

Pair-wise Convergence of Intra-city House Prices in Beijing

Tommaso Gabrieli¹, Theodore Panagiotidis², Yishuang Xu³

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Abstract

This paper examines the long-run convergence of houses price across the eighteen Beijing districts using monthly dataset that span from January 2006 to December 2014. Following a pair-wise approach, we conduct unit root tests on all $N(N-1)/2$ possible pairs of housing price differentials across the N districts of Beijing. By doing so we do not select any base-district or regional average as the benchmark. A two-stage approach is employed. In the first stage, unit root tests are employed to investigate the convergence (stationarity) of house price differentials across Beijing. Over half of the intra-city house price differentials are found to be stationary. The second stage of the investigates the drivers of convergence. The probability of a pair being stationarity is affected by income differentials across the eighteen districts, as well as the demographics differentials and supply-side factors. Last, we reveal that the half-life of a shock towards long-run price equilibrium is positively affected by distance and housing supply while little evidence can be found for the influence of income and population density.

Keyword: House Price Convergence, pair-wise approach, cointegration

JEL Classification: C2 • C3 • R1 • R2 • R3

¹ Bartlett School of Planning, University College London, UK; E-mail: t.gabrieli@ucl.ac.uk

² Department of Economics, University of Macedonia, Thessaloniki, Greece; email: tpanag@uom.gr

³ School of Environment, Education & Development, The University of Manchester, UK; email: Yishuang.xu@manchester.ac.uk

1. Introduction

Given the spectacular growth of Chinese house prices in recent years, a growing body of research is aiming to understand housing dynamics in China (see for example the review articles of Glaeser et al., 2017 and Fang et al., 2015). Existing research has identified and analysed different tiers of cities and different regional dynamics. Given this heterogeneity across cities, the size of the country and the economy it seems particularly interesting to look at regional and city dynamics, rather than solely to the aggregate Chinese housing market.

Many scholars advocate the investigation into a series of interrelated regional markets rather than a single national market (see for example Meen, 1996 and Yunus and Swanson, 2013). At the regional level, fluctuations in relative house prices have the potential to influence regional economic activity. Variations in relative prices also have the possibility to affect labour mobility (and thus unemployment, Oswald 1999) through the affordability of housing and relocation costs. Those issues seem particular relevant for the Chinese economy, given the intensity and the speed of its economic growth, regional disparities and migration dynamics.

However, to this date, only few studies have aimed at the analysis of the relation between house prices across and within different Chinese regional markets. Wang et al. (2008) examined the long-run and short-run properties of house prices based on cities within 5 sub-national areas during the period 1997Q4–2007Q1. Huang et al. (2010) conducted research on nine major Chinese cities during a similar time span (1999Q1–2008Q3). In general, following studies confirmed the spatial co-dependence of housing markets among different cities and they found long-run equilibrium relationships between these markets. Herrerias and Ordoñez (2012) find that Chinese regions are characterised by club convergence by applying the clustering procedure of Phillips and Sul (2007). Examining different panels of cities, Liu et al. (2018) find evidence of regional convergence by applying a panel selection method, while Zhang and Fan (2018) find evidence of regional spillover effects in urban house prices.

