Understanding Clusters in China's Real Estate Market

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Abstract

The paper studies the convergence of regional house prices in China. We find that the commercial property market is more homogeneous, while there is substantial heterogeneity in residential property prices. The formation of convergence clubs varies over time and across types of properties. The market for newly-constructed housing becomes more integrated over time, with a smaller number of regional clusters identified in the latter period, while the second-hand housing market becomes more fragmented. Using regression analysis, we find that rent, land supply, air quality, and economic development of cities play an important role in explaining house price convergence across cities.

Keywords: House prices, Log-t test, Regional convergence, China.

JEL Classification: R3, R11, O53.

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1 Introduction

The real estate market has played an important role in the Chinese economy since the reform of the commercial housing system in 1998. Han et al. (2021) show that the share of the real estate market in China's GDP has increased by approximately 3% between 1998 and 2019, and today the real estate sector contributes 15% to the Chinese economy. Though the housing market is one of the most important sectors of the economy, its rapid development may cause problems. According to Wu et al. (2020), recognition of the real estate industry as one "pillar industry" of the national economy in March 2003 significantly contributed to the growth of housing prices, which may lead to the misallocation of resources. Zhang et al. (2016) show that many first-tier cities in China face a rapid growth of house prices and a shortage of general housing, while the housing in most second- and third-tier cities is oversupplied.

The housing sector is a major consideration in monetary and fiscal policy (Maynou et al., 2021) because the dynamics of house prices are essential for understanding household wealth, financial stability risks, and business cycles (Ganioğlu and Seven, 2021; Catte et al., 2004; Maynou et al., 2021). Real estate in China has become very expensive and unaffordable to the majority of the Chinese population, which may have a spillover effect on other sectors of the economy, e.g., by reducing total factor productivity growth (Funke et al., 2019). Moreover, the high volatility of house prices generates cycles, where a house price boom with the sequential collapse of prices may lead to negative macroeconomic consequences, including the risk of a financial crisis (Moench and Ng, 2011). Therefore, in recent years, the Chinese government has imposed several macroprudential measures in order to stabilize and control property prices.

A growing literature focuses on regional convergence of house prices because the disintegration of regional house markets is indicative of resource misallocation. First, a long-run divergence of house prices reflects unequal wealth distribution. Second, the national disintegration of the housing market may result in labor market frictions, with more expensive locations (e.g., inner city suburbs) being less attractive for employees and thus presenting higher demand for the labor resources, which ultimately affects labor productivity and household income (Churchill et al., 2018). The empirical evidence on regional convergence of the housing sector is mixed. According to one strand of the literature, regional economic integration should lead to house price convergence since different locations within the same country are exposed to similar shocks. For instance, synchronization of regional house prices may occur due to the convergence in fundamentals affecting the housing sector, such as income and interest rates (see, for example, Maynou et al., 2021; Abbott and De Vita, 2013; and Churchill et al., 2018). Another line of the research argues that there could still be heterogeneity in regional housing markets associated with different responses to monetary policy and macroeconomic fluctuations (Fratantoni and Schuh, 2003; Moench and Ng, 2011; Del Negro and Otrok, 2007).

Literature on regional (dis)integration of the real estate market in China also provides inconclusive results. Recent papers find evidence in favor of regional property price synchronization in China. For instance, Funke et al. (2019) record an increasing synchronization of housing prices up until 2015 due to the effect of the macroprudential policy. Chow et al. (2016) provide evidence for price convergence from 2000 to 2008. On the other hand, Zhang and Morley (2014) and Gong et al. (2016) find no long-run regional convergence in the real estate market in China for the period 1998-2010 and 2005-2015, respectively. The key reasons for mixed results are the differences in the data and methods used by the researchers.

The methodology employed to test for price convergence mainly relies on cointegration and panel unit root tests. The shortcomings of these methods emerge if there is heterogeneity across regions. Moreover, they do not study the transitory dynamics of the time series - they do not distinguish between locations that have already converged and locations that are converging. Finally, these methods ignore non-linearity of the price convergence process and the existence of convergence clubs within a country. Our paper contributes to the literature by re-examining the integration of housing market in China by allowing for the existence of regional convergence clubs and using the nonlinear time-varying heterogeneous factor model proposed by Phillips and Sul (2007).

This paper is closely related to Funke et al. (2019), who test for house price growth convergence using a Markov-switching framework and find evidence of price growth convergence within four clusters. Yet, our paper differs in several important dimensions, including its focus, data, and methods. First, the focus of our research is on house price market integration. For this purpose, we study the dynamics of actual property prices instead of price growth. While inflation convergence is informative about price changes over time, it does not reflect the actual price gap between the regions and its evolution over time. Thus, the convergence of inflation rates does not necessarily coincide with higher market integration. Second, we employ disaggregate price data for different types of property, which allows us to resolve the problem of aggregation bias[1] associated with the use of price indices, and estimate the degree of market integration for different types of property. Finally, we utilize the Phillips and Sul (PS) methodology that allows distinguishing between locations that have converged and locations that are converging by explicitly addressing the question of invariance of the time-series process for prices. Moreover, this methodology overcomes various problems associated with the validity of conventional price convergence tests, such as cross-sectional dependence and heterogeneity issues.

A similar approach has been used by Lin et al. (2015) and Cai et al. (2022) to investigate club convergence in the Chinese housing market. Applying Phillips and Sul (2007) *logt* test

[1] Crucini and Shintani (2008) and Imbs et al. (2005) show that using micro (disaggregate) prices with higher comparability across locations resolves estimation biases associated with the use of aggregate price indices, so the authors estimate relatively faster price convergence when using micro prices as compared to the results based on CPI.

to monthly housing price indices, the authors find evidence of segmentation across regions in China and the existence of regional convergence clubs. Our study further explores the existence of convergence clubs for seven different types of property using disaggregated price data. Moreover, we analyse the dynamics of club formation and the effect of COVID-19 on market integration.

This paper investigates the evolution of domestic real estate prices in China using a dataset of monthly prices for different types of property across 30 major Chinese cities from January 2004 to June 2021. We aim to answer several important questions. How do prices for different types of property change over time? What is the dynamics of cross-city price dispersion? Do prices across cities converge over time? Do cities form convergence clubs? Do the convergence patterns vary across different property types? What factor can explain the formation of real estate price clubs? Finally, how does the COVID-19 pandemic affect the property market?

The remainder of the paper is organized as follows. Next section describes the data used for the analysis and discusses interesting patterns in house price dynamics in China. Section 3 presents the PS nonlinear factor model of prices used to test domestic house price convergence. Section 4 reports the results of the convergence test and further explores the factor explaining the formation of convergence clubs. The final section briefly concludes.

2 Data and preliminary analysis

We utilize a panel of monthly house prices collected by the China Price Information Centre (CPIC). The price data include the average sale price of a property[2] per square meter (Yuan/m^2). Li et al. (2018) extensively discuss a number of issues related to the sample selection and reliability of this dataset, and conclude that this is one of the best available

[2] As discussed in Zheng et al. (2010) the municipal authority collects the data on all transaction contracts for different types of property.

sources of the desegregated price data in China. These price data are used to calculate official CPI and PPI in China, and therefore, the government and CPIC maintain a high quality of the data. The real estate CPIC data cover ten types of property in 34 major cities from January 2004 to June 2021. However, the availability of the data varies over time and across cities. The number of cities where each property is available and the period of coverage are summarized in Table 1.

Table 1: Availability of housing price data

Type	Item	Period	Number of cities
Commercial	Commercial building	Jan 2004-June 2021	29
	Commercial office building	Jan 2004-June 2021	30
	Second hand commercial building	Jan 2004-June 2021	22
Residential	Newly constructed residential, 1st	Jan 2004-Feb 2020	33
	Newly constructed residential, 2nd	Jan 2004-June 2021	34
	Newly constructed residential, 3rd	Jan 2004-June 2021	33
	Newly constructed luxury property	Jan 2004-June 2021	29
	Second hand residential, 1st	Jan 2004-June 2021	32
	Second hand residential, 2nd	Jan 2004-June 2021	32
	Second hand residential, 3rd	Jan 2004-June 2021	32
Overall	10 items	210 months	34 cities

Notes: 1st, 2nd, and 3rd refer to the type of the location. The first-class location refers to the city center, the third-class location covers suburb area of the city, and the second-class location refers to the urban area excluded from the previous two classes.

For the purpose of comparability, we apply a set of restrictions to the data. First, similar to Glushenkova and Zachariadis (2021), we exclude erroneous price movements, i.e., if there is a rise or fall in prices by more than 300%. Then, we linearly interpolate data for prices missing in only one month using the average of the prices at $t-1$ and $t+1$ as suggested in Parsley and Wei (2008). Finally, we construct a balanced panel of items by removing the property types that have missing observations for the period under study. Similarly, we drop cities with missing observations. We end up with a sample of seven property types available in 30 cities from January 2004 to June 2021[3]. A list of items and cities included in the final

[3]The newly constructed residential property on the first class location is available only for the period Jan

dataset is presented in Table 2 and Table 4, respectively.

Patterns in the Dynamics of Housing Prices

Different from previous studies, we distinguish between different types of property. First, we study prices for commercial buildings and residential buildings. Second, we explore the differences in prices of residential properties located in different city areas. Specifically, we include residential property prices on first-, second-, and third-class locations. According to the China Real Estate Information Center, the first-class location refers to the city center, the third-class location covers the city's suburban area, and the second-class location refers to the urban area excluded from the previous two classes. Looking at Figure 1a, we see that the dynamics of house prices in China vary a lot across different types of property. National average prices for commercial (office) property were systematically higher than prices of residential properties and had a similar tendency to grow between 2004 and 2012. Yet, the growth of commercial house prices stopped after 2012, so the residential prices reached the level of commercial house prices by the beginning of 2017 and exceeded it thereafter[4]. Similar catch-up effect we observe in Figure 1b when comparing residential property prices for newly-constructed buildings and second-hand residential property. Both housing types had similar trends, with second-hand buildings remaining slightly cheaper than the newly-constructed property at the beginning of the period but converging to the same level over time. We defer a more careful comparison of different property types for later on.

