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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 considers the evolving heterogeneity in China's house price dynamics across 70 cities and assess the main determinants. 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. After sorting city-level housing prices into four clusters sharing similar cyclical features, we see that each group shows increasing synchronization in the years leading up to 2015, and a decoupling pattern thereafter. We document high synchronization within each of the clusters of cities, but low synchronization among them. The empirical evidence suggests that differentials in the growth of households, income, investment and even differences in air quality explain housing price synchronization among cities.

Keywords: House Prices, Markov-Switching Models, Synchronization, China

JEL classification: E31, E32, C32

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1. Introduction

Chinese housing prices are increasingly an international concern. Following on the heels of an extraordinary real estate boom in the early 2000s, Chinese housing prices were boosted even higher in 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. A sudden collapse in house prices would have negative spillover effects on the macroeconomic situation and possibly pose financial stability risks.

Among recent historical precedents of housing markets gone bad, the most relevant is probably of build-up of property price overvaluations and subsequent collapse that triggered the Asian financial crisis in the late 1990s. Aware of these dangers, the Chinese government has imposed market-cooling measures and restrictions in recent years to bring house prices back to "reasonable" levels. Unfortunately, these interventions follow a now all-too-familiar pattern, whereby officials tasked with avoiding over-heating in the housing market reinstate accommodative policies to avoid a subsequent economic slump.[2] The result has been a Chinese housing market that fluctuates from hot to cool to hot again, generating cycles in the dynamics of property prices.[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.

[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 productivity growth.

[2] 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.

[3] 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).

Looking at Chart A in Figure 1,[4] we see property prices in China, fuelled by strong economic growth and cheap credit, rising from the early 2000s to 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 mandates bank lending. Developers quickly discovered that it is 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 response to this over-heating, officials introduce a series of macroprudential tightening measures.[5] Notably, major cities are required to publish an annual housing price control target, and branches of the People's Bank of China (PBoC) are requested to increase down-payment requirements in cities where house price rises exceeded the price control target. Tighter mortgage restrictions on second home purchases are introduced and buyers without local registration status are barred from buying more than one property. Given the differentiated price development across cities, as can be seen in Figure 1, some cities imposed tighter measures than others. For example, some local governments were required to boost low-income housing production. Additionally, the government introduced new property taxes. These tightening measures managed to cool the housing market gradually between 2011 and 2012. A new house price cycle gets underway in early 2013, when property prices begin to rise again. In March of the same year, the State Council introduces new measures to reassert control. During 2014, house prices in most of the major cities, even in the Tier 1 cities, exhibit a significant decline. In particular, property prices in Beijing and Shanghai drop by 3.4 % and 2.9 %, respectively, while property prices in some cities experience declines in the high single digits.

All these policy actions were taken with the aim of stabilizing housing prices. They also generated an increasing degree of similitude between the housing price cycles across cities in China as seen in Figure 2, which plots the dispersion of the distribution of property price inflation over time.

[4] The Chinese housing 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*)[4] and ii) price indices of second-hand residential buildings (*P2*). Both housing price indices cover 70 major cities in China, but only the housing prices in the urban area is included. Housing in in the county-level administrative areas (if any) are excluded. The dataset begins in July 2005 and our formula is $PA = P1^{0.5}P2^{0.5}$. The IMF and BIS both rely on housing price data released by China's National Bureau of Statistics in analyses on Chinese property prices.

[5] Macroprudential policy is generally defined as a suite of prudential tools deployed with the aim of promoting or preserving financial stability. The rationale for such policy is that standard monetary policy in itself is incapable of moderating booms without inflicting severe damage on the economy.

The government rolled out a new set of policy actions during the next significant slowdown in housing prices in late 2014. With house price dynamics increasingly out of sync across cities, cities started to relax their home-buying restrictions in mid-2014. Only Tier 1 cities kept the restrictions in place. 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 reduces the minimum down payment for second-home buyers three times. In March 2015, property sellers are exempted from paying the transaction tax if they have owned the sold property for at least two years.[6]

Policy actions to revive the housing market in early 2016 yield distinctly different results this time around. As we see in Figure 2, there is a significant increase in the heterogeneity of property prices dynamics across cities. The new boom sets warning lights flashing and local governments begin to introduce tightening measures in late 2016. With the large heterogeneity exhibited in housing prices, policymakers refrain from applying a blanket nationwide property “speed limit”, most likely for fear of a policy overshoot that triggers a sudden property sentiment reversal or causes a sharp deceleration in housing sales. Property policy tightening remains differentiated, targeting cities where the price dynamics are most pronounced.

In addressing housing bubble concerns, the initial challenge is simply a measurement problem. Policymakers need to have an accurate grasp of housing market developments before they can assess the degree of housing price overvaluation or decide on appropriate macroprudential policy actions to address outstanding concerns.

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 needs to be sufficiently flexible to address shifting vulnerabilities. Granular and timely information contributes to

[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.

the flexibility of macroprudential tools.[7] Adjusting the macroprudential tools in such a way makes it more effective in cooling hot spots, while leaving cold spots alone.[8] A differentiated macroprudential policy could, for example, be implemented through different standards in loan-to-value (LTV) ratios across Chinese cities to tame local house price booms. Naturally, such fine-tuning requires a mechanism to identify and monitor systemic risk in real time.[9]

Echoing this sentiment, we hold a magnifying glass to the house price dynamics of 70 Chinese cities to disentangle the evolving associations hidden in Figure 1 and 2. To the best of our knowledge, this is the first study to provide a descriptive analysis of synchronization in China's housing prices or the main drivers of synchronization in China's house price dynamics.[10] Our results indicate that housing prices across cities in China can be sorted into a few clusters sharing similar cyclical features. Those clusters generally remained stable and experienced increasing synchronization for many years up to 2015, when they began to exhibit a decoupling pattern. Moreover, we provide evidence about the specific economic, demographic and environmental factors that have played a significant role in explaining the heterogeneity of housing price synchronization during the recent decoupling period.

The remainder of this paper is laid out as follows. Section 2 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 3 reports the space-time dynamics of house prices linkages. Section 4 provides a regression analysis to assess the main determinants of housing prices interdependencies. Section 5 concludes.

[7] Monetary policy can take multiple forms when regional housing markets are out of sync. In most countries, however, preferences for city-specific macroprudential policies vary far more than views on what constitutes adequate national macroeconomic policy. Disagreements may rule out all but the least-controversial political bargains and lead to "second-best world" solutions. In any case, comprehensible calculations are needed, and the empirical estimates in this paper help advance the discussion.

[8] A regionalized macroprudential strategy was recently applied in New Zealand, where restrictions on high-LTV lending were tightened specifically for the Auckland housing market (Reserve Bank of New Zealand, 2015). 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. Given the large divergence in China's housing markets, Ding *et al*. (2017), pp. 16-17 and the IMF (2017, p. 51) has recommended macroprudential policies tailored to local conditions as a first line of defence. See Du and Zhang (2011) for an assessment of China's city-level home purchase limits.

[9] 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.

[10] 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 is only descriptive. It provides no information about potential drivers of housing price dynamics. We attempt to overcome both limitations in our proposed approach.

