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Transitional Dynamics and Spatial Convergence of House-Price-to-Income Ratio in Urban China

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Abstract

Employing distribution dynamics analysis, we examine the future spatial dynamics and convergence of the relative house-price-to-income ratio (RHPIR) across 171 major Chinese cities during the 2002-2016 period. We find that the convergence occurs at a slow pace and is heterogeneous across cities and periods. From the policymakers' perspective, our findings suggest that the policies implemented in China after the 2008 crisis to tackle housing unaffordability have been effective except for the least affordable housing markets of the four largest (first-tier) cities. Therefore, the housing markets in Shanghai, Beijing, Guangzhou, and Shenzhen require urgent policies to prevent the forecast growth in unaffordability and further divergence from other Chinese cities.

The authors confirm that this manuscript is original, has not been published elsewhere, and is not under consideration by another journal. The authors agree with Economics Bulletin submission policies. Furthermore, the authors confirm that there are no conflicts of interest to disclose. If you require any additional information, please do not hesitate to contact us directly at michalwojewodzki@hsu.edu.hk.
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1. Introduction

The real estate sector has been an important component of China's rapid economic growth. However, rapidly increasing housing prices in major Chinese cities during the last two decades are associated with housing unaffordability and wealth inequality. For instance, China's house-price-to-income ratio (HPIR) in 1998 stood at 7.1 (Li and Song 2016), more than quadrupled by 2011 reaching a value of 29.6. In 2021, Chinese HPIR ranks 8th highest in the world standing at 29 (Numbeo 2022). Such high HPIR is manyfold above the range of 3-5 considered by international institutions as an upper bound of affordable housing. Thus, Chinese housing has been a popular topic in the literature (e.g., Jiang and Wang 2021). Unaffordable housing is also one of the burning issues faced by Chinese policymakers who have implemented numerous policies to curb rising housing prices. However, some of these policies may cause misallocations in the housing market and impede the urbanization process (Zheng et al. 2021).

Empirical studies document significant heterogeneity in housing price and affordability at different spatial levels (e.g., Fang et al. 2016). For instance, housing prices and HPIRs in the largest (first tier) cities such as Shanghai, Beijing, Guangzhou, and Shenzhen have skyrocketed over the last two decades. However, during the same period, many of the second- and third-tier cities experienced slow growth or even a decrease in housing prices (Cheong et al. 2021, and Dong et al. 2017). Moreover, a regional divergence in housing affordability can lead to wealth polarization and a 'social disharmony' (Piketty 2014). Since the outbreak of Covid-19 in early 2020, housing prices and affordability as well household income have experienced even larger fluctuations and disparity at different spatial levels (e.g., Shen et al. 2021, and Chong and Liu 2020). Therefore, whether the inter-city disparity in housing affordability continues or instead a convergence takes place is a critical question for Chinese policymakers.

We make the following contributions to the literature. To the best of our knowledge, this research is the first to use the distribution dynamics analysis (thereafter DDA) and to identify the emergence of convergence clubs in years to come. Furthermore, we employ the mobility probability plot (thereafter MPP) introduced by Cheong and Wu (2018) to identify the specific probabilities of moving up or down within the HPIR distribution in the future, for Chinese cities. Consequently, both DDA and MPP can be considered augmenting tools, useful in future research on housing affordability. Besides, our study is based on a comprehensive sample of 171 major cities[1] and cut across different spatial levels. Furthermore, we examine HPIR's distribution dynamics across three distinct periods: pre-crisis (2002-2007), crisis (2008-2011), and post-crisis (2012-2016). This study's findings indicate that the convergence of the relative HPIR amongst 171 major cities in China occurs at a slow pace. Furthermore, we document that the convergence process is the most (least) significant for the third tier (first tier) Chinese cities. Besides, our results suggest the emergence of 'convergence clubs' during the 2008-2011 period as well as for medium- and small-size cities (fourth- and fifth tier). In addition, we show that overall, the convergence process is more significant during the post-crisis (2012-2016) period.

From the policymakers' perspective, our results suggest that the Chinese government should continue its policies limiting speculation in the housing market if they wish to achieve a long-term convergence in HPIR. Furthermore, we find that the housing markets in Shanghai,

[1] Most studies on housing prices and affordability examine either the four biggest cities of Beijing, Shanghai, Guangzhou, and Shenzhen (Fang et al. 2016), or a sample of the 35 largest cities (Dong et al. 2017).

Beijing, Guangzhou, and Shenzhen (first-tier cities) require expanded regulatory policies to prevent the forecasted growth in housing unaffordability and further divergence from other cities. Therefore, on the supply side, we advocate the removal of the so-called 'double monopoly' powers[2] over the land of these four super-sized cities' local governments. On the demand side, we advise a replacement of a one-off property tax payment levied on the buyers with an annual property tax imposed on the property owners. Moreover, we advocate adding inter-city periodic examinations of HPIR's distribution dynamics based on DDA and MPP into policymakers' arsenal of forecasting tools. This could provide them with up-to-date information about city-specific housing unaffordability hotspots, future mobility probabilities, and the emergence of convergence clubs. These, in turn, would aid the policymakers in formulating city-specific, pragmatic policies aiming at cooling down overheated housing markets and promoting a long-term inter-city convergence in HPIR.

