Shantou, Dongguan, Zhongshan, Chaozhou, Jieyang, Haikou, Xian, Tongchuan, Baoji, Xianyang, Weinan, Yanan, Hanzhong, Yulin, Ankang, Shangluo, Lanzhou, Baiyin, Tianshui, Wuwei, Zhangye, Pingliang, Jiuquan

Source: authors'calculation and NBSC

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