2. Measuring housing price synchronization

In the following discussion, 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 cycle 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.[11] The first is based around the notion of convergence. It focuses on identifying similarities and determinants of long-run behaviours of specific economic features such as inflation and GDP growth. Phillips and Sul (2007), for example, rely on a panel data model with factor structure to provide assessments about convergence and clustering patterns between the price levels of different US metropolitan areas. 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 determinants 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 time-varying bilateral relationship between housing cycles at the city level. Also, the pairwise approach that we adopt in this paper requires testing all the pairwise synchronization

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

measures and, as such, does not involve what can be a problematic choice of a single reference city in the computation of house price differentials. 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.

Here, 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). On the other hand, the complete set of pairwise models provides us with a rich data environment in which to perform a comprehensive analysis about clustering patterns and the main determinants of housing price cycles in China.[12]

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. Therefore, consider the following bivariate regime switching model:

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

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

[12] 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).

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

where $z_{ij,t}$ also take two values, that is, $z_{ij,t} = \{0,1\}$. 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 independent first-order Markov chains with constant transition probabilities. Here, we are want to assess the time-varying interdependence between the state variables measuring the housing price cycles $s_{i,t}$ and $s_{j,t}$. Once potential changes in volatility are taken into account, we model the joint dynamics of the state variables as

$$P\left(s_{i,t}, s_{j,t}, z_{ij,t}\right) = \delta_{ij,t} P\left(s_{i,t}^D, s_{j,t}^D, z_{ij,t}\right) + \left(1 - \delta_{ij,t}\right) P\left(s_{i,t}^I, s_{j,t}^I, z_{ij,t}\right), \tag{3}$$

where $P(s_{i,t}^D, s_{j,t}^D, z_{ij,t})$ denotes the probability that $s_{i,t}$ and $s_{j,t}$ are fully dependent, that is, $s_{i,t} = s_{j,t}$, and $P(s_{i,t}^I, s_{j,t}^I, z_{ij,t})$ denotes the probability that $s_{i,t}$ and $s_{j,t}$ are totally independent at time *t*. Accordingly, the term $\delta_{ij,t}$ measures the degree of interdependence between $s_{i,t}$ and $s_{j,t}$ at time *t*. It is defined as

$$\delta_{ij,t} = P\left(v_{ij,t} = 1\right), \tag{4}$$

where $v_{ij,t}$ denotes a latent variable that takes the value of one if $s_{i,t}$ and $s_{j,t}$ are fully independent, or the value of zero if they are totally independent, at time *t*.

The latent variable $v_{ij,t}$ is assumed to be driven by a first-order Markov chain with transition probabilities given by

$$P\left(v_{ij,t} | v_{ij,t-1}, v_{ij,t-2,} \ldots\right) = P\left(v_{ij,t} | v_{ij,t-1}\right) = p_{ij,\delta} \, . \tag{5}$$

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 filter, Hamilton (1989). For more details about the estimation and filtering procedures, see Leiva-Leon (2017). 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

$$\Delta_t = \begin{bmatrix} 1 & \delta_{12,t} & \delta_{13,t} & \cdots & \delta_{1N,t} \\ \delta_{21,t} & 1 & \delta_{23,t} & \cdots & \delta_{2N,t} \\ \delta_{31,t} & \delta_{32,t} & 1 & \cdots & \delta_{3N,t} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \delta_{N1,t} & \delta_{N2,t} & \delta_{N3,t} & \cdots & 1 \end{bmatrix}. \tag{6}$$

The information contained in the matrices Δ_t, for $t = 1,2, \dots, T$, represent the key piece of information to perform a detailed mapping of the housing price interdependence across time and space at the city level. 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

$$\delta_{ij,\delta} = \frac{1-p_{ij,\delta,11}}{2-p_{ij,\delta,00}-p_{ij,\delta,11}}, \tag{7}$$

where $p_{ij,\delta,00}$ 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

$$\bar{\Delta}_t = \begin{bmatrix} 1 & \bar{\delta}_{12} & \bar{\delta}_{13} & \cdots & \bar{\delta}_{1N} \\ \bar{\delta}_{21} & 1 & \bar{\delta}_{23} & \cdots & \bar{\delta}_{2N} \\ \bar{\delta}_{31} & \bar{\delta}_{32} & 1 & \cdots & \bar{\delta}_{3N} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \bar{\delta}_{N1} & \bar{\delta}_{N2} & \bar{\delta}_{N3} & \cdots & 1 \end{bmatrix} . \tag{8}$$

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

3. 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 potential changes over time in the relationship between 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.

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. It is based on a dendrogram, i.e. a tree-structured graph that lets us visualize the results of hierarchical clustering. Figure 3 shows the clear separation of Chinese cities into clusters. Note that the definition of the groups depends of the cut-off in the height of the tree. When we set the cut-off at 1, four well-defined groups of cities exhibiting similar property price cycles are identified. These are represented by four colours,[13] giving policymakers easy access to information useful in designing macro-prudential policies tailored to region-specific conditions. The International Monetary Fund (2017) has made visualization part of its recommended strategy for a first line of defence to potential housing bubbles in China.

In Figures 1 and 2, we see that the similarity between housing prices across cities experienced significant changes over time. In particular, it continuously decreased from the late 2000s to 2015, the 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 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

$$Stress(D,G) = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left(\delta_{ij,t} - \|d_{it} - d_{j,t}\|\right)^2}{\sum_{i=1}^{n}\sum_{j=1}^{n}\delta_{ij,t}^{\ 2}} + \alpha\sum_{i=1}^{n}\sum_{l=1}^{k} c_{il}\left\|d_{it} - g_{l,t}\right\|^2 + \beta\sum_{i=1}^{n}\left\|d_{it} - d_{i,t-1}\right\|^2, \qquad (9)$$

[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.

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 4 plots the maps of housing price associations for our 70 Chinese cities and the four selected time periods. These periods are bracketed two episodes of high property price inflation, one at the beginning and one at the end of the sample (June 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 that 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. These results may provide support for macroprudential policies that focus on a combination of both region-specific and nationwide measures in reducing the recent significant dissimilarities of housing price cycles across groups of cities that ostensibly threated an otherwise functional Chinese housing market.

We next focus on the temporal dimension of housing prices synchronization, "collapsing" 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 5 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 4, we will investigate which have been the economic factors that are mainly associated to such a decrease in synchronization.

[14] To assign a relatively higher importance to the temporal dimension, our penalty parameters are set to $\alpha = 0.01$ and $\beta = 1$.
[15] In the media file at https://sites.google.com/site/daniloleivaleon/china, the sequence of dendrograms is shown for every time period up to the end of our sample.

Regarding changes in the aggregate levels of synchronization with classification of cities based on tiers in Chart A of Figure 6, we see that within-tier synchronization tends to be larger than overall synchronization. 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 6 shows that across-tier synchronization contributes much less to the housing market overall interdependence, especially after 2015. Note that the largest disconnection occurs between Tier 2 and Tier 3 cities. A possible explanation 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.[16]

Overall, the methodology provides previously unavailable granular time-varying information about house price clusters across Chinese cities. It remains as an open question, however, as to 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.

4. Determinants of housing price synchronization

While providing a time-varying pattern of housing price convergence and divergence among pairs of cities over time, our analysis of housing price synchronization among Chinese cities has yet to offer up empirical reasons for the various levels of synchronization. This section investigates possible factors determining the inter-city synchronization in housing price cycles. In particular, a set of variables representing dissimilarities of socio-economic and environmental factors between the cities are used for explaining the synchronization measures ($\delta_{ij,t}$).