The rest of the paper is organized as follows. Section 2 presents the literature review. Section 3 reports the data sources and descriptive statistics. Section 4 introduces the methodology and its advantages. Section 5 provides the results and their discussions. Conclusions and implications are presented in Section 6.

2. Literature Review

Chinese housing sector had undergone an overhaul from a welfare system-oriented (in the early 1980s) to a market-driven through a series of housing reforms ending in 1998. However, the Chinese housing market remains highly regulated and influenced by central and local government policies. On the one hand, the housing sector has been one of the main engines behind Chinese economic growth and wealth redistribution. On the other hand, skyrocketing property prices, especially in the largest cities, have created two serious concerns for the government, i.e., housing unaffordability and pricing bubbles. E.g., Jiang and Wang (2021) report that between 1999 and 2016, housing prices increased by over 5.1 per cent annually.

Unique social, cultural, and economic factors have contributed to a rapid rise in China's housing prices. First, the traditional agrarian culture places great importance on house ownership as a symbol of social status. Second, there is a so-called 'mother-in-law' factor where the future husband is expected to purchase a 'wedding flat'. This, in turn, adds to the demand for urban housing (e.g., Li and Song 2016). Third, vital elements of Chinese social welfare, such as education and healthcare, are concentrated in major cities which adds to a demand for housing in the largest cities (e.g., Cai et al. 2022). Moreover, high saving rates coupled with capital controls and limited local investment opportunities for retail investors add to speculative demand for urban housing (e.g., Fang et al. 2016, and Li and Song 2016).

Many studies examine the determinants of China's housing prices focusing on the supply and demand factors such as central government policies (Jiang and Wang 2021), local government land policies (Wu et al. 2016), household income and migration (Cai et al. 2022). Wu et al. (2012) find that HPIRs in large cities fluctuate differently across regions. Fang et al. (2016) document that out of 120 cities, the fastest (slowest) housing price appreciation occurred in Beijing, Shanghai, Shenzhen, and Guangzhou (85 third-tier cities) between 2002 and 2013.

[2] The double monopoly powers mean that the local government is the sole buyer (and later seller) of the agricultural-to-urban converted land.

3. Data Source and Variable Selection

This paper uses data on the housing price per 100 square meters and disposable income per capita of 171 Chinese major cities obtained from the National Bureau of Statistics of China (NBSC) to calculate the city-level HPIR. The HPIR is an intuitive measure because income is a fundamental predictor of how much a prospective buyer can afford to pay for a house. HPIR is also one of the most widely used indicators to monitor housing market conditions worldwide[3]. To render the HPIR of different cities comparable, we compute a relative HPIR (thereafter RHPIR) equal to each city's HPIR divided by the average HPIR of 171 cities each year. Limited by the availability of data, we use the balanced panel dataset of 171 Chinese cities from 2002 to 2016. Therefore, our sample coincides with a period of boom in the Chinese housing market.

Chinese cities from different tier levels experience different patterns in house prices and affordability (e.g., Fang et al. 2016). Therefore, we group 171 cities into six subsamples: the first-, the new first-, the second-, the third-, the fourth- and the fifth-tier cities. This corresponds to the official classification issued by the State Council of the People's Republic of China[4] [SCPRC] (2014). There are four first-tier, 12 new first-tier, 18 second-tier, 44 third-tier, 49 fourth-tier, and 44 fifth-tier cities in the sample[5]. Considering the impact of the 2008 global financial crisis (thereafter GFC) on the housing market and government policies, we divide the sample into three periods: the pre-GFC (2002-2007), the GFC (2008-2011), and the post-GFC (2012-2016). This allows us to investigate HPIR's distribution dynamics corresponding to the business cycle and different central government approaches before, during and after the GFC.

Table 1 shows that the descriptive statistics of the RHPIR in first-tier cities (Beijing, Shanghai, Guangzhou, and Shenzhen) are significantly above other city-tiers. This is in line with the documented overheated housing market in four Chinese megacities (e.g., Fang et al., 2016). Furthermore, with exception of the maximum value (coefficient of variation (CV)) in the second- (third) tier cities, the descriptive statistics decrease as we move down the tier levels. This indicates two general characteristics of the housing stock. First, housing is more affordable in the smaller cities, while on average, the bigger the city, the less affordable housing. Second, the dispersion in the RHPIR is less severe across the smaller lower-tier cities.

Table 1. Summary statistics of the RHPIRs of 171 cities in China

Variables	Observations	Mean	St. Dev.	Min	Max	CV
RHPIR	2,565	1	0.330	0.441	5.124	0.330
RHPIR of the first-tier cities	60	2.133	0.653	1.262	5.124	0.306
RHPIR of the new first-tier cities	180	1.262	0.278	0.790	2.179	0.220
RHPIR of the second-tier cities	270	1.239	0.292	0.765	2.753	0.236
RHPIR of the third-tier cities	660	0.969	0.257	0.479	2.418	0.265
RHPIR of the fourth-tier cities	735	0.909	0.197	0.441	1.692	0.217
RHPIR of the fifth-tier cities	660	0.860	0.177	0.469	1.493	0.206
RHPIR 2002-2007 (pre-GFC)	1,026	1	0.298	0.441	2.903	0.298
RHPIR 2008-2011 (GFC)	684	1	0.337	0.441	2.832	0.337
RHPIR 2012-2016 (post-GFC)	855	1	0.377	0.512	5.124	0.377

3 For instance, the World Bank, OECD, and Asian Development Bank have been using the HPIR.

4 This classification is based on cities' respective populations and differs from the prior versions by adding additional tier levels (for more details regarding the population-based tiers, see SCPRC 2014).

