MAPPING CHINA'S TIME-VARYING HOUSE PRICE LANDSCAPE

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Abstract

The recent increase in China's house prices at the national level masks tremendous variation at the city level – a feature largely overlooked in the macroprudential literature. This paper measures the evolving heterogeneity in China's house price dynamics across 70 major cities and assesses its relationship with housing market characteristics. We gauge the heterogeneity of house price dynamics using a novel regime-switching modelling approach to estimate the time-varying patterns of China's city-level housing price synchronization. The estimates indicate an increasing synchronization leading up to 2015, and a decoupling pattern thereafter, which is associated to the heterogeneous strength of regional macroprudential policies. After sorting city-level housing prices into four clusters sharing similar cyclical features, we document high synchronization within clusters, but low synchronization among them. The empirical evidence suggests that differentials in the growth of population, income, and air quality are relevant explanatory factors of housing price synchronization among cities.

Keywords: house prices, Markov-Switching models, synchronization, China.

JEL classification: E31, E32, C32, R11.

Resumen

El reciente aumento de los precios de la vivienda en China a nivel nacional oculta una gran variación a nivel de ciudades, una característica que ha pasado relativamente desapercibida en la literatura de las políticas macroprudenciales. Este artículo se enfoca en medir la heterogeneidad en la evolución de los precios de la vivienda en 70 de las principales ciudades de China y en evaluar su relación con las características del mercado inmobiliario. Las estimaciones indican una sincronización creciente en los precios de la vivienda antes de 2015, y un patrón posterior de desacoplamiento, el cual está asociado a la considerable heterogeneidad de las políticas macroprudenciales regionales. Luego de clasificar ciudades en cuatro grupos que comparten características cíclicas de precios de vivienda similares, se documenta una alta sincronía dentro de los grupos, pero una baja sincronía entre ellos. La evidencia empírica sugiere que los diferenciales en el crecimiento de la población, los ingresos y la calidad del aire son factores explicativos relevantes de la sincronización del precio de la vivienda entre ciudades.

Palabras clave: precios de la vivienda, regímenes markovianos, sincronización, China.

Códigos JEL: E31, E32, C32, R11.

1. Introduction

Chinese housing prices are increasingly an international concern. Following on the heels of an extraordinary real estate boom before the global financial crisis, Chinese housing prices were boosted even higher since 2009 by the government's massive stimulus package and its mandate to banks to increase lending. With demand already fuelled by high rates of urbanization, rising incomes and rapid economic growth, buyers naturally took advantage of looser real estate lending terms and lower mortgage rates. As the expansionary monetary policy stance remained in place, optimistic house price expectations took hold, leading to excessive risk-taking in the banking sector.

Real estate in many cities has today become unaffordable to a broad swath of the Chinese population, but it is not the sole reason house prices are a concern for Chinese policymakers.[1] Property is a sizable component of household and corporate balance sheets. Given that the Chinese housing market fluctuates from hot to cool to hot time-to-time, generating cycles in the dynamics of property prices, a sudden collapse in house prices would have negative spillover effects on the macroeconomic situation and possibly pose financial stability risks.[2] Aware of these dangers, the Chinese government has imposed macroprudential measures and restrictions in recent years to bring house prices back to "reasonable" levels.[3] In this paper, we focus on providing a comprehensive analysis of the evolving synchronization between property price cycles of the main cities in China.

The remainder of this paper is laid out as follows. In a first step, Section 2 provides an overview of the house price dynamics in the 70 major Chinese cities over the past decade. Section 3 describes the methodology used to measure the interdependence between the housing price cycles across cities in China. We explore regional differences in the Chinese housing market and whether regional markets have become more or less synchronized over time. Section 4 reports the space-time dynamics of house prices linkages. Section 5 provides a regression analysis to evaluate the relation between synchronization patterns and housing market characteristics. Section 6 concludes.

2. The development of house prices in Chinese cities

As a first step, we analyze the trends in movements of house price growth across 70 major Chinese cities. The house price trends are calculated using house price data released by China's National Bureau of Statistics, which the data started from July 2005 (the detailed definition of our house price data can be found in Appendix A).[4] Looking at Figure 1, we see property prices in China, fuelled by strong economic

[1] High housing prices have knock-on effects across the economy. People are forced out into the suburbs. Cities become less dynamic. Workers waste time on lengthy commutes, and otherwise capable people cannot afford to move to the places where work is available. China's booming housing market may ultimately be a drag on total factor productivity growth.

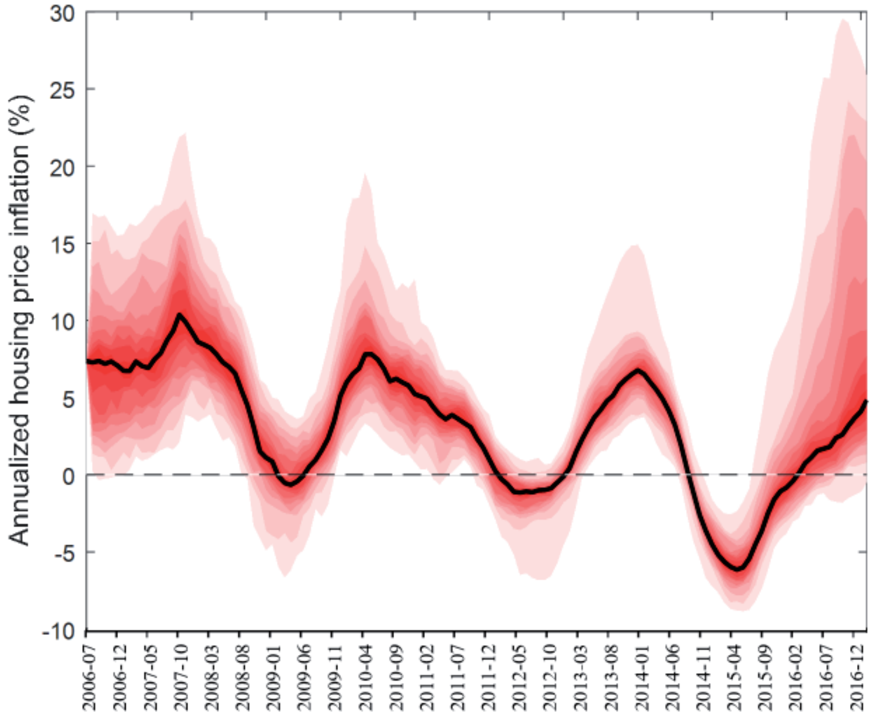
[2] For the case of other countries, such as the U.S., the cyclical pattern in housing prices has not been that notorious as for the case of China. See Del Negro and Otrok (2007) and Moench and Ng (2011).

[3] The recent work of Bai *et al*. (2014) and Du and Zhang (2015) evaluates the effects on house prices in China by home-purchase restrictions and the introduction of property taxes on a trial basis. Using counterfactual analyses, these researchers find that purchase restrictions in Beijing and the trial property tax in Chongqing and Shanghai significantly affected house prices.

[4] A discussion on the reliability of official house price data can be found in Appendix A.

growth and cheap credit, rising until the global financial crisis in 2008. With the advent of the global financial crisis, the housing market slows sharply from late 2008 to mid-2009. With the downturn, the Chinese government introduced a RMB 4 trillion stimulus package in November 2008 that mandated bank lending. Developers quickly discovered that it was easy to borrow with lower capital requirements. Buyers took advantage of looser lending conditions and lower interest rates, causing house prices to surge. Signs of overheating in the real estate sector emerged after early 2010, with housing prices rising at annual rates of 15–20 % by mid-2010 in some cities.

Figure 1. Annualized housing price inflation across 70 major cities in China



Notes: The black line plots the median annualized housing price inflation (% yoy) across the seventy major cities in China. The red area corresponds to the cross-sectional distribution over time with probability mass between the 5th and 95th percentiles. The definition of the house price used in the paper can be found in Appendix A.

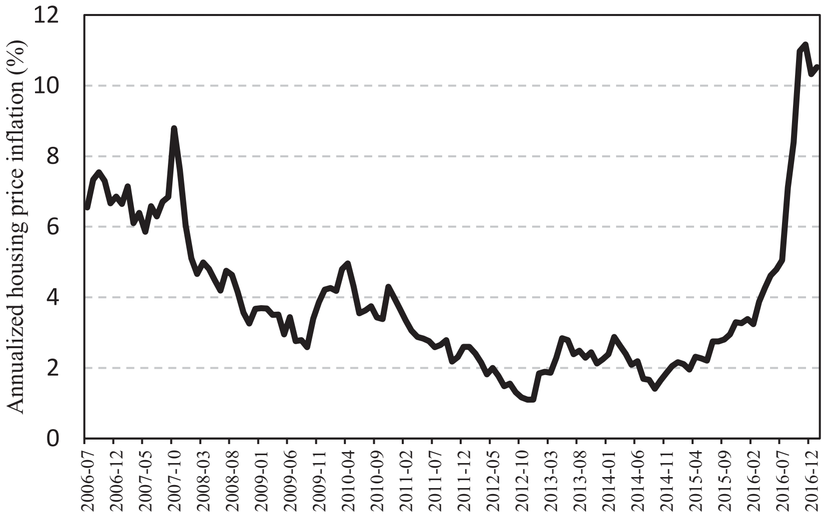
In response to this over-heating, the Chinese authorities introduced a series of macroprudential tightening measures. The different movements of house prices across markets provides a natural economic rationale for decentralized macro-prudential policies. China's authorities have emphasized differentiated adjustment in macroprudential housing policies since 2010, when the State Council called city-level macro-prudential policies.[5] These tightening measures managed to cool the housing market gradually between 2011

[5] For a thorough analysis of China's granular macroprudential policy approach, see Funke *et al.* (2018a). Macroprudential policy decisions are taken at the decentralised city level and prove to be increasingly differentiated over time. However, there are central guidelines of possible policy designs against the background of special house price dynamics. It must be added that China is by no means an isolated case. At a later time, other countries have also added city-level instruments to their macro-prudential toolkits to increase effectiveness of their macro-prudential policies. New Zealand introduced tighter macro-prudential measures for the Auckland metropolitan area. (https://www.rbnz.govt.nz/financial-stability/macro-prudential-policy). Norway introduced tighter macro-prudential policies to temper house prices in the metropolitan area of Oslo, and Denmark moved similarly for Copenhagen. (http://www.esrb.europa.eu/pub/pdf/reports/esrb.report180425_review_of_macroprudential_policy.en.pdf). The Korean experience is also instructive. Fifteen years ago, South Korea has put in place a differentiated application of LTV ratios determined according to zip code to tighten policy quickly in areas prone to overheating. As explained in detail by Igan and Kang (2011), limit-setting rules differ for "speculative" and "non-speculative" zones.

and 2012. When property prices began to rise again in early 2013, the State Council required the cities with city-specific macroprudential policies to strengthen their tightening measures.