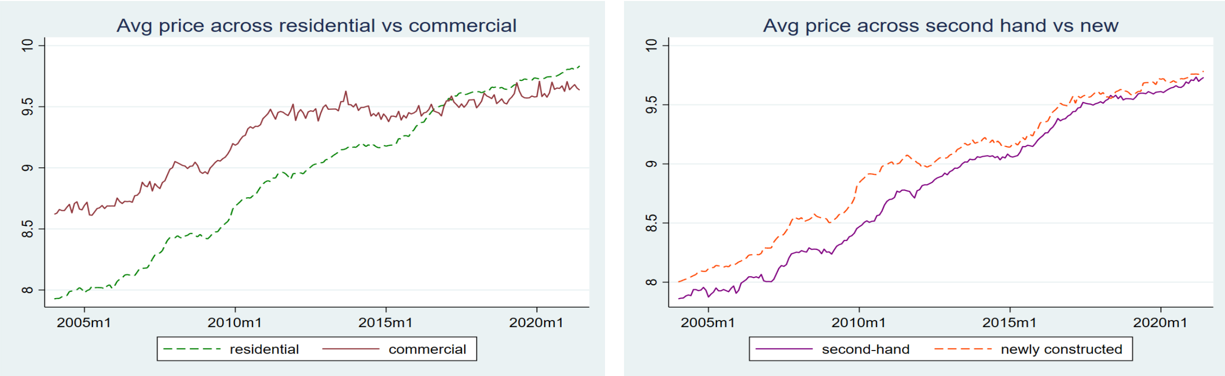
Figure 2 plots the average (over 30 major cities) annualized housing price inflation for com-

2004 - Feb 2020 as the more recent data contain a lot of missing observations. We use this type of property for the analysis of price convergence in Section 4.1, but we exclude it from the remaining analysis, especially from the calculation of average prices presented in this section, to ensure consistency of the sample over time.

[4]Significant changes in the growth of commercial housing prices in early 2012 could be explained by tightening the regulation of loans for commercial property projects. For instance, banks imposed higher criteria for approval of such loans as compared to loans for residential property. Moreover, the decrease in rental yields of commercial property also stimulated a reduction of the investment into commercial property projects.

Figure 1: Housing price dynamics over time

(a) Commercial vs. Residential (b) Residential property



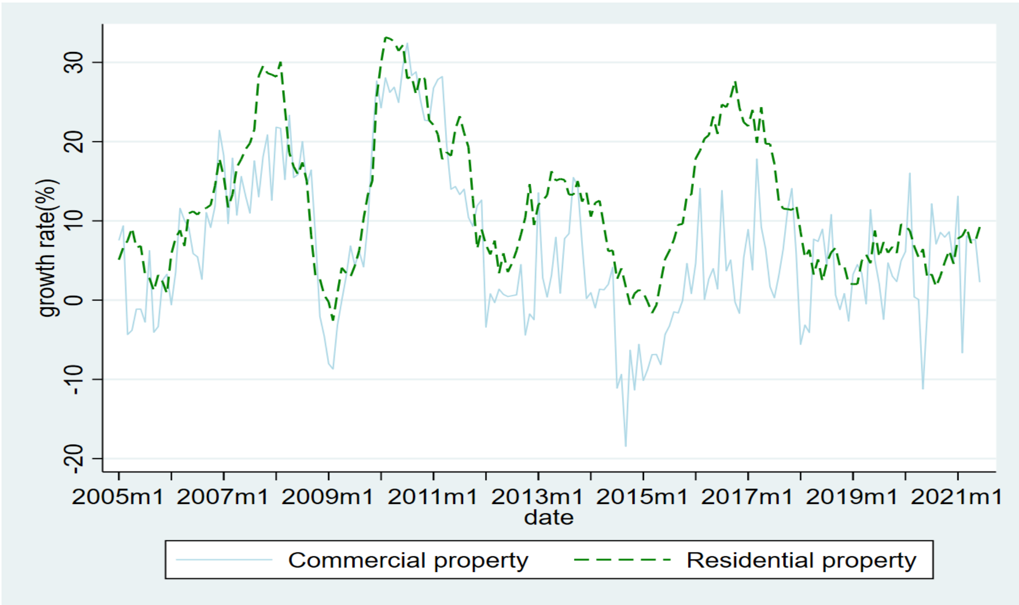
mercial and residential properties in China. Similar to Funke et al. (2019), we find house prices in China rising until the recent global financial crisis with faster growth for residential housing than for commercial property, followed by the downturn in the housing market in the aftermath of the crisis. The next boom in the housing market was recorded in early 2010 after the implementation of the stimulus packages that promoted bank lending in China. Interestingly, this policy had a very similar effect on both commercial and residential property prices. In an effort to cool the housing market, the Chinese government imposed a series of restrictions on the housing market that varied across cities[5]. This policy resulted in a gradual fall in prices between 2011 and 2013. Further policy tightening was implemented in early 2013 when prices showed positive dynamics again. Importantly, this tightening policy had a stronger effect on commercial property prices than on residential housing, which is most prominently displayed in early 2015.

Local house market restrictions were relaxed in mid-2014, which triggered house price growth. Again, this stimulus affected the residential property market much more than the commercial property[6]. The new boom in the housing sector was observed in the summer of 2016, but

[5]Funke et al. (2018) provide a detailed summary of key policies implemented by Chinese authorities in the housing market between 2004 and 2017.

[6]It could be because of the policy focus, which is biased towards residential housing. Specifically, in 2015 government reduced the minimum down-payment for second-home buyers and removed the transaction tax

Figure 2: Annualized housing price inflation across 30 major cities in China



this time only in the residential housing market, while the prices for commercial property remained low and stable. Credit conditions were tightened, and the down-payment ratio for second-home buyers was increased again by local governments in 2016-2017. The prices remained stable till the end of the period under study.

A slight drop in price growth was observed at the beginning of 2020 associated with the COVID-19 pandemic. Liu and Tang (2021) and Qian et al. (2021) showed that confirmed cases resulted in a housing price drop of 1.3% and 2.47%, respectively, in the communities where the cases were detected. The house price dynamics presented in Figure 2 supports these findings. Moreover, we see that as a result of an efficient epidemic-control policy, prices returned to their growing trend in mid-2020. In section 4, we will further investigate the effect of COVID-19 on house price convergence.

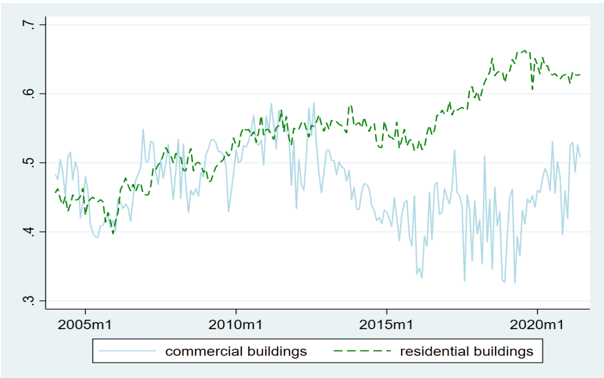
for second-hand residential housing, which affects the demand for residential property but not the demand for office buildings.

Housing Price Convergence

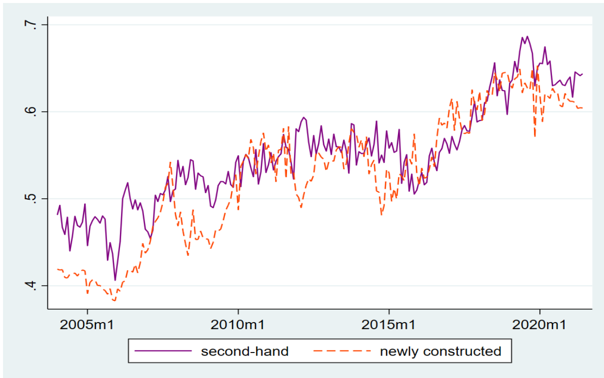
A standard approach to measure the degree of convergence across cities is known as "sigma-convergence" and refer to a reduction in the dispersion of a variable across locations. In order to capture the convergence of markets, the standard deviation of relative prices is used as a variable of interest. Specifically we calculate price dispersion across location for each property type j at time t as $\sigma_{jt} = \sqrt{\frac{N\sum_{i=1}^{N}(p_{ijt})^2 - (\sum_{i=1}^{N} p_{ijt})^2}{N^2(N-1)}}$, where $p_{ijt} = P_{ijt}/\overline{P}_{jt}$ is relative prices for property type j in city i at time t.[7] Figure 3 presents the evolution of price dispersion for different property types.

Figure 3: Housing price dispersion across 30 major cities in China

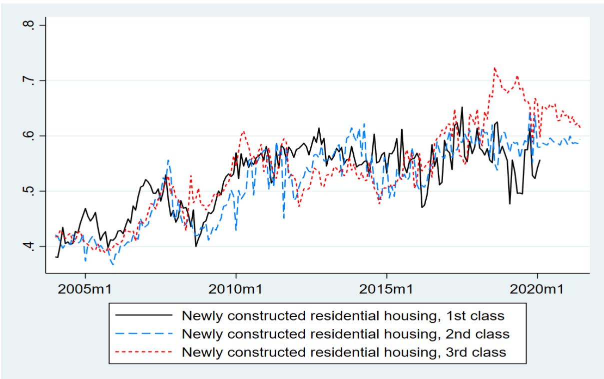
(a) Commercial vs. residential



(b) Newly constructed vs. Second-hand



(c) Newly constructed by location



(d) Second-hand by location

[7] Table A1 of the Online Appendix presents the relative prices for commercial and residential property in each city for different years, which could be also informative about the degree of market integration and price differences across locations.

In Figure 3a, we distinguish between commercial and residential property and plot changes in their price dispersion during the period Jan 2004 - Jun 2021. The results suggest that dispersion was increasing for residential housing over time (from 0.45 in 2004.1 to 0.65 in 2019.6), reflecting higher segregation of the domestic property market with a slight fall in the dispersion (i.e., convergence trend) in the most recent period associated with the COVID-19 pandemic. The price dispersion patterns for office buildings were very similar to those observed in the residential housing market up until August 2012, i.e., there was a prominent trend toward market disintegration, yet the picture had changed dramatically thereafter with a significant drop in the dispersion reflecting a higher level of domestic market integration between August 2012 and June 2019. Interestingly, COVID-19 has the opposite effect on the commercial property market integration as compared to the residential housing market integration, with the dispersion for the commercial house prices increasing since the end of 2019.

Figure 3b shows the housing price dispersion for newly constructed and second-hand residential properties. As we can see, both newly-built and second-hand property markets have become less integrated over time, with higher dispersion recorded in the recent period compared to the beginning of the sample. Similarly, there is not much difference in the evolution of the degree of integration for the housing built in different locations, as shown in Figure 3c and Figure 3d.