5 The details (including the name of each of the major cities) are presented in the Appendix.

4. Methodology

The DDA introduced by Quah (1993) offers several advantages in examining the evolution of HPIR distribution. Prior studies commonly use econometric regressions to examine and forecast the effects of explanatory variables on housing affordability. However, the HPIR's distribution is bi-dimensional. Thus, regression analysis estimation (a single numerical value) cannot deliver insights into the overall shape of the future distribution (Cheong et al. 2021). The DDA forecasts HPIR's future distribution and generates its shape in its entirety and across time. Moreover, the DDA forecasts the details of the future distribution. Lastly, we can use the DDA to derive the mobility probability plots (MPPs) of different entities, i.e., the probability that e.g., first-tier cities move up or down within the distribution in the long run.

The DDA can be divided into the Markov transition matrix analysis and the stochastic kernel approach. One critical issue of the former is the arbitrary demarcation of the state associated with the selection of the grid values. The stochastic kernel approach can be seen as an expansion of the Markov transition matrix analysis with its continuous infinite number of states, which mitigates the demarcation problem. Thus, we employ the stochastic kernel approach generally considered to be more accurate (Cheong et al. 2021). The bivariate kernel estimator is defined as follows:

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

Where n is the number of observations, h_1 and h_2 are the bandwidths that are calculated based on the procedure suggested by Silverman (1986). Besides, K is the normal density function, x is a variable representing the RHPIR of a city[6] at time t, and y is a variable representing the value of RHPIR of that city at time $t+1$. Additionally, $X_{i,t}$ is an observed value of RHPIR at time t, and $X_{i,t+1}$ is the observed value of RHPIR at time $t+1$. We use an adaptive kernel with a flexible bandwidth approach is adopted to consider the sparseness of the data (Cheong and Wu 2018). First, we compute a pilot estimate to establish the kernel density at all the points as in equation (1). Next, we rescale the bandwidth using a factor that reflects the kernel density. Assuming that the evolution is first-order and time-invariant, the distribution of the RHPIR at time $t+\tau$ depends on t only and not on previous distributions. Thus, the relationship between the distributions at time t and time $t+\tau$ is shown in equation (2).

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

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 that maps the distribution from time t to $t+\tau$, and $f_t(x)$ is the kernel density function of RHPIR's distribution at time t. The ergodic (long-run steady-state) density function, given that it exists, can be computed as follows.

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

Where $f_\infty(z)$ is the ergodic density function (with infinite τ) that can be viewed as a forecast of the steady-state equilibrium distribution in the long run of the RHPIR. Based on this, we can employ the MPP developed by Cheong and Wu (2018) to examine the mobility of

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[6] It should be reminded that the HPIR of each of the 171 cities, is measured relative to the average HPIR. That is, an RHPIR value greater (smaller) than one shows that this city's HPIR is greater (smaller) than the average HPIR.

HPIR for each of the 171 cities. The MPP is constructed by calculating $p(x)$, which is the net upward mobility probability of each city's HPIR as per equation (4) below.

$$p(x) = \int_x^\infty g_\tau(z|x)dz - \int_0^x g_\tau(z|x)dz \quad (4)$$

The MPP shows the net upward mobility probability of a city's HPIR against the sample's (a proxy for the national) average RHPIR and is expressed as a percentage ranging from -100 to 100. More specifically, a negative (positive) value implies that the city has a net probability of moving down (up) in the distribution in the future. The MPP has many advantages over the display tools used in transitional dynamics analysis and has been employed in recent empirical studies (e.g., Cheong et al. 2021, Lee et al. 2021, and Cheong and Wu 2018). For instance, the MPP enables us to easily facilitate comparisons of the HPIR's transitional dynamics across periods and tiers. In other words, we can observe which tier of Chinese cities has a greater probability of moving up or down and how these vary over time. This makes the MPP a powerful tool for the visualization and interpretation of transitional dynamics.

