(A)Synchronous Housing Markets of Global Cities

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Abstract

In this paper we examine house price synchronization in 15 global cities using real house price data from 1995:Q1-2020:Q2. We find that although there is evidence for bilateral positive phase synchronization, there is no evidence for an integrated global housing market for our sample of cities. Using a hierarchical clustering approach, we identify three clusters of cities with similar housing price cycles that are not solely determined by geographic proximity. We interpret this finding as suggestive of a rather segmented housing market for the global cities in our sample. Using a dynamic factor model with time-varying stochastic volatility we decompose a city's real housing price growth into a global component, a cluster-based component, and an idiosyncratic component. For most cities in our sample, the global component plays a minor role, whereas the cluster-based factor explains a large fraction of the observed variation in real house price growth with its contribution peaking during the Great Recession of 2007-09.

JEL Classifications: C38, E32, F36, F44, R30

Keywords: Global Housing Market, House Price Synchronization, Cluster Analysis, Dynamic Factor Model

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1 Introduction

The central role played by the housing market in the 2007-09 financial crisis spurred substantial interest in housing market dynamics and its implications for the macroeconomy. One feature of the housing market that has particularly drawn attention is intra- and inter-country synchronization of housing prices.[1] This research has been motivated by the observation that the housing market across many countries witnessed a rapid boom prior to 2008 and then experienced a sharp decline. The interest in synchronization has also been fueled by an increasingly globalized economy and greater financial sector openness especially in the advanced economies. The co-movement of housing prices is of interest to various stakeholders. For example, for investors looking for high yield opportunities and portfolio diversification, a high degree of synchronization in housing prices will reduce the diversification benefits of real estate assets in their portfolio. For policymakers, given the importance of housing price shocks as a leading indicator of financial sector instability, a high degree of synchronization would imply a greater susceptibility to external shocks. It will also require a careful assessment of the efficacy of macroeconomic prudential policies in taming housing price bubbles.[2]

There is large literature in recent years that has focused on examining housing market synchronization in terms of co-movement of housing prices across different countries. However, there is no consensus on the degree of synchronization. For example, several recent contributions have documented substantial and increasing level of house price synchronization across advanced economies (see, Otrok and Terrones (2005), Hirata et al. (2012), Katagiri (2018) and Kallberg et al. (2014)). In contrast, Miles (2017) and Tsai (2018) find a relative lack of such synchronization in international housing markets. Further, there is evidence that even within a country the housing market may not be fully integrated (see, Miles (2015) and Hernández-Murillo et al. (2017) for the U.S., Hiebert and Roma (2010) for Europe and the U.S., Klarl (2018) for Netherlands and Funke et al. (2018) for the U.K. housing market.).

It is reasonable to argue that global financial conditions and investor behavior is more likely to be prevalent in housing markets of major international cities that in turn drives the linkages observed in national housing markets. In fact, there has been great deal of media attention on the degree of integration in housing prices of the so called "Superstar Cities" or "Global Cities" that serve as hubs for global financial and trade linkages.[3]

[1] In our discussion we use housing market synchronization and house price synchronization interchangeably.

[2] There are various channels through which housing markets may synchronize across national borders. For instance if a group of countries share strong trade linkages and exhibit synchronization in real economic activity then it is reasonable to expect a high degree of synchronization in the housing market as well. Similarly, a higher degree of synchronization in interest rates across different countries may induce similar cycles in housing markets.

[3] Gyourko et al. (2013) use "Superstar Cities" term for major cities in the U.S. However, many business news platforms commonly use labels such as "global cities" or "superstar cities" to include major cities across the globe. For example, see

These cities also tend to have excellent physical and institutional infrastructure that can increase demand for housing in these cities. The Economist magazine provides an interactive guide on the housing prices of major international cities and offer regular commentary on the level of synchronization in some of the most desirable cities across the globe.[4] UBS Group provides a Global Real Estate Bubble Index where they track housing markets of 25 global cities.[5] This index is often used in the media to speculate on the formation of housing price bubbles in the globalized housing market.[6] One common theme in such discussions is the potential for housing price bubbles in these cities which is often attributed to an influx of funds from foreign investors seeking high yield investment opportunities. In many cases governments have imposed outright bans on foreign ownership of real estate or have used taxes to tame housing prices in their major cities. For example, in recent years Canada and Australia have used taxes and other restrictions to limit flow of funds from China in the housing market of their major cities such as Vancouver and Sydney.[7]

Although the housing market in the global cities have drawn attention worldwide through media specializing in business news, the academic literature on the evolution and synchronization is relatively scarce because of limited availability of time-series data.There are two exceptions: International Monetary Fund (2018) and Katagiri (2018). According to the 2018 Global Financial Stability Report by International Monetary Fund (IMF) the increase in synchronization for the 2013-2017 period is more pronounced across major cities than across countries, especially in the case of advanced economies International Monetary Fund (2018). Katagiri (2018) focuses on city-level variations within the economy. Both of these studies are constrained by a short sample period that was particularly affected by the after effects of the housing bust that took place during the financial crisis.[8] Our paper attempts to bridge this gap in the literature by using quarterly data from 1995:Q1 through 2020:Q2 on 15 global cities.[9] This paper seeks to answer the following research questions. First, are housing markets in major international cities highly integrated, or do we find evidence for a "cluster" of cities that share housing price dynamics? Answers to this question will inform us whether an integrated global housing market is a correct characterization. Following the literature on business cycles,

https://www.mckinsey.com/featured-insights/innovation-and-growth/superstars-the-dynamics-of-firms-sectors-and-cities-leading-the-global-economy.

4See, https://www.economist.com/graphic-detail/2016/03/31/global-house-prices. The discussion on global city housing price can be found at: https://www.economist.com/graphic-detail/2019/03/11/global-cities-house-price-index

5For details on this index see https://www.ubs.com/global/en/wealth-management/chief-investment-office/life-goals/real-estate/2020/global-real-estate-bubble-index.html.

6A recent example can be found at: https://www.cnbc.com/2020/09/30/these-cities-are-at-risk-of-a-housing-bubble-as-home-prices-inflate-worldwide.html

7https://www.wsj.com/articles/western-cities-want-to-slow-flood-of-chinese-home-buying-nothing-works-1528294587

8Our methodology also allows for endogenous treatment of clusters and more general treatment of time-varying volatility. See details in Section 4.

9Our sample of cities include Amsterdam, Chicago, Copenhagen, Hong Kong, London, New York City, Oslo, Paris, San Francisco, Singapore, Stockholm, Sydney, Tokyo, Toronto, and Vancouver.

we compute a pairwise phase synchronization measure that captures whether the housing price expansions (contractions) of two cities are synchronized. To provide suggestive evidence on how similar housing price dynamics of cities in our sample are, we employ a hierarchical cluster approach to identify the clusters of cities that exhibit similar house price dynamics. An integrated housing market would imply that there is a large cluster that encompasses all cities whereas a segmented housing market would imply multiple clusters of cities with similar housing price dynamics. Our second research question pertains to the evolution of the synchronization of city-level house prices over time. We use a dynamic factor model with time-varying stochastic volatility to estimate the contribution of a global common factor affecting all cities in our sample, a cluster-level factor that only affects cities in a given cluster, and an idiosyncratic city-level factor. These clusters are determined by the hierarchical cluster approach and our model allows us to estimate time varying contributions of these factors.

There are several findings of interest. First, we find evidence for significant pairwise synchronization in our sample of cities with several city-pairs likely to be in the same phase of the housing price cycle at the same time.[10] We also find that this finding is true for several city-pairs located in different continents. For example, Toronto is significantly synchronized with many cities in Europe and Sydney is positively synchronized with San Francisco. These findings indicate that geography is not the primary reason for housing price synchronization for city-pairs in our sample. Second, our cluster analysis reveals a rather segmented global housing market with three unique clusters of cities.The first cluster has Vancouver and three Asian cities: Hong Kong, Singapore and Tokyo. The second cluster has 4 cities: Amsterdam, Chicago, New York City and Oslo. The third cluster has seven cities: Copenhagen, London, Paris, San Francisco, Stockholm, Sydney and Toronto. Again, we find that geography does not seem to be the only factor driving synchronization in house price cycles in our sample.[11] The results from our dynamic factor model indicate that the global factor does not contribute significantly to housing price real growth for most cities in our sample. In contrast for many cities the cluster factor seems to play an important role with its contribution peaking during the Great Recession of 2008-09. Higher degree of synchronization of the cities within their respective clusters during the financial crisis seem to suggest state-dependence in housing price synchronization.[12]

The remainder of the paper is organized as follows: Section 2 discusses the data used in the paper;

[10] Phase implies expansion and contraction of housing market in this study.