Divergence in regional housing price development is well studied and suggests that regional heterogeneity in house prices may occur for a number of reasons.

[16] 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 the east and south, have fare the best. Thanks to better infrastructure links, however, more cities today are considered to have desirable locations.

Demographic differences are commonly cited. The expectation is that population growth and changes in demographic structure can affect the demand for housing. Here, we use the difference in growth in the number of households as a proxy for demographic change. This variable partly captures the population growth, but more importantly, the number of households can reflect a change in demographic structure. If the population is relatively young, growth of the number of households should be brisk. In an aging society, growth in the number of households should be lower.[17]

Economic factors may explain housing price divergence among cities. Highly different rates or levels of economic development might differentiate the housing demand and hence housing prices. Using the differentials in economics factor could explain the determinants of the housing price divergence. Here, we includes income (Real GDP), price (GDP deflator), consumption (real consumption expenditure per capita) and investment (real fixed assets investment or FAI) in our models explaining housing price synchronization.

Land use in urban areas could be another factor determining housing price synchronization. More developed land in an urban area implies a higher supply of land and housing. Therefore, we consider the variable of the developed area of city construction as a possible factor determining housing price divergence. Notably, revenue from the sale of land use rights is the major source of income for local governments in China. To raise revenue, local governments have an incentive to increase the supply of land available and support higher housing prices.[18] These two variables stated above could be treated as the proxies of land supply factors.

Alternatively, demographic and economic factors could be treated as demand factors to explain housing price synchronization.

Environmental factors are likely important in explaining the regional divergence of housing prices as they have to do with quality-of-life issues. Previous literature (Zheng and Kahn, 2008; Zheng *et al*., 2010 and Zheng *et al*., 2014) found that differences in climate and levels of pollution explain the property price

[17] Growth in number of households could also reflect internal migration within China. However, given the household registration system, the migration (particularly a change in location of the household registration) is difficult and limited in China.
[18] The IMF (2017) found the local government's fiscal behaviour to have a distortionary effect on the supply of land.

growth in some cities in China.[19] Therefore, this paper includes an air pollution indicator, PM10 concentration, in the models of determining the housing price synchronization.

The relationship between the housing prices synchronization and the differences in the factors at the city level can be assessed by estimating the regression:

$$\delta_{ij,t} = \alpha_0 + \sum_n \alpha_{1n} * |X_{n,i,t-k} - X_{n,j,t-k}| + v_{ij,t} \qquad (10)$$

where X_n is a set of socio-economic and environmental factors, where the socio-economic component can include compound annual growth rate of number of households, real GDP, GDP deflator, real consumption expenditure per capita, real FAI, developed area of city construction or fiscal revenue, and the environmental component is the latest annual average of PM10 concentration.

In explaining the housing price synchronization, the absolute differences between city *i* and city *j* are applied to the factors. The compound annual growth rate since 2008 (when China introduced its RMB 4 trillion stimulus to reduce the impact the global financial crisis) is applied for the socio-economic factors. The air quality measure, in contrast, uses the latest annual average. Given the expectation that the divergence in housing prices between two cities reflects the cumulative differentials in recent years, using compound growth rate could better reflect this cumulative difference and avoid short-term volatility. A similar calculation approach is also used by the Economist Intelligence Unit (2015) in explaining the divergence in the cities of China. The details of our data definitions and data sources are provided in Appendix B.

The negative relationships between the housing prices synchronization and factor differentiations are expected. As stated in the previous section, there is a significant variation in the patterns of housing prices synchronization, especially in recent years. To tease out the variables determining the latest trend in housing price synchronization, we investigate our factors at three selected time points (Jan-2015, Jan-2016 and Jan-2017). Due to the lack of data for air quality, nine cities are excluded from the estimation.

[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.

Therefore, synchronization of 1,830 pairs of cities (instead of 2,415 pairs of cities), are included in the final sample.

Given high variation of characteristics among a large number of pairs of cities, the problem of outliers may be serious. For this reason, least trimmed squares estimation (LTS) is used to estimate the relationship between housing price synchronization and differences in the factors following the method proposed by Rousseeuw and Leroy (1987). LTS is a robust, high-breakdown regression estimator, i.e. it can withstand many outliers in a sample.[20] The maximum breakdown point for a linear regression method is 50 %, i.e. the regression method can cope with samples in which as many as half the observations are contaminated. If over half of the data are outliers, a linear regression method cannot tell the good observations from the bad ones. However, using a resampling algorithm, LTS locates observations in the uncontaminated half of the sample and uses these good observations to pinpoint the outliers. Rousseeuw and Leroy (1987) propose drawing a large number of subsamples, each of size K (the number of regression coefficients, including the constant term). When the number of subsamples is large, they demonstrate that at least one is virtually certain to be uncontaminated by outliers. This LTS estimation technique based on “clean” observations has proven to be a powerful approach for complex multi-dimensional and noisy datasets.

Table 1 reports the cross-section estimation results for equation (10) with the LTS method. The number of iterations is 500. The full models include all the variables introduced above. In general, real consumption expenditure per capita, developed area of city construction and fiscal revenue are insignificant. GDP deflator is a significant variable, but with a counterintuitive sign. Thus, we drop them and re-estimate the reduced models, which only include number of households, real GDP, real FAI and PM10 concentration. The results suggest that demographic and environmental factors may be the prime determinants for housing price synchronization. Among the economic factors, only real GDP and real investment are significant. Real consumption expenditure per capita is not significant.

Regarding the counterintuitive sign of GDP deflator, Ahuja *et al*. (2010) suggest housing prices have deviated from fundamental prices in some cities in China. This housing price misalignment is persistent

[20] Regression methods are evaluated by several well-known criteria, including unbiasedness, efficiency and consistency. A relatively new criterion is a high “breakdown point.” Ordinary least squares (OLS) has a very low breakdown point. A single outlier can throw the OLS line far off target. This comment also applies to OLS residuals and thus to residual-based diagnostics. Stated plainly, diagnostics with low breakdown points can be quite misleading in the presence of outliers.

and may have worsened in recent years, possibly due to the lack of good alternative asset investments in China (IMF, 2017). The implication is that housing prices have deviated from economic fundamentals and the general price level. Given the rapid growth in the service sector with high productivity growth, growth in the general price level has been limited since 2010. However, given the high demand for housing, housing prices have diverged from the general price level. Comparing the estimated impact from consumption and investment, the significant impact from investment, instead of the insignificant impact from consumption, seems to confirm that fixed investment remains the main driver of economic growth, which is a factor boosting housing demand.