5. Results and Discussion

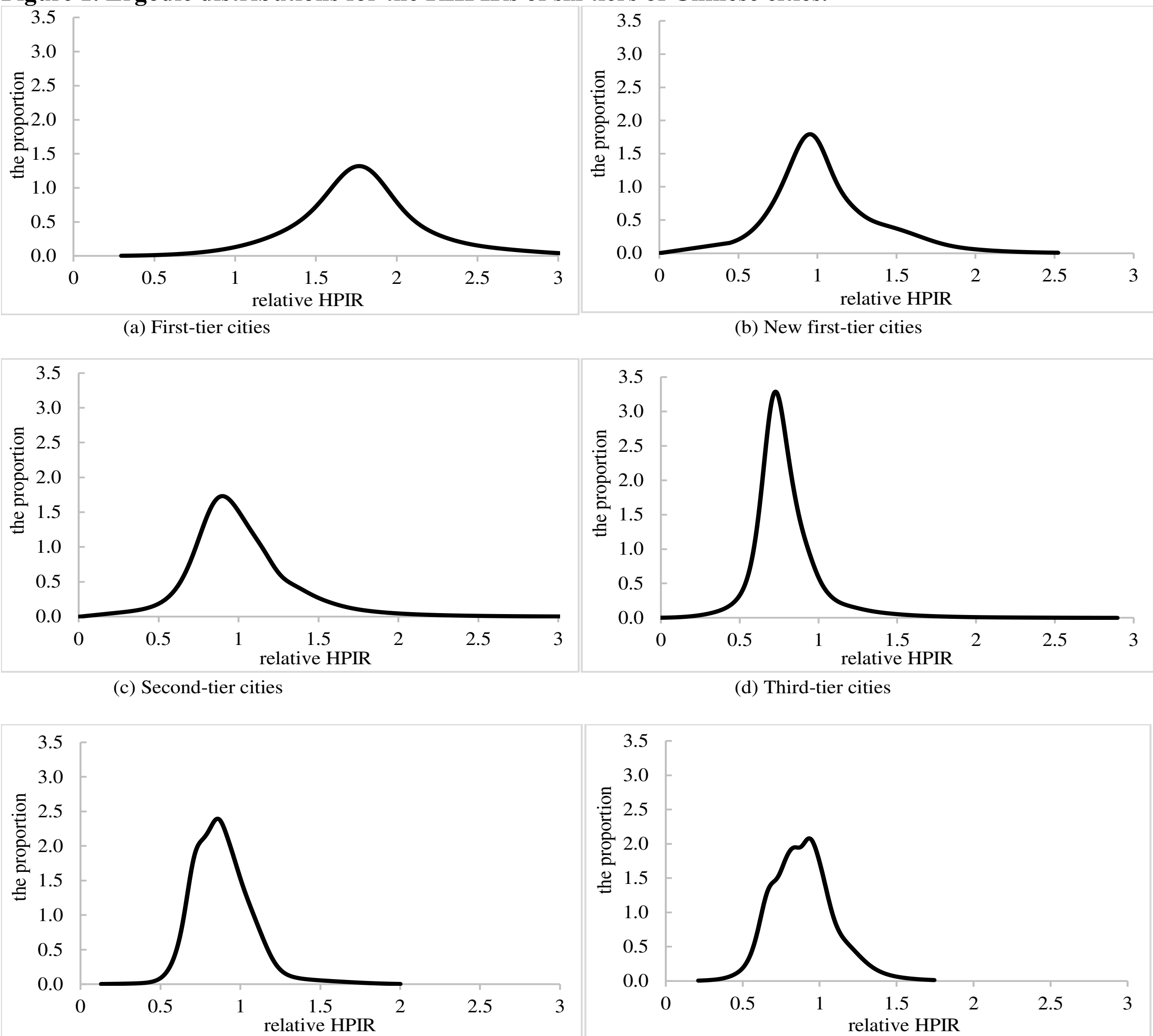
5.1. Transitional dynamics at different city tiers

Divergence in private housing prices and affordability can contribute to wealth polarization and 'social disharmony' (see Piketty 2014, and Cheong et al. 2021). Prior studies document significant heterogeneity in both HPIR and prices across Chinese cities (e.g., Dong et al. 2017, and Fang et al. 2016). Thus, the examination of future convergence in HPIR for different city-tiers fills the gap in the literature and could provide useful insights to the policymakers. The ergodic distributions and the MPPs across six tiers of cities are shown in Figures 1 and 2, respectively.

Figure 1 shows that although ergodic distributions for all six city-tiers are unimodal, their respective major peaks differ significantly. For instance, the peak in panel a (first-tier cities) has a value of around 1.8, whereas the peaks of the new first- and second-tier cities take values of 1 and 0.9, respectively. Furthermore, the peaks in panels d, e, and f, i.e., for the third-, fourth- and fifth-tier cities have values of around 0.7, 0.85, and 0.95, respectively. Assuming the transitional distribution dynamics remain unchanged, such results imply that first tier cities' HPIRs will converge to a value far above the national average, while new first-tier cities will converge to the national average HPIR in the long run. However, most of the remaining Chinese cities in the sample (panels c to f) are expected to converge to HPIRs below the national average. In addition, we can observe one (two) minor peak(s) at the RHPIR values of around 0.75 (0.65 and 0.85) in panels e and f. This reflects the emergence of convergence clubs in the fourth- and fifth-tier cities, i.e., only conditional long-run convergence with groups of cities clustering around different HPIRs. Besides, Figure 1 shows the highest and narrowest (the lowest and most spread out) shape of the distribution in panels d (a). This suggests the most (least) significant convergence in the future HPIRs of the third- (first) tier cities.