[11] Note that there is some evidence that geography may not be the primary factor driving housing price cycles for the U.S. For example, Hernández-Murillo et al. (2017) found that different clusters of cities do not necessarily share geographic similarity and exhibit their own idiosyncratic volatility.

[12] Hale (2012) documents state-dependence for banking networks with a decline in the number of bank relationships in the global banking network during episodes of recessions in the U.S. For the housing market. Claessens et al. (2010, 2012) document that housing price cycles are highly synchronized and the degree of co-movement is higher during periods of synchronized recessions.

Section 3 details the model specification for synchronization and cluster analysis; Section 4 provides a model framework for a dynamic factor model with stochastic volatility and its results; Section 5 discusses the empirical results and policy implications ; and Section 6 provides a conclusion.

2 Data

The main variable of interest is the real housing price index. Our sample composition is primarily driven by our objective to include as many large international cities as allowed by the availability of reasonably long quarterly time series. Our final sample consists of quarterly data from 1995Q1 through 2020Q2 and covers 15 cities spanning North America, Europe, Asia, and Australia. We include the following six cities from Europe: Amsterdam, Copenhagen, London, Paris, Oslo, and Stockholm. Five North American cities include Chicago, New York City (NYC), San Francisco, Toronto, and Vancouver. Finally, we include three cities from Asia (Hong Kong, Singapore, and Tokyo) and Sydney from Australia.[13] The data is sourced from national statistical agencies, Bank of International Settlements, and FRED database maintained by the Federal Reserve Bank of St. Louis. Table A.1 in the appendix A provides a detailed description of the housing price index for each city in our sample.

Our main variable of interest is the annualized growth rate of real housing price index of city i at time t:

$$y_{it} = \left[\left(\frac{RHPI_{it}}{RHPI_{it-1}} \right)^4 - 1 \right] \cdot 100 \tag{1}$$

where $RHPI_{it}$ denotes real housing price index of city i at time t.[14]

Table 1 provides descriptive statistics for real housing price growth for each city in our sample. Over our sample period Copenhagen experienced highest average growth in real housing prices followed by Paris. Tokyo experienced negative growth. Further, average housing price growth seems to be much higher in Europe when compared to cities in North America, Asia, and Australia. We also provide data on peak and trough in housing growth for each city. One interesting finding is that for many cities in our sample the trough seems to center around the Great Recession spanning 2007 and 2009. In contrast, there is no synchronization in the peak across these cities. The higher synchronization in trough date is suggestive of state-dependence in the relationship between housing price growth across cities in our sample. This finding is consistent with

[13] Singapore is a city-state and Hong Kong is a metropolitan area that is officially a special administrative region of the People's Republic of China.

[14] To compute real housing price index of a city we deflate the nominal index by city or metropolitan area level consumer price index where available. For Amsterdam, Copenhagen, London, Paris, Oslo, and Stockholm we use national consumer price index data as the city level data was not available for these cities in our sample.

the literature on banking networks where number of connections decrease during recessions(Hale, 2012) and greater degree of synchronized housing price cycles during downturns (Claessens et al., 2010, 2012).

3 Synchronization in Housing Prices

In this section we present the econometric methodology used to measure synchronization in housing price dynamics of 15 cities in our sample. We use the framework of Mink et al. (2012) for business cycle synchronization based on whether positive (negative) output gaps coincide across nations. This approach has been used for national house price synchronization (Miles, 2017) and credit cycle synchronization(Meller and Metiu, 2017). The discussion in this section closely follows the regression-based framework used in Meller and Metiu (2017) to measure and test for the presence of phase synchronization between housing cycles of pairs of cities in our sample.

3.1 Phase synchronization between city-pairs

One of the recurrent issues in the synchronization literature is how to transform the variable of interest: should it be the growth rate of the variable or a trend-cycle decomposition based cycle. In order to avoid the complications associated with model based cycles, we use a model free approach and use annualized growth rate of housing prices from equation (1). This approach is also consistent with the existing work in the literature. See for example, Hirata et al. (2012) and Kose et al. (2003), among others. We create a binary variable to identify whether a city is experiencing positive or negative housing price growth as follows:

$$D_{it} = \frac{y_{it}}{|y_{it}|} = \begin{cases} 1 & \text{if housing price growth is positive} \\ -1 & \text{if housing price growth is negative} \end{cases} \tag{2}$$

We interpret D_{it} as a measure of the housing market phase that the city i is experiencing at t. Based on this we define a measure of pairwise phase synchronization, denoted by $PS_{i,j,t}$ between two cities i and j, as follows:

$$PS_{i,j,t} = D_{it} \cdot D_{jt} = \begin{cases} 1 & \text{if cities } i \text{ and } j \text{ are in the same phase at time } t \\ -1 & \text{if cities } i \text{ and } j \text{ are not in the same phase at time } t \end{cases} \tag{3}$$

An alternative way to measure synchronicity would have been to look at the Pearson's correlation coefficient between housing price growth of pairs of cities. This approach does not require transforming our continuous data into a binary variable which as noted in this comment amounts to losing information. However, for our purpose we believe that such a measure is not suitable for the following reason. Depending on their respective standard deviations, two time series can have a low correlation and yet experience a high degree of phase synchronization in the following sense: they enter periods of expansions or contractions in their housing markets roughly at the same time. In this paper we want to measure synchronization between different phases of house price cycles in our sample of cities. The binary transformation we implement in equations (2) and (3) is a more appropriate measure for this purpose.[15]

Following Meller and Metiu (2017) we use the over time average of the above measure to test for phase synchronization between each pair of cities in our sample. Formally, let $\omega_{ij} = E(PS_{ijt})$ denote the unconditional mean of phase synchronization between cities i and j. Then our null hypothesis is given by:

$$H_0 : \omega_{ij} \leq 0 \rightarrow \text{ no synchronization or negative synchronization} \tag{4}$$

The right-tailed alternative hypothesis is given by:

$$H_A : \omega_{ij} > 0 \rightarrow \text{ positive synchronization} \tag{5}$$

In order to implement the above test, we estimate the following linear regression model using OLS and adjust standard errors for possible serial correlation:

$$PS_{ijt} = \omega_{ij} + \nu_{ijt} \tag{6}$$

Table 2 presents the results of pairwise phase synchronization for 15 cities in our sample. We find that for several city-pairs there is evidence for positive phase synchronization that is both statistically significant and economically meaningful. First, in our sample, only the US and Canada have more than one city and in both cases we find strong evidence for positive phase synchronization for city-pairs in each country. The two largest values for phase synchronization occur between pairs of cities in the U.S.: Chicago-NYC (0.703) and NYC-San Francisco (0.625). For Chicago-San Francisco the measure is 0.446. For all three city-pairs the

[15] Note that our approach is similar to the measure of business cycle coherence based on a binary transformation proposed by Harding and Pagan (2006). Similar methodology has been adopted to study international synchronization in business cycles, credit-GDP gaps, and credit gaps (see Mink et al. (2012), B. et al. (2016), and Meller and Metiu (2017)).

measure of phase synchronization is statistically significant as well. These results suggest that the existence of a national U.S. housing market is reasonable. However, the synchronization between Toronto and Vancouver is small and not statistically significant. The results presented in Table 2 show a clear evidence for a geographically segmented regional housing market. For example, San Francisco shares strong and significant positive phase synchronization with European cities such as Amsterdam (0.287), Copenhagen (0.525), and London (0.347). Indeed San Francisco is more strongly synchronized with Copenhagen than Chicago. Similarly, both Chicago and NYC share strong and statistically significant phase synchronization with several European cities. Similarly, Vancouver is not synchronized with its North American counterparts but shares strong and statistically significant phase synchronization with Tokyo. Toronto is significantly synchronized with Sydney and Hong Kong, along with several European cities in our sample. The heterogeneity in the pairwise synchronization is consistent with the findings in Hoesli (2020). With the exception of strong links among the majority of cities in Europe these pairwise synchronization estimates seem to suggest that geography is not the dominant factor underlying observed phase synchronization in housing cycles in our sample of international cities.