In addition, the difference in the growth of a developed area of city construction is not a significant factor. This may be because of the offsetting force due to this factor. The rising supply of land may constrain housing prices, while a higher level of urbanization may push up housing prices. While sales of land use rights is the major source of revenue for local governments, the difference in the growth of fiscal revenue is not a significant factor. Given the finite supply of land in the urban area, the insignificance of land supply in housing prices suggests that demand factors (demographic, economic and environmental factors) are the main drivers of divergence in housing prices among Chinese cities.[21]

In the previous section, we found that the high intra-synchronization within the different tiers of cities has largely contributed the overall synchronization among cities, while the inter-synchronization between three tiers of cities was lower, particularly between Tier 2 cities and Tier 3 cities. Thus, the impact of socio-economic and environmental factors on the property price synchronization could be varied for different tiers of cities. Therefore, we extend the equation (10) to include the interactive terms of the factors with a dummy for different tiers of cities:

$$\delta_{ij,t} = \alpha_0 + \sum_n \alpha_{1n} * \left|X_{n,i,t-k} - X_{n,j,t-k}\right| + \sum_n \alpha_{2n} * Tier1 * \left|X_{n,i,t-k} - X_{n,j,t-k}\right| + \sum_n \alpha_{3n} * Tier2 * \left|X_{n,i,t-k} - X_{n,j,t-k}\right| + v_{ij,t} \, , \qquad (11)$$

[21] In addition to the variables employed, we also consider other potential determinants such as the growth rate of population (usual residence), the growth rate of exports, the annual average of PM2.5 concentration and the number days with poor air quality (defined as the air quality below Grade II). All of these potential variables yield insignificant and inferior results, so they are not included in the model specification finally chosen by the general-to-specific modelling approach.

where $Tier1$ is the dummy variable if one city in the pair is Tier 1 city, and $Tier2$ if one city in the pair is a Tier 2 city.[22]

Table 2 presents the estimated results for equation (11), which add the interactive dummies to the reduced model in Table 1. Explanatory power (R-squared) improves significantly after imposing the interactive dummies multiplying the dummy variables of tiers of cities and the socio-economic and environmental factors. This is particularly valuable in explaining housing price synchronization in the Jan-2015 and Jan-2016 periods, although the R-squared for Jan-2017 results are still low. This suggests that among different tiers of cities, factor differentials have different impacts on the difference in housing price synchronization. The estimation results with added interactive dummies may provide an empirical explanation of the results in the previous section. In any case, the selected socio-economic factors are significant when interacting with the dummy for Tier 1 cities.

This implies the impact of socio-economic factor differentials in determining synchronization between a Tier 1 city and other cities is significantly different from those between other cities. This result implies that the difference in socio-economic factors may explain the higher inter-synchronization between Tier 1 cities and other tiers of cities.[23] On the other hand, similar to the socio-economic factors, air quality is significant when interacting with the dummy for Tier 1 cities. However, it is also significant when interacting with the dummy for Tier 2 cities for the models of housing price synchronization in Jan-2016 and Jan-2017. This suggests that the air quality could partly explain the high intra-synchronization within tiers, particularly after 2015.

5. Conclusions

In this paper, we provided city-level results regarding (i) the descriptive analysis of synchronization in China's housing prices, and (ii) evidence of the main drivers of synchronization in China's house price dynamics. Applying the regime-switching modelling approach proposed by Leiva-Leon (2017), we studied the housing price synchronization among 70 major cities in China. The econometric techniques

[22] The classification of the tiers of cities are based on 2017 Ranking of New Tier 1 Cities in CBN (2017).

[23] The impact of different factors could vary over time, however, in general, we find that the difference in socio-economic factors may explain the higher inter-synchronization between Tier 1 cities and other tiers of cities.

employed should be of interest not just to housing and regional economists, but to applied econometricians as well.

We found significant variation 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, including growth in the number of households, income, investment, and differences in air quality may explain the cross-sectional heterogeneity of housing price synchronization. After classifying cities into three tiers, we found high intra-synchronization within the different tiers of cities, with air quality a leading candidate as a main explanatory factor. Notably, this has largely contributed the overall synchronization among cities. On the other hand, the inter-synchronization between three tiers of cities was lower, particularly that between Tier 2 cities and Tier 3 cities. The empirical evidence suggests that the socio-economic factors could partly explain the relatively higher inter-synchronization between tier 1 cities and other cities.

With the nature of housing stability risks changing over time, 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. To our best knowledge, this paper is the first to discuss out-of-sync housing prices in China in a full-fledged time-varying empirical model setting.

This paper has both important academic contributions and timely policy implications. Supervisory authorities currently lack the granular data at the city-level that are indispensable when applying regionalized macroprudential measures. 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 hinges 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 macroprudential tool box.[24] The bottom line is that the increase in China's house prices at the national level masks tremendous variation at the city level, a feature that has

[24] Further analysis may employ a factor-augmented VAR model (FAVAR), where the information in the factor equation contained in all the time-varying pairwise synchronization measures is summarized in a small set of factors. In the VAR equation, a few such factors may be related with variables containing information about nationwide macroprudential policies. Impulse response analysis could then be employed to assess the effect of a shock in a given macroprudential policy on all pairwise synchronization measures to see which cities are most affected by such policies. We leave the exploration of these tantalizing issues to future investigations.

been largely overlooked in the macroprudential literature. Correspondingly, the findings point to a critical role for policy in regionalizing macroprudential tools.[25]

The divergence of regional housing prices, which is well covered in the real estate literature, is typically abstracted from or treated with some naiveté in macroprudential policy frameworks. Of course, addressing macroprudential policy challenges with intertemporal implications requires structural models as a next step. It is not enough to rely on time series or cross-sectional empirical evidence. In his famous critique of the Burns and Mitchell (1946) empirical characterization of business cycles seven decades ago, Koopmans (1947) articulated the limited nature of conclusions that follow measurement without theory. Thus, extension of the present modelling approach with a view to optimizing macroprudential policies holds potential as a subject for future research.[26]

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[25] Significant divergences in regional house prices may matter for the efficacy of monetary policy. For example, the policy response to a regional housing shock may depend on the region where the shock originated. Similarly, the response to a policy tightening may depend on issues such as whether the most rapidly expanding regions are the most interest sensitive. More generally, the aggregate effects of macroprudential policy depend on the distribution of regional sensitivities and the initial distribution of regional economic conditions at the time of tightening. For more, see Carlino and DeFina (1999).

[26] While much of the literature on housing and business cycles relies on macro models with limited heterogeneity, there is considerable promise in modelling frameworks that allow for richer heterogeneity. An interesting illustration of this is the explicit incorporation of geography. See e.g. Van Nieuwerburgh and Weill (2010).

References

Abbott, A. and G. De Vita (2012). “Pairwise Convergence of District-Level House Prices in London,” *Urban Studies* 49, 721-740.

Ahuja, A., L. Cheung, G. Han, N. Porter and W. Zhang (2010). “Are House Prices Rising Too Fast in China?” IMF Working Paper WP/10/274, Washington, DC.

Bai, C.E., Li, Q. and M. Ouyang (2014). “Property Taxes and Home Prices: A Tale of Two Cities,” *Journal of Econometrics* 180, 1-15.

Burns, A.F. and W.C. Mitchell (1946). Measuring Business Cycles, Cambridge (National Bureau of Economic Research).

Camacho, M. and D. Leiva-Leon (2017). “The Propagation of Industrial Business Cycles,” *Macroeconomic Dynamics*, (forthcoming).

Carlino, G. and R. DeFina (1999). “Do States Respond Differently to Changes in Monetary Policy?” Business Review, July/August, 17-27.

China Business News [CBN] (2017). “2017 Ranking of New Tier 1 Cities,” CBN Weekly 455, May 2017.

Cotter, J., Gabriel, S. and R. Roll (2015). “Can Metropolitan Housing Risk be Diversified? A Cautionary Tale from the Recent Boom and Bust,” *Review of Financial Studies* 28, 913-936.

Del Negro M. and C. Otrok (2007). “99 Luftballons: Monetary Policy and the House Price Boom Across U.S. States”, *Journal of Monetary Economics* 54, 1962-1985.

