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Revisiting the determinants of house prices in China's megacities: cross-sectional heterogeneity, interdependencies and spillovers*

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Abstract

We revisit the determinants of house prices in China's megacities. Previous work on similar topics fails to account for the widespread cross-sectional heterogeneity and interdependencies, despite the importance of them. Using a PVAR estimated by the Bayesian method allowing for these features, we find each city is rather unique, especially on the extent to which local house prices are disturbed by external house price shocks. The spillovers are mainly due to direct housing market interdependence, which seems related more to demand before 2010, but more to supply thereafter due to property purchase restrictions. The new evidence we establish therefore suggests that city-level stabilisation of house prices should fully respect local features, including how local markets respond to external disturbances.

Keywords: house price; Chinese megacities; PVAR; cross-sectional heterogeneity and interdependencies

JEL Classification: C11, R15, R31

1 Introduction

Research on China's house prices is not new. Indeed, since the marketisation reform in the late 1990s, the 'Great Housing Boom' of China (Chen and Wen, 2017) has always been an important topic on the research agenda, not only because the boom is unprecedented itself, but also because the housing market is believed to have supported (if not 'hijacked') the Chinese economy over the past two decades. The growing body of literature has been developing in three main dimensions, one on the determinants of house prices and whether 'bubbles' exist, one on the interaction between local house prices, and one on that between the housing market and other markets of the economy. Studies are usually built on a model for the country as a whole, or on one for a selected panel of cities or provinces where differences between the cross-sectional units are summarised by a fixed-effect dummy, and there is no, or just limited, structural interdependencies among those units. Such 'standard' practice has a clear advantage, in that it hugely saves the degrees of

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freedom, especially when time series information is lacking which is often the case with Chinese data. But the simplification also comes with an apparent cost: by imposing such restrictions, it could bias the model; and 'average' implications from the model may not always be as helpful for policy-makers of each individual city/province.

In this paper, we revisit the determinants of house prices in four megacities in China, viz., Beijing, Shanghai, Guangzhou and Shenzhen, taking into account potential heterogeneity and interdependencies among them. The research is motivated by two observations: first, although the four cities are generally accepted to be the core of house price inflation in China, the literature has established little on what determines the house price dynamics in each of them respectively. Most work has only studied them as a panel of 'first-tier' cities (based on their similarity in economic development), without allowing for potential heterogeneity and interdependencies among them. Second, there has been a few discussions on how house prices in these cities interact. However, all of them have just focused on the empirical questions of whether price diffusions exist and which (from an econometric viewpoint) may be the source(s) of the diffusions. The more important policy questions of what could have caused such diffusions and how such diffusions contribute to local house price fluctuations are, however, far less studied.

The aim of our paper is to fill these gaps. The approach we take here is to construct a panel vector autoregressive (PVAR) model allowing for both cross-sectional heterogeneity and interdependencies in the spirit of Canova and Ciccarelli (2009, 2013). The model is estimated on standard macroeconomic and house price data between 2003Q1 and 2017Q4, using the Bayesian method, with shocks identified by the Cholesky decomposition. We find that house prices in the megacities – when evaluated as a whole – are dominated by the housing price shock. However, each city has its unique mixing of the causes, especially on the extent to which local house prices are disturbed by house price shocks from the other cities. Such 'house price spillovers' are mainly due to direct housing market interdependence, which seems to be related more to the demand side before 2010, but less so thereafter, due to property purchase restrictions. Our finding suggests that city-level stabilisation of house prices should fully respect local features, including how local markets respond to external shocks. That both cross-sectional heterogeneity and interdependencies are affecting substantially also suggests these are important model properties not to be omitted in regional house price studies.

To the best of our knowledge, this is the first time the determinants of house prices in these core Chinese cities are examined in a model considering both their uniqueness and connections. It is also the first time the potential channels through which the widely documented regional house price spillovers happen are identified with counterfactual experiments, without imposing any hypothetical channel *ex-ante*.

The remainder of this paper is organised as the following: Section 2 reviews the literature; Section 3 elaborates and estimates the model; Section 4 discusses the findings; Section 5 concludes.