In this paper, we analyse intra-city house price convergence in Beijing and we contribute to the growing body of research on house price convergence in China, as well as to the analysis of fast-growing house prices in Chinese cities. Being the administrative capital as well as the main economic and financial centre in China, Beijing has the highest average house prices in China. A growing body of research papers has investigated China's fast-rising house price dynamics in recent years, and Beijing is often cited as the main example of real estate dynamics in China. Chen and Wen (2017) provide a model of a self-fulfilling, growing housing bubble that can account for the growth dynamics of Chinese house prices. Garriga et al. (2017) analyze a general equilibrium model of migration and urban economic transformation; they show that migration flows combined with an inelastic land supply account for two-thirds of house and land price movements. Bian and Gete (2015) employ a structural autoregressive model to study the effect of seven factors (population growth, credit, preferences, savings rate, productivity progress, land supply, tax policy) simultaneously. Wang and Zhang (2014) study the effect of fundamental factors of demand and supply in several major Chinese cities. Liang and Cao (2007) investigate the relationship between property prices and bank lending in China over the period 1999–2006. Zhang et al (2012) analyze the link between house prices and changes in macroeconomic variables over the period 1999-2010. Guo and Huang (2010) analyze the impact of foreign investments. Liu and Wray (2010) argue that the liquidity driving the property prices in China is the result of massive intervention in the foreign exchange market by the Peoples Bank of China; similarly Xu and Chen (2012) show that Chinese monetary policy actions are the key driver of real estate price growth in in China over the period 1998 to 2009 and Dreger and Zhang (2013) show a large rise in the real estate market as a direct result of the fiscal stimulus package unleashed by the Chinese authorities as a response to the global financial crisis. Wu et al (2012) show that rises in land prices have been a major force in driving up house prices in China, with land prices rising over 800% between 2003 and 2010. Gabrieli et al. (2018), among others, study the existence of bubble dynamics in the Chinese real estate market. Our investigation on house price convergence across the districts in Beijing as well as the divers of the convergence thus complements this fast growing research on the dynamics of house prices in China. Moreover, since our dataset is limited to newly built properties in Beijing, our research contributes specifically to the understanding of speculative, bubble-type dynamics in the prime markets for flats in China.

In our investigation, the stationarity of house price differentials is employed as a proxy for long-run regional house price convergence. As argued by DiPasquale and Wheaton (1996), one might expect house prices across all locations to rise and fall with a market's fortune, but the relative price of the more desirable versus less desirable locations may change very little in the long-run. Our analysis specifically addresses whether the expected general stability of relative prices, or property price premia, is a generalised phenomenon throughout the 18 administrative districts of Beijing.

In the spirit of the earlier studies by Abbott and De Vita (2012) and in particular Holmes et al. (2011, 2017), we utilise an econometric procedure advocated by Pesaran (2007) and Pesaran et al. (2009) for our empirical analysis. Within this approach, a probabilistic definition of convergence is employed and forms the basis of the test. The idea behind this is that for a sample of N different districts, unit root tests are conducted on all $N(N - 1)/2$ house price differentials. Under the null hypothesis of non-stationarity or non-convergence, one would expect the fraction of house price differentials for which the unit-root hypothesis is rejected to be close to the size of the underlying unit-root tests, denoted as α . However, Pesaran (2007) shows that the null of non-stationarity for all state pairs can be rejected if the fraction of rejections exceeds α . Although the underlying individual unit-root tests are not cross-sectionally independent, under the null of non-convergence (or divergence) it can be shown that the fraction of the rejections converges to α , as $N, T \rightarrow \infty$, where T is the time dimension of the panel.

We examine the long-run convergence of houses price across the eighteen Beijing districts using monthly dataset that spans from January 2006 to December 2014.⁴ The source of the house price series is the database CRIC China (<http://www.cricchina.com/>). In the spirit of Holmes et al (2017), we conduct the unit root tests on all 153 possible pairs of housing price differentials across the 18 districts of Beijing. In this way, we do not need to select any base-district or regional average as the benchmark. We analyse the drivers of house price convergence as well as the determinants of the speed of adjustment of house price convergence.

⁴ The series 2006-2014 presents a full cycle of strong appreciation and depreciation, as well as both periods of stimulating and restrictive housing policies; see Gabrieli et al (2018) for more details.

More recent time series were not available when the research project was funded and conducted. A two-stage approach is employed in this study. In the first stage, the unit root tests are carried out to investigate the convergence of house price differentials across Beijing. We find that over half of the intra-city house price differentials are stationary. Next, we move to the second stage of the investigation where the drivers of convergence are analysed. In particular, we investigate whether the probability of stationarity is affected by income differentials across the eighteen districts, as well as the demographics differentials and supply-side factors. The findings in this study reveal that the half-life of a shock to the long-run price equilibrium is positively affected by distance and housing supply while little evidence can be found for the influences from income or population density.