Dieleman F.M., Clark W.A.V. and M.C. Deurloo (2000). “The Geography of Residential Turnover in Twenty-Seven Large US Metropolitan Housing Markets, 1985–95,” *Urban Studies* 37, 223-245.

Ding, D., Huang, X., Jin, T. and W.R. Lam (2017). “Assessing China’s Residential Real Estate Market,” IMF Working Paper No. WP/17/248, Washington, DC.

Du, Z. and L. Zhang (2015). “Home-Purchase Restriction, Property Tax and Housing Price in China: A Counterfactual Analysis,” *Journal of Econometrics* 182, 558-568.

Ductor, L. and D. Leiva-Leon (2016). “Dynamics of Global Business Cycle Interdependence,” *Journal of International Economics* 102, 110-127.

Economist Intelligence Unit (2015). “Rising Stars, Fading Comets: China Emerging City Rankings, 2015,” London.

Hamilton, J.D. (1989). “A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle,” *Econometrica* 57, 357-384.

Hernández-Murillo, R., Owyang, M. and M. Rubio (2017). “Clustered Housing Cycles,” *Regional Science and Urban Economics* 66, 185-197.

Holmes, M.J., Otero, J. and T. Panagiotidis (2011). “Investigating Regional House Price Convergence in the United States: Evidence from a Pair-Wise Approach,” *Economic Modelling* 28, 2369-2376.

Igan, D. and H. Kang (2011) “Do Loan-To-Value and Debt-To-Income Limits Work? Evidence from Korea,” IMF Working Paper No. 11/297, Washington, DC.

International Monetary Fund (2017). “People’s Republic of China: Selected Issues,” Washington, DC.

Kallberg, J.G., Liu, C.H. and P. Pasquariello (2013). “On the Price Comovement of U.S. Residential Real Estate Markets,” *Real Estate Economics* 42, 71-108.

Koopmans, T.C. (1947). “Measurement Without Theory,” *Review of Economics and Statistics* 29, 161-172.

Leiva-Leon, D. (2017). “Measuring Business Cycles Intra-Synchronization in US: A Regime-Switching Interdependence Framework,” *Oxford Bulletin of Economics and Statistics* 79, 513-545.

Mao, G. (2016). “Do Regional House Prices Converge or Diverge in China?” *China Economic Journal* 9, 154-166.

Moench, E. and S. Ng (2011) “A Hierarchical Factor Analysis of U.S. Housing Market Dynamics”, *The Econometrics Journal* 14, C1-C24.

Pesaran, M.H. (2007). “A Pair-Wise Approach to Testing for Output and Growth Convergence,” *Journal of Econometrics* 138, 312-355.

Phillips, P. and D. Sul (2007). “Transition Modelling and Econometric Convergence Tests,” *Econometrica* 75(6), 1771-1855.

Phillips, P. and D. Sul (2009). “Economic Transition and Growth,” *Journal of Applied Econometrics* 24, 1153-1185.

Rousseeuw, P.J. and A.M. Leroy (1987) Robust Regression and Outlier Detection, New York (Wiley).

Van Nieuwerburgh, S. and P.-O. Weill (2010). “Why Has House Price Dispersion Gone Up?” *Review of Economic Studies*, 77, 1567-1606.

Xu, K.S., M. Kliger and A.O. Hero III (2012). “A Regularized Graph Layout Framework for Dynamic Network Visualization,” *Data Mining and Knowledge Discovery* 27, 84-116.

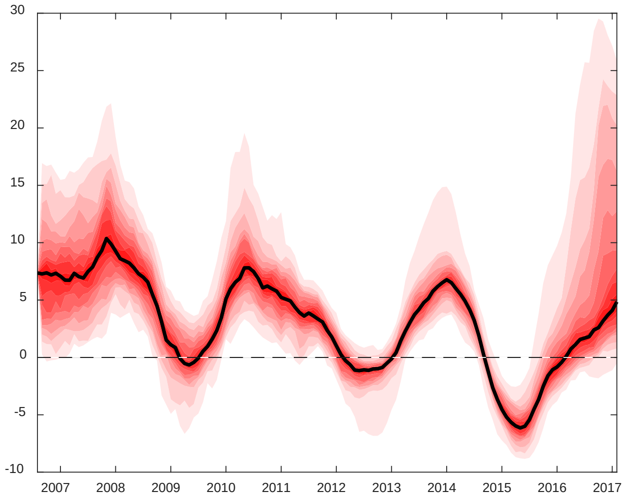
Zheng, S., J. Cao, M.E. Kahn and C. Sun (2014). “Real Estate Valuation and Cross Boundary Air Pollution Externalities: Evidence from Chinese Cities,” *Journal of Real Estate Finance and Economics* 48, 398-414.

Zheng, S., and M.E. Kahn (2008). “Land and Residential Property Markets in a Booming Economy: New Evidence from Beijing,” *Journal of Urban Economics* 63, 743-57.

Zheng, S., M.E. Kahn and H. Liu (2010). “Towards a System of Open Cities in China: Home Prices, FDI Flows and Air Quality in 35 Major Cities,” *Regional Science and Urban Economics*, 40, 1-10..

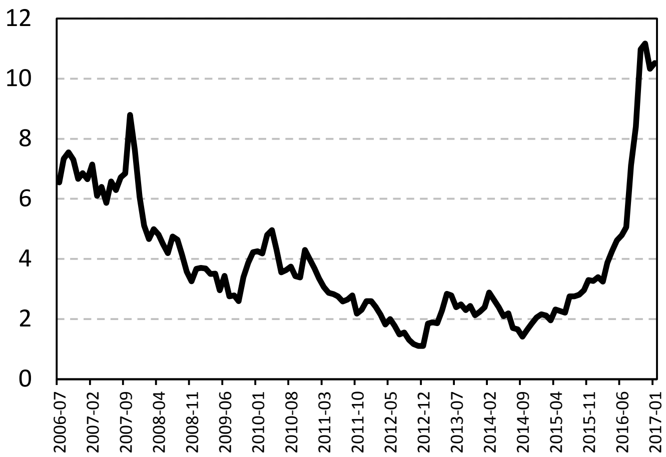
Figure

Figure 1. Housing price inflation across 70 major cities in China.