During 2014, house prices in most of the major cities, even in the Tier 1 cities, exhibited a significant decline. In particular, property prices in Beijing and Shanghai dropped by 3.4 % and 2.9 %, respectively, while property prices in some cities experienced declines in the high single digits. Most of the cities started to relax their home-buying restrictions in mid-2014. Only Tier 1 cities kept the macroprudential restrictions in place. With a time lag, the macroprudential policy relaxation also started at the national-level. In September 2014, the central bank loosened mortgage restrictions, giving homeowners with paid-off mortgages the same terms for second properties as first-time buyers. In October, the central bank cuts its benchmark one-year lending rate by 25 basis points to 4.35 %. In early 2015, the government reduced the minimum down payment for second-home buyers three times. In March 2015, property sellers were exempted from paying the transaction tax if they have owned the sold property for at least two years.[6]

Figure 2. Dispersion of the distribution of housing price inflation over time



Note: The chart plots the interquantile range of the distribution of housing price inflation (% yoy) over time.

The new boom set warning lights flashing and local governments began to introduce tightening measures in the summer of 2016. The tightening policies were introduced again in some of the cities during 2016-2017, when housing prices surged again. Policy actions to revive the housing market in 2016 yielded distinctly different results. Figure 2 plots the dispersion of the distribution of property price inflation over time, showing a significant increase in the heterogeneity of property prices dynamics across cities since 2016. With the large heterogeneity exhibited in housing prices, policymakers refrained from applying a blanket nationwide property "speed limit", most likely for fear of a policy overshoot triggering a sudden property sentiment reversal or a sharp deceleration in housing sales. Property policy tightening remained differentiated, targeting cities where the price dynamics were most pronounced.

[6] Capital controls, progressively tightened by the Chinese authorities in recent years, have also played a role in housing price dynamics. Following the stock market collapse in 2015, housing became the most appealing asset to own – especially as the Chinese authorities were encouraging banks to increase mortgage lending to boost the economy.

China's geographically differentiated house price dynamics imply that leaning-against-the-wind policies need to be granular across regions. In shaping the optimal contour of macroprudential policy, policymakers must address regional housing market divergence, possibly with regionally-differentiated macroprudential policies. As housing stability risks change over time, macroprudential policy also needs to be sufficiently flexible to address shifting vulnerabilities. Granular and timely information contributes to the flexibility of macroprudential tools. Adjusting the macroprudential tools in such a way makes it more effective in cooling hot spots, while leaving cold spots unchanged. Funke *et al*. (2018b) show, from a theoretical standpoint, that stabilising house prices by means of targeting the region-specific LTV ratio proves to be the most effective tool, especially if the shocks originate on the demand side of the economy. Naturally, such fine-tuning requires a mechanism to identify and monitor systemic risk in real time.[7]

Echoing this sentiment, we hold a magnifying glass to the house price dynamics of 70 Chinese cities to disentangle the evolving associations hidden in figures 1 and 2. To the best of our knowledge, this is the first study to provide a framework to endogenously identify time-varying synchronization in China's housing prices and related housing market characteristics.[8] Our results indicate that housing prices cycles across cities in China experienced an increasing synchronization for many years up to 2015, when they began to exhibit a decoupling pattern. Also, we show that cities can be sorted into a few clusters sharing similar cyclical housing market dynamics.

3. Measuring housing price synchronization

In the section, we discuss how changes in the synchronization between the housing price cycles across the main cities of China might be measured. We refer to a housing price cycle as the alternation of housing prices between periods of sustained high and low growth, and thereby avoid relying on simple Pearson correlation measures between data on housing prices. Pearson measures do not account for cyclical persistence and are sensitive to outliers common in Chinese data, thereby yielding imprecise estimates of the synchronization of housing price cycles. Here, we are interested in simultaneously assessing the phases of the housing price cycles for a given city and the degree of time-varying interdependence between the housing price cycles of different cities.

There are two strands of methodologies used to analyse similarities between key features of a set of economies, defined at different levels of disaggregation.[9] The first is based on the notion of convergence. It focuses on identifying similarities and explanatory factors of long-run behaviours of specific economic features such as inflation and GDP growth. For example, Phillips and Sul (2007) rely on a panel data model

[7] A caveat here is that policymakers must use considerable discretion in implementing region-specific policies. A further concern is that a geographically differentiated policy may draw the central bank into unwanted political controversies if the instrument affects a sensitive sector such as housing. Thus, policy requires a high degree of macroprudential transparency. The supervisory authorities must communicate their plans and policy objectives to the public in a timely and clear fashion.

[8] While Mao (2016) tests for convergence in housing prices in Chinese cities, his information ends in 2011. Thus, he misses the subsequent and significant de-synchronization of housing prices that begins in 2014 (as we document in our aggregate synchronization index). Furthermore, his analysis does not assess the economic factors associated with such patterns.

[9] While the literature is fairly extensive, here we only comment briefly on a few recent econometric frameworks with special relevance.

with factor structure to provide assessments about convergence and clustering patterns between the price levels of different US metropolitan areas. Also, Phillips and Sul (2009) apply a similar econometric framework to analyse convergence and clustering patterns in economic growth of OECD countries.

The second strand, which is more related with the scope of this paper, focuses on the synchronization of short-term fluctuations of macroeconomic variables. In their recent work, Hernández-Murillo *et al.* (2017) rely on a multivariate Markov-switching model to analyse both grouping patterns and explanatory factors of housing cycles at the US city level. They find that similarities affecting the demand for housing are more important than similarities affecting the supply for housing. The main advantage of the framework set forth in Hernández-Murillo *et al.* (2017) is that cyclical commonalities between the cities are inferred from a unified panel with large cross sectional and time series dimension. However, such a framework does not allow to investigate the endogenous time-varying bilateral relationship between housing cycles at the city level. In this paper, we adopt a bilateral approach that requires testing all the pairwise synchronization measures and, as such, does not involve the choice of a single reference city in the computation of house price differentials, which can be a problematic. Moreover, the entire set of pairwise synchronization measures allows us to compute aggregate measures of time-varying synchronization both at the national and subnational level. This is useful from a policy maker standpoint since the framework provides information not only about changes in the overall degree of housing prices synchronization but also about the regions acting as main sources of those changes over time. For other pairwise studies of house prices, see Holmes *et al.* (2011) and Abbott and De Vita (2012). The pairwise study of Pesaran (2007), which has a different context, also provides valuable background.

We rely on the econometric framework proposed in Leiva-Leon (2017). This allows us to estimate the bilateral time-varying synchronization between housing price cycles in China by incorporating Markov-switching dynamics. We view this Markov-switching modelling choice as a convenient device for capturing the time-varying aspect of house price cycles. This modelling approach also provides a convenient shortcut for dealing with house price dynamics without taking an initial view on the reason housing markets drift apart. A limitation of the Leiva-Leon (2017) framework is the need to estimate a model for each pair of cities, rather than estimating a single unified model as in the case of Hernández-Murillo *et al.* (2017). Although, the complete set of pairwise models provides us with a rich data environment to perform a comprehensive analysis about clustering patterns and assess its relation with housing market characteristics in China.[10]

Let $y_{i,t}$ be the annualized growth rate of the price index of residential buildings corresponding to the i-th city of China. We are interested in measuring the time-varying synchronization of housing price cycles across the major $N = 70$ cities, with the sample period from July 2006 to January 2017. Therefore, consider the following bivariate regime switching model:

[10] Markov-switching models perform better than alternative linear frameworks, such as rolling correlations, as they are based on a persistent process, a Markov chain, that is able to capture the inertia imbedded in the underlying changes in the synchronization of cycles. This econometric framework was previously used to analyse changes in synchronization of output across different levels of disaggregation. Examples include the country-level study of Ductor and Leiva-Leon (2016) and the sectoral-level of the US economy of Camacho and Leiva-Leon (2017).

$$\begin{bmatrix} y_{i,t} \\ y_{j,t} \end{bmatrix} = \begin{bmatrix} \mu_{i,0} + \mu_{i,1} s_{i,t} \\ \mu_{j,0} + \mu_{j,1} s_{j,t} \end{bmatrix} + \begin{bmatrix} \varepsilon_{i,t} \\ \varepsilon_{j,t} \end{bmatrix}, \tag{1}$$

where each latent variable, $s_{i,t}$, can take two values. If $s_{i,t} = 0$, it implies that the housing prices of i-th city are in a low growth regime at time t, given by $\mu_{i,0}$. In contrast, if $s_{i,t} = 1$, it indicates that the housing prices associated to the i-th city are experiencing a high growth regime at time t, given by $\mu_{i,0} + \mu_{i,1}$. The vector of disturbances, $\epsilon_{ij,t} = [\epsilon_{i,t}, \epsilon_{j,t}]$, is assumed to be normally distributed, $\epsilon_{ij,t} \sim N(0, \Omega_{z_{ij,t}})$, with the variance-covariance matrix defined as

$$\Omega_{z_{ij,t}} = \Omega_0 \left(1 - z_{ij,t}\right) + \Omega_1 z_{ij,t} \ , \tag{2}$$

where $z_{ij,t}$ also take two values, that is, $z_{ij,t} = \{0,1\}$. Therefore, Ω_0 and Ω_1 denote the variance-covariance matrices corresponding to regimes 0 and 1, respectively. Note that the latent variable $z_{ij,t}$ accounts for regime changes in volatility, while the latent variables, $s_{i,t}$ and $s_{j,t}$ account for the phases of housing price cycles corresponding to cities i and j, respectively.