In section 4, we will formally test whether there is evidence of price convergence across Chinese cities using the PS nonlinear time-varying heterogeneous factor model and explore the factors that can explain the formation of house price convergence clubs.

3 Method

We study convergence patterns in the real estate market for different property types in China using Phillips and Sul (2007) *logt* test. This method has two key advantages as compared to other convergence tests. First, it allows capturing the transitional dynamics in prices across cities. Second, in the case when there is no evidence of national convergence, the method implies further testing for the existence of convergence clubs using a data-driven clustering algorithm based on the *logt* test[8].

Following Phillips and Sul (2007), we assume that for each good j the logarithm of prices, $p_{ijt} = ln(P_{ijt})$, in city i at time t could be expressed as a combination of price growth component, μ_{jt}, which is common for all locations, and a time-varying idiosyncratic component, δ_{ijt}, that captures both city and goods specific transition:

$$p_{ijt} = \delta_{ijt}\mu_{jt}. \tag{1}$$

Then we use the idea of relative convergence, which assumes that two series share the same stochastic or deterministic trend elements in the long run so that their ratio eventually converges to unity. $P_{ijt+k}/P_{ljt+k} \to 1$ as $k \to \infty$ for any pair of cities $i \neq l$ or equivalently $\delta_{ijt+k} = \delta_j$ as $k \to \infty$. Relative convergence is allied to standard σ-convergence discussed in previous section.

We first use the Whittaker–Hodrick–Prescott smoothing filter to remove the business cycle component of the data (μ_{jt}) before we apply the *logt* test. Then, the relative convergence is tested by estimating coefficients on the logarithm of time in the following regression:

$$\log\left(\frac{D_{1j}}{D_{tj}}\right) - 2\log\log t = \alpha_{0j} + \alpha_{1j}\log t + \epsilon_{tj}, \tag{2}$$

[8]According to the previous literature (see, e.g., Glushenkova et al., 2018) price convergence process is non-linear, and lack of overall convergence may be associated with existence of local convergence clubs arising due to factors associated with regional factors rather than nationwide characteristics.

where $D_{jt} = \frac{1}{N}\sum_{i=1}^{N}(h_{ijt}-1)^2$ is the sample transition distance, which is a measure of price dispersion across cities, and $h_{ijt} = P_{ijt}/N^{-1}\sum_{i=1}^{N} P_{ijt}$ is the relative transition curve for $t = [rT], [rT]+1, ..., T$ with some trimming percentage $r > 0$.[9] Then, the null of national convergence holds if the coefficient of $\log t$, $H_0 : \alpha_{1j} \geq 0$ vs. $H_1 : \alpha_{1j} < 0$. The magnitude of the coefficient α_{1j} measures the convergence speed of P_{ijt}; if $0 \leq \alpha_{1j} < 2$ there is evidence of growth convergence, and if $\alpha_{1j} \geq 2$ we can conclude that there is level convergence in log prices.

We apply the *logt* test to each property type and check whether there is evidence of price convergence across cities. However, the absence of convergence across all cities in China, i.e., national convergence, does not exclude the possibility of convergence within some clubs of cities. We use PS clustering procedure to uncover the existence of possible price convergence clubs. The clustering mechanism includes the following steps. First, cities must be ordered according to the final period prices, and the *logt* test is applied to identify the 'core group' of cities against which other cities will be compared. Then, cities are added to the 'core group' one at a time, and the *logt* test is run to check for their possible membership in the convergence club. These steps are repeated to check for the existence of other convergence clubs. If there is no evidence of further clubs, one can conclude that the remaining observations have divergent behavior, i.e., the cities do not converge with any of the uncovered before clubs. One limitation of the PS test is that it may find more convergence clubs than the true number. The study uses *logt* regression tests across the clubs to check whether identified clubs can be merged into larger clubs to overcome the overidentification problem. A detailed description of the clustering process is presented in Phillips and Sul (2007) paper.

[9] Following Phillips and Sul(2007) paper, we choose $r = 0.3$ based on the size our sample.

4 Empirical results

4.1 Clusters in China's real estate market

We first apply the *logt* test to each property type and check whether there is evidence of price convergence across cities. The first column of Table 2 presents the results of the convergence test for the period of our study, i.e., January 2004-June 2021. We reject the null of the national convergence for all housing types at the 1% significance level. Then, we examine how the results of the national convergence test change over time. In column 2 and column 3 of Table 2, we present the *logt* regression for two sub-periods, before and after the recent financial crisis (Jan 2004 - Nov 2008 and Dec 2008 - Jun 2021). The results indicate a rejection of the null of price convergence for all property types in both periods.

Table 2: National convergence test

	2004.1-2021.6		2004.1-2008.11		2008.12-2021.6	
Item	α	T-stat	α	T-stat	α	T-stat
Commercial office buildings	-0.20	-5.19	-0.89	-125.83	-0.35	-7.98
Newly constructed residential housing, 1st class location†	-1.18	-94.32	-0.71	-177.71	-0.92	-237.63
Newly constructed residential housing, 2nd class location	-1.07	-82.49	-0.75	-206.11	-0.81	-117.24
Newly constructed residential housing, 3rd class location	-0.83	-121.66	-0.86	-200.46	-0.82	-136.72
Second hand residential housing, 1st class location	-1.09	-83.33	-0.88	-80.17	-0.82	-319.08
Second hand residential housing, 2nd class location	-1.12	-350.68	-0.83	-84.02	-0.90	-315.25
Second hand residential housing, 3rd class location	-0.88	-83.09	-0.88	-63.26	-0.86	-349.81

Notes: This table presents estimates of the national convergence coefficient α and its t-statistics using the *logt* test of Phillips and Sul (2007). The null of price convergence cannot be rejected at the 5% significance level if test statistic (T-stat) takes value larger than -1.65. † - Due to the limited availability of the data, the overall convergence for the newly constructed residential housing on first class location is tested for the period 2004.1-2020.2; similarly, the after-crisis period presented in the last two columns covers only 2008.12-2020.2 for this property type.

Rejecting the null of national convergence leaves open the possibility of regional club convergence, i.e., convergence within a group of cities. Thus, we proceed by examining the existence of convergence clubs in the market. The first column of Table 3 presents the identified clubs for the period of our study. The PS clustering algorithm reveals the existence of up to four convergence clubs in China depending on the property types. Interestingly, for the commercial office buildings, we find only one large convergence club consisting of 29 out of 30 cities and one city presenting divergent behavior. Therefore, we can conclude that there is convergence across all major cities in China (except Shenzhen[10]) in the market for commercial property. This supports our previous finding shown in Figure 3a that the price dispersion across locations falls over time for commercial housing, implying an increase in the level of domestic market integration.

Table 3: House price convergence clubs

	2004.1-2021.6					2004.1-2008.11				
Item	Club1	Club2	Club3	Club4	Diverg.	Club1	Club2	Club3	Club4	Diverg.
Commercial office building	0.12				NA	-2.60	0.28	0.06		-1.25*
New residential housing, 1st†	1.77	0.64	0.48		-1.65*	0.17	-0.01	0.25		
New residential housing, 2nd	0.09	0.11	0.37		NA	0.16	0.24	0.15	0.22	NA
New residential housing, 3rd	0.03	0.08	0.54	1.25		0.40	0.22	0.62	0.25	-1.00*
Second hand residential housing, 1st	0.30	0.23	0.21			0.34	0.14	0.28		-1.23*
Second hand residential housing, 2nd	0.15	0.19	-0.02			0.43	0.12	0.27		-0.73*
Second hand residential housing, 3rd	1.00	0.00	0.51			0.11	2.42			-1.56*

	2008.12-2020.1 (excl. COVID)					2008.12-2021.6				
Item	Club1	Club2	Club3	Club4	Diverg.	Club1	Club2	Club3	Club4	Diverg.
Commercial office building	-0.01				NA	0.01	1.89			NA
New residential housing, 1st†	0.03	0.13	0.04	1.06						
New residential housing, 2nd	0.00	0.02	0.23		NA	0.10	0.11	0.33		NA
New residential housing, 3rd	0.16	0.13	0.22		-3.36**	-0.03	0.37	0.38	1.42	
Second hand residential housing, 1st	0.25	0.20	0.53		-0.60*	0.09	0.47	0.16		-0.71*
Second hand residential housing, 2nd	-0.01	0.05	0.27		NA	0.22	0.18	0.01	0.40	NA
Second hand residential housing, 3rd	0.02	0.06	0.49		-1.54*	0.64	0.02	0.37	1.82	NA