Summing up, the results indicate painfully slow convergence and unaffordable housing in first-tier cities. Thus, the Chinese government should implement policies aiming at cooling the housing sector in the largest cities. On the supply side, the policymakers may wish to consider removing 'double monopoly' powers over the land of the local governments. On the demand side, the central government could introduce an annual property tax levied on the owners to increase the costs of holding unused real estate.

Figure 1. Ergodic distributions for the RHPIRs of six tiers of Chinese cities.



(a) First-tier cities

(b) New first-tier cities

(c) Second-tier cities

(d) Third-tier cities

(e) Fourth-tier cities

(f) Fifth-tier cities

Source: authors' calculation

Figure 2 presents six MPPs corresponding with six city-tiers. We can observe that the first-tier cities (the black plot) with RHPIR values between 1 and 1.8, 2.2 and 2.55, and above 3.45 are more likely to move higher in the future distribution, thereby meriting a place on the '*policy priority list*', i.e., urgent implementation of stricter housing policies. Moreover, especially the first-tier cities with RHPIR values of around four are the most likely (60 per cent probability) to have even more unaffordable housing in years to come[7]. On the other hand, first-tier cities with RHPIR values around three have the highest negative net upward mobility probabilities and thus are highly likely to become more affordable in the future, relative to the other cities.

The MPP can precisely identify city tier-specific RHPIR values corresponding to the net upward mobility probability of -100, i.e., the so-called '*development trap*'. Upon achieving the '*development trap*' a city's RHPIR will certainly move down relative to other cities in the future.

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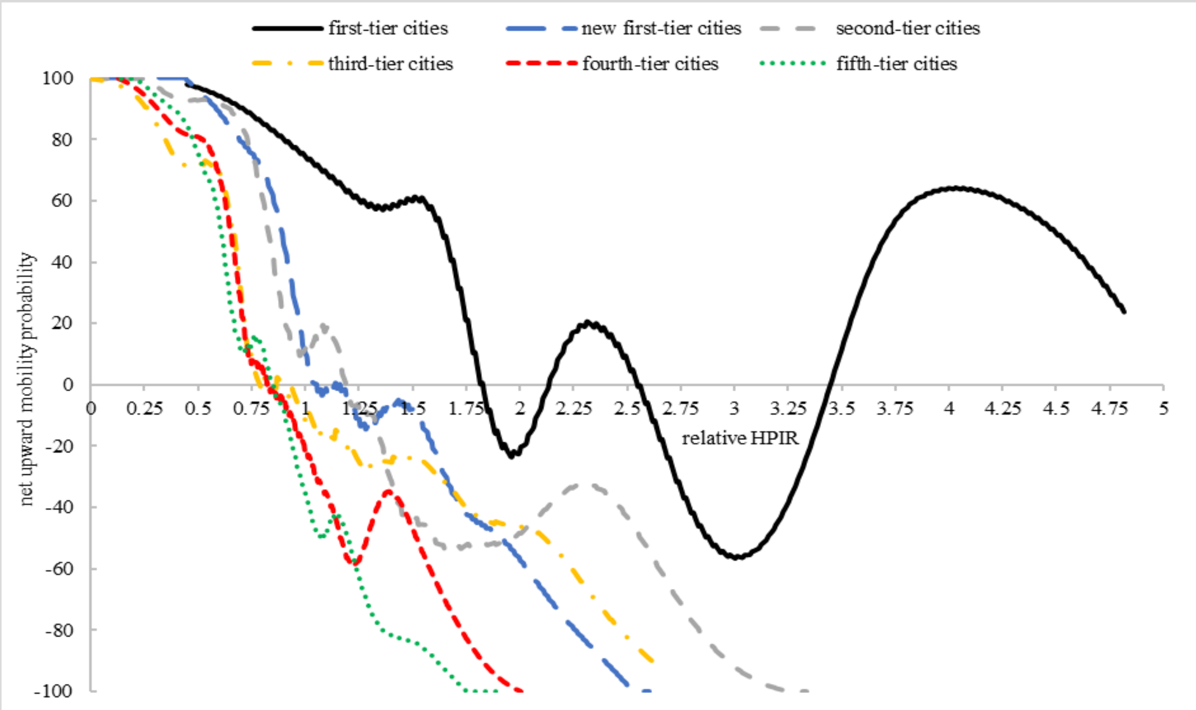
[7] Therefore, these cities require the most urgent and radical housing policies.

Figure 2 shows that the '*development trap*' is reached by four MPPs. More specifically, the fifth-, fourth, new first-, and second-tier MPPs reach the net mobility probability of -100 at RHPIR values of 1.75, two, 2.5, and 3.25 respectively. Furthermore, we can observe that the MPP of the fifth-tier cities plots consistently below the other MPPs, implying that the fifth tier (small-sized) cities exhibit the highest (lowest) overall tendency of moving downward (upward) in the future distribution. In contrast, the MPP of the first-tier cities lies significantly above the other MPPs and reaches the highest maximum RHPIR value of 4.8. This finding, together with the above '*policy priority list*', suggests further HPIR's polarization in the years to come, especially between the super large-sized (first tier) and the small-sized (fifth tier) cities.

Figure 2. MPPs for the RHPIRs of six tiers of Chinese cities.