2. Data and Empirical Analysis

Beijing is the capital city of China, covering an area of 16,411 square kilometres. Beijing locates in the northern part of China, next to He Bei Province and Tianjin City. As it is not only the capital in China but also the centre in terms of economic, political and cultural influences, Beijing is the most popular region in China. Geographically, the 18 administrative districts compose the whole city. Official statistics distinguish three tiers among the districts in Beijing: Inner Beijing, also known as “Cheng liu Qu”, is the city's central urban area consisting of 6 district; Middle Beijing is a middle tier consisting of 4 suburban districts that have long been well connected to Inner Beijing by the 3rd to 6th ring road; Outer Beijing consisting of 8 macro districts which extend well beyond the sixth ring road and that have urbanized a very high pace since the beginning of the new Millennium.⁵ Figure 1 shows the geographical distribution of the 18 administrative districts across Beijing.

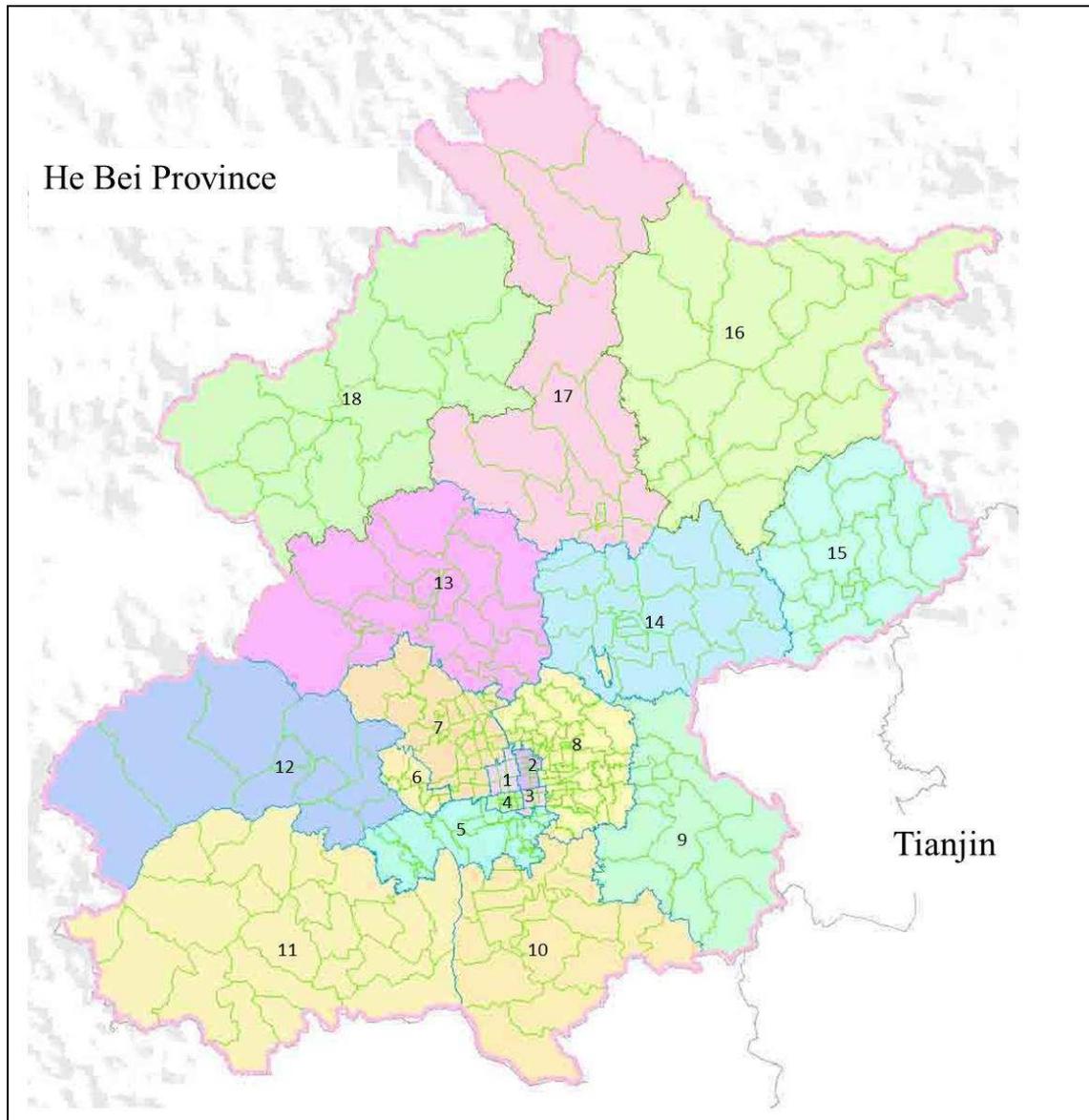
As a result of urbanization in Beijing, many districts experienced rapid population growth and urbanization. From 1990 to 2014, the population in Beijing has nearly doubled from 10.86 million to 21.71 million. Districts vary in terms of land area and size of population. The last official statistics (from 2010) show that 46%, 27%, 27% of the total population respectively live in the Inner, Middle, and Outer tier of districts.