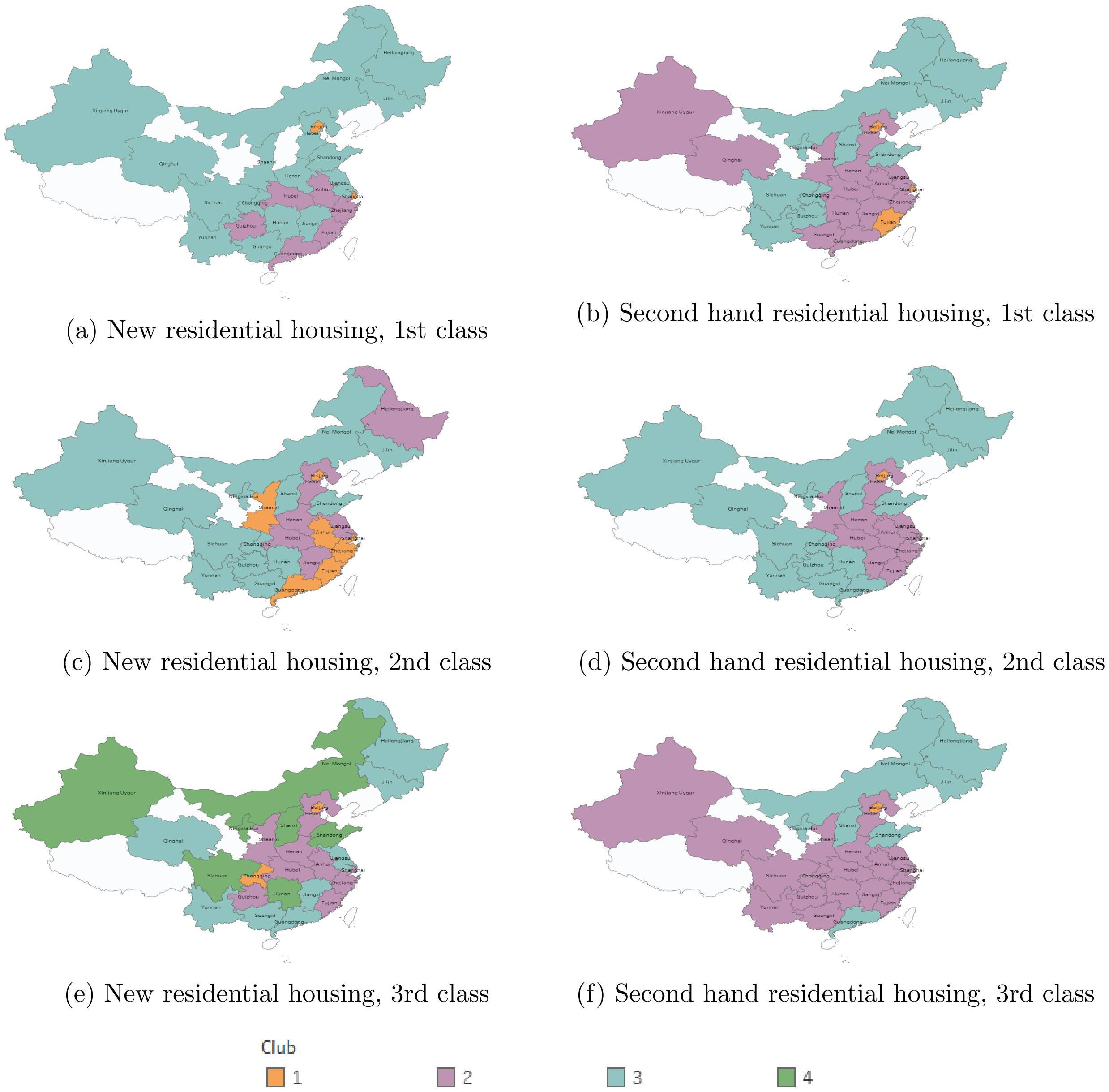
Notes: This table presents estimates of the club convergence coefficients for different periods. The last column in each period presents coefficient estimates of the divergent group. NA refers to the situation when there is only one divergent city, so the convergence coefficient cannot be obtained. Asterisks indicate a significance level of *1% at which the null of convergence is rejected. The table presents the final club classification after testing for the potential existence of large convergence clubs and merging small clubs into larger ones where possible in accordance with Phillips and Sul (2009) club merging procedure. † - Due to the limited availability of the data in the recent period, the overall convergence for the newly constructed residential housing on 1st class location is tested during the period 2004.1-2020.2, and there is no analysis for the after-COVID period for this property type.

For the residential housing, we identified three clubs regardless of the location and property type, with one exception of the newly constructed buildings on 3rd class location for which we have recorded four clubs. Figure 4 presents on a map the set of cities in each convergence

[10] As shown in Table A2 of the Online Appendix, Shenzhen belongs to the divergent group for the majority of property types; therefore, we treat this city as an outlier.

club by property type[11], and Table A2 of the Online Appendix provides a detailed list of cities forming different convergence clubs for each property type.

Figure 4: Convergence clubs for the period 2004.1-2021.6



(a) New residential housing, 1st class

(b) Second hand residential housing, 1st class

(c) New residential housing, 2nd class

(d) Second hand residential housing, 2nd class

(e) New residential housing, 3rd class

(f) Second hand residential housing, 3rd class

[11]For the presentation purpose we do not show the map for the commercial property in Figure 4 as all cities form one convergence club with the exception of Shenzhen.

Figure 5 presents the evolution of average log prices over time within each convergence club for different types of housing. The first club is characterized by the highest price level for each property, the second club by the second-highest price, and so on. Hence, in what follows, we refer to the first, second, third, and fourth clubs as high-price, medium-price, low-price, and cheap clubs, respectively. Moreover, trends in average prices changed a lot over time. In the initial years, the average prices were very similar for many clubs, while around 2012, the gap between clubs started to increase.[12] Therefore one might be interested in the analysis of the short-run price convergence.

Figure 5: Average price in convergence clubs

[12]Similarly, the dynamics of the relative transition curves, presented in Figure A2 of the Online Appendix, shows that the convergence patterns changed a lot over time.

The remainder of Table 3 presents the club convergence tests for three sub-periods, namely Jan 2004 - Nov 2008 (i.e., before the crisis), Dec 2008 - Jan 2020 (i.e., after the crisis, and excluding the effect of COVID-19), and Dec 2008 - Jun 2021 (i.e., after the crisis, and including the impact of COVID-19). We find that the markets for the newly constructed property on the second and third class locations become more integrated over time, with a smaller number of clubs existing between 2008.12 and 2020.1 compared to the previous period of 2004.1-2008.11. Yet, COVID-19 contributed to market segregation, especially in the second-hand property market. For the newly-constructed residential property on 3rd class location and second-hand property on both 2nd and 3rd class locations we find the existence of four convergence clubs in the period 2008.12-2021.6 versus three clubs in the period 2008.12-2020.1. Similarly, we observe two clubs for the commercial office buildings during the period 2008.12-2021.6 versus only one club in 2008.12-2020.1. These results imply an increasing degree of market segregation in the recent period. Table A2 and Figure A3 of the Online Appendix provide a detailed description of the convergence club classification and geographic maps for each property type and different sub-period.

In Table 4 we present the frequency of belonging to each club for each city during the period 2004.1-2021.6 — that is, the share of property types for which the city lies in the high-, medium-, low-price, and cheap clubs. Tier 1 cities such as Beijing, Shenzhen, Guangzhou, and Shanghai tend to form only the high- and medium-price clubs. New Tier 1 cities, such as Wuhan, Zhengzhou, Ningbo, and Xi'an tend to form a medium-price club for the great majority of the property types. Finally, the vast majority of Tier 2 and Tier 3 cities tend to frequently form low-price clubs (for at least 50% of the property types). We infer that regional development might play a role in the formation of different clubs and investigate more systematically the role of socio-economic and other factors in determining price convergence clubs in the following subsection.

Table 4: Frequency of club formation

City	Tier classifications of cities	Club1	Club2	Club3	Club4
Beijing	Tier 1	100.0%			
Xiamen	Tier 2	85.7%			
Qingdao	Tier 1*	71.4%	28.6%		
Shenzhen	Tier 1	71.4%			
Shanghai	Tier 1	57.1%	42.9%		
Wuhan	Tier 1*	14.3%	85.7%		
Ningbo	Tier 1*	28.6%	71.4%		
Hefei	Tier 2	28.6%	71.4%		
Zhengzhou	Tier 1*	14.3%	71.4%	14.3%	
Shijiazhuang	Tier 2	14.3%	71.4%	14.3%	
Xi'an	Tier 1*	28.6%	57.1%	14.3%	
Guangzhou	Tier 1	42.9%	57.1%		
Fuzhou	Tier 2	42.9%	57.1%		
Nanchang	Tier 2	14.3%	57.1%	28.6%	
Nanjing	Tier 2	14.3%	57.1%	28.6%	
Shenyang	Tier 1*	14.3%		85.7%	
Changchun	Tier 2	14.3%		85.7%	
Harbin	Tier 2	14.3%	14.3%	71.4%	
Kunming	Tier 2	14.3%	14.3%	71.4%	
Hohhot	Tier 3	14.3%		71.4%	14.3%
Jinan	Tier 2	14.3%		71.4%	14.3%
Taiyuan	Tier 2	14.3%		57.1%	14.3%
Yinchuan	Tier 3	14.3%		57.1%	14.3%
Chongqing	Tier 1*	28.6%	14.3%	57.1%	
Nanning	Tier 2	14.3%	28.6%	57.1%	
Xining	Tier 3	14.3%	28.6%	57.1%	
Chengdu	Tier 1*	14.3%	14.3%	57.1%	14.3%
Guiyang	Tier 2	14.3%	42.9%	42.9%	
Changsha	Tier 1*	14.3%	28.6%	42.9%	14.3%
Urumqi	Tier 3	14.3%	28.6%	42.9%	14.3%

Notes: This table presents the frequency of club information is calculated based on the long run formation presented in Table A3. The details on tier classifications of cities are presented in Funke et al. (2019). The * refers to the 'New Tier 1' cities.

4.2 Determinants of house price convergence clubs

We investigate the factors that sort cities into price convergence clubs using ordinal logistic regression. Factors determining price differences in the housing market in China are well-studied in the literature. For instance, Li and Chand (2013) find that house prices in China are determined by personal income, construction cost, user costs, and land price. Du et al. (2011) also show that house prices depend on land market determinants, e.g., land supply and land price. Liu and Ma (2021) present the most recent evidence on the importance of different factors in determining Chinese house prices by examining the role of 30 various provincial socio-economic variables mentioned in previous literature. The authors find that land price, loans of real estate developers, per capita savings, the proportion of people with college or above educational degrees, and the number of unemployed population can explain 72% of regional heterogeneity in house prices.

The focus of our research is on cities rather than provinces, which limits the analysis of possible factors due to the lack of city-level information. We collect data on industrial output, unemployment rate, education expenditure, wages, disposable income, construction area, population growth, and land price. Moreover, previous literature (see, e.g., Funke et al., 2019, and Zheng et al., 2010) shows that environmental factors, such as climate and pollution level, play an important role in determining house prices in China. So we include the discharge of industrial smoke and dust in our regression. Finally, since we focus on analyzing different property types, we must control for item-specific characteristics in our model. Based on economic theory and empirical literature (e.g., Fu et al., 2000; Chen, 1996), we include monthly rent for each property type in our regressions. More details about all explanatory variables are given in Table 5.

We use the club classification for the overall period 2004.1-2021.6 for different types of property[13] and estimate the following ordinal logit regression:

$$S_{ih} = \beta_1 R_{ih} + \beta_2 C_{ih} + \beta_3 LP_{ih} + \beta_4 U_i + \beta_5 Y_i + \beta_6 S_i + \beta_7 E_i + \beta_8 W_i + \beta_9 P_i + \epsilon_{iht}. \tag{3}$$

Then, the probability of each outcome can be calculated as follows:

$$Pr(y_{ih} = i) = Pr(\kappa_{i-1} < S_{ih} + u \leq \kappa_i), \tag{4}$$

where κ_i is the threshold parameter for club i.

Alternatively, we also estimate the following multinomial logit model with club 1 set as the reference group:

$$\begin{aligned} log(\frac{prob(Y_{iht} = k)}{prob(Y_{iht} = 1)}) = \beta_{0,k} + \beta_{1,k} R_{ih} + \beta_{2,k} C_{ih} + \beta_{3,k} LP_{ih} + \beta_{4,k} U_i \\ + \beta_{5,k} Y_i + \beta_{6,k} S_i + \beta_{7,k} E_i + \beta_{8,k} W_i + \beta_{9,k} P_i + \epsilon_{iht,k} \end{aligned} \tag{5}$$

where $prob(Y_{iht} = k)$ is the probability that city i belongs to the club k for property h.