3.2 A cluster analysis of phase synchronization

The results from Table 2 indicate that many city pairs in our sample exhibit positive phase synchronization. However, this finding cannot address whether these cities can be characterized by a highly integrated global housing market. To this end, in this section we use cluster analysis to identify various clusters in our sample. If the housing market in these global cities is highly integrated, we should expect a large cluster encompassing all cities in our sample. In contrast, if the housing market is segmented we should expect small clusters of cities experiencing similar phase of house price cycles at the same time. Use of cluster analysis is appropriate here as we seek to partition our data into distinct groups so that the cities within each group experience very similar housing price growth cycles whereas cities in different groups have very dissimilar cycles.[16] We use the hierarchical clustering approach that does not require us to pre-specify the number of clusters expected in the data. However, we do need to provide input on two important elements. First, what is a measure of dissimilarity between a pair of observations in the data? Second, what is a measure of linkage that captures distance between pair of groups of observations?

We compute a dissimilarity index given by $DS_{ij} = 1 - \omega_{ij}$ between housing growth of a city pair ij. Note that this index can take values between 0 indicating perfect positive synchronization and 2 indicating perfect

[16] Meller and Metiu (2017) apply similar approach to credit cycles for 14 advanced economies.

negative synchronization. Further, a value of 1 indicates no synchronization between the two pairs of cities. We use the furthest-neighbor algorithm or complete linkage to extend this measure of dissimilarity between two city pairs to distance between two clusters of cities. Under this scheme, the dissimilarity between two groups of observations is defined to be the maximum distance between any two elements from the two groups.

The hierarchical clustering algorithm starts by treating each city in our sample as its own cluster leading to N clusters in the first step. Thereafter, the algorithm proceeds iteratively by grouping cities that are least dissimilar into the same cluster. The resulting output is a tree-like structure known as a dendrogram where each "leaf" represents one of the cities and each "branch" of leaves represent a cluster of cities that exhibit positive synchronization in their housing price growth and in this sense are similar to each other. These branches themselves can combine with other leaves or branches to form a large branch or cluster. Note that clusters that are formed earlier have more similar groups of observations than those that occur higher up in the tree. In this sense the vertical height of the dendrogram measures how distant two observations are and by cutting the dendrogram at a given height, we can identify number clusters in our data by considering clusters that are formed beneath this threshold. In this sense, the number of clusters identified in this process is dependent on the cut-off point with a lower value yielding larger number of clusters than a higher value. In the extreme, for a very low cut-off point, we will have as many clusters as the number of cities in our sample. In a way the notion of how many clusters to have in cluster analysis is related to the idea of overfitting in a regression model. Instead of relying on a purely descriptive approach of selecting this cut-off value, we use a threshold value of $DS_{ij} = 1$ that indicates no synchronization and hence provide a natural cut-off point for the clustering algorithm.[17]

Figure 2 presents the dendrogram for groups of cities that are clustered based on their level of housing price similarity. There are three clusters identified by: Hong Kong, Singapore, Tokyo and Vancouver (Cluster 1); Amsterdam, Chicago, NYC, and Oslo (Cluster 2); Copenhagen, London, Paris, Sydney, San Francisco, Stockholm, and Toronto (Cluster 3).[18]Two main findings emerge from this analysis. First, using our threshold value represented by the dashed horizontal line in Figure 2, we do not find a global cluster that encompasses all cities in our sample. Second, we also do not find a regional cluster where only cities from the same geographic region cluster together. For instance, the Vancouver housing market is more similar to the housing market in Asian markets than its counterparts in North America. Similarly, San Francisco and

[17]A similar approach for identifying number of clusters is used by by Meller and Metieu (2017) where they investigated clusters in aggregate credit gaps between 14 developed nations.

[18]Note that these clusters are dependent on the cut-off value of 1 we used in our algorithm as a stopping rule. For instance, if we use a cut-off point of 0.7 then we will get four clusters with Cluster 2 splitting into two clusters containing Chicago and New York in one cluster, and Chicago and Oslo in another separate cluster.

Sydney exhibit positive synchronization with European cities.

The cities in the second cluster that includes Amsterdam, Chicago, NYC and Oslo do not fit in as naturally as the other two clusters. This suggests that Amsterdam, Chicago, Oslo, and NYC housing markets are combined into one cluster because they experience expansions (and contractions) more synchronously with each other than other cities in our sample. These findings provide further evidence for the main findings reported in Table 2 that for our sample cities there is evidence for more segmentation than what a global or a regional housing cycle would suggest.[19].

Our finding that there are clusters of cities that have significantly synchronized house price dynamics does not address the issue of time-variation in synchronization. Following Meller and Metiu (2017), we use the city-pair phase synchronization measure, $PS_{i,j,t}$ and compute a measure of degree of synchronization for a cluster at any given point. For each cluster identified above, we take the cross-sectional average of $PS_{i,j,t}$ for all pairs of cities belonging to that cluster in each quarter:

$$S_{ct} = \frac{1}{N_c \cdot (N_c - 1)/2} \sum_i \sum_{j>i} PS_{i,j,t} \tag{7}$$

where N_c is the number of cities in cluster c, $i = 1, 2, ..., N_c$ and $j = 1, 2, ..., N_c$. In Figure 3 we provide a plot of 5-year rolling average for this measure of cluster-level phase synchronization measure. We observe that there is substantial time variation in phase synchronization for each cluster. We also find that for cluster 2 and 3, there was a decline in the degree of phase synchronization in early 2000s followed by an increase whereas for cluster 1 the degree of synchronization increased in the early part of the sample followed by a secular decline. In the next section we formally address this time variation by specifying a dynamic factor model with time-varying stochastic volatility.

4 A Latent Factor Model with Time-varying Stochastic Volatility

Our results from the pairwise phase synchronization and cluster analysis suggest that the housing markets in our sample of cities cannot be characterized as an integrated global market. Instead we should think of a segmented market with clusters of cities that exhibit high degree of phase synchronization in their house price growth. In this section, we formally investigate the role of a global component and these clusters in explaining real housing price growth for our sample of cities. Importantly, we also allow the importance of these factors

[19] We also implemented a cluster analysis at the country level to investigate the degree of housing price growth synchronization at the national level. The results are presented in Figure A.1 of the appendix A. We find that housing markets at the city-level show a greater segmentation of the housing market than at the national level.

to vary over time. For this purpose, we adopt a multivariate latent factor model with time-varying stochastic volatility. A factor model decomposes the movements in variables to movements due to latent factors and idiosyncratic factors. The standard factor models do not attempt to model the dynamics of the volatility and usually assume that the variance-covariance matrix is constant. Empirical evidence suggests that multivariate factor stochastic volatility models are a promising approach for modeling multivariate time-varying volatility. In addition, standard factor models are usually characterized by zero restriction blocks usually associated with geography. Francis et al. (2017) show that even a small misspecification in block restrictions can lead to substantial declines in fit. They propose choosing factors based on endogenous clusters. Both of these features are incorporated in our dynamic factor model described below.

The multi-factor stochastic volatility model decomposes the variations in real house price growth into three components: the common factor, which applies to all cities, a cluster based factor and an idiosyncratic factor. Specifically, the model is given by

$$y_t = \Lambda \cdot f_t + \Sigma_t^{\frac{1}{2}} \varepsilon_t, \varepsilon_t \tilde{\ } N_m(0, I_m) \tag{8}$$

$$f_t = V_t^{\frac{1}{2}} u_t, u_t \tilde{\ } N_r(0, I_r) \tag{9}$$

where $\mathrm{y}_t = (y_{1t}, y_{2t}, ...y_{mt})'$ consists of m observed time series. Let f_t be a vector of r unobserved latent factors. $\Sigma_t = Diag(\exp(h_{1t}), ... \exp(h_{mt}))$, $V_t = Diag(\exp(h_{m+1,t}), ... \exp(h_{m+r,t}))$ and Λ is an unknown $m \times r$ matrix with elements Λ_{ij}. Our model has one global factor that accounts for the common movement across all cities and three cluster-based factors identified in Section 3.3 using the hierarchical clustering approach. Cluster 1 and 2 has four members each whereas Cluster 3 has 7 cities.[20] Therefore, in our model $r = 4$ and $m = 15$ giving us a 15×4 Λ matrix. The first column of this matrix has all the elements unrestricted, the second column represents the first cluster with the first four unrestricted entries corresponding to the member cities and the remaining nine entries are restricted to be zero. Similarly, the third column in matrix corresponds to the second cluster where the first four entries are restricted to be zero and the next four entries corresponding to the cities in the second cluster are unrestricted. The last column corresponds to the third cluster and hence, the last 7 entries are unrestricted.