All three latent variables follow first-order Markov chains with constant transition probabilities, $p_{i,}$, p_j , and p_{z}. The main goal is to assess the time-varying interdependence between the state variables measuring the housing price cycles $s_{i,t}$ and $s_{j,t}$. Therefore, we define

$$P\left(s_{i,t} = s_{j,t}\right) \ = P\left(v_{ij,t} = 1\right) = \delta_{ij,t} \tag{3}$$

where $v_{ij,t}$ denotes a latent variable that takes the value of one if $s_{i,t}$ and $s_{j,t}$ are fully dependent, or the value of zero if they are totally independent, at time t. Accordingly, the term $\delta_{ij,t}$ provides inference about the interdependence between $s_{i,t}$ and $s_{j,t}$ at time t. The latent variable $v_{ij,t}$ is assumed to also be driven by a first-order Markov chain with transition probabilities given by

$$P\left(v_{ij,t} | v_{ij,t-1}, v_{ij,t-2}, \ldots\right) = P\left(v_{ij,t} | v_{ij,t-1}\right) = p_{ij,\delta}\,. \tag{4}$$

The estimation of the bivariate regime-switching model is performed with Bayesian methods and the inferences of the latent variables are extracted by using a modified version of the Hamilton (1989) filter. Let θ a vector that collect all the parameters involved in the model, the steps of the Gibbs sampler can be briefly described as:

Step 1: Generate $s_{i,t}, s_{j,t}, v_{ij,t}, z_{ij,t}$, conditional on θ and y_t .

Step 2: Generate $p_{i,}, p_j$, and p_z , and $p_{ij,\delta}$, conditional on $s_{i,t}, s_{j,t}, v_{ij,t}, z_{ij,t}$ and y_t.

Step 3: Generate $\mu_{i,0}, \mu_{i,1}, \mu_{j,0}, \mu_{j,1}$, conditional on $s_{i,t}, s_{j,t}, v_{ij,t}, z_{ij,t,} \Omega_0, \Omega_1$, and y_t .

Step 4: Generate Ω_0, Ω_1, conditional on $s_{i,t}, s_{j,t}, v_{ij,t}, z_{ij,t,} \mu_{i,0}, \mu_{i,1}, \mu_{j,0}, \mu_{j,1}$ and y_t.

The steps above are sequentially iterated 6,000 time, and we discard the first 1,000. This information allows us to simulate the posterior density of both parameters and latent variables involved in the model. We do not report details about the estimation procedure, first, to save space and second, because they rely on widely used sampling techniques. However, the details about the estimation and filtering procedures are described in the Appendix of Leiva-Leon (2017).[11]

The bivariate regime-switching model is estimated for all the possible pairs of the $N = 70$ major cities in China to study in detail the associated cross-sectional heterogeneity. Next, the pairwise time-varying synchronization measures, for $\forall\, i, j = \{1, \ldots, N\}$, are collected in the adjacency matrix

$$\Delta_t = \begin{bmatrix} 1 & \delta_{12,t} & \delta_{13,t} & \cdots & \delta_{1N,t} \\ \delta_{21,t} & 1 & \delta_{23,t} & \cdots & \delta_{2N,t} \\ \delta_{31,t} & \delta_{32,t} & 1 & \cdots & \delta_{3N,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta_{N1,t} & \delta_{N2,t} & \delta_{N3,t} & \cdots & 1 \end{bmatrix}. \tag{5}$$

The information contained in the matrices Δ_t, for $t = 1,2, \ldots, T$ (the sample ranges from July 2006 to January 2017 in this study), represent the key piece of information to perform a detailed mapping of the housing price interdependence across time and space at the city level. Notice that the adjacency matrix Δ_t is symmetric since it contains information on contemporaneous synchronization. An additional advantage of the econometric framework in Leiva-Leon (2017) is that the time-varying synchronization patterns, $\delta_{ij,t}$, can be collapsed through the time dimension to obtain time-invariant, or steady-state, measures of synchronization. This can be done by computing the ergodic probabilities of synchronization, defined by

$$\bar{\delta}_{ij} = \frac{1 - p_{ij,\delta,11}}{2 - p_{ij,\delta,00} - p_{ij,\delta,11}}, \tag{6}$$

where $p_{i,j,\delta,00}$ and $p_{ij,\delta,11}$ are the probabilities of remaining in state 0 and in state 1, respectively.

Similar to the time-varying case, all the steady state synchronization measures are collected in the adjacency matrix

$$\bar{\Delta} = \begin{bmatrix} 1 & \bar{\delta}_{12} & \bar{\delta}_{13} & \cdots & \bar{\delta}_{1N} \\ \bar{\delta}_{21} & 1 & \bar{\delta}_{23} & \cdots & \bar{\delta}_{2N} \\ \bar{\delta}_{31} & \bar{\delta}_{32} & 1 & \cdots & \bar{\delta}_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{\delta}_{N1} & \bar{\delta}_{N2} & \bar{\delta}_{N3} & \cdots & 1 \end{bmatrix}. \tag{7}$$

This matrix $\bar{\Delta}$ should provide insights about the stationary associations or clustering patterns of housing prices across cities in China.

4. Mapping housing price interdependencies

This section provides a comprehensive analysis of the associations between the housing price cycles across cities in China. The aim of the section is threefold. First, we focus on determining the groups of Chinese cities that experience similar housing price dynamics. Second, we identify changes over time in the

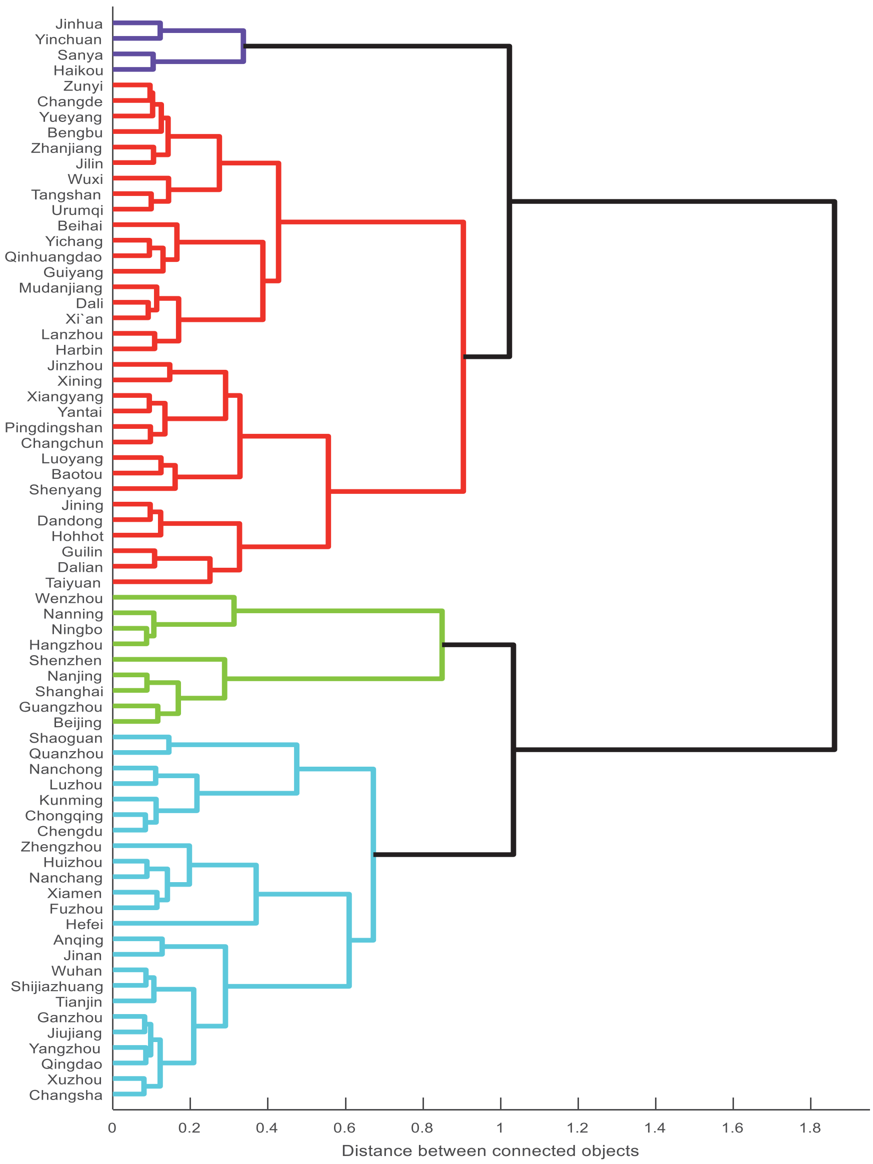
[11] The corresponding appendix can be found in the following link: https://onlinelibrary.wiley.com/action/downloadSupplement?doi=10.1111%2Fobes.12157&file=obes12157-sup-0001-AppendixS1-S2.pdf

relationship between the groups of cities that share commonalities in housing prices. Third, we assess which cities have played a major role in driving changes of the overall degree of housing prices commonality.

4.1 Cross-sectional dimension

We start with the grouping patterns of housing price cycles across China's cities from a steady-state perspective using the time-invariant synchronization measures collected in the adjacency matrix $\bar{\Delta}$. For this purpose, we create a classification scheme of cities that share similar housing price cycles. This classification is defined with the information collected in the adjacency matrix $\bar{\Delta}$. It is based on a dendrogram, i.e. a tree-structured graph that lets us visualize the results of hierarchical clustering. Figure 3

Figure 3. Housing price clustering patterns across major Chinese cities

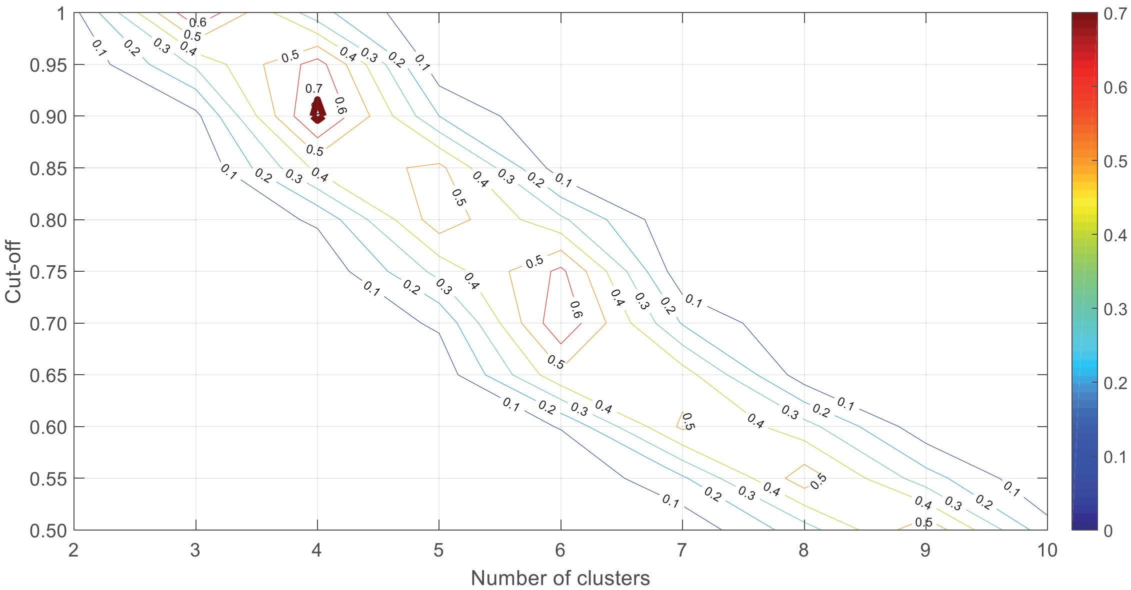


Note: The figure plots the dendrogram based on the stationary (or time-invariant) synchronization between housing prices across 70 major cities in China, collected in $\bar{\Delta}$.

shows the clear separation of Chinese cities into clusters, where the height of each U-shaped lines represents the distance between the two objects being connected.