[13] For the comparability purpose, we exclude the newly constructed residential property on the first class location from the analysis.

Table 5: List of variables

Variable	Description (unit)	Data Source
Rent (R_{ih})	Arithmetic average (over the period) of logarithm monthly rent for each type of property (Yuan/m^2)	CPIC
Construction (C_{ih})	Arithmetic average (over the period) of logarithm annual construction area for residential and commercial property (1000 m^2)	CEIC
Land price growth (LP_{ih})	Average (over the period) growth rate of land price for residential and office land (Yuan/m^2)	CSMAR
Unemployment (U_i)	Arithmetic average (over the period) of annual registered unemployment rate in urban area (% of population)	EPS China
Industrial Output (Y_i)	Arithmetic average (over the period) of logarithm annual industry gross output (10,000 Yuan)	EPS China
Industrial Smoke (S_i)	Arithmetic average (over the period) of logarithm annual discharge of industrial smoke and dust (ton)	EPS China
Education (E_i)	Arithmetic average (over the period) of annual expenditure on education reported by Municipal Bureau of Statistics of local cities (% of GDP)	CEIC
Income growth (W_i)	Average (over the period) growth rate of disposable income (%)	EPS China
Wage growth (W_i)	Average (over the period) growth rate of total wages (%)	EPS China
Population growth (P_i)	Average (over the period) growth rate of total population in the city (%)	EPS China

Column (1)-(4) of Table 6 reports the results of ordinal logit model, while column (5)-(7) of Table 6 show the results of multinomial regressions for the best model specification.

The results show that rent and construction play an important role in explaining the formation of house price convergence clubs. For the property types with low rental prices (large construction areas), we tend to observe the formation of lower-price clubs more often than those characterized by high rent (small construction areas). Interestingly, land prices are less critical than rent based on our multinomial logit analysis presented in columns (5)-(7) of Table 6. Land prices only affect the formation of the fourth club, while rent can explain the formation of each club. At the same time, the economic development of cities may explain the existence of house price convergence clubs. We find that high unemployment and

Table 6: Determinants of regional convergence clubs

VARIABLES	(1)	(2)	(3)	(4)	(5) club=2	(6) club=3	(7) club=4
Rent	-1.771***		-1.445**	-1.413***	-2.425***	-2.385*	-7.111***
	(0.537)		(0.578)	(0.538)	(0.923)	(1.276)	(1.918)
Construction	2.805***	3.238***	3.023***	3.026***	3.196***	7.875***	4.169*
	(0.580)	(0.501)	(0.592)	(0.616)	(1.068)	(1.740)	(2.400)
Land price growth		-3.547***	-2.272*	-2.880**	-0.681	-5.748	-22.54**
		(1.224)	(1.346)	(1.337)	(6.197)	(6.497)	(11.39)
Unemployment	0.819***	1.053***	0.981***	1.109***	2.496**	4.078***	2.655*
	(0.291)	(0.311)	(0.309)	(0.343)	(1.215)	(1.404)	(1.440)
Industrial Output	-2.876***	-3.499***	-3.080***	-3.232***	-3.686***	-9.192***	-7.427***
	(0.437)	(0.415)	(0.443)	(0.484)	(1.143)	(2.001)	(2.163)
Education	-2.115***	-1.881***	-1.928***	-1.355***	-2.917***	-5.980***	-7.384***
	(0.441)	(0.448)	(0.464)	(0.471)	(0.935)	(1.680)	(1.845)
Industrial Smoke	1.124***	1.104***	1.064***	1.119***	1.738**	4.007***	1.480
	(0.365)	(0.355)	(0.369)	(0.368)	(0.742)	(1.220)	(1.400)
Income growth	-0.401***	-0.307**	-0.354**				
	(0.138)	(0.134)	(0.142)				
Wage growth				-0.468*	-1.195**	-0.527	-2.539**
				(0.270)	(0.568)	(0.999)	(1.098)
Population growth	-1.087***	-1.210***	-1.169***	-0.954***	-1.248*	-2.822***	-1.043
	(0.248)	(0.213)	(0.237)	(0.216)	(0.656)	(0.748)	(0.737)
κ_1	-30.51***	-30.95***	-31.14***	-33.14***			
	(5.760)	(5.589)	(5.694)	(6.370)			
κ_2	-26.27***	-26.95***	-26.91***	-29.32***			
	(5.500)	(5.389)	(5.446)	(6.310)			
κ_3	-22.23***	-22.83***	-22.76***	-25.03***			
	(5.404)	(5.287)	(5.353)	(6.120)			
Constant					44.10***	70.77***	143.1***
					(16.89)	(19.97)	(35.82)
Pseudo R2	0.520	0.510	0.527	0.518	0.594	0.594	0.594
Observations	178	178	178	178	178	178	178

Notes: Standard errors presented in parenthesis. Asterisks indicate a significance level of the coefficients ***1%, **5%, and *10%.

pollution levels contribute to the formation of a larger number of clubs; for instance, club 2 and club 3 are formed more often than club 1 by cities with high unemployment and/or high pollution level. Other variables, such as industrial output, education expenditure, wage (income) growth, and population growth have negative effect on the probability of identifying a larger number of clubs, suggesting that industrialized cities with high spending on education, high income and large population tend to form high-price convergence club more often than less developed cities. Our results suggest that rent, land supply, pollution, and economic development play an essential role in explaining the formation of regional convergence clubs in the Chinese housing sector.

5 Conclusion

This paper assessed the extent of price integration across Chinese cities for different property types and provided new insights into the changes of domestic convergence patterns that took place over time, especially in the recent period associated with the COVID-19 pandemic. Using a non-linear time-varying factor model proposed by Philips and Sul (2007), we investigate the evolution of housing prices and the formation of convergence clubs among 30 major cities in China for various types of property. Our results confirm those of Lin et al. (2015) and Cai et al. (2022) who show that the Chinese housing market is highly segmented. Yet, we find that the degree of market segmentation varies significantly across property types and over time.

We record different convergence patterns for office buildings and residential housing. While the commercial property market becomes more integrated over time with solid evidence of convergence across all major cities in China (except Shenzhen), the residential housing market remains highly segregated, characterized by the existence of up to four various convergence clusters depending on the location of the property and the use. We show that clubs' formation varies over time and across types of properties. The markets for the new residential housing in the second and third locations become more integrated over time with a smaller number of regional clusters identified in the latter period, while the second-hand housing markets become more fragmented.

In this paper, we also try to estimate the impact of the COVID-19 pandemic on housing prices and convergence patterns. The data show a slight drop in house price growth at the beginning of 2020 coincided with the COVID-19 lockdown and the return to a growing trend in mid-2020 that could be associated with the efficient epidemic-control policy. Our *logt* test reveals that the COVID-19 pandemic contributed to market segregation, especially in the second-hand property market leading to a formation of a larger number of regional convergence clusters.

Finally, the paper shows that the formation of price convergence clubs can be explained by the land/property market determinants (such as rent and land supply), pollution, and the economic development of cities. We find that cities with high unemployment and/or high pollution levels tend to form low-price convergence clubs more likely than cities with low unemployment and/or low air pollution. Also, fast-growing industrialized cities form high-price clubs more often than cities characterized by slower income growth or socioeconomic development. Finally, we observe the formation of low-price clubs more often for the property types with low rental prices and/or large construction areas than for the property characterized by high rent and/or small construction areas.

Since the housing market is important for macroeconomy and resource allocation, the implication of this paper is that the Chinese government needs to ensure greater harmony across the regional housing markets within the country. This could be achieved by more centralized and unified regulation of housing markets. Our study also provides information necessary for the design of the macro-prudential policy. We find that housing market determinants, such as construction area and rent, play a key role in regional price convergence. Therefore, the government can efficiently use these tools to regulate housing prices.

Statements and Declarations

Competing Interests: The authors declare that they have no competing interests.

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Data Availability Statement

The data that support the findings of this study are available from the China Price Information Center (CPIC). Restrictions apply to the availability of these data, which were used under license for this study. According to the license, users are not permitted to allow an unauthorized user to have access to the Licensed Information.

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Online Appendix

Table A1: Relative prices and income by cities

City	Commercial property relative price			Residential property relative price			Relative income		
	Jan/2004	Jan/2012	Jan/2021	Jan/2004	Jan/2012	Jan/2021	2004	2012	2018
Beijing	2.35	1.27	1.90	2.00	2.87	3.53	1.51	1.34	1.39
Changchun	0.87	0.48	0.47	0.61	0.45	0.28	0.86	0.90	0.95
Changsha	0.51	1.15	0.81	0.62	0.80	0.54	0.73	1.38	1.36
Chengdu	0.70	0.66	0.58	0.76	0.97	0.45	0.84	0.88	0.94
Chongqing	0.74	0.99	0.70	0.41	0.35	0.30	0.39	0.60	0.66
Fuzhou	0.60	1.35	1.18	0.89	1.41	1.20	0.59	0.61	0.68
Guangzhou	2.50	0.99	1.13	1.52	1.48	1.53	2.29	1.63	1.55
Guiyang	0.87	0.63	0.79	0.78	0.71	0.54	0.52	0.59	0.78
Harbin	1.06	0.63	0.70	0.61	0.61	0.41	0.71	0.70	0.66
Hefei	0.45	0.48	0.57	0.67	0.69	0.97	0.54	0.85	0.97
Hohhot	0.74	0.49	0.50	0.55	0.44	0.39	1.07	1.30	0.92
Jinan	1.12	0.72	0.62	0.79	0.73	0.36	1.12	1.07	1.06
Kunming	0.68	0.39	0.55	0.86	0.85	0.50	0.76	0.71	0.76
Nanchang	0.76	0.60	0.55	0.93	0.71	0.63	0.70	0.90	0.95
Nanjing	1.11	0.88	0.86	1.82	0.92	0.67	1.34	1.36	1.52
Nanning	0.58	1.13	0.53	0.74	0.84	0.61	0.37	0.54	0.56
Ningbo	1.56	0.73	1.09	1.60	1.64	1.61	1.59	1.32	1.32
Qingdao	1.37	1.00	0.82	1.07	0.89	1.16	1.14	1.27	1.28
Shanghai	2.44	1.48	2.14	2.00	2.84	2.53	2.25	1.31	1.34
Shenyang	0.81	0.69	0.73	0.85	0.58	0.41	1.12	1.24	0.75
Shenzhen	1.62	4.88	4.48	2.20	2.48	4.56	2.41	1.89	1.88
Shijiazhuang	0.61	0.74	0.87	0.87	0.66	0.83	0.73	0.67	0.55
Taiyuan	0.87	0.58	0.48	0.84	0.64	0.33	0.76	0.84	0.88
Urumqi	0.76	2.41	0.76	0.75	0.68	0.49	0.93	0.92	0.87
Wuhan	1.13	1.43	1.73	1.23	1.07	0.96	1.01	1.22	1.34
Xiamen	0.71	0.97	0.85	1.02	1.41	1.87	1.63	1.19	1.17
Xian	0.83	0.61	0.97	0.85	0.62	0.82	0.57	0.79	0.85
Xining	0.45	0.38	1.52	0.61	0.44	0.50	0.34	0.58	0.54
Yinchuan	0.81	0.58	0.53	0.72	0.55	0.32	0.72	0.87	0.84
Zhengzhou	0.39	0.68	0.62	0.85	0.67	0.68	0.86	0.95	1.01