2 The Literature

Our work here brings together two strands of literature on house prices which are broadly related, but often handled separately in empirical studies – one on the determinants of house prices, the other on local house price interactions. The former is usually built on a country-wide or regional model designed for uncovering what determines house prices as a whole. The model is either structural or semi-structural, with no or limited cross-sectional heterogeneity (usually modelled as fixed effects) and interdependencies. The latter is mainly econometric work. The focus is on the time series properties of local house prices, including their lead-lag relations.

Ng (2015), Wen and He (2015) and Liu and Ou (2020) are among the first who study what determines the house price dynamics in China using a dynamic stochastic general equilibrium (DSGE) model of the type of Iacoviello and Neri (2010). It is generally agreed that house price fluctuations in China are dominated by demand disturbances, of which Ng points to variations in gender imbalance, stock market performance, the number of potential buyers, and urban unemployment. Liu and Ou (2019) extend the model to study the role of fiscal policy. They find that government spending has a weak crowding-out effect on housing demand, while government investment – by generating a wealth effect – encourages housing consumption; and the surge of house prices in 2009 was much a by-product of the 'Four-trillion Stimulus Packages' in response to the global financial crisis. Minetti et al. (2019), from the perspective of human psychology, study the impact of 'keeping up with the Joneses'. They find evidence of the mechanism being at work, with house prices destabilised by a deepened, prolonged response of housing demand to a typical demand shock, especially in the long run.

In the meanwhile there is evidence established by models with less theoretical restrictions. These are usually 'long-run' models testing an equilibrium condition of house prices, or dynamic models focusing more on short-run relations. Examples of the former include Deng et al. (2009), Wang et al. (2011), Xu and Chen (2012), Li and Chand (2013) and Wang and Zhang (2014). However, except for a limited number of factors (such as disposable income and land price), these studies rarely reach a consensus on a wider set of the determinants. Similar lack of shared understanding is also common regarding the short-run dynamics. In this case, disagreement has mainly been on whether disposable income and growth Granger-causes house price inflation (E.g., Wen and Goodman (2013) v.s. Chow and Niu (2015), Liang and Cao (2007) v.s. Zhang, Hua and Zhao (2012)). Nevertheless, most also agree that monetary expansion is one important cause (E.g., Guo and Huang (2010) point to the inflow of 'hot money'; Zhang, An and Yu (2012) point to the growth of M2 and low mortgage rate).

On the other hand, a small group of authors have studied the time series properties of local house prices, focusing on tests of cross-border price diffusion and convergence. The research follows the well-established UK literature on the 'ripple effect' of regional house prices, first documented by Holmans (1990), then developed extensively by a number of others[1]. The work is mainly empirical, based on statistical tests encompassing two key conditions of the ripple effect set by Meen (1999): a) regional house prices have long-run relationships; b) prices in different regions respond to exogenous disturbances with a time difference. The former is usually tested by a cointegration test on the prices or a unit root test on the ratios of them. The latter is examined with a dynamic model allowing for lead-lag relations among the prices.

Zhang and Liu (2009) study eight representative cities with clear differences in economic development. They find that price cointegration widely exists; and that short-run price diffusion generally happens in one direction, from the more developed cities to the less developed. Chiang (2014) focuses on the first-tier cities, which are found to be 'inextricably intertwined'. Using the Toda–Yamamoto (1995) causality test, he also identifies a rich set of long-run causal relations. Zhang and Morley (2014), however, find no evidence of price convergence when a panel of 35 capital cities and municipalities are considered; but they echo the others on price diffusions from Beijing, Shanghai and Guangzhou. Zhang et al. (2017) study at the level of regions. They find that – compared to the national average – the North and the East (which are also more developed) are always deviating, while the other regions are catching up. They also verify the existence of 'spatial lags'

[1] Giussani and Hadjimatheou (1991), MacDonald and Taylor (1993), Alexander and Barrow (1994), Muellbauer and Murphy (1994), Holmans (1995), Drake (1995), Meen (1996, 1999), Ashworth and Parker (1997), Cook (2003, 2005a, b), Tsai (2014) and Cook and Watson (2016) are among the most cited examples.

in the spirit of Meen (1999), where they find the North and the East also lead the other regions.