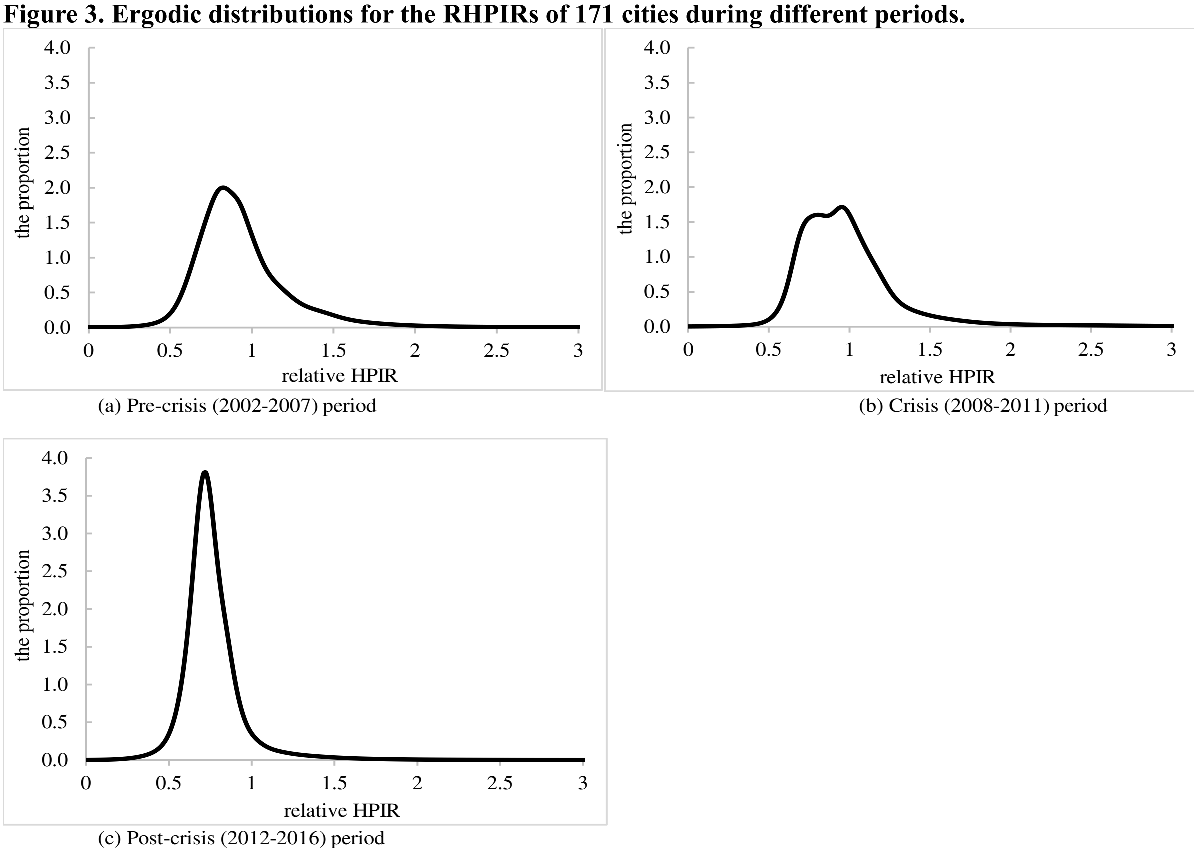
Source: authors' calculation

5.2. Transitional dynamics for different periods

The Chinese government implemented a series of market-cooling policies between 2003 and 2007 (Li and Song 2016). However, the GFC had a significant effect on the Chinese economy and caused a reversal in the government's policies. E.g., between 2008 and 2010, the Chinese government implemented a four trillion Yuan expansionary package largely focused on stimulating the housing market (Li and Song 2016). Contrary to the expansionary policies of the GFC period, the second decade of the twenty-first century witnessed the government's efforts to cool down the urban housing market and make it more affordable (Zheng et al. 2021).

Based on the above evidence, we split the overall sample into pre-GFC (2002-2007), GFC (2008-2011), and post-GFC (2012-2016) subsamples. The ergodic distributions (MPPs) of RHPIR during the three periods are presented in Figures 3 (4). Figure 3 indicates that the peaks of the long-run distributions for the periods characterized by cooling governmental policies (pre-GFC and post-GFC) correspond to the RHPIR values of around 0.8, and 0.7, respectively. In contrast, in the distribution representing the GFC period, there are two distinct peaks: the major (minor) peak with a value of around one (0.75). Furthermore, the peak for the post-GFC period is by far the narrowest and the tallest with a value of around 3.7. Moreover, the distributions of the RHPIRs in earlier periods are significantly more dispersed than that of the post-GFC period. Figure 3 also suggests the least significant and only conditional convergence to relatively higher HPIR values during the GFC period. This, in turn, corresponds with the unprecedented expansionary governmental policies of that period. On the other hand, the convergence in inter-city HPIR post-GFC is the most significant with many major Chinese cities congregating around a below national average HPIR. Such findings suggest that assuming transitional distribution dynamics remain unchanged, in years to come urban housing unaffordability will be effectively limited in many cities. This could be related to the post-GFC tightened housing policies, stressing that houses are meant for living, not for speculation.