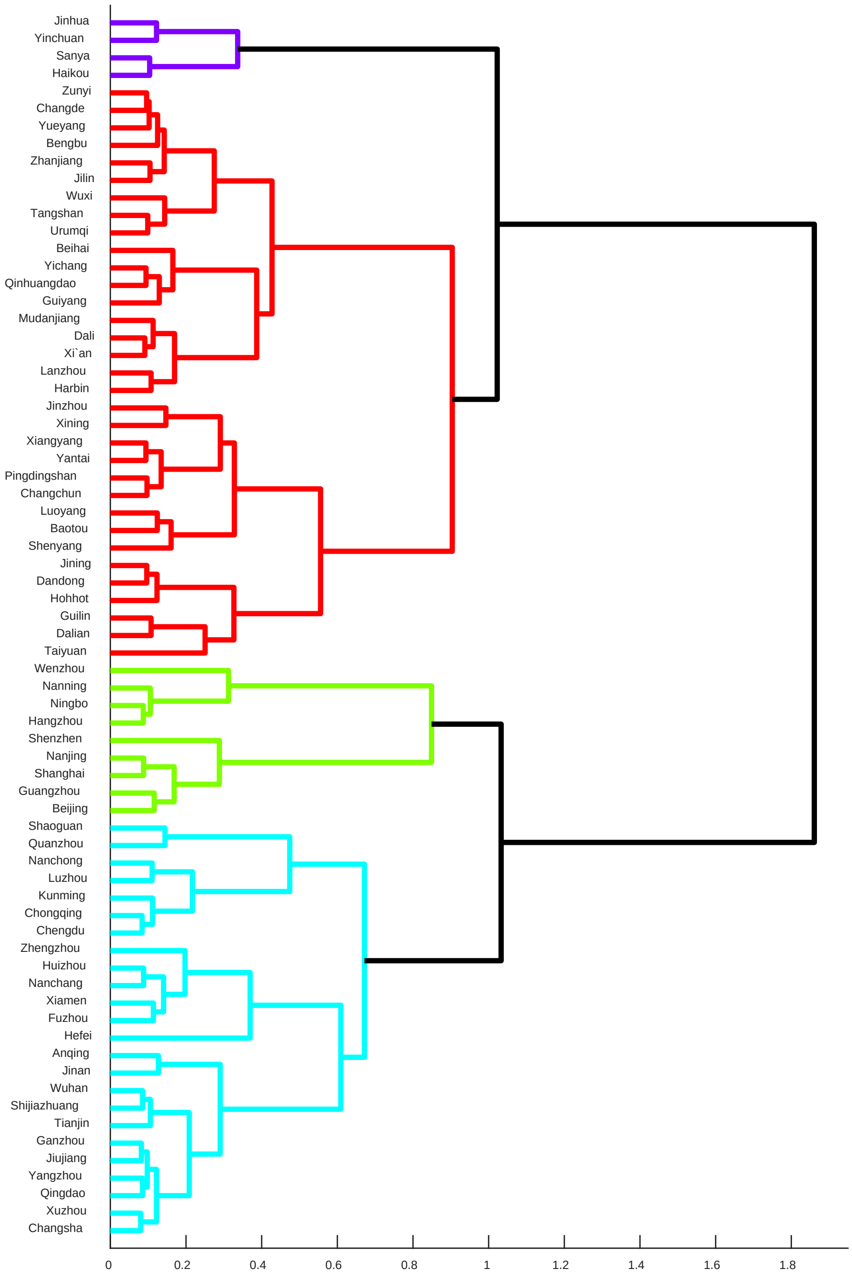
Notes: The black line plots the median annualized housing price inflation across the seventy major cities in China. The red area corresponds to the distribution over time with probability mass between the 5th and 95th percentiles.

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



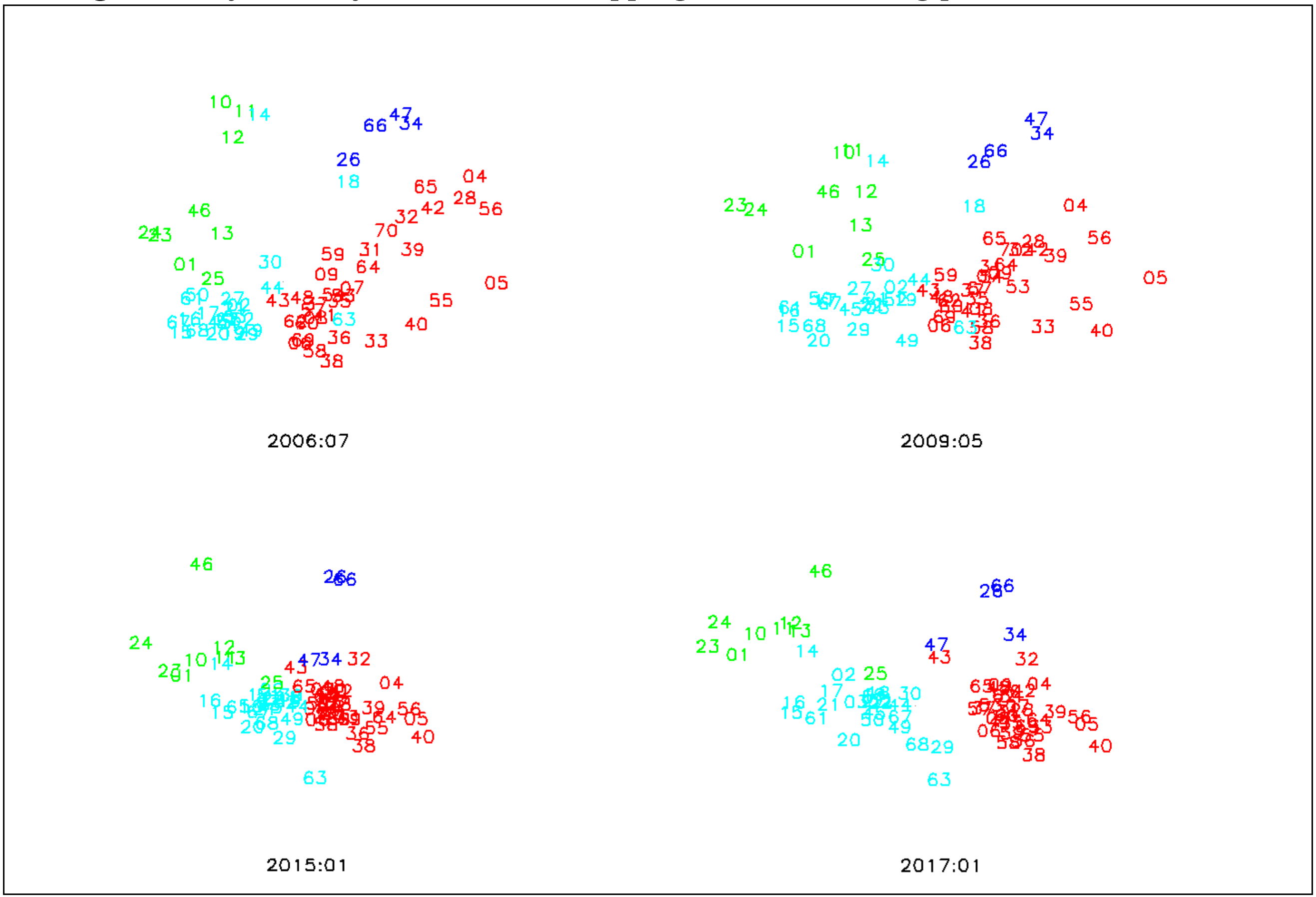
Note: The chart plots the interquantile range of the distribution of housing price inflation over time.

Figure 3. Housing price clustering patterns across major Chinese cities.



Note: The figure plots of this dendrogram are based on the synchronization between housing prices across 70 major cities in China.