However, what could have caused the pervasive price diffusions? Unfortunately, the empirical literature has established very little on this issue. Holmans (1990, 1995) and Meen (1999) suggest this can be purely statistical, reflecting cross-sectional heterogeneity either in the determinants of house prices or in the structure of the economy. Tsai and Chiang (2019) in more recent work show this tends to follow the overheating of local prices. The theoretical literature has pointed to migration (Giussani and Hadjimatheou, 1991; Alexander and Barrow, 1994), equity transfer (Muellbauer and Murphy, 1994) and spatial arbitrage (Pollakowski and Ray, 1997), all reflecting cross-border transfer of housing demand broadly embraced by local-market interdependence. Of course, considering other potential determinants of house prices it can also be due to interdependencies in other aspects, such as the deep structure of local economies or policies of local authorities, which are barely examined by the literature. Indeed, a natural following-up question after all these considerations would be 'how do such spillovers contribute to the determination of local house prices?' These two questions are precisely what we want to shed light on, using our semi-structural panel model allowing for both cross-sectional heterogeneity and interdependencies, which we go on to elaborate in the following.

3 A dynamic model with cross-sectional heterogeneity and interdependencies

We confine our scope of investigation to the four megacities in China – Beijing, Shanghai, Guangzhou and Shenzhen. This choice is made for two practical reasons. The first is that these are well recognised, core cities distributed in different regions of the country, which best witnessed the Great Housing Boom over the past twenty years. Second, the fact that our model is generalised to allow for both cross-sectional heterogeneity and interdependencies determines that it is very demanding for degrees of freedom, which, on this occasion, can only be compensated by the length of data sample which is, however, quite limited with Chinese data. Nevertheless, there is no reason why a fuller set of sample cities should not be investigated when richer time series information becomes available in future work.

Our model is a panel vector autoregressive (PVAR) model in the spirit of Canova and Ciccarelli (2009, 2013)[2]:

$$y_{i,t} = A_i(L)Y_{t-1} + B_i(L)X_t + u_{i,t} \qquad i = 1, ..., N;\ t = 1, ..., T \tag{1}$$

where y_i is a $G \times 1$ vector of endogenous variables for city i, Y_{t-1} is a $G \times N$ vector stacked with y_i, X_t is a $K \times 1$ vector of exogenous variables, $u_{i,t}$ is a $G \times 1$ vector of i.i.d. errors, $A_{i,p}$ is a $G \times NG$ matrix for each lag $p = 1, ..., P$, and $B_{i,q}$ is a $G \times K$ matrix for each lag $q = 0, 1, ..., Q-1$[3]. We consider, for each city, four endogenous variables, which are real housing price, inflation, real GDP and real government expenditure. The exogenous variable, which is identical across all cities, is chosen to be the nominal interest rate. The model can be viewed as a parsimonious description of interactions between house prices, the macro-economy (inflation and GDP), and fiscal and monetary policies (government expenditure and the nominal interest rate).

Two features of the model are worth highlighting: first, by letting $A_{i,p} \neq A_{j,p}$ and $B_{i,q} \neq B_{j,q}$ ($i \neq j$), it

[2] See also Canova and Pappa (2007) and Canova, et al. (2012).

[3] All deterministic terms of the model are omitted as demeaned and detrended data will be used in the following.

allows for cross-sectional heterogeneity in the determination of house prices, which existing studies have failed to reflect; second, by letting $y_{i,t}$ respond also to $y_{j,t}$ $(i \neq j)$, it allows for cross-sectional interdependencies which are essential for house price spillovers documented in some of these studies which are, however, silent about how they could have happened. Our choice of the endogenous variables naturally implies interdependency in four dimensions: one between local housing markets, one between local macro-economies, one between local fiscal policies, and the other between different sectors across the cross-sectional units.