Note that the definition of the groups depends of the cut-off in the height of the tree. Therefore, in order to robustly assess the number of clusters that best characterizes the cyclical similarities across China's housing price cycles, we provide inference the relationship between the cut-off and the number of clusters in random sampling framework. In particular, for a given cut-off value c, we generate 1,000 random samples. Each sample contains all the pairwise relationships between $M = 70 - m$ cities, where m denotes the number of cities that are dropped, and are uniformly randomly selected across samples.[12] Next, for each sample we count the number of clusters that are identified based on the given cut-off c. Based on the information from all the 1,000 random samples, we compute the probability of the number of clusters, that is, $\Pr(\#clusters = i)$, for $i = 2, \dots, 10$. The same procedure is then performed for different values of the cut-off. Specifically, we use a grid for the cut-off with an interval given by $[0.5 < c < 1]$. The results of this exercise provide a probabilistic assessment on the relationship between the cut-off and the number of clusters.

Figure 4. Inference on the number of clusters of Chinese cities



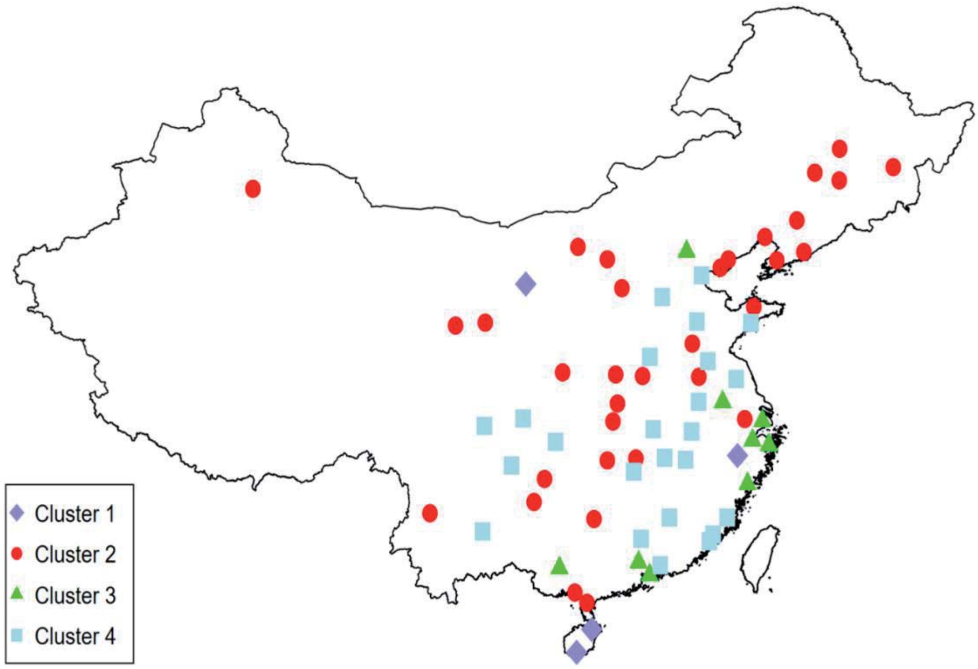
Note: The figure plots the contours of the distributions associated to the relationship between the number of clusters and the cut-off in a dendrogram. The right vertical coloured bar indicates the range of probability values that are attained to each combination of cut-off and number of clusters.

Figure 4 plots the contours of the distributions associated to the relationship between the number of clusters and the cut-off in the dendrogram, which is clearly negative. The figure indicates that the largest probability attained (0.73) is associated with a number of clusters equal to 4 and a cut-off around 0.9. Therefore, based on the probabilistic information gathered from this exercise, we claim that housing price

[12] Since the size of some clusters might be relatively small, we set $m = 5$, to avoid deleting the information of an entire cluster. Although similar results were obtained for different values of m.

cycles dynamics across China's cities can be well characterized with four groups of cities that exhibit similar dynamics. These groups are represented by four colours in the dendrogram of Figure 3, giving policymakers easy access to information useful in designing macro-prudential policies tailored to region-specific conditions.[13] The IMF (2017) has made visualization part of its recommended strategy for a first line of defence to potential housing bubbles in China.

Figure 5. Geographical map of the dendrogram clustering



The geographical map in Figure 5 offers a further interpretation of the cluster membership. Do the clusters correspond to meaningful categories of cities? The clusters are classified according to the property price changes in the cities. Comparing the housing price growth since the global financial crisis, the cities in Cluster 1 (purple cluster) had high housing price growth in 2009 – 2010 but moderate housing price growth in 2015 – 2016. Cluster 2 (red cluster) contains those cities with comparatively moderate housing price increases throughout, while Cluster 3 (green cluster) includes those cities with throughout high price increases. In the remaining cluster 4 (blue cluster) the housing price increases were initially minor, but then increased significantly in recent years.

Chinese cities are also typically classified into different Tiers according to the cities' development. How does the classification of the clusters relate to the Tiers? In this study, we compare the clusters with a three-Tier classification (the details of classification of Tiers are summarized in Appendix B). Our classification of the clusters exhibit some relationship with the classification of the Tiers of cities. Cluster 3 includes all Tier 1 cities and those Tier 2 cities with faster housing price growth. The cities in Cluster 4 are mainly the Tier 2 cities or the Tier 3 cities in Eastern China, which have faster economic growth in recent

[13] Empirical evidence for spatial house price heterogeneity is also found by Dieleman *et al*. (2000). They detect three clusters in their analysis of 27 metropolitan housing markets in the US. Cotter *et al*. (2015) and Kallberg *et al*. (2013) document that the correlation among 14 US metropolitan areas increased significantly between 1992 and 2008. They attribute the increase to ongoing integration of those markets.

years. Most of the cities in Cluster 2 are Tier 3 cities and the Tier 2 cities in the regions with lower economic growth in the recent decade (including Northeast China, Central China, and Western China China). Cluster 1 could be treated as an exceptional case, which contains two Tier 2 cities and two Tier 3 cities. Compared with the surrounding cities, these cities have experienced slower economic development. For this reason, the initial price increases in 2009-2010 did not continue in the later period 2015-2016. Table 1 summarizes how the clusters relate to the Tiers.

Table 1. Summary statistics for different clusters of cities

	Average cumulative housing price growth Jan 2009 to Jun 2010	Average cumulative housing price growth Jul 2015 to Dec 16	No. of Tier 1 Cities	No. of Tier 2 Cities	No. of Tier 3 Cities
Cluster 1	32.8%	4.2%	0	2	2
Cluster 2	8.1%	2.3%	0	11	22
Cluster 3	13.5%	29.4%	4	5	0
Cluster 4	7.0%	16.1%	0	17	7

Notes: The cumulative growth in housing price is the growth from Jan 2009 to Jun 2010, measuring the housing price growth until the tightening in 2010. The figures are comparing the price in Jun 2010 with that in Dec 2008 (the lowest price during 2008-2009). The cumulative growth in housing price is the growth from Jul 2015 to Dec 2016 (the housing price growth until the tightening in 2016-2017), comparing the price in Dec 2016 against that of Jun 2015 (the lowest price during 2015–2016).

In Figure 2, we show that the dissimilarity between housing prices across cities has experienced significant changes over time. In particular, it continuously decreased from the late 2000s to 2015, and rose dramatically in 2016 and 2017. However, these figures provide no information about the granularity of these movements, i.e. about which cities or groups of cities mainly contributed to such changes. Such information would be valuable to policymakers when defining reassessments about region-specific macroprudential measures. Once we have grouped cities, we therefore analyse potential changes over time in the relationship between such groups. For this purpose, we rely on dynamic multidimensional scaling analysis (DMS) and employ the framework proposed by Xu *et al*. (2012). Such a framework provides a mapping of the association between cities by controlling for the importance of steady-state grouping patterns and the importance of the temporal dimension. It also provides a mental map of such associations over time. In particular, the goal consists on minimizing the following stress function