⁵ Chongwen and Xuanwu were respectively merged into Dongcheng and Xicheng on 1st July 2010.

The annual disposable income per capita (in constant RMB) has almost tripled from RMB 17.7 thousand in 2005 to RMB 48.5 thousand in 2015 and the rising population and disposable income has led to a growing demand of residential housing units in Beijing.

Figure 2 shows the plot of the monthly average price (in RMB per square meter) of newly-built residential property sold within the 18 administrative districts in Beijing which is employed in this study. Those house price data span from January 2006 to December 2014, for a total of 108 time observations of each administrative district. The source of the house price series is the private database CRIC China (<http://www.cricchina.com/>), which is available online to subscribers. These time series plots show that the house price of each district in Beijing moves together over time and could be co-integrated across districts. Besides, it is clearly shown by figure 2 that in some cases the price differentials could reach very significant magnitudes. For example, the largest observed district-level difference between the maximum and minimum house price in all given month is RMB 92,328 per square meter.

Figure 1: geographical distribution of the 18 administrative districts across Beijing



Notes:

Inner Beijing: 1, 2, 3, 4, 7, 8

Middle Tier Districts: 5, 6, 9, 10

Outer Beijing: 11, 12, 13, 14, 15, 16, 17, 18

1: Xicheng District

2: Dongcheng District

3: Chongwen District

4: Xuanwu District

5: Fengtai District

6: Shijingshan District

7: Haidian District

8: Chaoyang District

9: Tongzhou District

10: Daxing District

11: Fangshan District

12: Mentougou District

13: Changping District

14: Shunyi District

15: Pinggu District

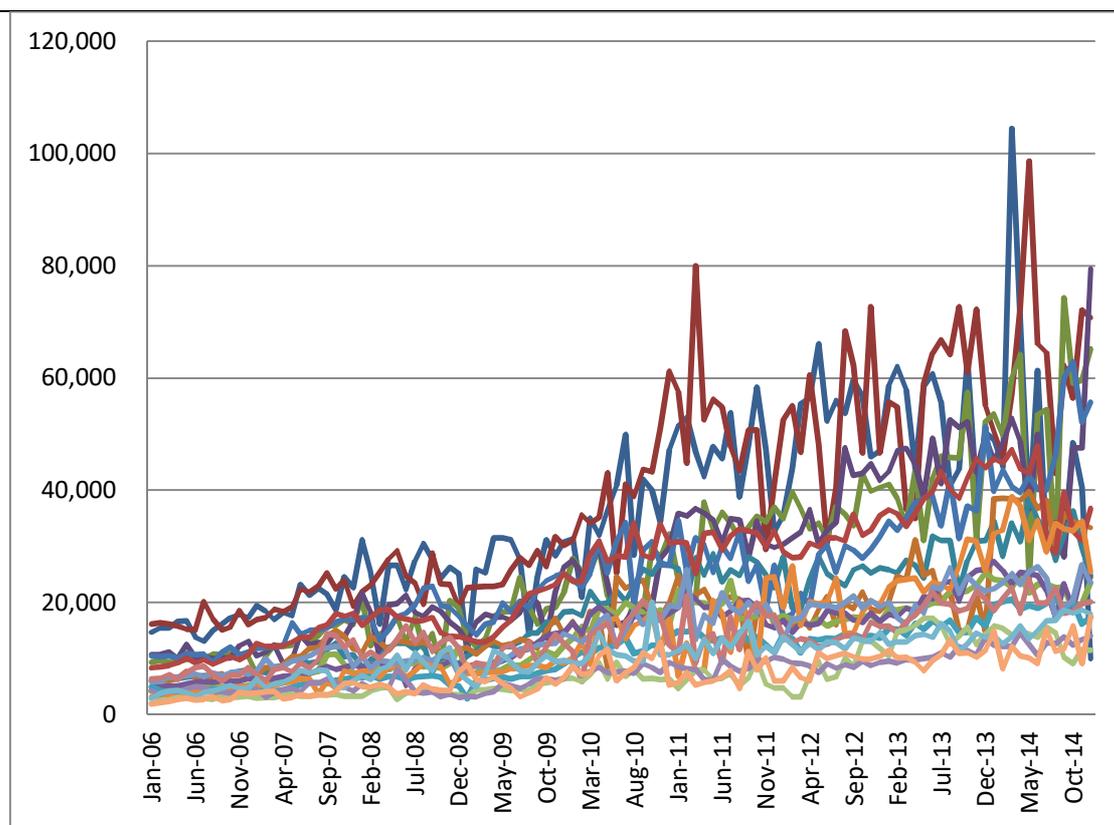
16: Miyun District

17: Huairou District

18: Yanqing District

Source: by author

Figure 2 Monthly house prices (in RMB per square meter) in 18 districts in Beijing



Source: CRIC China (<http://www.cricchina.com/>)