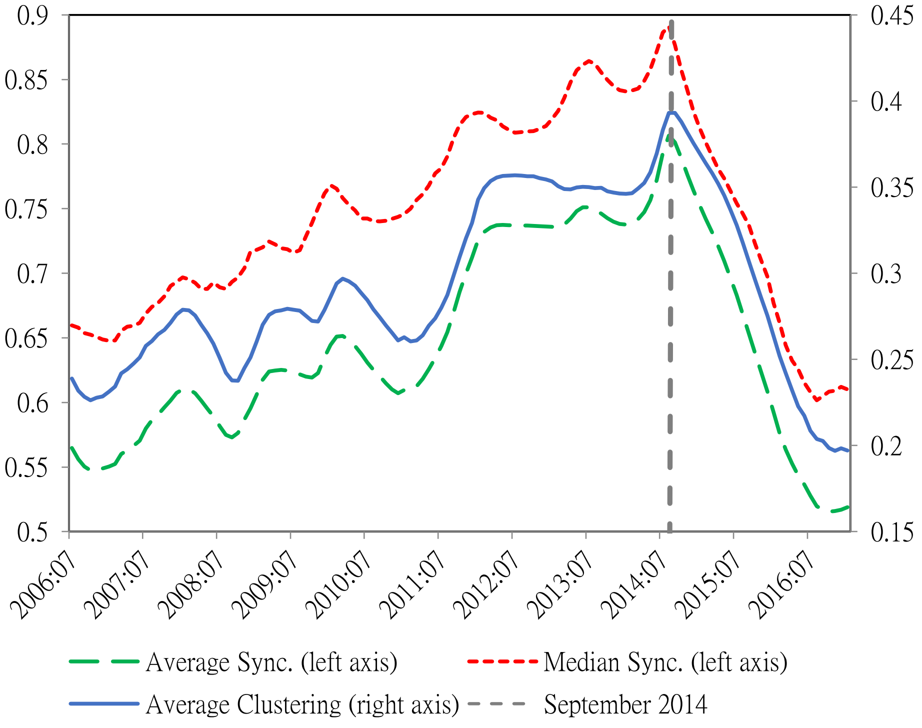
Figure 4. Dynamic synchronization mapping between housing prices of Chinese cities.



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

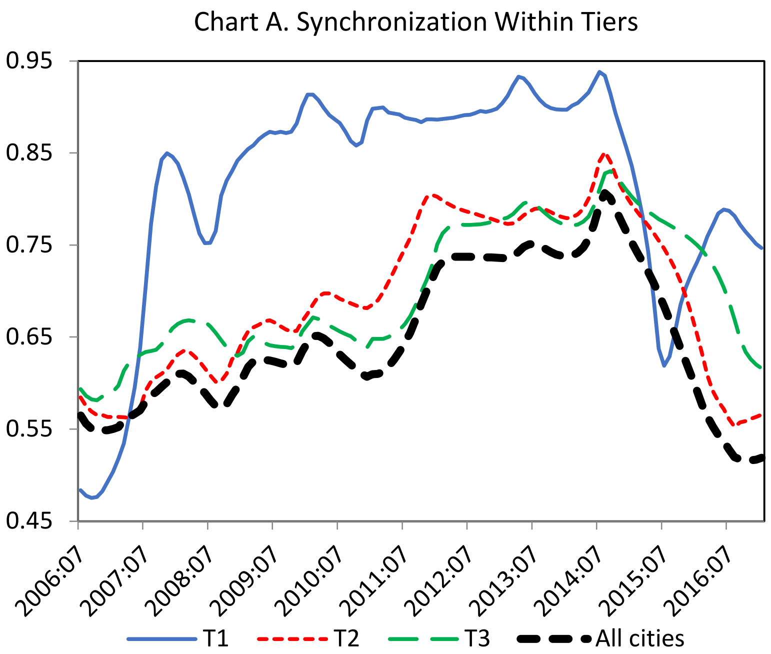
Notes: Each chart in the figure plots the multi-dimensional scaling map based on housing prices synchronization for the corresponding time period. Numbers are used to represent the 70 major Chinese cities. A full animated version of the synchronization mapping is available at https://sites.google.com/site/danileivaleon/china.

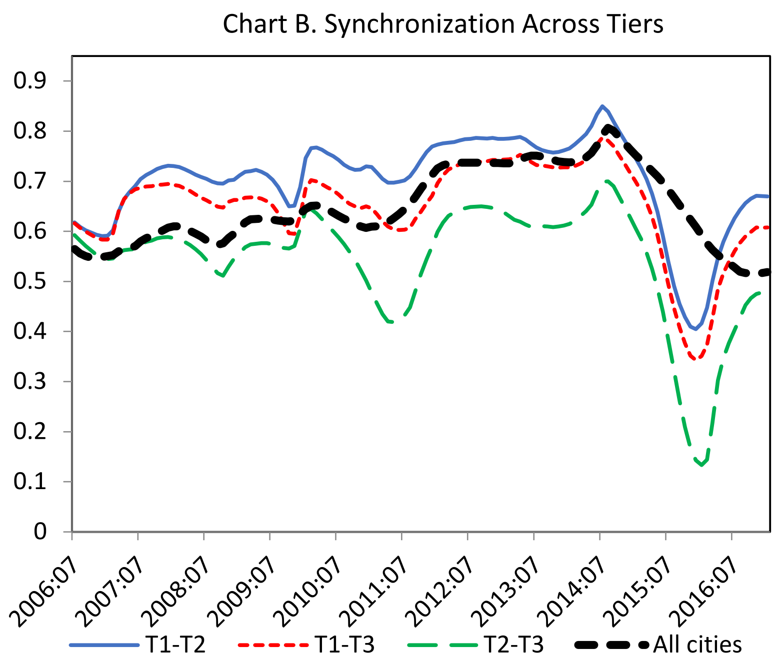
Figure 5. Aggregate synchronization of housing prices.



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

Figure 6. Aggregate synchronization of housing prices within and across tiers of cities.





Table

Table 1. Factors determining synchronization measure of property price changes among major cities in China (LTS)

Date Model	Jan-2017 Full	Jan-2017 Reduced	Jan-2016 Full	Jan-2016 Reduced	Jan-2015 Full	Jan-2015 Reduced
Constant	0.615 ***	0.718 ***	0.680 ***	0.741 ***	0.848 ***	0.858 ***
	(24.982)	(35.801)	(30.928)	(43.356)	(92.213)	(114.966)
$\|HH_i\text{-}HH_j\|$	-0.016 ***	-0.008	-0.023 ***	0.005	-0.003 *	-0.004 **
	(-2.864)	(-1.467)	(-4.614)	(1.111)	(-1.747)	(-2.366)
$\|RGDP_i\text{-}RGDP_j\|$	-0.012 **	0.005	-0.018 ***	-0.012 ***	-0.005 **	-0.005 ***
	(-2.062)	(1.072)	(-3.465)	(-2.807)	(-2.439)	(-2.781)
$\|PGDP_i\text{-}PGDP_j\|$	0.019 ***		0.015 ***		0.004 **	
	(3.049)		(2.741)		(2.090)	
$\|RCE_i\text{-}RCE_j\|$	0.003		0.009 ***		-0.003 *	
	(0.942)		(3.661)		(-1.834)	
$\|RFAI_i\text{-}RFAI_j\|$	-0.004 **	-0.008 ***	-0.004 **	-0.006 ***	0.000	-0.002 **
	(-2.298)	(-4.695)	(-2.511)	(-4.470)	(0.259)	(-2.509)
$\|UrLand_i\text{-}UrLand_j\|$	0.001		0.002		-0.002 ***	
	(0.734)		(1.300)		(-3.357)	
$\|FREV_i\text{-}FREV_j\|$	0.003		0.000		-0.002 ***	
	(1.439)		(-0.058)		(-3.514)	
$\|PM10_i\text{-}PM10_j\|$	-0.002 ***	-0.002 ***	-0.001 ***	-0.001 ***	0.000 **	-0.001 ***
	(-5.310)	(-7.984)	(-4.684)	(-3.894)	(-2.472)	(-7.868)
Observations	1,830	1,830	1,830	1,830	1,830	1,830
Included Observations	1,742	1,624	1,763	1,618	1,610	1,619
R-Squared	0.029	0.047	0.040	0.031	0.031	0.047
Adjusted R-Squared	0.024	0.045	0.035	0.028	0.026	0.045

Notes: The results are estimated by using the Least Trimmed Squares (LTS) method. ***, ** and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. *t*-statistics are given in parenthesis beneath the coefficient estimates. Adjusted R^2 estimates are provided in the row labelled “Adjusted R-Squared.” For the models determining synchronization measures in Jan-2016 and Jan-2017, $|PM10_i\text{-}PM10_j|$ is absolute value of the difference of the annual average of PM10 concentration (μg/m^3) in 2015, while other independent variables are the absolute value of the difference of compound annual growth rate between city *i* and city *j* during 2008–2015. For the models determining synchronization measures in Jan-2015, $|PM10_i\text{-}PM10_j|$ is the figure in 2014. The rest are based on the compound annual growth rate during 2008–2014.