Table A2: Formation of convergence clubs

Cities	Newly constructed residential housing, 1st class			Newly constructed residential housing, 2nd class				Newly constructed residential housing, 3rd class			
	L.R.	Sh.R.		L.R.	Sh.R.			L.R.	Sh.R.		
		01/04-11/08	12/08-02/20		01/04-11/08	12/08-01/20	12/08-06/21		01/04-11/08	12/08-01/20	12/08-06/21
Beijing	1	1	1	1	D	1	1	1	D	D	1
Changchun	3	2	3	3	3	2	2	3	3	2	2
Changsha	3	2	3	3	1	3	3	4	2	3	3
Chengdu	3	2	4	3	2	3	3	4	2	3	3
Chongqing	3	3	3	3	4	3	3	1	D	2	2
Fuzhou	2	2	2	1	1	1	1	2	1	2	2
Guangzhou	2	2	2	1	1	2	1	2	1	1	1
Guiyang	2	2	2	3	1	2	2	2	2	2	1
Harbin	3	2	3	2	3	3	3	3	4	2	3
Hefei	2	3	1	1	3	1	1	2	3	1	2
Hohhot	3	3	4	3	4	3	3	4	4	3	4
Jinan	3	3	4	3	3	3	3	4	2	3	4
Kunming	3	2	4	3	2	3	3	3	2	2	2
Nanchang	3	3	3	2	3	2	2	3	D	2	3
Nanjing	3	2	3	2	2	2	2	3	1	2	2
Nanning	3	2	4	3	2	3	3	3	3	3	3
Ningbo	2	1	2	1	1	1	1	2	1	1	1
Qingdao	2	3	3	1	3	1	1	2	3	2	1
Shanghai	1	1	1	1	1	1	1	2	1	1	1
Shenyang	3	3	3	3	3	3	3	3	3	3	3
Shenzhen	1	2	D	D	1	D	D	1	1	D	1
Shijiazhuang	3	2	3	2	2	2	1	2	2	2	2
Taiyuan	D	2	4	3	2	3	3	4	3	3	4
Urumqi	3	3	4	3	1	3	3	4	3	3	3
Wuhan	2	2	3	2	1	2	2	2	2	2	2
Xiamen	D	1	1	1	1	1	1	1	1	1	1
Xi'an	3	3	3	1	3	1	1	2	3	2	2
Xining	3	3	4	3	3	3	2	3	4	3	3
Yinchuan	D	3	4	3	4	3	3	4	4	3	4
Zhengzhou	3	3	3	2	2	2	2	2	2	2	2

Notes: This table presents formation of convergence clubs for each property type. The first column for each property presents long run (L.R.) clubs, i.e. clubs identified for the period 2004-2021. The remaining columns present short run (Sh.R.) clubs, i.e. clubs identified for sub-periods. D refers to cities presenting divergent behavior.

Table A2 (cont.): Formation of convergence clubs

Cities	Second hand residential housing, 1st class				Second hand residential housing, 2nd class				Second hand residential housing, 3rd class			
	L.R.	Sh.R.			L.R.	Sh.R.			L.R.	Sh.R.		
		01/04-11/08	12/08-01/20	12/08-06/21		01/04-11/08	12/08-01/20	12/08-06/21		01/04-11/08	12/08-01/20	12/08-06/21
Beijing	1	1	D	D	1	1	1	1	1	D	1	1
Changchun	3	3	3	3	3	3	3	4	3	2	3	4
Changsha	2	2	2	3	3	1	2	2	2	1	2	2
Chengdu	3	1	3	3	3	1	2	3	2	1	2	2
Chongqing	3	3	3	3	3	D	3	4	2	D	2	2
Fuzhou	1	2	1	1	2	2	1	1	2	1	2	2
Guangzhou	1	2	D	D	2	2	1	1	2	1	2	2
Guiyang	3	2	2	3	3	2	3	3	2	1	2	2
Harbin	3	3	3	3	3	3	3	3	3	2	3	3
Hefei	2	2	2	2	2	2	1	1	2	1	1	2
Hohhot	3	3	3	3	3	2	2	2	3	1	3	2
Jinan	3	2	3	3	3	2	3	3	3	1	3	3
Kunming	3	2	3	3	3	2	2	3	2	1	2	2
Nanchang	2	3	2	2	2	2	2	2	2	1	2	2
Nanjing	2	2	2	2	2	1	2	2	2	1	2	2
Nanning	2	2	2	2	3	2	2	2	2	1	2	2
Ningbo	2	2	2	2	2	1	2	1	2	D	1	1
Qingdao	1	2	1	1	1	2	1	1	1	2	1	1
Shanghai	1	1	1	1	2	1	1	1	2	1	1	1
Shenyang	3	2	3	3	3	2	3	4	3	1	3	3
Shenzhen	1	D	1	1	1	1	D	D	1	1	D	D
Shijiazhuang	2	2	2	1	2	2	1	1	2	1	1	1
Taiyuan	3	2	3	3	3	2	3	3	3	1	3	3
Urumqi	2	2	2	2	3	1	2	3	2	1	3	2
Wuhan	2	2	D	1	2	1	1	2	2	1	1	2
Xiamen	1	2	1	1	1	2	1	1	1	1	1	1
Xi'an	2	3	2	2	2	D	2	1	2	1	2	2
Xining	2	D	3	3	3	2	2	3	2	2	3	2
Yinchuan	3	3	3	3	3	3	3	3	3	2	D	4
Zhengzhou	2	3	2	2	2	2	1	2	2	1	2	2

Notes: This table presents formation of convergence clubs for each property type. The first column for each property presents long run (L.R.) clubs, i.e. clubs identified for the period 2004-2021. The remaining columns present short run (Sh.R.) clubs, i.e. clubs identified for sub-periods. D refers to cities presenting divergent behavior.

Table A2 (cont.): Formation of convergence clubs

Cities	Commercial office building			
	L.R.	Sh.R.		
		01/04-11/08	12/08-01/20	12/08-06/21
Beijing	1	D	1	1
Changchun	1	D	1	1
Changsha	1	3	1	1
Chengdu	1	3	1	1
Chongqing	1	3	1	2
Fuzhou	1	3	1	1
Guangzhou	1	1	1	1
Guiyang	1	3	1	1
Harbin	1	3	1	1
Hefei	1	3	1	1
Hohhot	1	D	1	2
Jinan	1	3	1	1
Kunming	1	3	1	2
Nanchang	1	3	1	2
Nanjing	1	2	1	1
Nanning	1	3	1	2
Ningbo	1	3	1	1
Qingdao	1	2	1	1
Shanghai	1	1	1	1
Shenyang	1	3	1	2
Shenzhen	D	2	D	D
Shijiazhuang	1	3	1	1
Taiyuan	1	3	1	2
Urumqi	1	3	1	1
Wuhan	1	3	1	1
Xiamen	1	2	1	1
Xian	1	3	1	1
Xining	1	3	1	1
Yinchuan	1	D	1	1
Zhengzhou	1	3	1	1

Notes: This table presents formation of convergence clubs for each property type. The first column for each property presents long run (L.R.) clubs, i.e. clubs identified for the period 2004-2021. The remaining columns present short run (Sh.R.) clubs, i.e. clubs identified for sub-periods. D refers to cities presenting divergent behavior.