The empirical investigation of this paper focuses on the co-integration (stationarity of differentials) and the differentials of house prices in 18 districts in Beijing. We start by examining the stationary properties of all relative prices. We are interested in price differentials, rather than price levels, and as a result the use of data nominal or real terms makes no difference to the results. Based on all $N(N-1)/2 = 153$ differentials that can be computed using $N=18$ districts, ADF and KSS (Kapetanios et al 2003) unit root tests were carried out at the 10% significance level and the optimal lag length was chosen using the information criteria advocated by Schwarz (1978) and Ng and Perron (2001), denoted SIC and MAIC respectively, allowing for a maximum of $p_{max} = 12$ lags.

The unit-root test results when the optimal lag length is chosen using SIC indicate that at the 10% significance level both the ADF and KSS tests yield rejection frequencies of 47.06%. Since the rejection frequencies exceed the size of the individual ADF tests, we have evidence that the house price series across districts of Beijing are cointegrated with

a unity coefficient.

Once the order of integration of the price differentials, p_{ijt} , is determined, we consider the pairs that are found to be stationary, and for these we compute the average price differential over the sample period, which we denote $\bar{p}_{ij} = T^{-1} \sum_t p_{ijt}$. Here, it ought to be noticed that the sub-index t is dropped since we focus on stationary differentials and for these the mean and variance are constant. Table 2 reports the (absolute value of) the average price differentials that can be computed using the 18 administrative districts in which the city of Beijing is divided, where the entries displayed in bold (red) correspond to the pairs that are found stationary based on the ADF test at the 10% significance level.

Table 1 Average price differential between administrative districts.

(Log) Price differentials are in absolute value. Numbers in bold (red) indicate that the corresponding differential is stationary based on ADF unit root test at the 10% significance level.