Table 2. Factors (with dummies for tiers of cities) determining synchronization measure of property price changes among major cities in China (LTS method)

Date	Jan-2017	Jan-2016	Jan-2015
Constant	0.576 ***	0.650 ***	0.849 ***
	(26.334)	(43.542)	(116.040)
$\lvert HH_i\text{-}HH_j \rvert$	-5.941E-05	0.012 *	0.002
	(-0.005)	(1.711)	(0.620)
$\lvert RGDP_i\text{-}RGDP_j \rvert$	-0.001	0.011	-0.005
	(-0.101)	(1.430)	(-1.288)
$\lvert RFAI_i\text{-}RFAI_j \rvert$	0.001	0.003	0.000
	(0.201)	(1.062)	(0.139)
$\lvert PM10_i\text{-}PM10_j \rvert$	0.001	0.001 *	-2.209E-04
	(1.330)	(1.853)	(-0.998)
Tier 1 multiplied by			
$\lvert HH_i\text{-}HH_j \rvert$	-0.070 **	-0.073 ***	0.014 **
	(-2.309)	(-5.688)	(2.022)
$\lvert RGDP_i\text{-}RGDP_j \rvert$	0.035 *	-0.065 ***	0.045 ***
	(1.832)	(-5.818)	(7.159)
$\lvert RFAI_i\text{-}RFAI_j \rvert$	-0.018 ***	-0.011 ***	-0.033 ***
	(-3.038)	(-3.179)	(-14.674)
$\lvert PM10_i\text{-}PM10_j \rvert$	-0.002 *	-0.006 ***	-0.003 ***
	(-1.705)	(-10.306)	(-9.371)
Tier 2 multiplied by			
$\lvert HH_i\text{-}HH_j \rvert$	-0.018	0.009	-0.005
	(-1.482)	(1.123)	(-1.374)
$\lvert RGDP_i\text{-}RGDP_j \rvert$	-0.006	-0.002	-0.003
	(-0.475)	(-0.178)	(-0.583)
$\lvert RFAI_i\text{-}RFAI_j \rvert$	0.004	0.002	0.000
	(1.024)	(0.897)	(-0.247)
$\lvert PM10_i\text{-}PM10_j \rvert$	-0.002 ***	-0.002 ***	-2.964E-04
	(-2.599)	(-3.897)	(-1.320)
Observations	1,830	1,830	1,830
Included Observations	1,755	1,630	1,607
R-Squared	0.048	0.422	0.405
Adjusted R-Squared	0.041	0.418	0.401

Notes: The results are estimated with the Least Trimmed Squares (LTS) method. ***, **, and * indicate significance at the 1 %, 5 % and 10 % levels, respectively. *t*-statistics are given in parenthesis beneath the coefficient estimates. Adjusted R^2 estimates are provided in the row labelled "Adjusted R-Squared." For models determining synchronization measures in Jan-2016 and Jan-2017, $\lvert PM10_i\text{-}PM10_j \rvert$ is absolute value of the difference of the annual average of PM10 concentration (μg/m^3) in 2015, while other independent variables are the absolute value of the difference of compound annual growth rate between city *i* and city *j* during 2008–2015. For models determining synchronization measures in Jan-2015, $\lvert PM10_i\text{-}PM10_j \rvert$ is the figure in 2014. The rest are based on the compound annual growth rate during 2008–2014.

Appendix

Appendix A. 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 legal councels and volumes 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 B. List of variables for determining housing price synchronization

Group	Variable	Description (Data Source)
Demography	$\|HH_i\text{-}HH_j\|$	Absolute value of the difference of compound annual growth rate of number of households between city *i* and city *j* (Source: China's National Bureau of Statistics)
Income	$\|RGDP_i\text{-}RGDP_j\|$	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)
Inflation	$\|PGDP_i\text{-}PGDP_j\|$	Absolute value of the difference of compound annual growth rate of GDP deflator between city *i* and city *j* (Source: Calculations based on real GDP growth and nominal GDP growth data from China's National Bureau of Statistics)
Domestic Real Activities	$\|RCE_i\text{-}RCE_j\|$	Absolute value of the difference of compound annual growth rate of real consumption expenditure per capita (urban household, deflated by provincial CPI) between city *i* and city *j* (Source: China's National Bureau of Statistics)
Domestic Real Activities	$\|RFAI_i\text{-}RFAI_j\|$	Absolute value of the difference of compound annual growth rate of real fixed asset investment (FAI) (deflated by provincial FAI price deflator) between city *i* and city *j* (Source: China's National Bureau of Statistics)
Land	$\|UrLand_i\text{-}UrLand_j\|$	Absolute value of the difference of compound annual growth rate of developed area of city construction between city *i* and city *j* (Source: China's National Bureau of Statistics)
Fiscal	$\|FREV_i\text{-}FREV_j\|$	Absolute value of the difference of compound annual growth rate of fiscal revenue between city *i* and city *j* (Source: China's National Bureau of Statistics)
Air quality	$\|PM10_i\text{-}PM10_j\|$	Absolute value of the difference of annual average of PM10 concentration (μg/m^3) (Source: China Statistical Yearbook)
Dummy	*Tier 1*	Dummy if one city in the pair is a Tier 1 city (Source: Tier classifications of cities are based on CBN, 2017)
Dummy	*Tier 2*	Dummy if one city in the pair is a Tier 2 city (Source: Tier classifications of cities are based on CBN, 2017)

Notes: For the models determining synchronization measures in Jan-2016 and Jan-2017, $|PM10_i\text{-}PM10_j|$ is the absolute value of the difference of the annual average of PM10 concentration (μg/m^3) in 2015, while other independent variables are the absolute value of the difference of compound annual growth rate between city *i* and city *j* during 2008–2015. For the models determining synchronization measures in Jan-2015, $|PM10_i\text{-}PM10_j|$ is the figure in 2014. Others are based on the compound annual growth rate during the period 2008–2014. There are 6 tiers in the CBN classification: Tier 1 to Tier 5, plus "New Tier 1," which lies between Tier 1 and Tier 2. In this paper, the definition of a Tier 1 city is same that used in the CBN classification. A Tier 2 city in this paper includes cities classed as "New Tier 1" or "Tier 2" in the CBN classification, while, Tier 3 covers all cities in CBN Tier 3 or below. Our sample contains no CBN Tier 5 cities.