It is not difficult to see that these nice model properties come with a high computational cost: in our simple four-city, four-variable framework where we consider only one lag and one exogenous variable, it implies as many as $N(GNP + KQ) = 4 \times (4 \times 4 \times 1 + 1 \times 1) = 68$ coefficients, which can easily use up the degrees of freedom given the size of typical macro data samples. To reduce such a problem of dimensionality, some restrictions have to be imposed. In particular, we adopt the *structural factor approach* where we follow Canova and Ciccarelli (2009, 2013) to first rewrite (1) as:

$$Y_t = Z_t \gamma + U_t \tag{2}$$

where $Z_t = I_{NG} \otimes W_t'$, $W_t' = (Y_{t-1}', Y_{t-2}', ..., Y_{t-P}', X_t', X_{t-1}', ..., X_{t-Q+1}')$, $\gamma = vec(\Gamma)$, $\Gamma = (A_{1,t-1}', ..., A_{1,t-P}'$, $B_{1,t}', ..., B_{1,t-Q+1}', ..., A_{N,t-1}', ..., A_{N,t-P}', B_{N,t}', ..., B_{N,t-Q+1}')'$, and $U_t = (u_{1,t}', ...u_{N,t}')'$. The coefficient vector γ, which is a reduced-form representation of the transmission mechanism, is then assumed to be a linear combination of a set of structural factors, governed by:

$$\gamma = \Xi_1 \theta_1 + \Xi_2 \theta_2 + \Xi_3 \theta_3 + \Xi_4 \theta_4 \tag{3}$$

where $\theta_{k,k=1,...,4}$ are vectors containing loadings of the 'common components', 'unit-specific components', 'variable-specific components' and exogenous variables, respectively, for each cross-sectional units; $\Xi_{k,k=1,...,4}$ are matrices with entries equalling either 0 or 1, which map the loadings with elements in Y_t according to the structural factor restrictions. Note (3) can be substituted into (2), such that:

$$Y_t = (Z_t \Xi_1)\theta_1 + (Z_t \Xi_2)\theta_2 + (Z_t \Xi_3)\theta_3 + (Z_t \Xi_4)\theta_4 + U_t \tag{4}$$

Let Beijing, Shanghai, Guangzhou and Shenzhen be indexed, respectively, by BJ, SH, GZ and SZ. Our PVAR of housing price $(\dot{q}_h)$, inflation (π), GDP $(\dot{y})$ and government expenditure $(\dot{g})$ can be reduced to be:

$$
\underset{(=Y_t)}{\begin{bmatrix} \dot{g}_t^{SZ} \\ \dot{y}_t^{SZ} \\ \pi_t^{SZ} \\ \dot{q}_{h,t}^{SZ} \\ \dot{g}_t^{GZ} \\ \dot{y}_t^{GZ} \\ \pi_t^{GZ} \\ \dot{q}_{h,t}^{GZ} \\ \dot{g}_t^{SH} \\ \dot{y}_t^{SH} \\ \pi_t^{SH} \\ \dot{q}_{h,t}^{SH} \\ \dot{g}_t^{BJ} \\ \dot{y}_t^{BJ} \\ \pi_t^{BJ} \\ \dot{q}_{h,t}^{BJ} \end{bmatrix}}
=
\underset{(=Z_t\Xi_1)}{\begin{bmatrix} F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \\ F_{1,t} \end{bmatrix}}
\underbrace{\theta_1}_{1\times 1}
+
\underset{(=Z_t\Xi_2)}{\begin{bmatrix}
F_{2,1,t} & 0 & 0 & 0 \\
F_{2,1,t} & 0 & 0 & 0 \\
F_{2,1,t} & 0 & 0 & 0 \\
F_{2,1,t} & 0 & 0 & 0 \\
0 & F_{2,2,t} & 0 & 0 \\
0 & F_{2,2,t} & 0 & 0 \\
0 & F_{2,2,t} & 0 & 0 \\
0 & F_{2,2,t} & 0 & 0 \\
0 & 0 & F_{2,3,t} & 0 \\
0 & 0 & F_{2,3,t} & 0 \\
0 & 0 & F_{2,3,t} & 0 \\
0 & 0 & F_{2,3,t} & 0 \\
0 & 0 & 0 & F_{2,4,t} \\
0 & 0 & 0 & F_{2,4,t} \\
0 & 0 & 0 & F_{2,4,t} \\
0 & 0 & 0 & F_{2,4,t}
\end{bmatrix}}
\overbrace{\begin{bmatrix} \theta_{2,1} \\ \theta_{2,2} \\ \theta_{2,3} \\ \theta_{2,4} \end{bmatrix}}^{\theta_2}
\tag{5}
$$