District	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
2	0.10																
3	0.18	0.18															
4	0.16	0.17	0.08														
5	0.29	0.31	0.16	0.17													
6	0.32	0.35	0.19	0.21	0.08												
7	0.18	0.19	0.10	0.09	0.14	0.17											
8	0.17	0.19	0.08	0.08	0.13	0.17	0.07										
9	0.42	0.45	0.28	0.29	0.14	0.13	0.26	0.27									
10	0.40	0.43	0.26	0.27	0.12	0.11	0.25	0.25	0.05								
11	0.53	0.56	0.39	0.40	0.25	0.22	0.38	0.38	0.12	0.14							
12	0.44	0.47	0.30	0.31	0.17	0.17	0.29	0.29	0.10	0.12	0.13						
13	0.37	0.40	0.23	0.24	0.10	0.10	0.22	0.22	0.08	0.06	0.16	0.14					
14	0.40	0.43	0.27	0.28	0.15	0.12	0.25	0.25	0.11	0.10	0.15	0.17	0.08				
15	0.72	0.75	0.58	0.60	0.44	0.41	0.57	0.57	0.31	0.33	0.20	0.29	0.35	0.32			
16	0.67	0.70	0.53	0.54	0.39	0.35	0.52	0.52	0.26	0.27	0.15	0.25	0.30	0.27	0.12		
17	0.52	0.56	0.39	0.40	0.24	0.22	0.37	0.37	0.13	0.14	0.09	0.15	0.16	0.14	0.21	0.16	
18	0.70	0.73	0.56	0.57	0.42	0.39	0.55	0.55	0.28	0.30	0.18	0.26	0.33	0.30	0.12	0.12	0.19

The Pesaran (2007) pair-wise approach can then be extended in order to investigate the drivers and speed of convergence. The first step is to explore the drivers that affect the likelihood that \bar{p}_{ij} is stationary. Given the ADF test score for each price differential, we employ the indicator function $z_{ij} = 1$ if the ADF test is rejected at the 10% significance level and 0 otherwise; by means of a probit model we then test for the factors that affect the likelihood that $z_{ij} = 1$.⁶ As a second step, we examine the factors that determine the magnitude of the average price differentials in absolute terms ($|\bar{p}_{ij}|$) by a linear regression model. Our analysis focuses mainly on the arbitrage opportunities offered by prices given by square meters, which are reflected in the magnitude of the price differentials and, rather than the sign, only requires considering differentials in absolute terms. Here the variable to be explained is given by the numbers reported in Table 1 for which $z_{ij} = 1$. As a third step, we investigate the factors that affect the speed at which house price levels adjust when they deviate from their implied long-run equilibrium relationship. For each relative price differentials that turns out to be stationary, i.e. for which $z_{ij} = 1$, we employ an approximation of the half-life of a shock to long-run equilibrium based on the estimated autoregressive parameters obtained from the unit root tests. We compute the estimation of half-life with the formula $-\ln(2)/\ln(1 + \hat{\delta})$, where $\hat{\delta}$ is the autoregressive coefficient in the corresponding ADF test regression.⁷ The estimated half-life between prices in districts i and j , which is denoted as hl_{ij} , is inversely related to the speed of adjustment.

We follow the approach of Holmes et al (2017) in the choice of the explanatory variables that we employ for our regression-based investigation. First, we consider a cost or supply-side factor in the form of the average yearly percentage change in the number of housing units in district i between 2006 and 2014, which we denote as $houug_i$. Those data are obtained from the CRIC China database (<http://www.cricchina.com/>). We use this variable to construct the differential between district i and j in absolute terms, which is $|houug_{ij}| = |houug_i - houug_j|$.

Second, we consider a range of demand-side variables that includes the difference in

⁶ The robustness of the results is assessed by constructing the same variable through the KSS test at the 10% significance level as well.