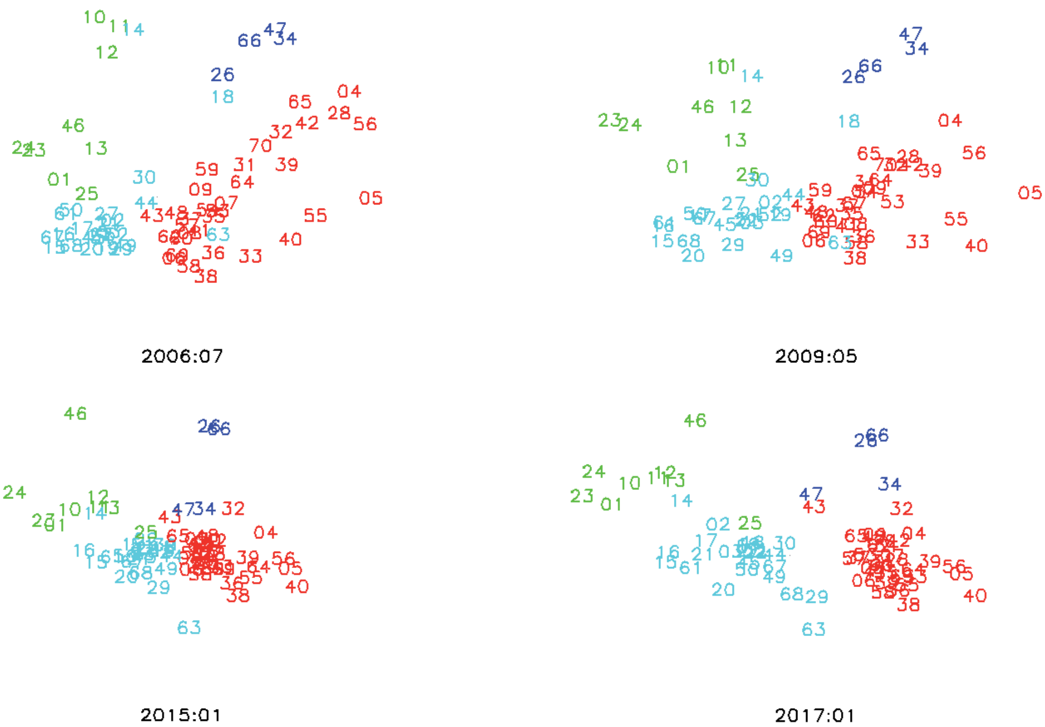
$$Stress(D,G) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\delta_{ij,t}-\|d_{it}-d_{j,t}\|\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_{ij,t}{}^2} + \alpha\sum_{i=1}^{n}\sum_{l=1}^{k}c_{il}\left\|d_{it}-g_{l,t}\right\|^2 + \beta\sum_{i=1}^{n}\left\|d_{it}-d_{i,t-1}\right\|^2, \quad (8)$$

where the first term of the stress function is the $d_{i,t}$ and $d_{j,t}$ are the k-dimensional projections of the objects i and j, α and β are the grouping and temporal regularization parameters, respectively, and $g_{l,t}$ denotes the position of the l-th representative group. For more details, see Xu *et al*. (2012).[14]

Figure 6 plots the maps of housing price associations for our 70 Chinese cities and the four selected time periods. In the figures, the cities are plotted on the Euclidean plan, and therefore, the Euclidean

[14] To assign a relatively higher importance to the temporal dimension, our penalty parameters are set to $\alpha = 0.01$ and $\beta = 1$.

Figure 6. Dynamic synchronization mapping between housing prices of Chinese cities



Beijing	01	Nanjing	11	Wuhan	21	Xi'an	31	Jilin	41	Jiujiang	51	Huizhou	61
Tianjin	02	Hangzhou	12	Changsha	22	Lanzhou	32	Mudanjiang	42	Ganzhou	52	Zhanjiang	62
Shijiazhuang	03	Ningbo	13	Guangzhou	23	Xining	33	Wuxi	43	Yantai	53	Shaoguan	63
Taiyuan	04	Hefei	14	Shenzhen	24	Yinchuan	34	Yangzhou	44	Jining	54	Guilin	64
Hohhot	05	Fuzhou	15	Nanning	25	Urumqi	35	Xuzhou	45	Luoyang	55	Beihai	65
Shenyang	06	Xiamen	16	Haikou	26	Tangshan	36	Wenzhou	46	Pingdingshan	56	Sanya	66
Dalian	07	Nanchang	17	Chengdu	27	Qinhuangdao	37	Jinhua	47	Yichang	57	Luzhou	67
Changchun	08	Jinan	18	Guiyang	28	Baotou	38	Bengbu	48	Xiangyang	58	Nanchong	68
Harbin	09	Qingdao	19	Kunming	29	Dandong	39	Anqing	49	Yueyang	59	Zunyi	69
Shanghai	10	Zhengzhou	20	Chongqing	30	Jinzhou	40	Quanzhou	50	Changde	60	Dali	70

Notes: Each chart in the figure plots the multi-dimensional scaling map based on housing prices synchronization for the corresponding time period. Numbers are used to represent the 70 major Chinese cities. A full animated version of the synchronization mapping is available at https://sites.google.com/site/daniloleivaleon/china.

distance approximates the synchronization measures contained in the adjacency matrix from Equation (8). These periods include two episodes of high property price inflation, one at the beginning and one at the end of the sample (July 2006 and January 2017, respectively), and two episodes of low property price inflation occur in May 2009 and January 2015. The maps for the remaining periods in the sample are available online.[15] The results indicate an increasing synchronization pattern of housing price cycles within and across groups of cities occurred from 2006 to 2015. Since 2016, the groups significantly decoupled. This result is consistent with the large dispersion in the distribution of housing prices across cities shown charts of Figure 1. Despite the decoupling pattern, note that cities within each group remain highly synchronized with each other. This evidence provides an insight into the design of city-level macroprudential policies to curb overly high house price increases.

The heterogeneity in housing prices across China prompted the Chinese government to change its macroprudential policy. On April 17, 2010, the Chinese State Council, China's cabinet, issued new rules

[15] In the media file at https://sites.google.com/site/daniloleivaleon/china, the sequence of synchronization maps is shown for every time period up to the end of our sample.

designed to cool house prices under the auspices of No. 10 National Notice Under these new rules, housing related macroprudential policies were formally localized. In other words, the macroprudential policy was delegated to the cities.

This raises a relevant question; how the identified cluster pattern relates to indicators of the strength and intensity of macroprudential policy at the city level? Table 2 reports the average strength of different macroprudential policy measures across cities for the last two housing price rising periods, that is, for the periods April 2010 – May 2014 and September 2016 – December 2017. These policy measures comprise (i) transaction restrictions, (ii) loan restrictions, and (iii) taxes and fees, respectively. The transaction

Table 2. Strength of City-level Macro-prudential Policy Measures

City	Apr 2010 – May 2014	Sep 2016 – Dec 2017
Cluster 1		
Haikou	0.42	0.14
Jinhua	0.39	0.03
Sanya	0.42	0.45
Yinchuan	0.42	0.03
Cluster 2		
Baotou	0.30	0.03
Beihai	0.30	0.05
Bengbu	0.30	0.03
Changchun	0.42	0.03
Changde	0.30	0.03
Dali	0.30	0.03
Dalian	0.42	0.03
Dandong	0.30	0.03
Guilin	0.30	0.03
Guiyang	0.42	0.04
Harbin	0.42	0.03
Hohhot	0.41	0.03
Jilin	0.30	0.03
Jining	0.30	0.03
Jinzhou	0.30	0.03
Lanzhou	0.41	0.22
Luoyang	0.30	0.03
Mudanjiang	0.30	0.03
Pingdingshan	0.30	0.03
Qinhuangdao	0.30	0.16
Shenyang	0.42	0.05
Taiyuan	0.42	0.03
Tangshan	0.30	0.19
Urumqi	0.42	0.03
Wuxi	0.40	0.21
Xian	0.42	0.25
Xiangyang	0.30	0.03
Xining	0.42	0.03
Yantai	0.30	0.03
Yichang	0.30	0.03
Yueyang	0.30	0.03
Zhanjiang	0.30	0.03
Zunyi	0.30	0.03

City	Apr 2010 – May 2014	Sep 2016 – Dec 2017
Cluster 3		
Beijing	0.60	0.75
Guangzhou	0.44	0.67
Hangzhou	0.43	0.48
Nanjing	0.43	0.58
Nanning	0.41	0.06
Ningbo	0.43	0.19
Shanghai	0.45	0.62
Shenzhen	0.44	0.74
Wenzhou	0.42	0.03
Cluster 4		
Anqing	0.30	0.03
Changsha	0.42	0.23
Chengdu	0.42	0.50
Chongqing	0.33	0.10
Fuzhou	0.42	0.35
Ganzhou	0.30	0.21
Hefei	0.42	0.34
Huizhou	0.30	0.04
Jinan	0.42	0.30
Jiujiang	0.30	0.08
Kunming	0.40	0.03
Luzhou	0.30	0.07
Nanchang	0.42	0.43
Nanchong	0.30	0.07
Qingdao	0.43	0.15
Quanzhou	0.30	0.03
Shaoguan	0.30	0.03
Shijiazhuang	0.42	0.25
Tianjin	0.43	0.48
Wuhan	0.42	0.39
Xiamen	0.43	0.48
Xuzhou	0.41	0.05
Yangzhou	0.30	0.05
Zhengzhou	0.42	0.28

Scale
1.00
0.97
0.95
0.92
0.89
0.87
0.84
0.82
0.79
0.76
0.74
0.71
0.68
0.66
0.63
0.61
0.58
0.55
0.53
0.50
0.47
0.45
0.42
0.39
0.37
0.34
0.32
0.29
0.26
0.24
0.21
0.18
0.16
0.13
0.11
0.08
0.05
0.03
0.00

Notes: The table reports the average intensity of the macroprudential measures for two specific periods. The intensity is comprise exactly the same method as used in Funke *et al.* (2018a). The information for the tightening of the city-level macroprudential policies is collected from various issues of "Monthly China Real Estate Policy Tracking Report" (published by China Index Academy under fang.com), press release of the local governments and news agencies.

restrictions in turn comprise the four subcategories (a) purchase restriction on local household (number of residential properties), (b) purchase restriction on local individual (number of residential properties), (c) purchase restriction on non-locals (residence requirement), and (d) sales restriction (embargo period on resale). The loan restrictions have the five sub-measures (a) loan restrictions (minimum downpayment, %), (b) mortgage on primary residence for non-local buyers (no restrictions, restrictions, not allowed), (c) mortgage on second residence for non-local buyers (no restrictions, restrictions, not allowed), (d) mortgage on third residence (allow or not), and (e) housing Provident Fund (minimum downpayment, %). Finally, the third category of transaction restrictions includes exclusively taxes and fees. The weighted average of all individual measures provides an indicator for assessing the relative strength of the city-level macroprudential policy. In particular, we can (i) assess the relative strength of the macroprudential policy of a specific city over time, and (ii) compare the relative strength of the macroprudential policies among cities in a particular period. The remarkable result is a close correspondence between the clustering patterns of housing prices and the intensity of city-level macro-prudential measures.[16]

Table 2 also illustrates that the strength of macroprudential policy measures has changed over time. In particular, the strength of the macroprudential policy measures in the first subperiod from 2010-2014 was comparatively uniform across cities. In the second subperiod from 2016-2017, on the other hand, a greater degree of differentiation is noticeable.