In the static factor model, the observations are assumed to be driven by the latent factors and the

[20]In Section 3.3 we identified three clusters in our sample. : The first cluster has 4 cities: Hong Kong, Singapore, Tokyo and Vancouver. The second cluster also has 4 cities: Chicago, NYC, Amsterdam and Oslo. The third cluster has 7 cities: London, Paris, Sydney, Toronto, Copenhagen, San Francisco and Stockholm.

idiosyncratic innovations that are homoscedastic. In the case of the factor stochastic volatility model, however, both the idiosyncratic innovations as well as the latent factors are allowed to have time-varying variances, depending on $m + r$ latent volatilities. Following the broader literature on the factor models, we also assume that the shocks to the common and idiosyncratic components are orthogonal to each other. Both the latent factors and idiosyncratic factors are allowed to follow different stochastic volatility processes:

$$h_{it} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \sigma_i \eta_{it}, \eta_{it} \tilde{} N(0, 1) \tag{10}$$

Time variation in the factor volatility permits contributions of various factors to evolve dynamically. As a result, the variance decomposition of real house price growth (conditional on knowing Λ) is given by:

$$Var(y_{i,t}) = \Lambda^2 \cdot Var(f_t) + \Sigma_t \tag{11}$$

Due to its large scale, this model is typically estimated using a Bayesian Markov Chain Monte Carlo (MCMC) estimation algorithm. Bayesian MCMC estimation is a very efficient estimation method, however, it is associated with a considerable computational burden when the number of variables is moderate too large. To overcome this, Kastner et al. (2017) avoid the usual forward-filtering backward sampling algorithm by sampling "all without a loop", and consider various reparameterizations such as (partial) non-centering, and apply an ancillary-sufficiency interweaving strategy for boosting MCMC estimation at an univariate level, which can be applied directly to heteroscedasticity estimation for latent variables such as factors.[21] To make stochastic volatility draws, the model relies on the approximation method developed by Kim et al. (1998), which has been shown to perform well and widely used in the recent literature, see e.g., Stock and Watson (2007, 2016) and Primiceri (2005) Finally, since the means of factors are not separately identifiable, we follow the past literature and demean the series before the estimation.

4.1 Estimation Results from the Dynamic Factor Model

In this section we present the estimation results from our multi-factor stochastic volatility model outlined above. Table 3 reports the posterior mean of the estimated factor loadings.[22] We observe that with the exception of Vancouver, Paris, and Toronto the estimated common factor is small and negative in some cases suggesting that this component does not play a significant role in the real housing price growth of most

[21] For details on the estimation, the readers are referred to Kastner et al. (2017) and Hosszejni and Kastner (2020).

[22] Note that loadings for different factors are not reported when they are restricted to be zero in the model presented in the previous section. Further, we did not impose sign constraints on loading parameters in our estimation.

cities in our sample.[23] In contrast, for each of the three latent factors based on clusters, we find estimated factor loadings to be positive and reveal the importance of certain cities in driving the cluster house price dynamics. For example, the estimated loading parameter for the first cluster shows the dominant role of Singapore and Vancouver. The factor represented by the second cluster is dominated by Chicago and NYC effectively making it an American cluster. The other two European cities in the second cluster display little or almost no loading on the estimated latent factor. The third cluster is dominated by London, Stockholm, Sydney and San Francisco.

In Figure 4 we present the results of the variance decomposition analysis to investigate the relative importance of different factors in explaining the real house price growth, and how this role has evolved over time for each city in our sample. With the exception of Vancouver, Toronto and Paris, we find that the common factor has not played a dominant role in explaining the real house price growth for most cities over our sample period. This is especially true for the pre-2008 and the post-2010 sample period. This result is consistent with our cluster analysis and suggests that a global and highly integrated housing market is not an appropriate characterization for global cities. In contrast, we find that cluster-based factors have played an important role in housing price growth for many cities. For example, the first cluster based latent factor plays a significant role in the evolution of real house price growth in Singapore, Hong Kong and Tokyo. The second cluster based factor plays a significant role for Chicago and NYC. The third cluster based factor mainly dominates the house price growth variations in London, Sydney, San Francisco and Stockholm.

Our results also show that the role of the cluster-based factor has changed over time with a significant increase during the financial crisis of 2008-09 for most of the cities in the sample. The result that factors based on clusters account for a large portion of variation in real house price growth in most of the cities during the financial crisis is also consistent with the "tail" dependence" literature in the financial market. For example, Zhou and Gao (2012) and Hoesli and Reka (2013) find asymmetric correlation in local and international real estate markets during the financial crisis. Finally, for Amsterdam, Oslo, Paris, Toronto, Hong Kong and Tokyo, the idiosyncratic factor has dominated the overall variation in real house price growth with its share staying above 40 percent for the entire sample period. Based on this analysis we find that the cluster-based factor plays the most important role for Singapore, Chicago, NYC, London, San Francisco and Sydney. In terms of over time variation few other interesting patterns are worth noting. The role of the common factor in Vancouver's house price variations has increased over time after the financial crisis.

[23] We also conducted a principal component analysis and found that the first two principal components 43 percent of the overall variation in the housing price growth, with first component accounting for only 29 percent. These results are not included in the paper for brevity and are available upon request.

Although the role of idiosyncratic component has been large throughout the sample period for Toronto, we observe a secular increase in its role, implying that Toronto's housing market has been decoupling not only from the global market, but also from the cluster of housing markets that it belongs to based on our analysis. Finally, although most of the European cities are in the third cluster, this factor is most important for housing price growth dynamics in London, Stockholm and Copenhagen.

Our findings from the variance decomposition analysis are also reinforced by the evolution of different factors for these cities presented in Figure 5. We plot posterior means of the MCMC draws of the estimated factors. Three key results emerge from this plot: first, all the factors witnessed a decline during the financial crisis of 2008-09. Secondly, the length and the depth of the decline varies across different factors. The recovery in the first two clusters was much more rapid than the third cluster. Thirdly, variations in common factor are small compared to the other factors based on different clusters, especially, for the first and the second cluster. In terms of the overall size of variations, the estimated factor for the third cluster that has most of the European cities and the two cities from Canada, displays smaller variations than the other two cluster-based factors.

Figure 6 plots estimated stochastic volatility of the estimated factors. Consistent with the findings reported for the variance decomposition exercise, estimated stochastic volatility of the common factor shows smaller variation than the factors based on different clusters. Not surprisingly, the volatility measure peaks at the height of the financial crisis for all the factors. If we compare the evolution of the stochastic volatility across different factors, we observe a significant degree of heterogeneity. The estimated stochastic volatility shows another peak in the late 1990s for the factor based first cluster with mostly Asian cities. This is understandable as many Asian economies were experiencing the Asian Financial crisis during this period. The factor based on the second cluster, the variation of which is dominated by Chicago and NYC, exhibits consistent decline in the estimated volatility after the financial crisis of 2008-09.

To summarize this section, our findings from the dynamic factor model with time-varying stochastic volatility reinforces the results obtained in the previous section that the housing markets across the global cities are not highly integrated with each other. Moreover, we do not find any evidence of an increased degree of synchronization in the recent periods. Instead our findings suggest a much more segmented housing market for global cities with clusters of cities that share housing price dynamics. This is especially true for London, NYC, Singapore, and Sydney. Over all our findings imply substantial heterogeneity in the housing market dynamics across global cities.

5 Discussion

A few interesting questions arise against the backdrop of our findings from Sections 3 and 4. First, why do we find a lack of integration in housing markets of global cities? Second, what factors can explain the emergence of clusters of cities that are more integrated with members within the cluster? Finally, what implications can be derived for policy and investment from these two observations about the nature of housing price dynamics for global cities?