⁷ See Goldberg and Verboven (2005) and Holmes et al (2017, 2019) for details on this methodology.

per capita income between district i and j in absolute terms, which we denote as $|INC_{ij}| = |INC_i - INC_j|$. The data are obtained from the Beijing Statistical Yearbook (2006 – 2014). We include this variable as a barometer of economic conditions as well as an indicator of income stability across districts, and we expect differences in income to negatively affect house price convergence.⁸

Third, we include population density as a measure of demand pressure and an indirect measure of supply shortage in the context of demographic impacts. Intuitively the high level of population density may imply the limited of land endowment and the restrained possibilities of increasing housing supply. The density variable is calculated as the population divided by the size of the district; both population and size data in each district are accessed from the Beijing Statistical Yearbook (2006 – 2014). The general indicator of population density in district i between 2006 and 2014 is denoted as $DENS_i$. We use this variable to construct the differential between district i and j in absolute terms, which is $|DENS_{ij}| = |DENS_i - DENS_j|$.

We also include the logarithm of the distance between each pair of districts, denoted as $\ln DIST_{ij}$. Those data are obtained from Baidu Map (<https://map.baidu.com/>). By including this variable, we wish to examine whether a longer distance is associated with a slower speed of adjustment towards long-term equilibrium. Indeed, shorter distances between districts may facilitate arbitrage mechanisms that bring house prices into line. Previous literature such as Clapp and Tirtiroglu (1994), Pollakowski and Ray (1997) and Meen (1999) have considered the hypothesis that house price relationships between non-contiguous regions might be stronger than between non-contiguous regions, but the evidence is not conclusively in favour of this. In terms of the pair-wise methodology, statistical evidence of the existence of a negative relationship involving distance between any two administrative districts and speed of adjustment towards long-run equilibrium would support this hypothesis. In summary, the following regression models are estimated:

$$z_{ij} = \alpha_1 + \alpha_2 |houug_{ij}| + \alpha_3 \ln |INC_{ij}| + \alpha_4 |DENS_{ij}| + \alpha_5 \ln DIST_{ij} + \mu_{ij} \quad (1)$$

$$|\bar{p}_{ij}| = \beta_1 + \beta_2 |houug_{ij}| + \beta_3 \ln |INC_{ij}| + \beta_4 |DENS_{ij}| + \beta_5 \ln DIST_{ij} + \varepsilon_{ij} \quad (2)$$

⁸ We choose to include per capita income rather than the unemployment rate because the latter is not computed in a consistent way at the district level.

$$hl_{ij} = \gamma_1 + \gamma_2 |houug_{ij}| + \gamma_3 \ln |INC_{ij}| + \gamma_4 |DENS_{ij}| + \gamma_5 \ln DIST_{ij} + \theta_{ij} \quad (3)$$

The results from the estimation of the probit model (equation 1) are reported in Table 2, where the dependent variable $z_{ij} = 1$ if the ADF test is rejected at 10% significance level and zero otherwise. In this model, the estimated coefficients on all independent variables, other than density, are negative and statistically significant as expected. The results support the argument that the probability of price differentials being stationary decreases with distance, and with the magnitude of differences in income, population density and growth of housing supply.

Table 2 Probit models for the determinants that price differentials are stationary

Variable:	Coeff.	(s.e.)	Prob.
Intercept	9.775	1.594	0.000
$\ln INC_{ij} $	-0.706	0.127	0.000
$\ln DIST_{ij}$	-1.115	0.209	0.000
$ DENS_{ij} $	0.000	0.000	0.015
$ houug_{ij} $	-0.148	0.060	0.012
Observations	152		
McFadden R-squared	0.285		
LR statistic	59.779	[0.000]	

Standard errors are heteroskedasticity consistent.

Table 3 reports the results regarding the estimation equation (2), where the same independent variables are tested as potential drivers of the magnitude of the stationary price differential in absolute value ($|\bar{p}_{ij}|$). Also for this second regression, as expected on the basis of our hypothesis, all explanatory variables, other than density, have a positive effect on the magnitude of the stationary price differentials. Examining to the size of the coefficients in tables 2 and 3, it is worth noticing that in both model (1) and (2) the marginal effect of a change in the distance variable is much stronger than a change in the income variable; this is consistent with the results of Holmes et. al. (2017) for Paris. We also notice that the density variable has no effect in both model 1 and 2.