$$
+
\underset{(=Z_t\Xi_3)}{\begin{bmatrix}
F_{3,1,t} & 0 & 0 & 0 \\
0 & F_{3,2,t} & 0 & 0 \\
0 & 0 & F_{3,3,t} & 0 \\
0 & 0 & 0 & F_{3,4,t} \\
F_{3,1,t} & 0 & 0 & 0 \\
0 & F_{3,2,t} & 0 & 0 \\
0 & 0 & F_{3,3,t} & 0 \\
0 & 0 & 0 & F_{3,4,t} \\
F_{3,1,t} & 0 & 0 & 0 \\
0 & F_{3,2,t} & 0 & 0 \\
0 & 0 & F_{3,3,t} & 0 \\
0 & 0 & 0 & F_{3,4,t} \\
F_{3,1,t} & 0 & 0 & 0 \\
0 & F_{3,2,t} & 0 & 0 \\
0 & 0 & F_{3,3,t} & 0 \\
0 & 0 & 0 & F_{3,4,t}
\end{bmatrix}}
\overbrace{\begin{bmatrix} \theta_{3,1} \\ \theta_{3,2} \\ \theta_{3,3} \\ \theta_{3,4} \end{bmatrix}}^{\theta_3}
+
\underset{(=Z_t\Xi_4)}{\begin{bmatrix} F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \end{bmatrix}}
\underbrace{\theta_4}_{1\times 1}
+
\underset{(=U_t)}{\begin{bmatrix} u_{1,t}^{SZ} \\ u_{2,t}^{SZ} \\ u_{3,t}^{SZ} \\ u_{4,t}^{SZ} \\ u_{1,t}^{GZ} \\ u_{2,t}^{GZ} \\ u_{3,t}^{GZ} \\ u_{4,t}^{GZ} \\ u_{1,t}^{SH} \\ u_{2,t}^{SH} \\ u_{3,t}^{SH} \\ u_{4,t}^{SH} \\ u_{1,t}^{BJ} \\ u_{2,t}^{BJ} \\ u_{3,t}^{BJ} \\ u_{4,t}^{BJ} \end{bmatrix}}
$$

where variables denoted with '$\cdot$' are measured in growth rate, $F_{1,t} = \sum \dot{g}_{t-1}^{i,} + \sum \dot{y}_{t-1}^{i} + \sum \pi_{t-1}^{i} + \sum \dot{q}_{h,t-1}^{i}$, $_{i=SZ,GZ,SH,BJ}$ is the common component, $F_{2,1,t} = \dot{g}_{t-1}^{SZ} + \dot{y}_{t-1}^{SZ} + \pi_{t-1}^{SZ} + \dot{q}_{h,t-1}^{SZ}$, $F_{2,2,t} = \dot{g}_{t-1}^{GZ} + \dot{y}_{t-1}^{GZ} + \pi_{t-1}^{GZ} + \dot{q}_{h,t-1}^{GZ}$, $F_{2,3,t} = \dot{g}_{t-1}^{SH} + \dot{y}_{t-1}^{SH} + \pi_{t-1}^{SH} + \dot{q}_{h,t-1}^{SH}$ and $F_{2,4,t} = \dot{g}_{t-1}^{BJ} + \dot{y}_{t-1}^{BJ} + \pi_{t-1}^{BJ} + \dot{q}_{h,t-1}^{BJ}$ are the unit-specific components, $F_{3,1,t} = \dot{g}_{t-1}^{SZ} + \dot{g}_{t-1}^{GZ} + \dot{g}_{t-1}^{SH} + \dot{g}_{t-1}^{BJ}$, $F_{3,2,t} = \dot{y}_{t-1}^{SZ} + \dot{y}_{t-1}^{GZ} + \dot{y}_{t-1}^{SH} + \dot{y}_{t-1}^{BJ}$, $F_{3,3,t} = \pi_{t-1}^{SZ} + \pi_{t-1}^{GZ} + \pi_{t-1}^{SH} + \pi_{t-1}^{BJ}$ and $F_{3,4,t} = \dot{q}_{h,t-1}^{SZ} + \dot{q}_{h,t-1}^{GZ} + \dot{q}_{h,t-1}^{SH} + \dot{q}_{h,t-1}^{BJ}$ are the variable-specific components, $F_{4,1,t} = R_{t-1}$ (the lagged nominal interest rate) is the exogenous variable.