We believe that the lack of a global market that drives house price dynamics of major international cities is not surprising. Unlike financial markets with greater integration due to increasing financial sector openness and regulations encouraging such synchronization, the case of housing market is different due to persistent local affects that can influence prices as well as a regulatory environment that focuses more on local housing needs than synchronization with other global cities.[24] In recent years many major cities facing ballooning cost of home ownership have adopted policies that either ban foreign ownership outright or discourage it via taxation and other means. In fact, even within a country there is evidence that housing markets are not integrated.[25]

One may think that geographic proximity may play a role in explaining the segmentation of global cities housing markets into clusters with cities that have synchronized movements in housing prices. However, we find that cities from different continents are clustered together implying factors other than geography may be at play. For instance, there is anecdotal evidence that an influx of overseas funds may have played a big role in the housing markets of Vancouver and Hong Kong. Hence, a common source of capital flows can be a factor determining which markets are more synchronized. At present we are not aware of any study that systematically investigates factors that can affect the degree of synchronization for global cities and we believe this is an important research question for future research on this topic.[26]

Finally, Our findings have important implications for both policymakers as well as investors in international real estate. In response to the housing market crash that triggered the financial recession of 2008-09, many countries adopted macroprudential policies with the objective of reducing the systemic risk from rapid

[24] Using a very long-sample, Jorda et al. (2019) have found that since 1980, house prices have tended to be much less connected globally than equity markets.

[25] For example, Miles (2019, 2020) have shown that the housing market within the U.S. and the U.K. shows a significant degree of regionalization. Factors like population growth (Oikarinen et al., 2018), local variations in credit supply (Favara and Imbs (2015); Cerutti et al. (2017); Mian and Sufi (2019)) and heterogeneity in housing supply elasticity (Glaeser et al. (2008);Oikarinen et al. (2018); Paciorek (2013)) are also important determinants of house prices.

[26] Note that a relative lack of easily accessible data on economic activity at city-level makes it difficult to rigorously examine this issue. We believe a case-study approach with focused analysis of few cities in a cluster is perhaps a way forward to examine factors that help explain why housing price cycles of certain cities in a cluster are more integrated than with those outside their cluster.

buildup of housing prices. Most of these policies target domestic housing conditions and in principle may serve to reduce the degree of synchronization with foreign housing markets. Our finding that at the city-level, the housing market is much more segmented with clusters of cities suggests that it is important to account for such heterogeneity in the macroprudential framework. For instance, it is possible for macroprudential policies to be more effective at taming housing price growth in housing markets with lower degree of synchronicity with foreign housing markets (Alter et al., 2018). [27] In terms of impact on investment behavior, our finding of relative lack of synchronization in house prices of global cities has implications for benefits from portfolio diversification. Real estate has emerged as an important asset class for the global investor community. An increase in housing market integration may have benefits in terms of policy coordination, but it creates its own set of challenges for portfolio managers in diversifying their real estate portfolios. The results obtained in this paper suggest that portfolio diversification objectives can still be attained if we take into account different clusters. It should also be noted that in periods of crisis like the 2008-09 financial crisis, diversification objective is hard to achieve within the clusters given a high degree of synchronization in housing price growth in cities in each cluster.

6 Conclusion

Contrary to the common narrative about housing markets in global cities, the analysis of house price dynamics presented in this paper suggests that an integrated global housing market is not an appropriate characterization for housing markets of major international cities. Further, we do not find evidence for an increase in the degree of synchronization in housing price dynamics over time. Our findings seem to suggest a more segmented housing market with many city-pairs exhibiting significant phase synchronization and existence of city clusters that do not always align with geography. To understand the time-varying nature of the role of the global and the cluster-based factors we utilize a dynamic factor model with time-varying stochastic volatility. We find that the global factor does not play a significant role for most cities, cluster factors play a large role for many cities, and the contribution of this factor varies over time and is state-dependent with greater degree of synchronization within the cluster during the Great Recession of 2008-09.

[27] Similar finding was supported by Funke et al. (2018) who suggest that regionally differentiated macroprudential policy such as regional loan-to-value ratios perform best in reducing variance of housing prices in an environment with regionally segmented housing markets.

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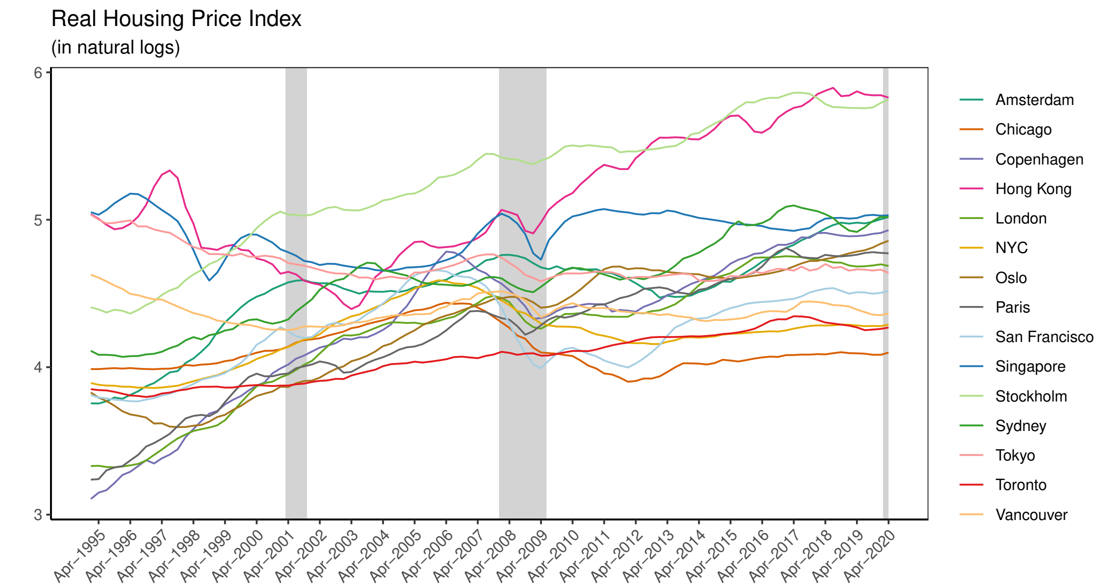

Figure 1: Real Housing Price Index (log scale)