Table 3 Determinants of the magnitude of stationary price differentials

Variable:	Coeff.	(s.e.)	Prob.
Intercept	-0.378	0.085	0.000
$\ln INC_{ij} $	0.020	0.008	0.013
$\ln DIST_{ij}$	0.113	0.012	0.000
$ DENS_{ij} $	0.000	0.000	0.000
$ houug_{ij} $	0.009	0.004	0.023
Observations	152		
R-squared	0.570		
F-stat	48.689	[0.000]	

Table 4 summarises our findings regarding model (3), where we regress the speed of adjustment of stationary relative price series (hl_{ij}) against all explanatory variables. We find that the estimated coefficients of the independent variables measuring distance, i.e. $\ln DIST_{ij}$, and differences in housing supply, i.e. $|houug_{ij}|$, are significant and have positive signs as expected by our hypothesis. Meanwhile, the other two variables measuring differences in income, i.e. $\ln|INC_{ij}|$, and in density, i.e. $|DENS_{ij}|$, are not statistically different from zero. Those results show that the more different are districts in the context of housing supply, and the further away they are in terms of distance, the slower is the speed of adjustment towards long-run equilibrium. Also in this case, the size of the coefficients show that the marginal effect of the distance variable is much larger than the one of the supply variable.

Table 4 Determinants of the half-life of stationary price differentials

Variable	Coeff.	(s.e.)	Prob.
Intercept	-0.134	0.741	0.857
$\ln INC_{ij} $	0.050	0.069	0.470
$\ln DIST_{ij}$	0.261	0.106	0.015
$ DENS_{ij} $	0.000	0.000	0.875
$ houug_{ij} $	0.060	0.035	0.087
Observations	152		
R-squared	0.058		
F-stat	2.279	[0.064]	

3. Conclusions

In this paper we have investigated the house price convergence across the 18 administrative districts of Beijing, using monthly data from 2006 to 2014. We adopted the pair-wise approach developed by Pesaran (2017) that allowed us to conduct a probabilistic test of convergence which is based on unit root testing of all pair-wise house price combinations; as shown by Holmes et al. (2017), this is an approach that provides significant advantages over panel unit root testing procedures available in the literature. We have documented ADF rejection frequencies above 50 %, such that price differentials across districts are co-integrated with a unity coefficient. Regression results show that the probability of stationarity in the differential is negatively affected by the geographical distance between districts, income differentials across districts and differentials in housing supply. After examining the determinants of the half-life of shocks to relative prices, distance and housing supply differentials emerge as significant drivers of out of equilibrium dynamics.

Focusing on the convergence between districts, our results show that there exists some stable relationship across tiers of districts, but not necessarily within each tier. Examining the central urban districts, we notice from table 1 that district 1 (Xicheng) is stationary with all peripheral districts from 14 to 18, while district 2 (Dongcheng) is stationary with

districts 7, 15, 16. The rest of the central districts (3,4,7,8) exhibit stationary differentials with peripheral districts 14-18 and to a certain extent between each other. Also districts from the middle tier (5,6,9,10) present stationary differentials with most of peripheral districts, and, with the exception of 5 and 6, between each other. Peripheral districts from the outer tier do not generally exhibit stationarity between each other. This result of convergence between central and peripheral districts may seem quite surprising. Holmes et al (2018 and 2019) find four convergence clubs for London, loosely corresponding to areas in Central, Suburban, East-London, out of London; however they find that flats are the property type that is most likely to converge. It is also interesting to notice that also for the case of Paris Holmes et al (2017) find that not many peripheral areas exhibit convergence among each other. On the basis of existing research and the fact that our dataset focuses on new-built properties, i.e. mainly flats, we attribute the documented convergence between prime very central areas and fast growing external in Beijing to speculative investment dynamics in the market for new flats. We hope that future research may specifically investigate this hypothesis.

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