Figure A1: Relative transition curves by property type

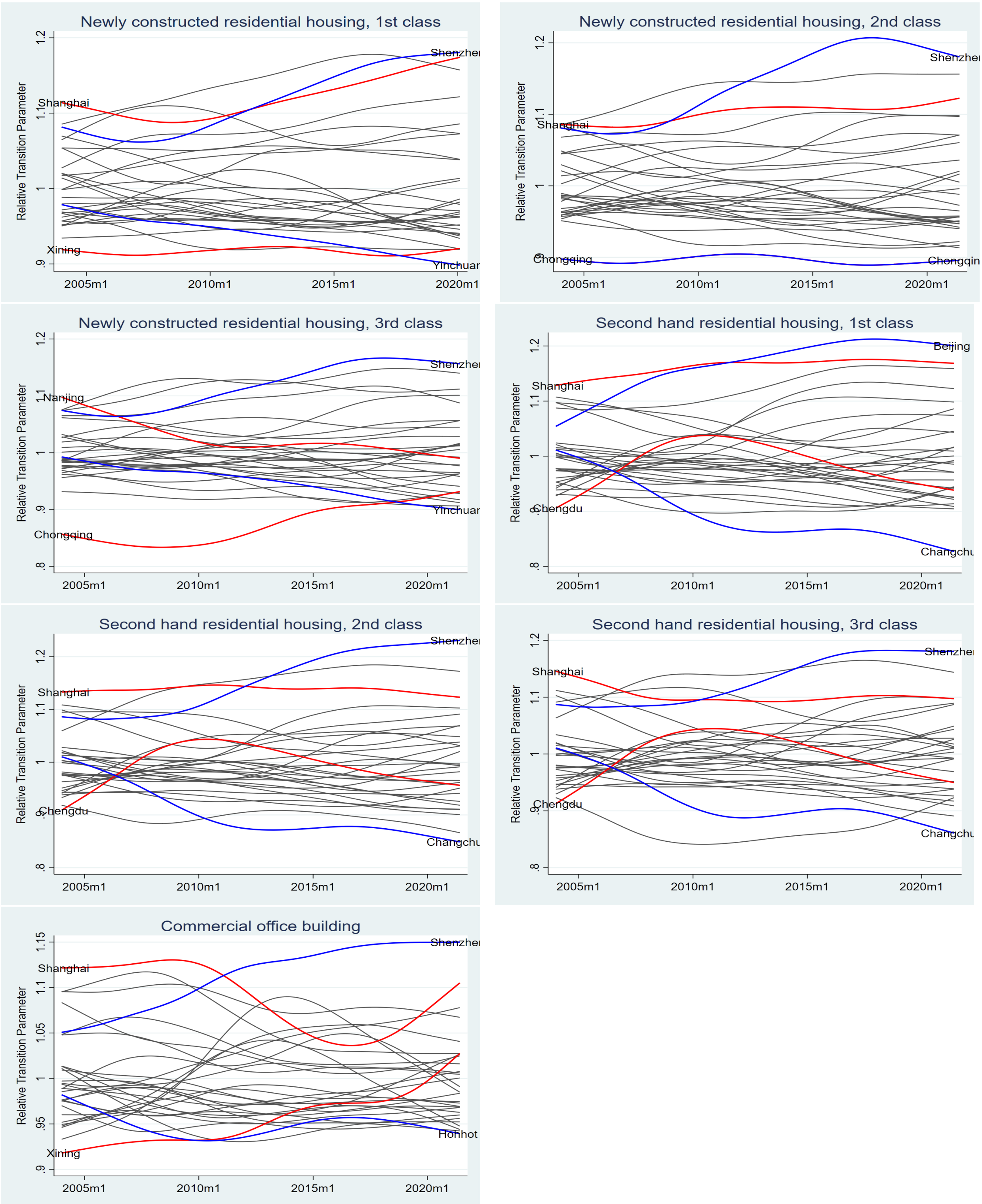
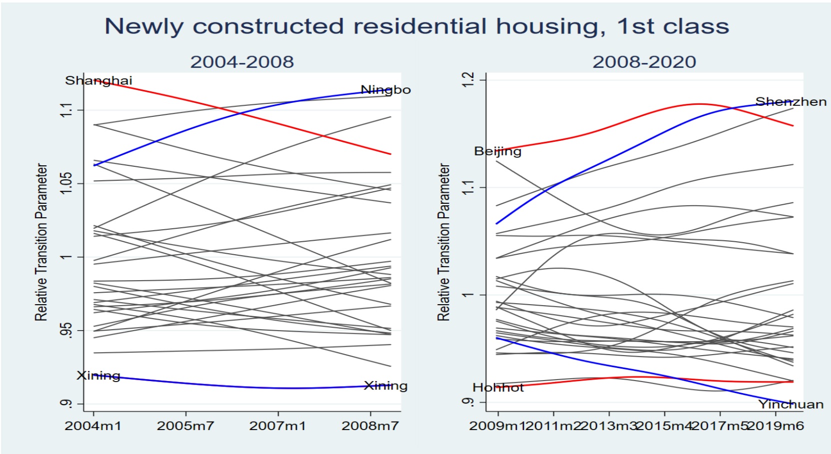
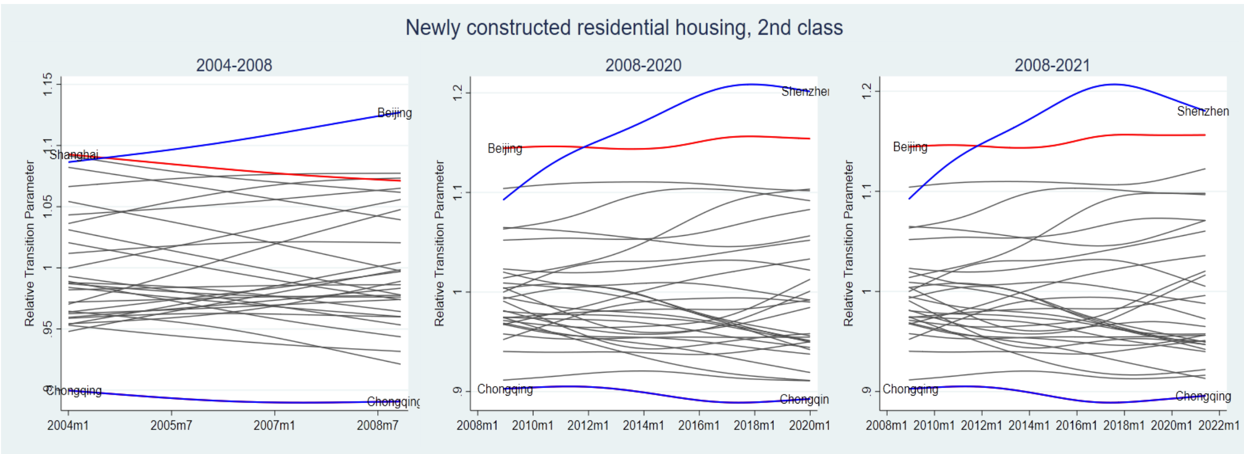