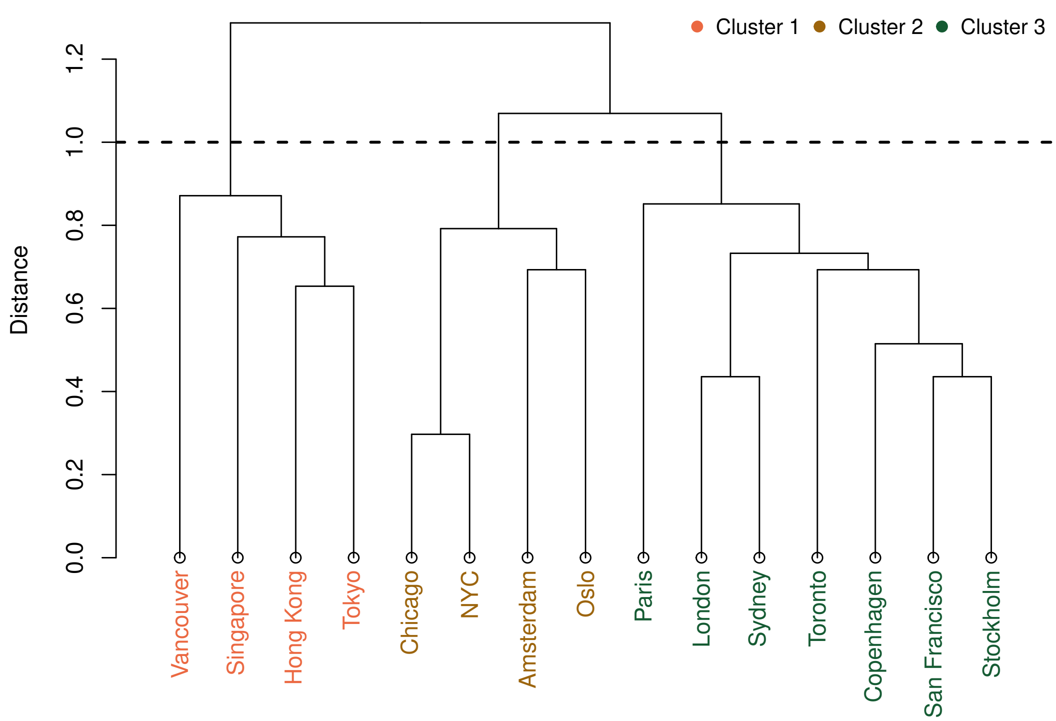

Figure 2: City-Clusters based on similarity of housing cycles

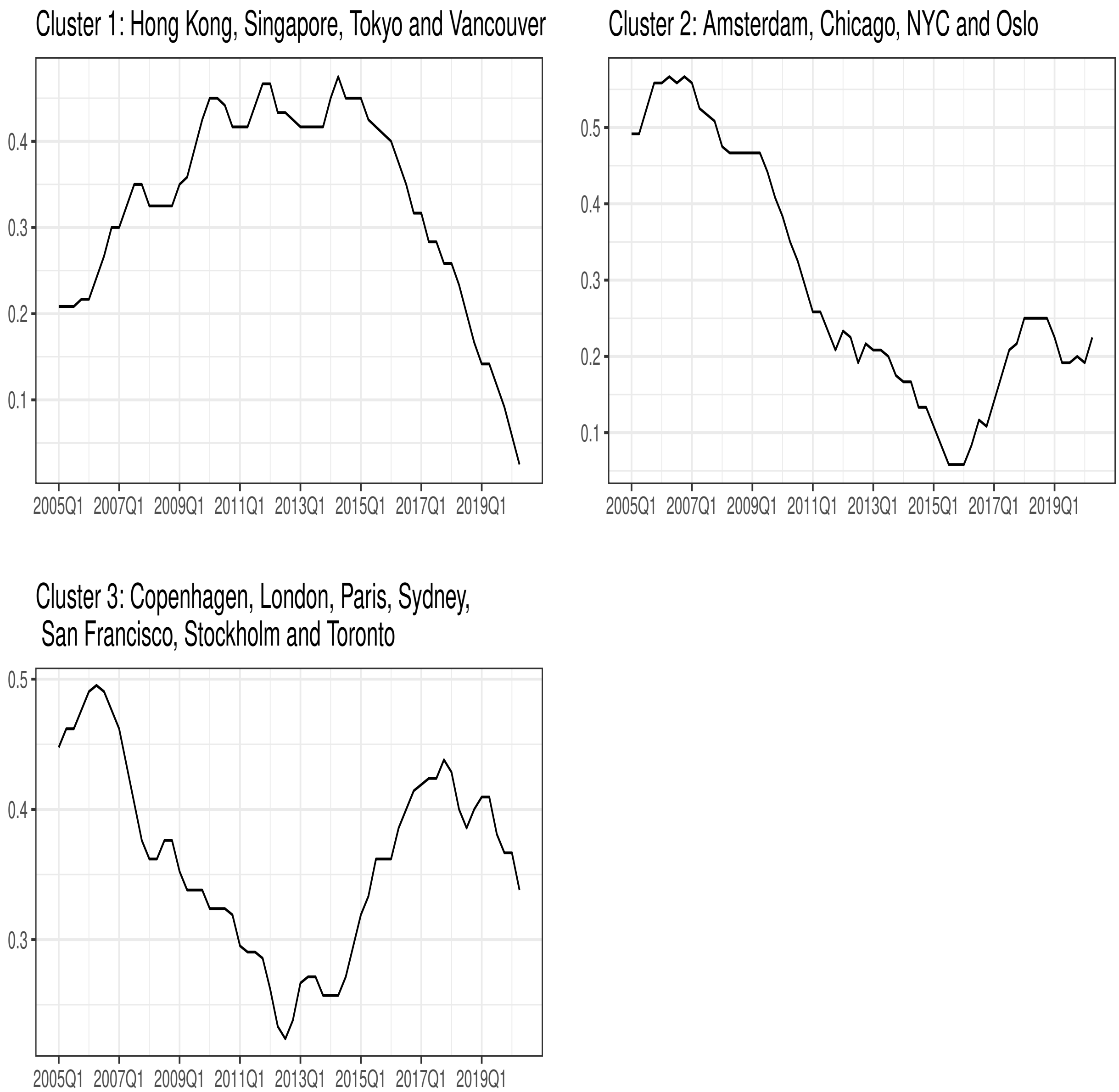

Figure 3: 10-year rolling average of cluster-level phase synchronization

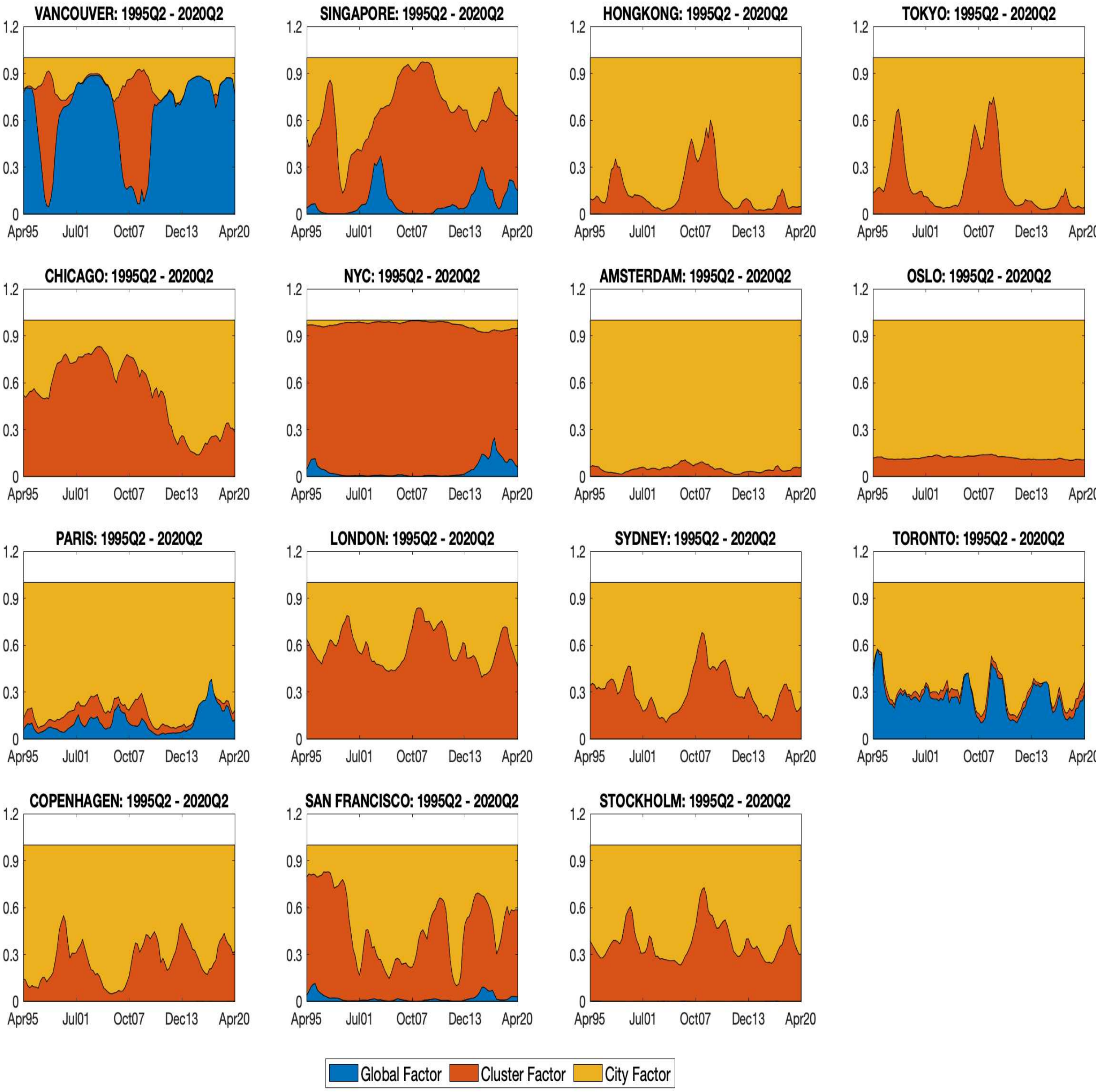

Figure 4: Variance Contribution by Factor

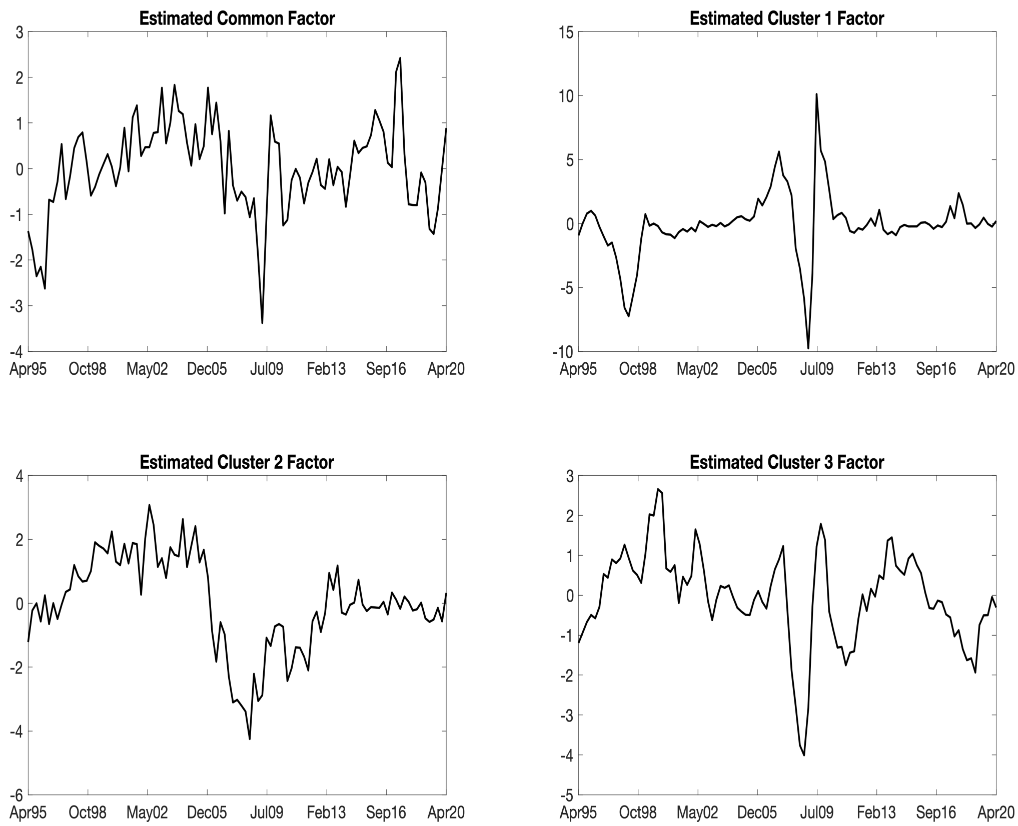

Figure 5: Estimated Common factor and three cluster-based factors

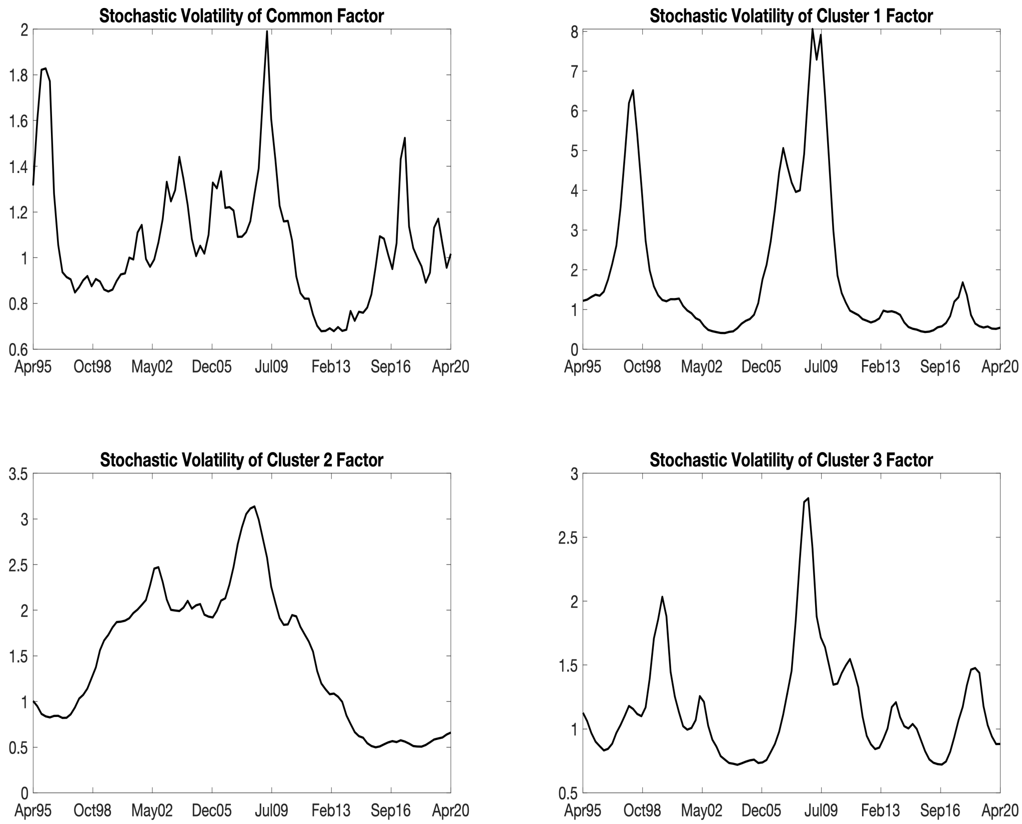

Figure 6: Estimated Stochastic Volatility by Factor

Table 1: Descriptive Statistics: 1995Q2-2020Q2

	N	Mean	S.D.	Max	Min	Peak	Trough
Amsterdam	101	5.58	9.83	38.80	-17.56	1999 Q1	2013 Q1
Chicago	101	0.68	6.77	13.84	-21.65	2013 Q3	2009 Q1
Copenhagen	101	8.30	13.10	40.78	-28.88	2005 Q3	2009 Q1
Hong Kong	101	5.20	20.06	64.38	-54.65	1997 Q1	1998 Q1
London	101	5.95	9.51	27.28	-23.13	1999 Q4	2008 Q3
NYC	101	1.80	6.74	17.56	-14.73	2002 Q3	2008 Q3
Paris	101	6.76	10.18	30.14	-20.72	1999 Q2	2008 Q4
Oslo	101	4.46	7.88	20.69	-15.02	2010 Q4	1997 Q1
San Francisco	101	3.73	13.10	33.42	-35.25	2000 Q2	2008 Q2
Singapore	101	1.16	16.12	69.21	-40.53	2009 Q3	2009 Q1
Stockholm	101	6.12	9.09	27.38	-14.51	2000 Q2	2018 Q2
Sydney	101	4.17	10.43	32.80	-17.34	2015 Q2	2018 Q4
Tokyo	101	-1.30	6.97	18.11	-17.18	2005 Q2	2008 Q4
Toronto	101	1.74	3.88	11.60	-7.23	2016 Q3	2019 Q3
Vancouver	101	-0.81	6.80	17.79	-21.30	2017 Q3	2009 Q1

i) We report descriptive statistics for annualized growth in real housing price index.

ii) Peak is defined as the maximum growth rate and Trough is defined as the minimum growth rate over the sample period.