Figure 3. Ergodic distributions for the RHPIRs of 171 cities during different periods.

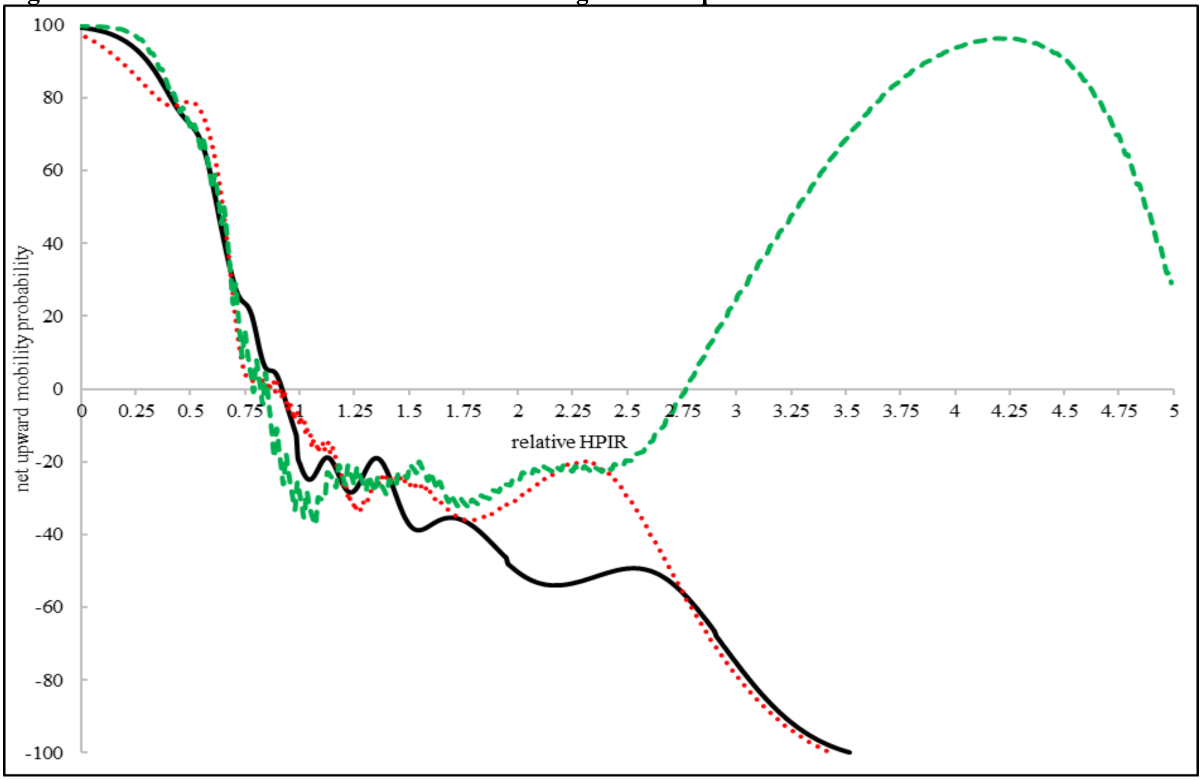


Source: authors' calculation

Figure 4 suggests for the RHPIR values in the range of 0.6 to 0.8 (1.2 to 1.4), there are many overlaps amongst the three MPPs. This suggests that regardless of the period, the probability of moving up or down in the distribution remains similar for cities with the above range of RHPIR values. However, for the RHPIR values between 0.8 and 1.2, the post-GFC plot lies significantly below the other two plots. This indicates that in the post-GFC period the cities with such a range of RHPIRs exhibit a higher tendency to move down in the distribution, in comparison with the other two periods. That is a positive piece of news for the policymakers.

By contrast, in the range of RHPIR values from 1.45 to 2.2, the post-GFC MPP lies marginally above the other two MPPs. This means that the less affordable housing markets in the post-GFC period exhibit a somewhat lower proclivity to move down in the distribution as compared with the earlier periods. Moreover, the post-GFC MPP shows that the cities with the most unaffordable housing stock (HPIR above 2.75) are more likely to move further up in the distribution in the coming years. Thus, from the policy perspective, cities with such RHPIR values merit a place on '*the priority list'*. In particular, the cities with RHPIR values around 4.25 are associated with a positive net mobility probability of circa 100 per cent. In other words, it is almost certain that they will diverge further above the national average in years to come.

Figure 4. MPPs for the RHPIRs of 171 cities during different periods.



Notes: the black solid line represents the pre-GFC period's MPP, the red dotted line corresponds to the GFC period's MPP, and the green dashed line represents the post-GFC period's MPP.
Source: authors' calculation

6. Conclusions and Policy Implications

Whether there will be a convergence in Chinese cities' HPIR is a critical question for the policymakers balancing between cooling the speculative demand for houses on the one hand and boosting the economy and urbanization on the other hand. Despite numerous studies examining housing prices and affordability, very little attention has been devoted to the convergence and transitional dynamics of the HPIR across cities and time. This paper contributes to the literature by providing findings on transitional dynamics of the HPIR based on a sample of 171 major cities during the 2002-2016 period using the DDA and the MPP tools.