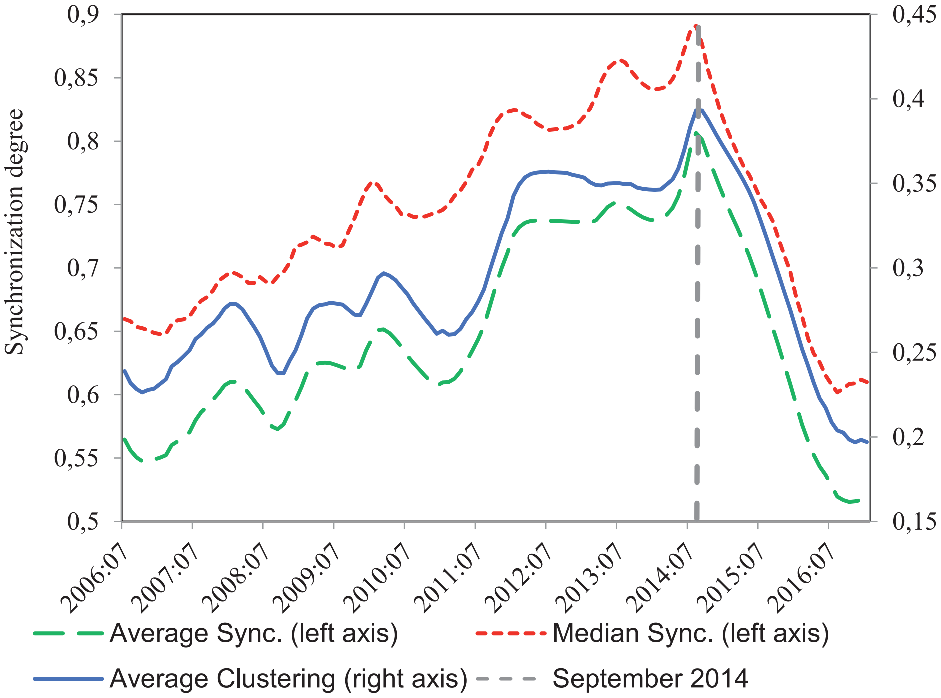
4.2 Temporal dimension

We next focus on the temporal dimension of housing prices synchronization. In doing so, we "collapse" the cross-sectional dimension by summarizing all pairwise synchronization measures collected in the out-of- diagonal entries of Δ_t into a single composite measure. This index provides useful information for policymakers and investors about the overall degree of synchronization in the Chinese housing market. Figure 7 plots three indices of aggregate housing market synchronization obtained with different procedures. The first consists of the simple cross-sectional mean. The second corresponds to the cross-sectional median. The third is computed based on the degree of clustering between the cities. All three indices suggest an increasing degree of interdependence between housing price cycles from the mid-2000s to 2014. From 2015 onwards, the overall degree of synchronization abruptly declines until the sample end in January 2017. Again, this result is consistent with the increasing dispersion of the housing price distribution around that time, observed in Figure 2.

In Section 5, we will investigate which have been the economic factors that are mainly associated to such a decrease in synchronization since late 2014. For now, we focus on assessing the contribution of each group of cities to the overall changes in synchronization of housing prices. First, we construct measures of average synchronization between housing prices of cities that belong to specific clusters, as defined in the dendrogram of Figure 3. These measures of within-cluster average synchronization are plotted in Figure 8 for the four groups of cities. We see that, in general, each group shows an increasing synchronization

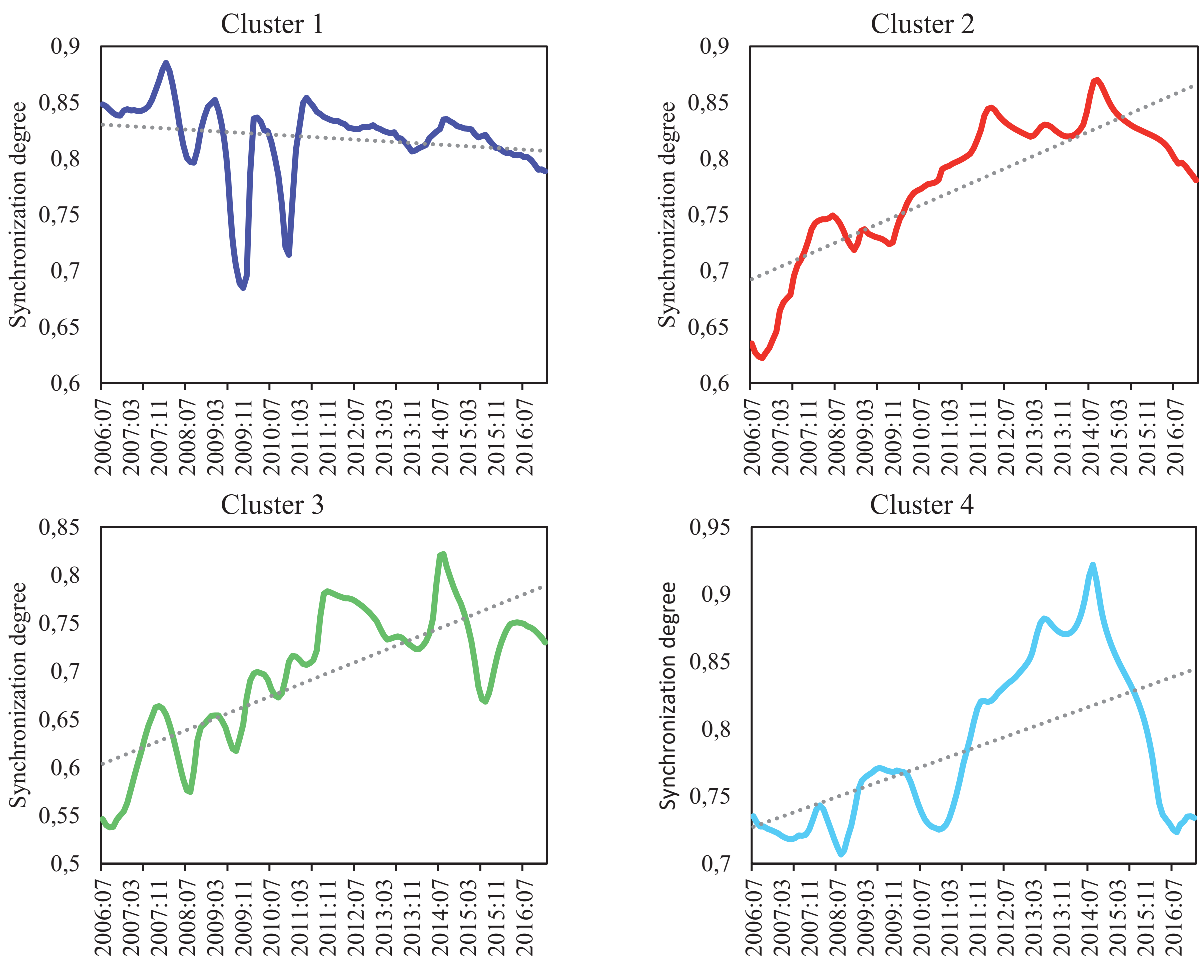
[16] For a thorough analysis of the methodology, see Funke et al. (2018a). The narrative index of macroprudential policy intensity in 70 Chinese cities from April 2010 – December 2017 is available at https://helda.helsinki.fi/bof/handle/123456789/15956.

Figure 7. Aggregate synchronization of housing prices.



Note: The figure plots indices of aggregate synchronization computed from pairwise synchronization measures.

Figure 8. Aggregate synchronization of housing prices within clusters.

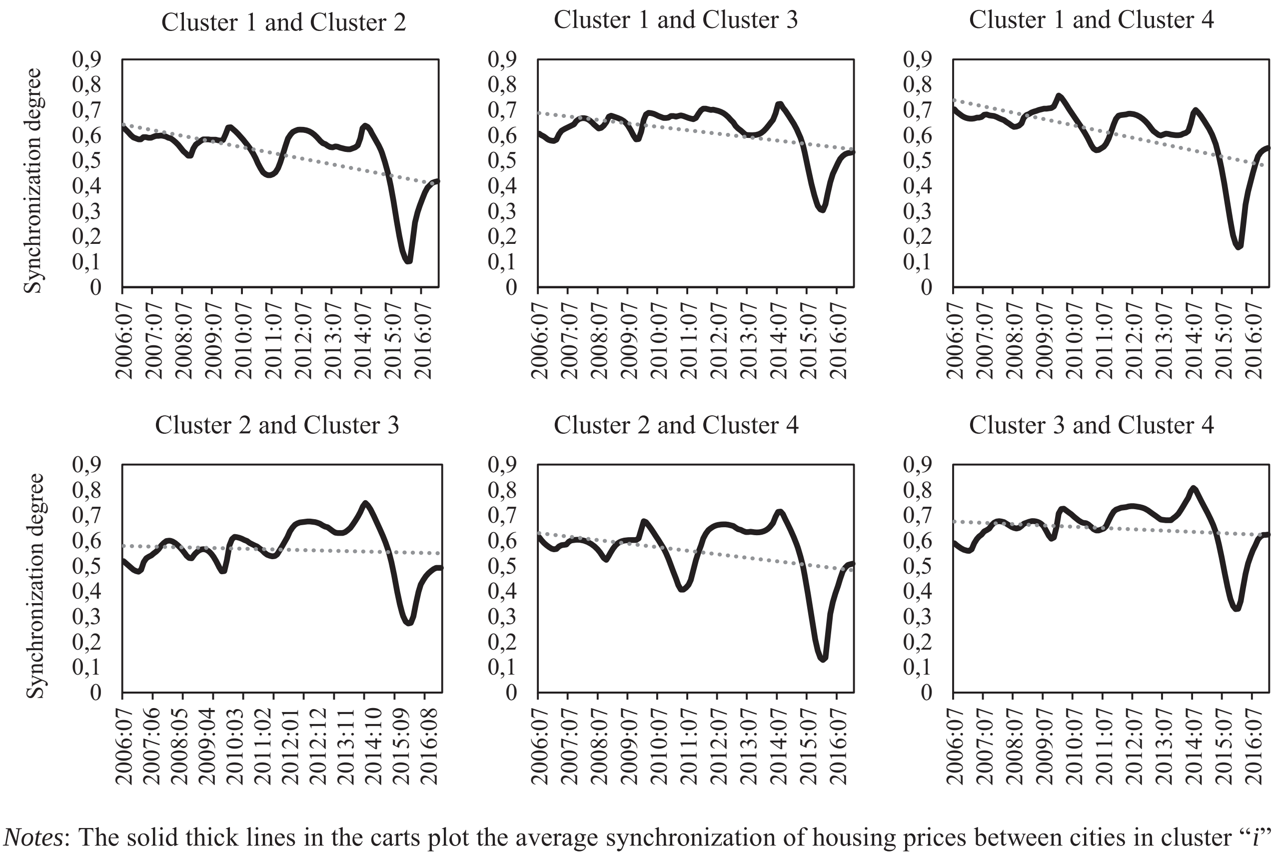


Notes: The solid thick lines in the carts plot the average synchronization of housing prices between cities within a given cluster. The dotted line plots the corresponding linear trend.

pattern in the years leading up to 2015, and a decoupling pattern thereafter. Cluster 1, which is composed by only four cities, is the exception in that its intra-synchronization has remained relatively stable over time. The figure also shows that the main source of the drop in the overall housing prices co-movement since 2015 are the cities that belong to Cluster 4, which is a sizable one in terms of number of cities included. Interestingly, cities in Cluster 4 are the ones that exhibit the largest heterogeneity regarding the strength in the degree of the implemented macroprudential measures after 2015, as it is reported in Table 2. These results illustrate the importance of macroprudential policies in inducing changes to housing prices in China, since the substantial decline in the prices synchronization, in particular, for cities in Cluster 4, can be associated to the different strengths in policies implemented across cities.