Figure A2: Relative transition curves for sub-periods by property type





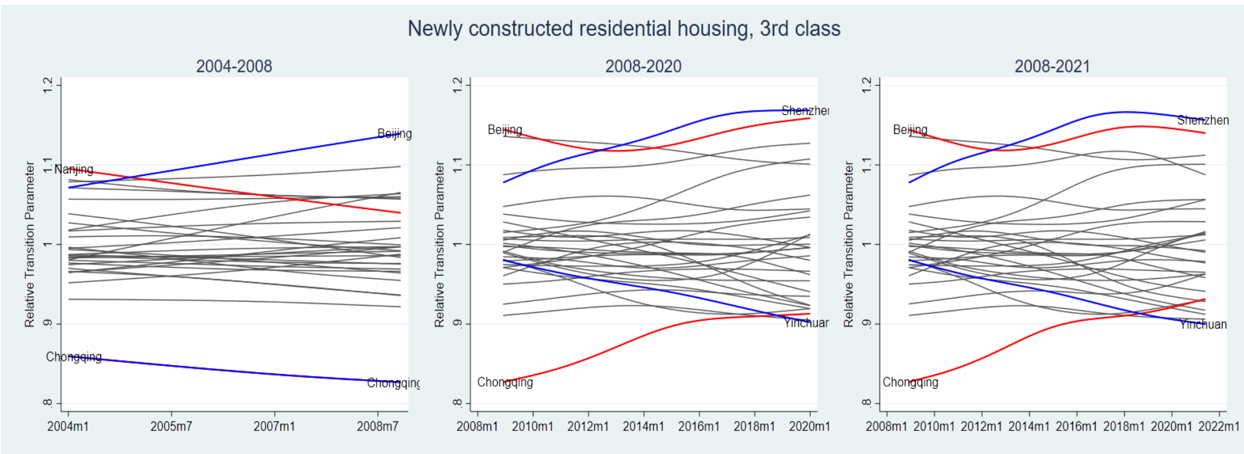


Figure A2 (cont.): Relative transition curves for sub-periods by property type

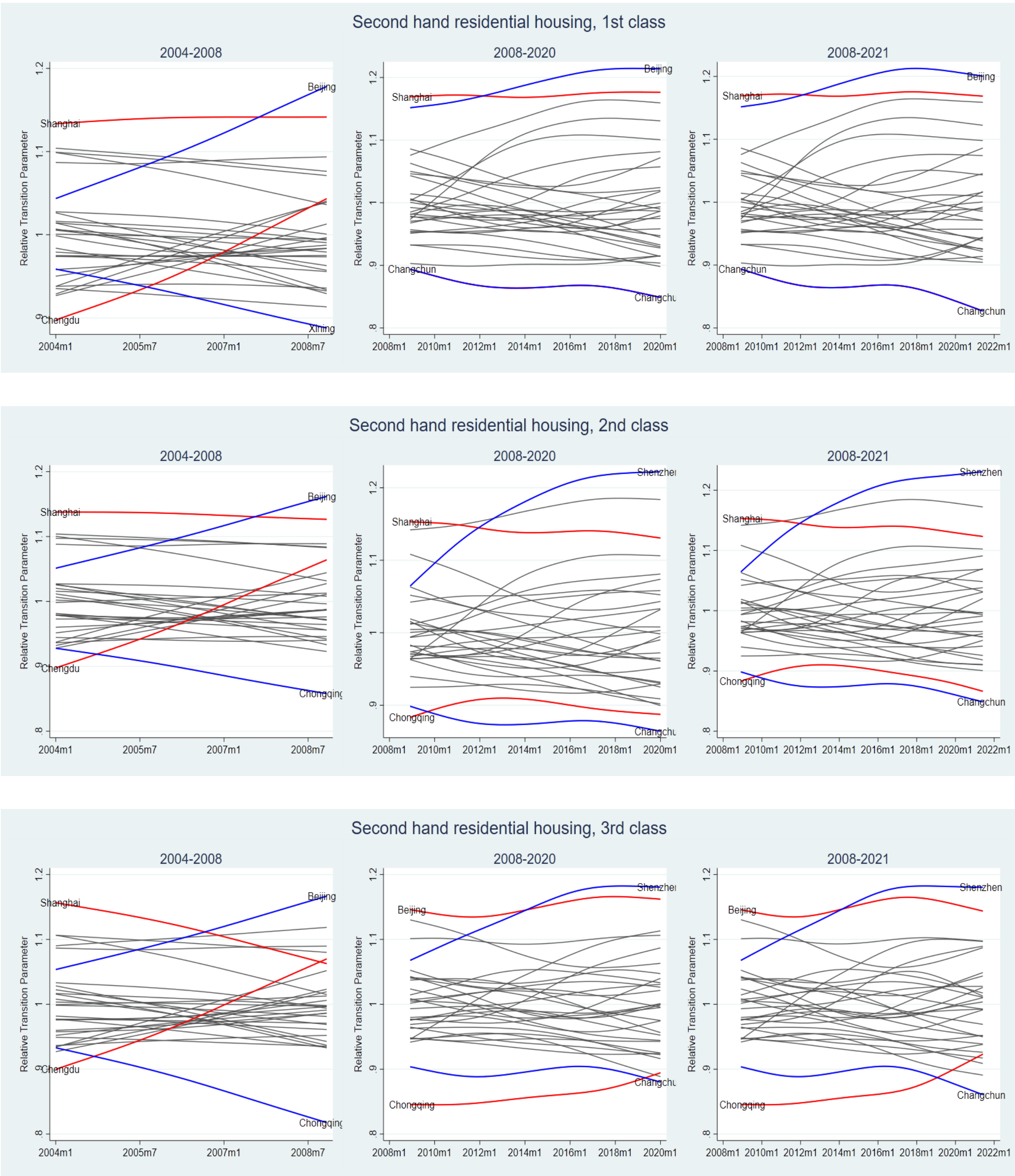


Figure A2 (cont.): Relative transition curves for sub-periods by property type

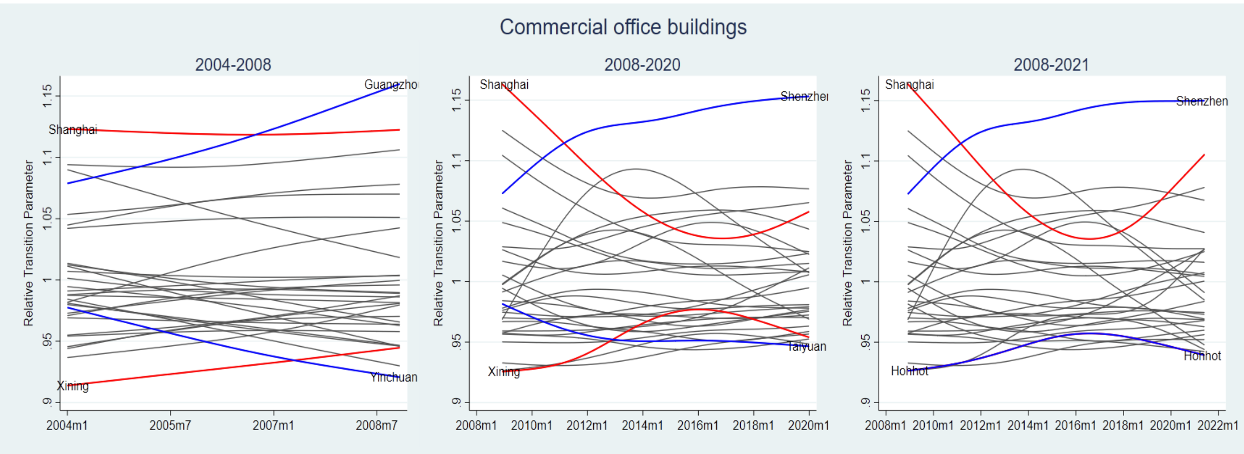
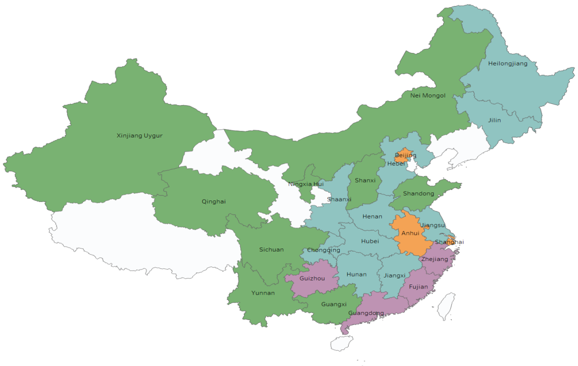


Figure A3: Short-run convergence clubs by property type

(a) New residential housing, 1st class

2004-2008

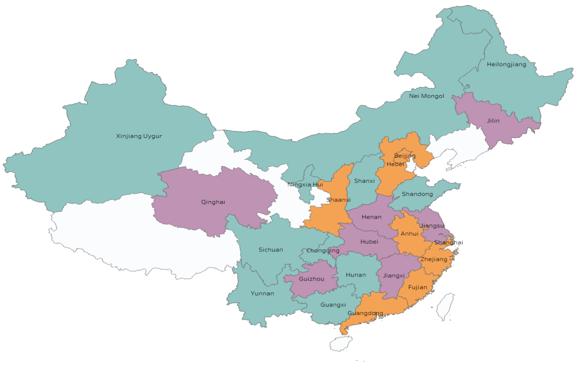


2008-2020

(b) New residential housing, 2nd class

2004-2008

2008-2020



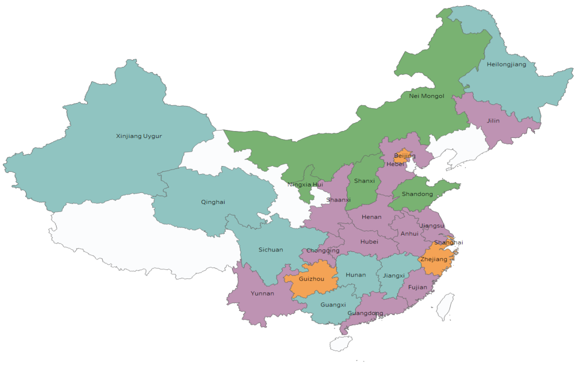
2008-2021

Figure A3 (cont.): Short-run convergence clubs by property type

(c) New residential housing, 3rd class

2004-2008

2008-2020

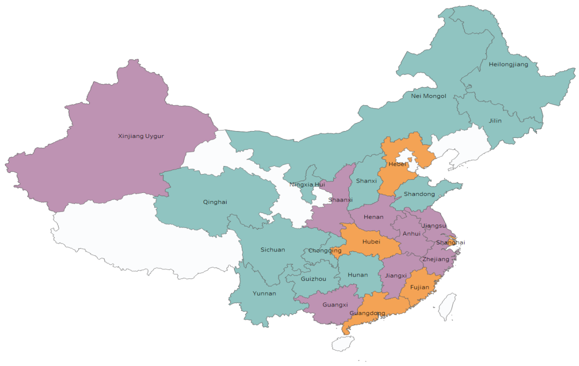


2008-2021

(d) Second-hand residential housing, 1st class

2004-2008

2008-2020



2008-2021

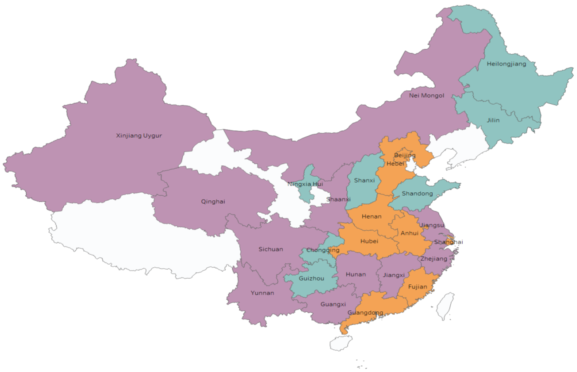
Club

1 2 3 4

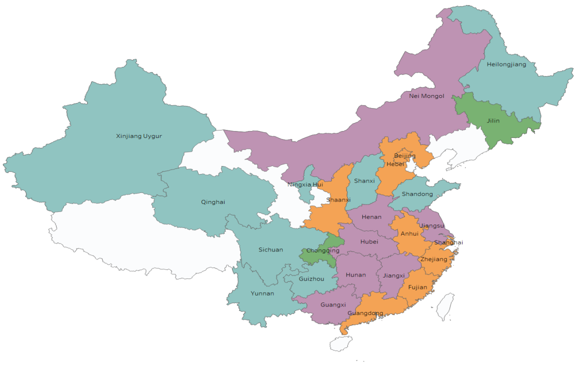
Figure A3 (cont.): Short-run convergence clubs by property type

(e) Second-hand residential housing, 2nd class

2004-2008

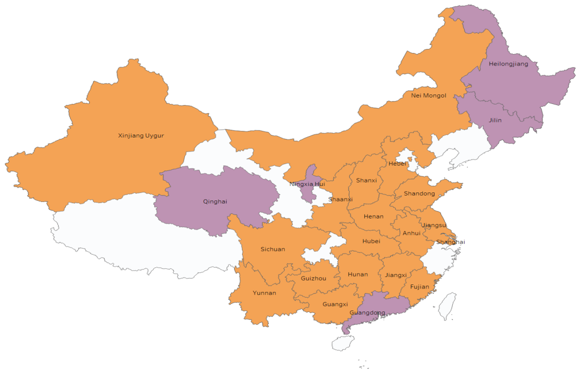


2008-2020

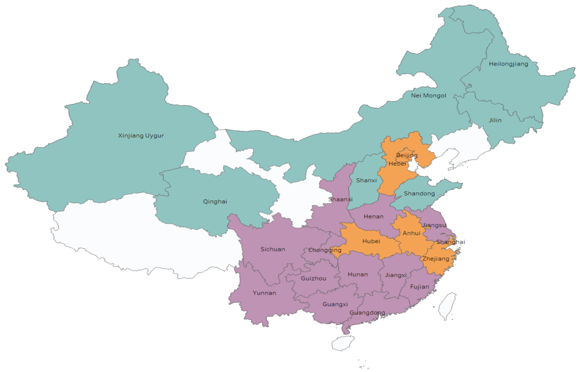


2008-2021

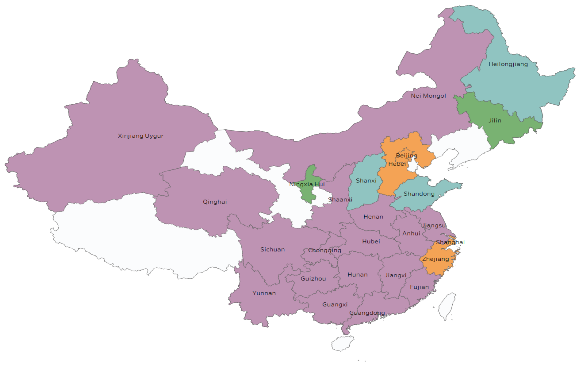
(f) Second-hand residential housing, 3rd class



2004-2008



2008-2020



2008-2021

Club

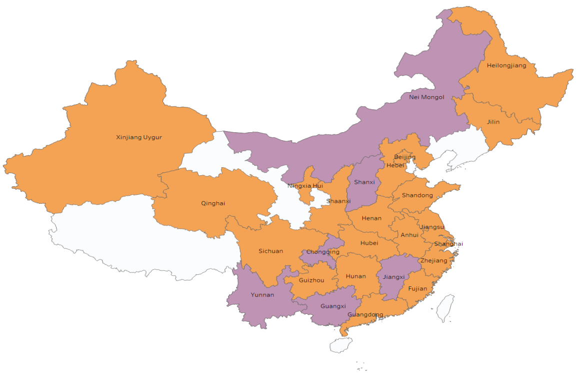
1 2 3 4

Figure A3 (cont.): Short-run convergence clubs by property type

(g) Commercial office buildings

2004-2008

2008-2020



2008-2021