The main findings can be summarized in four points. First, there is a convergence of the RHPIR, but the process is very slow. Second, the convergence and transitional dynamics vary across city tiers. E.g., the convergence in the third- (first) tier cities is the most (least) significant. Third, we identify the emergence of convergence clubs during the GFC period as well as for the small- and medium-size (fourth- and fifth tier) cities. Fourth, we document that the convergence occurs mainly around the lower (below the national average) RHPIR values. Finally, extremely unaffordable housing in the first-tier cities is highly likely to become even more unaffordable compared with the rest of the Chinese cities in the following years.

From the policy perspective, our finding that most of the cities will converge to low RHPIR demonstrates that the Chinese government's policies of the last decade have been largely effective. Second, instead of a one-size-fits-all policy, the government should formulate and implement housing policies in line with the city-specific RHPIRs. In particular, the first-tier cities require urgent regulatory actions, to prevent the forecasted upward divergence in RHPIRs. On the supply side, we advocate the removal of local governments' 'double monopoly' over the purchases and sales of the land. As for the demand-side policies, a single property tax levy paid by the house buyers could be replaced with a property tax levy paid annually by the owners.

To summarize, our study shows that both the DDA and the MPP are highly informative tools, and thus we suggest their application in the inter-city periodic examinations of housing affordability. Such examinations would equip the policymakers with up-to-date information on city-specific HPIR hotspots, convergence clubs, and future mobility probabilities. This, in turn, could augment the formulation and implementation of pragmatic city-specific policies aiming at cooling overheated housing markets and promoting a long-term inter-city convergence.

The outbreak of Covid-19 has different impacts on the housing price and household income in different cities (Shen et al. 2021, and Chong and Liu 2020), which may affect the evolution of inter-city disparity in housing affordability. However, due to the data availability, this paper has not directly investigated the impact of Covid-19 on the spatial evolution of HPIR. Thus, the impact of Covid-19 on HPIR disparity at various spatial levels (e.g., city-tiers, regions, and provinces) is an important research direction worthy of follow-up studies.

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Appendix

The first-tier: Super large-sized cities (above 10 million people)
Beijing, Shanghai, Guangzhou, Shenzhen
The new first-tier: Very large-sized cities (five to 10 million people)
Tsingtao, Xian, Hangzhou, Tianjin, Dongguan, Chongqing, Shenyang, Changsha, Zhengzhou, Wuxi, Ningbo, Chengdu
The second-tier: "Type I" large-sized cities (three to five million people)
Jiaxing, Taiyuan, Changchun, Nanning, Jinhua, Shaoxing, Taizhou, Guiyang, Hefei, Shijiazhuang, Nanchang, Lanzhou, Harbin, Dalian, Zhongshan, Wenzhou, Baoding, Jinan
The third-tier: "Type II" large-sized cities (one to three million people)
Xiangtan, Xianyang, Xiangyang, Tangshan, Yinchuan, Liuzhou, Zhuzhou, Mianyang, Chuzhou, Nanyang, Handan, Xuchang, Tongling, Huzhou, Fuyang, Xining, Luoyang, Xingtai, Langfang, Yangcheng, Xingxiang, Yichang, Wuhu, Cangzhou, Bengbu, Chaozhou, Shangqiu, Qinhuangdao, Yueyang, Hohhot, Hengyang, Anshan, Taizhou, Zhenjiang, Huanggang, Zhuhai, Jinlin, Jieyang, Changde, Shantou, Haikou, Baotou, Zhumadian, Deyang
The fourth-tier: Medium-sized cities (500 thousand to one million people)
Quzhou, Suzhou, Yingkow, Jinzhong, Maanshan, Lishui, Hulunbuir, Leshan, Chengde, Jinzhou, Jiamusi, Baoji, Zhangjiakou, Luzhou, Ordos, Chenzhou, Loudi, Fushun, Huaihua, Zhoushan, Datong, Puyang, Yibin, Kaifeng, Shaoyang, Huainan, Tonghua, Bozhou, Pingdingshan, Neijiang, Huangshan, Suining, Anyang, Dandong, Panjin, Beihai, Anqing, Weinan, Nanchong, Luan, Xuancheng, Songyuan, Yulin, Tongliao, Yuncheng, Louhe, Linfen,

Chifeng, Hengshui
The fifth-tier: “Type I” small-sized cities (200 to 500 thousand people)
Liaoyang, Shangluo, Tieling, Benxi, Wuwei, Huaibei, Yanan, Hanzhong, Wuhai, Changzhi, Ankang, Jincheng, Siping, Luliang, Zhangye, Dazhou, Fuxin, Guangan, Zhangjiajie, Chaoyang, Bazhong, Wuzhong, Guangyuan, Liupanshui, Tongchuan, Pingliang, Shuozhou, Jingmen, Qinzhou, Xinzhou, Jiuquan, Shizuishan, Yangquan, Ziyang, Bayannur, Ulanqab, Baiyin, Ezhou, Baishan, Tianshui, Sanmenxia, Chizhou, Huludao, Zigong
Source: SCPRC (2014)

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