Next, we focus our attention on analysing the cross-cluster synchronization. We construct measures of average synchronization between cities that belong to different clusters. This information is show in Figure 9 for all the possible pairwise combinations of clusters. All the charts in the figure robustly indicate the same message, which points to a relatively stable, and slightly declining, synchronization pattern across clusters. Also, notice that in terms of degrees of co-movement, the level of intra-cluster synchronization of housing prices is higher than the level of cross-cluster synchronization. Summarizing these results, we have that housing prices in China have exhibited an increasing co-movement since mid-2000s, which is explained by the fact that price dynamics of cities within specific groups have become more similar. However, since 2015, there has been a sudden decline in co-movement, which is associated to the large heterogeneity in strength of macroprudential policies implemented across regions.

Figure 9. Aggregate synchronization of housing prices across clusters.



Notes: The solid thick lines in the carts plot the average synchronization of housing prices between cities in cluster "*i*" and in cluster "*j*". The dotted line plots the corresponding linear trend.

Regarding changes in the aggregate levels of synchronization with classification of cities based on tiers, in Chart A of Figure 10 we see that within-tier synchronization tends (coloured lines) to be larger than the overall synchronization, which takes into account all the cities in the sample (dashed black line). This implies that the within-tier synchronization contributes positively to the interdependence of the Chinese housing market. In particular, the highest levels of synchronization are experienced among Tier 1 cities. In contrast, Chart B of Figure 10 shows that across-tier synchronization (coloured lines), in general, contributes much less to the housing market overall interdependence (black dashed line), especially after 2015. Note that the largest disconnection occurs between Tier 2 and Tier 3 cities. A possible explanation

Figure 10. Aggregate synchronization of housing prices within and across tiers of cities.

Chart A. Synchronization Within Tiers

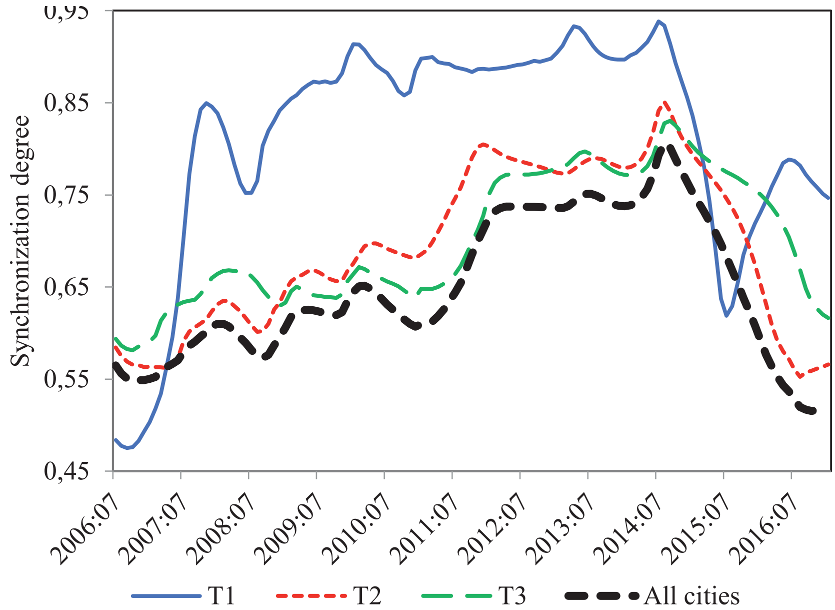
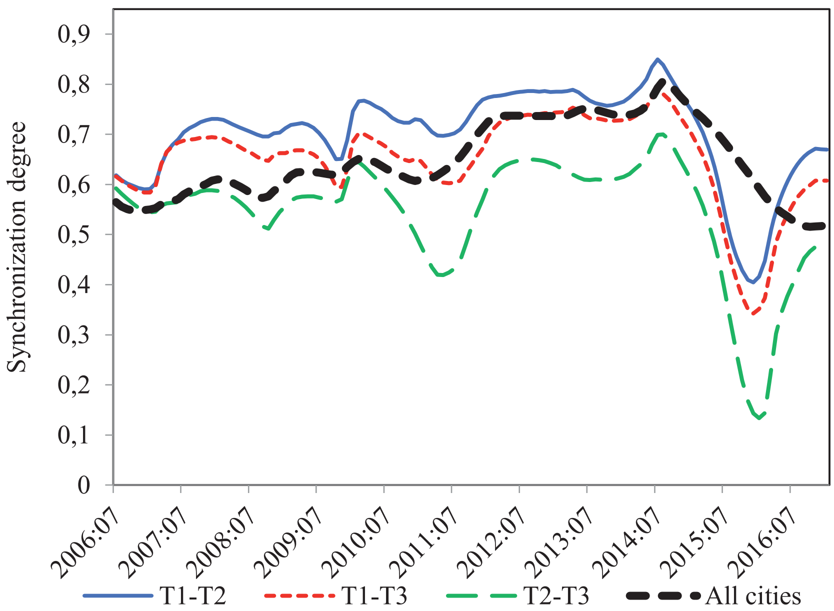


Chart B. Synchronization Across Tiers



Notes: Coloured lines in chart A plot the synchronization between housing prices of cities within the *i*-th tier. Black dashed line makes reference to the average synchronization across all cities in the sample. Chart B plots the synchronization between housing prices corresponding to cities in the *i*-th and *j*-th tier. Black dashed line makes reference to the average synchronization across all cities in the sample.

for the higher synchronization within tiers than across tiers is that macroprudential policies in Tier 1 cities were still tightening during 2014–2016, while those of other cities were loosing due to the weak real estate price growth.[17]

Overall, our analysis provides previously unavailable granular time-varying information about house price clusters across Chinese cities. However, it remains as an open question whether region-specific macroprudential policies would have been more effective if implemented based on tier classifications, or if they were applied to groups of cities based on a classification that considers commonalities in cyclical dynamics of the corresponding housing markets, as proposed in Figure 3.

5. Related housing market characteristics

Besides identifying patterns of housing prices convergence and decoupling among pairs of cities over time, our analysis on Chinese housing prices synchronization also attempts to offer up empirical explanation for the various levels of synchronization. How do economic and structural factors affecting house price valuations identified in past studies help to explain the synchronization metric $\delta_{ij,t}$?

Due to the significant divergence in the synchronization of housing price cycles across Chinese cities, occurred during 2015 and 2017, as shown in figures 1 and 7, we focus our attention on this specific period. Divergence in regional housing price development in China is well studied and suggests that regional heterogeneity in house prices may occur for a number of reasons.[18] The expectation is that distinct population growth rates (*POP*) affect the demand for housing and thus house prices. In addition to this, it can be assumed that different income levels have an impact on regional house prices. For this reason, we consider demographic changes and real GDP growth (*RGDP*) in the econometric analysis.

Moreover, previous literature (Zheng and Kahn, 2008; Zheng *et al*., 2010 and Zheng *et al*., 2014) have found that differences in climate and levels of pollution help to explain the dynamics of Chinese house prices.[19] Therefore, we include an air pollution indicator, PM10 concentration (*PM10*), in the empirical models that aim to explain housing prices synchronization.

The relationship between the housing prices synchronization and city-level characteristics can be assessed by estimating the regression:

$$\delta_{ij,\tau} = \alpha_0 + \sum_n \alpha_{1n} \cdot |X_{n,i,\tau-1} - X_{n,j,\tau-1}| + \beta_1^i \delta_i + \beta_2^j \delta_j + v_{ij,\tau} \tag{9}$$

[17] The increasing synchronization and price surge in Tier 3 cities at the end of the sample period is not evenly spread around China, but rather concentrated in markets with more desirable locations. Places that fall within the gravitational pull of China's most prosperous cities, particularly rich cities in the east and south, have fare the best. Thanks to better infrastructure links, however, more cities today are considered to have desirable locations.

[18] For example, Zheng *et al*. (2010) examined the explanatory factors of house prices across Chinese cities, while Glaeser *et al.* (2017) analysed the heterogeneous house price dynamics across different tiers of cities in China.

[19] In a compensating differentials study, Zheng and Kahn (2008) find that all else equal, an increase of 10 micrograms per cubic metre in PM10 particulate pollution reduces home prices by 4.1 % in Beijing. In an intercity study of 35 Chinese large cities, Zheng *et al*. (2010) find that home prices are lower in cities with higher ambient pollution levels, and the marginal valuation for green amenities have risen over time. Zheng *et al*. (2014) exploit the fact that particulate matter imported into a city depends on the prevailing wind direction, emissions from nearby cities and even Gobi sandstorms. Using wind and sandstorms as instrumental variables, they find that on average, a 10 % decrease in imported pollution from nearby sources is associated with a 0.76 % increase in local home prices.

where X_n is the set of regressors lagged by one period. In explaining the housing price synchronization, all the explanatory variables are in the terms of the absolute differences between city i and city j. It is expected that the divergence in housing prices between two cities reflects the cumulative differentials in recent years. Therefore, we employ 8-year compound growth rates for the socio-economic factors. The air quality measure, in contrast, uses the annual average in the previous year due to the data limitations. Finally, we have added two fixed effects. The term δ_i denotes a fixed effect for the first city in the pair and δ_j is a fixed effect for the second city in the pair. The use of fixed effects is analogous to the standard procedure in the empirical international trade literature estimating gravity equations.[20] The details of our data definitions and data sources are provided in Appendix C.