Table 2: Average pairwise phase synchronization ($\widehat{\omega_{ij}}$)

	Amsterdam	Chicago	Copenhagen	Hong Kong	London	NYC	Paris	Oslo	San Francisco	Singapore	Stockholm	Sydney	Tokyo	Toronto
Chicago	0.248**													
	(0.097)													
Copenhagen	0.287*	0.366**												
	(0.152)	(0.185)												
Hong Kong	0.069	-0.168*	0.03											
	(0.113)	(0.087)	(0.130)											
London	0.267**	0.188	0.465***	0.01										
	(0.121)	(0.159)	(0.134)	(0.148)										
NYC	0.307**	0.703***	0.426***	-0.188*	0.248									
	(0.137)	(0.086)	(0.161)	(0.105)	(0.163)									
Paris	0.168	0.089	0.446***	0.188*	0.386***	0.03								
	(0.146)	(0.190)	(0.091)	(0.104)	(0.103)	(0.197)								
Oslo	0.307***	0.228	0.228	0.089	0.168	0.208	0.228*							
	(0.113)	(0.196)	(0.164)	(0.201)	(0.202)	(0.250)	(0.132)							
San Francisco	0.287*	0.446***	0.525***	0.109	0.347**	0.624***	0.168	0.267						
	(0.160)	(0.087)	(0.091)	(0.144)	(0.141)	(0.085)	(0.116)	(0.173)						
Singapore	0.168	-0.109	-0.109	0.228	-0.208	-0.248***	-0.109	0.188	-0.188					
	(0.179)	(0.088)	(0.124)	(0.145)	(0.201)	(0.090)	(0.147)	(0.168)	(0.116)					
Stockholm	0.366***	0.287***	0.485***	0.109	0.505***	0.386***	0.287***	0.149	0.564***	-0.069				
	(0.089)	(0.078)	(0.070)	(0.142)	(0.055)	(0.099)	(0.106)	(0.208)	(0.111)	(0.200)				
Sydney	0.188	0.069	0.307**	-0.03	0.564***	0.208*	0.149	-0.069	0.267*	-0.287**	0.347*			
	(0.143)	(0.134)	(0.125)	(0.118)	(0.109)	(0.123)	(0.149)	(0.130)	(0.146)	(0.136)	(0.187)			
Tokyo	0.129	0.01	-0.03	0.347***	0.03	-0.168	-0.069	-0.01	0.05	0.327**	0.089	-0.168		
	(0.185)	(0.197)	(0.171)	(0.069)	(0.224)	(0.154)	(0.146)	(0.167)	(0.171)	(0.135)	(0.191)	(0.175)		
Toronto	0.109	0.228	0.307**	0.01	0.406***	0.287*	0.307***	0.287*	0.386***	-0.248	0.386***	0.287*	-0.089	
	(0.098)	(0.146)	(0.121)	(0.124)	(0.073)	(0.169)	(0.110)	(0.151)	(0.095)	(0.174)	(0.094)	(0.161)	(0.162)	
Vancouver	-0.089	0.109	-0.089	0.129	-0.03	0.129	-0.168	0.168	0.03	0.149	0.03	-0.069	0.267***	0.208
	(0.186)	(0.130)	(0.180)	(0.103)	(0.228)	(0.142)	(0.167)	(0.141)	(0.152)	(0.146)	(0.197)	(0.113)	(0.096)	(0.152)

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Newey-West standard errors are provided in the brackets.

Table 3: Posterior Mean of Estimated Factor Loadings

City	Common	Cluster 1	Cluster 2	Cluster 3
Singapore	-0.136	0.370		
Tokyo	0.015	0.240		
Vancouver	0.777	0.262		
Hong Kong	-0.026	0.159		
Amsterdam	0.020		0.009	
Chicago	0.005		0.433	
NYC	0.154		0.502	
Oslo	-0.001		0.001	
London	0.001			0.638
Stockholm	0.015			0.518
Sydney	-0.000			0.436
Copenhagen	0.002			0.278
Paris	0.235			0.002
San Francisco	0.051			0.383
Toronto	0.547			0.001

A Appendix

Table A.1: Data source for city-level housing price index

City	Data Source
Amsterdam	StatLine by Statistics Netherlands
Chicago	S&P/Case-Shiller Home Price Index from FRED
Copenhagen	BIS Detailed Residential Property Price Statistics
Hong Kong	BIS Detailed Residential Property Price Statistics
London	HM land registry
New York City	S&P/Case-Shiller Home Price Index from FRED
Oslo	BIS Detailed Residential Property Price Statistics
Paris	BIS Detailed Residential Property Price Statistics
San Francisco	S&P/Case-Shiller Home Price Index from FRED
Singapore	Singapore Department of Statistics
Stockholm	Statistics Sweden
Sydney	BIS Detailed Residential Property Price Statistics
Tokyo	BIS Detailed Residential Property Price Statistics
Toronto	Statistics Canada
Vancouver	Statistics Canada

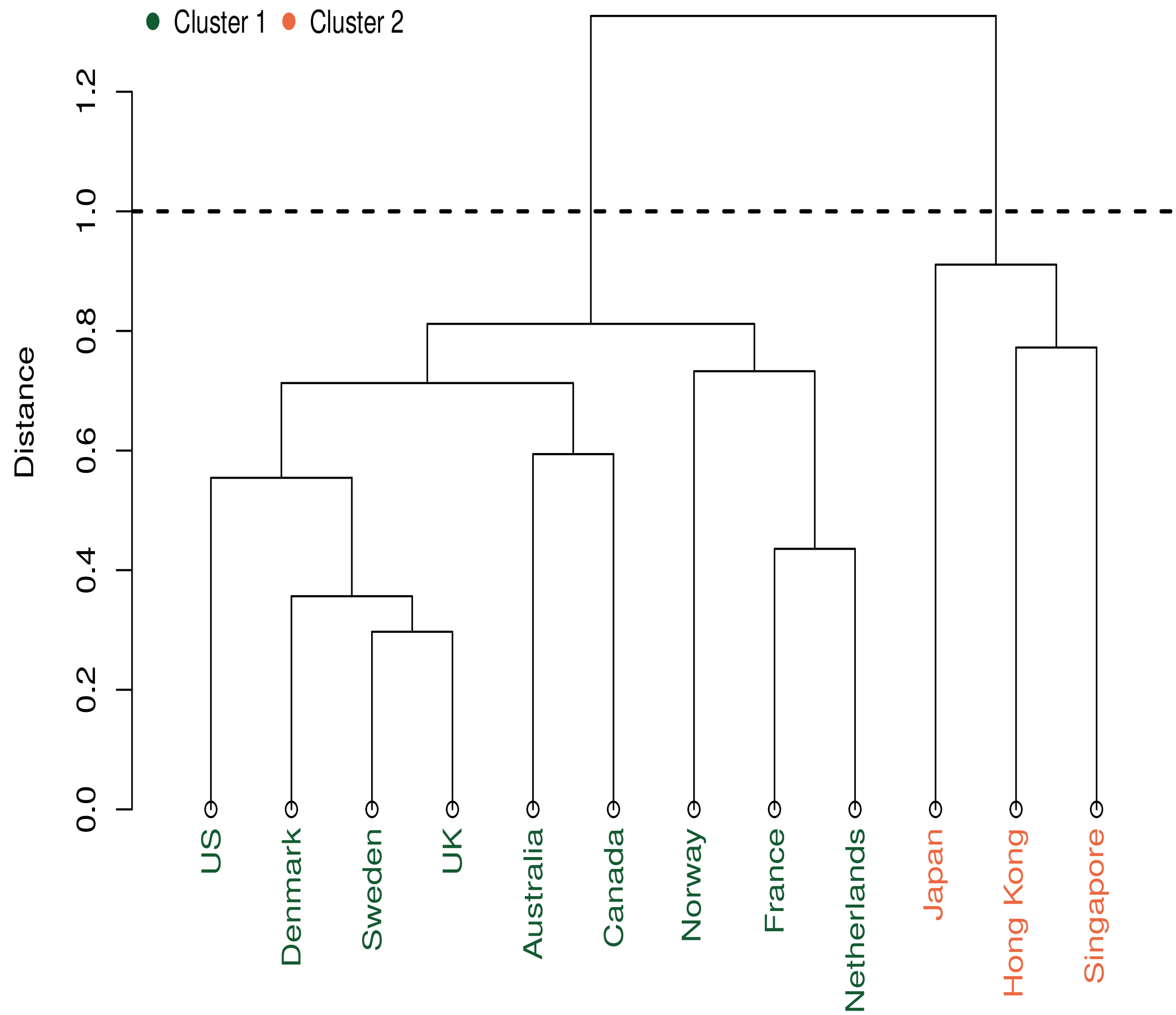

Figure A.1: Country-Clusters based on similarity of housing cycles