We estimate equation (9) by using OLS method, with and without city fixed effects.[21] In the models with city fixed effects, standard errors are two-way cluster-robust with clustering on city i and city j which relaxes the i.i.d. assumption of independent errors, allowing for arbitrary correlation between errors within clusters of observations (see Cameron et al., 2011). As explained above, there has been a significant change in the patterns of housing prices synchronization since late 2014. For this reason, we estimate equation (9) for the time periods τ associated to January 2015, January 2016 and January 2017. Due to the lack of data for air quality, nine cities are excluded from the estimation. Therefore, synchronization measures of 1,830 pairs of cities (instead of 2,415 pairs of cities for all 70 cities), are included in the final sample. The estimation results are given in Table 3. As expected, the demand variable $|POP_i\text{-}POP_j|$ has a significant impact throughout. Also, the income variable $|RGDP_i\text{-}RGDP_j|$ and the pollution variable $|PM10_i\text{-}PM10_j|$

Table 3. Factors associated with the synchronization measure of property price changes among major cities in China

Date	Jan-2017	Jan-2017	Jan-2016	Jan-2016	Jan-2015	Jan-2015
Constant	0.576***	0.799***	0.748***	0.469***	0.845***	0.869***
	(0.019)	(0.036)	(0.016)	(0.037)	(0.009)	(0.021)
$\lvert POP_i\text{-}POP_j\rvert$	-3.486***	-3.737***	-7.385***	-4.554***	-2.844***	-1.605***
	(0.662)	(1.129)	(0.584)	(0.984)	(0.319)	(0.430)
$\lvert RGDP_i\text{-}RGDP_j\rvert$	0.201	0.189	-2.631***	-1.310**	-1.543***	-0.579
	(0.541)	(0.669)	(0.473)	(0.616)	(0.289)	(0.359)
$\lvert PM10_i\text{-}PM10_j\rvert$	-0.321	-0.328	-0.456*	-0.658***	-0.600***	-0.506***
	(0.315)	(0.358)	(0.273)	(0.246)	(0.142)	(0.139)
Fixed effects	No	Yes	No	Yes	No	Yes
Observations	1,830	1,830	1,830	1,830	1,830	1,830
R-Squared	0.015	0.272	0.100	0.542	0.068	0.546
Adjusted R-Squared	0.014	0.221	0.098	0.510	0.067	0.514

Notes: The results are estimated by using the OLS method. ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. Standard errors are given in parenthesis beneath the coefficient estimates. For the models with city fixed effects, standard errors are two-way cluster-robust with clustering on city i and city j. The city fixed effects include a fixed effect for the first city in the pair and a fixed effect for the second city in the pair. Adjusted R^2 estimates are provided in the row labelled “Adjusted R-Squared.”

[20] See, for example, Feenstra (2016) p. 143, Harrigan (1996) and Redding and Venables (2004).

[21] It is important to be aware of the limitations of the regressions. Causal assessments cannot be demonstrated directly from these exercises. The regression results can only present relevant empirical evidence serving as a link in a chain of reasoning about causal mechanisms. This also applies to the case of lagged explanatory variables (see, inter alia, Reed, 2015).

are significant in the cross-sectional regressions for January 2015 and January 2016. These results suggest that differentials in the growth of population, income, and air quality are relevant explanatory factors of housing price synchronization among Chinese cities.

6. Conclusions

In this paper, we provide city-level results regarding (i) the descriptive analysis of synchronization in China's housing prices, and (ii) evidence of related housing market characteristics. Applying the regime-switching modelling approach proposed by Leiva-Leon (2017), we study the housing price synchronization among 70 major cities in China. We find significant changes over time in the patterns of China's city-level housing price synchronization, and provide empirical evidence indicating that differentials in socio-economic and environmental factors among cities, such as, growth in population, income, and air quality, are associated with the cross-sectional heterogeneity of housing price synchronization.[22]

What can policymakers do with this knowledge? The divergence of regional housing prices, which is well covered in the housing literature, is typically abstracted from or treated with some naiveté in macroprudential policy frameworks. What complicates matters is that macroprudential policy needs to be sufficiently flexible to address shifting vulnerabilities. To this end, granular and timely information is increasingly being requested to contribute to the flexibility of macroprudential tools. Such data are necessary for calibrating envisaged measures, making ex-ante impact assessments and monitoring implemented measures. An effective and risk-adequate implementation of the measures hinge on a solid data basis. This paper aims at supplying such information. Employing advances in econometric methodology allow us to provide guidance in addressing the composition of the regional macroprudential tool box.

[22] Recently, the IMF (2019, Box 2.3, pp. 86-87) has also accentuated the fragmented Chinese housing market.

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Appendix A. House price indices for China

Construction of house price indices

The Chinese house price indices for 70 cities surveyed in this paper are the price indices of all residential buildings (PA), which combine the two housing price indices released by China's National Bureau of Statistics: (i) price indices of newly constructed residential buildings ($P1$) and (ii) price indices of second-hand residential buildings ($P2$). Our formula is $PA = P1^{0.5}P2^{0.5}$.

Both housing price indices cover 70 major cities in China. The list of the 70 major cities is shown in Table A1. All cities are prefectural-level cities, except Dali. Only the housing prices in the urban area is included, and the housing prices in the county-level administrative areas (if any) are excluded.

Table A1. List of 70 cities

Beijing	01	Nanjing	11	Wuhan	21	Xi'an	31	Jilin	41	Jiujiang	51	Huizhou	61
Tianjin	02	Hangzhou	12	Changsha	22	Lanzhou	32	Mudanjiang	42	Ganzhou	52	Zhanjiang	62
Shijiazhuang	03	Ningbo	13	Guangzhou	23	Xining	33	Wuxi	43	Yantai	53	Shaoguan	63
Taiyuan	04	Hefei	14	Shenzhen	24	Yinchuan	34	Yangzhou	44	Jining	54	Guilin	64
Hohhot	05	Fuzhou	15	Nanning	25	Urumqi	35	Xuzhou	45	Luoyang	55	Beihai	65
Shenyang	06	Xiamen	16	Haikou	26	Tangshan	36	Wenzhou	46	Pingdingshan	56	Sanya	66
Dalian	07	Nanchang	17	Chengdu	27	Qinhuangdao	37	Jinhua	47	Yichang	57	Luzhou	67
Changchun	08	Jinan	18	Guiyang	28	Baotou	38	Bengbu	48	Xiangyang	58	Nanchong	68
Harbin	09	Qingdao	19	Kunming	29	Dandong	39	Anqing	49	Yueyang	59	Zunyi	69
Shanghai	10	Zhengzhou	20	Chongqing	30	Jinzhou	40	Quanzhou	50	Changde	60	Dali	70

The dataset begins in July 2005. The details of the official data can be found in the annotations in the press release:
http://www.stats.gov.cn/english/PressRelease/201801/t20180118_1574960.html

Reliability of house price indices

The reliability of official house price data from China is every now and then critically discussed. Whether house price indices can accurately capture price movements crucially depends on how well the data capture unobserved and time-varying characteristics and qualities. Fang *et al*. (2016) have used sequential sales of apartments in the same development to generate alternate city-level house price indices. The obvious drawback of this method is that developers may use different unobservable pricing policies for units that go on the market in different months. In addition, these house price data are only available until the end of 2013. Therefore, the current developments of particular interest cannot be investigated with these data.

Since the IMF and BIS consider the National Bureau of Statistics data as broadly informative and rely on these housing price data in their analyses of Chinese property prices (see, e.g., https://www.imf.org/external/research/housing/ and https://www.bis.org/statistics/pp_detailed.htm). We follow the major international institutions in the use of the National Bureau of Statistics data. Ding et al. (2017) also relied on the National Bureau of Statistics data.

Appendix B. Tiers of Cities in China

The classification of the tiers of cities used in this paper follows the list released by the financial magazine CBN Weekly (CBN = China Business News). CBN began releasing its list in 2013. The classification uses survey results from approximately 400 enterprises on the distributions of branches and the focus of development among cities. The survey also measures the perceived attractiveness of other cities based on feedback from over a thousand young professionals based in traditional Tier 1 cities (Beijing, Shanghai, Guangzhou and Shenzhen). CBN also collects the data of city-level GDP, per-capita income, number of branches of Fortune Top 500 enterprises, number of top universities, number of international flights, number of foreign consulates and volume of freight carriers. The list is updated annually, with the latest list released in May 2017. The latest classifications were refereed by experts, who reviewed the city data, including the business data of 160 large enterprises, the user data of 17 internet firms and the big data of the cities. The vetted data are used to produce a City Fascination Index, which is compiled from scores in five categories: (i) Business Resource Concentration (weight: 0.24); (ii) Connectedness (weight: 0.18); (iii) Activeness of Urban Population (weight: 0.18); (iv) Diversification of Lifestyle (weight: 0.20) and (v) Potentials (weight: 0.20). The detailed weighting of the sub-categories of data is calculated with principal component analysis.

For our purposes, Tier 1 cities include the traditional four megalopolises (Beijing, Shanghai, Guangzhou and Shenzhen). These cities enjoy the highest business resource concentration and function as regional centres. They also have the highest and most diversified consumption, as well as the highest potentials. They are cities with rich offerings in education, culture and lifestyle. Tier 2 cities, which are combined with "New Tier 1 cities" and Tier 2 cities in the CBN classification, include most of the provincial capitals and larger prefectural cities in Eastern China. They also have high business resource concentration, connectedness with surrounding regions, high levels of consumption, as well as diversified consumption patterns and high potentials. The remaining cities are classed as Tier 3 cities in this discussion.

Appendix C. List of variables for determining housing price synchronization

Variable	Description (Data Source)
$\lvert POP_i\text{-}POP_j\rvert$	Absolute value of the difference of compound annual growth rate of the population between city *i* and city *j* (Source: China's National Bureau of Statistics)
$\lvert RGDP_i\text{-}RGDP_j\rvert$	Absolute value of the difference of compound annual growth rate of real GDP between city *i* and city *j* (Source: China's National Bureau of Statistics)
$\lvert PM10_i\text{-}PM10_j\rvert$	Absolute value of the difference of annual average of PM10 concentration (μg/m^3) (Source: China Statistical Yearbook)

Notes: For the models determining synchronization measures in Jan-2015, Jan-2016 and Jan-2017, $\lvert PM10_i\text{-}PM10_j\rvert$ is the absolute value of the difference of the annual average of PM10 concentration (μg/m^3) in 2014, 2015 and 2016 respectively, while other independent variables are the absolute value of the difference of 8-year compound annual growth rate between city *i* and city *j*.