It is worth noting that the transformation from (1) to (5) has significantly reduced the dimension of the model (from 68 coefficients to only 10 θ's), while the properties of cross-sectional heterogeneity and interdependencies remain. Both the frequentist method and the Bayesian method can be good candidates for estimating the model – though, as our sample is relatively small (as we detail below), we use the latter here to prevent overfitting.

3.1 Priors and posteriors

Let $\theta = \{\theta_1, \theta_2, \theta_3, \theta_4\}$, $U_t\tilde{}N(0, \sigma\tilde{\Sigma}_{uu})$, where σ is a scaler which allows for fat tail for the distributions of the error terms, and $\tilde{\Sigma}_{uu}$ is the variance-covariance matrix. The Bayesian estimation of the model is to calculate the posteriors of θ, σ and $\tilde{\Sigma}_{uu}$, based on prior information of them and the data sample. The calculation is based on the Bayes rule:

$$p(\theta, \sigma, \tilde{\Sigma}_{uu}|Y) = \frac{p(y|\theta, \sigma, \tilde{\Sigma}_{uu}) \cdot p(\theta) \cdot p(\sigma) \cdot p(\tilde{\Sigma}_{uu})}{p(Y)} \propto p(y|\theta, \sigma, \tilde{\Sigma}_{uu}) \cdot p(\theta) \cdot p(\sigma) \cdot p(\tilde{\Sigma}_{uu}) \tag{6}$$

where $p(\cdot)$ is the probability density function and $Y = \{Y_1, ..., Y_T\}$ is the data. Since an analytical solution of (6) does not exist, calculation of $p(\theta, \sigma, \tilde{\Sigma}_{uu}|Y)$ in practice is done by numerical methods, where here we follow the literature to use the Markov Chain Monte Carlo (MCMC) method aided by the Gibbs sampler. The estimation procedure involves:

1. Calculate the Least Squares estimates of θ and $\tilde{\Sigma}_{uu}$ (setting $\sigma = 1$); then, set $\theta^{(0)} = \theta^{(OLS)}$, $\tilde{\Sigma}_{uu}^{(0)} = \tilde{\Sigma}_{uu}^{(OLS)}$, $\sigma^{(0)} = 1$.

2. Calculate the conditional distribution of $\tilde{\Sigma}_{uu}$; draw $\tilde{\Sigma}_{uu}^{(1)}$ from $p(\tilde{\Sigma}_{uu}^{(1)}|Y, \theta^{(0)}, \sigma^{(0)})$.

3. Calculate the conditional distribution of σ; draw $\sigma^{(1)}$ from $p(\sigma^{(1)}|Y, \theta^{(0)}, \tilde{\Sigma}_{uu}^{(1)})$.

4. Calculate the conditional distribution of θ; draw $\theta^{(1)}$ from $p(\theta^{(1)}|Y, \sigma^{(1)}, \tilde{\Sigma}_{uu}^{(1)})$.

5. Repeat 2-4 until the trace plots of θ, σ and $\tilde{\Sigma}_{uu}$ become stationary, i.e., when the posterior distributions of θ, σ and $\tilde{\Sigma}_{\varepsilon\varepsilon}$ have converged to their 'true' distributions.

The joint distribution in (6) and the conditional distributions in steps 2-4 can be calculated given the standard prior assumptions:

$$p(\theta) \propto \exp\left(-\frac{1}{2}(\theta - \theta_0)'\Theta_0^{-1}(\theta - \theta_0)\right) \tag{7}$$

$$p(\sigma) \propto \sigma^{-\frac{\alpha_0}{2}-1} \exp\left(\frac{-\delta_0}{2\sigma}\right) \tag{8}$$

$$p(\tilde{\Sigma}_{uu}) \propto \left|\tilde{\Sigma}_{uu}\right|^{-(NG+1)/2} \tag{9}$$

where (7) assumes θ follows a multivariate normal distribution with mean θ_0 and covariance Θ_0, (8) assumes σ follows an inverse gamma distribution with shape parameter α_0 and scale parameter δ_0, and (9) assumes $\tilde{\Sigma}_{uu}$ follows the Jeffrey's diffuse prior[4].

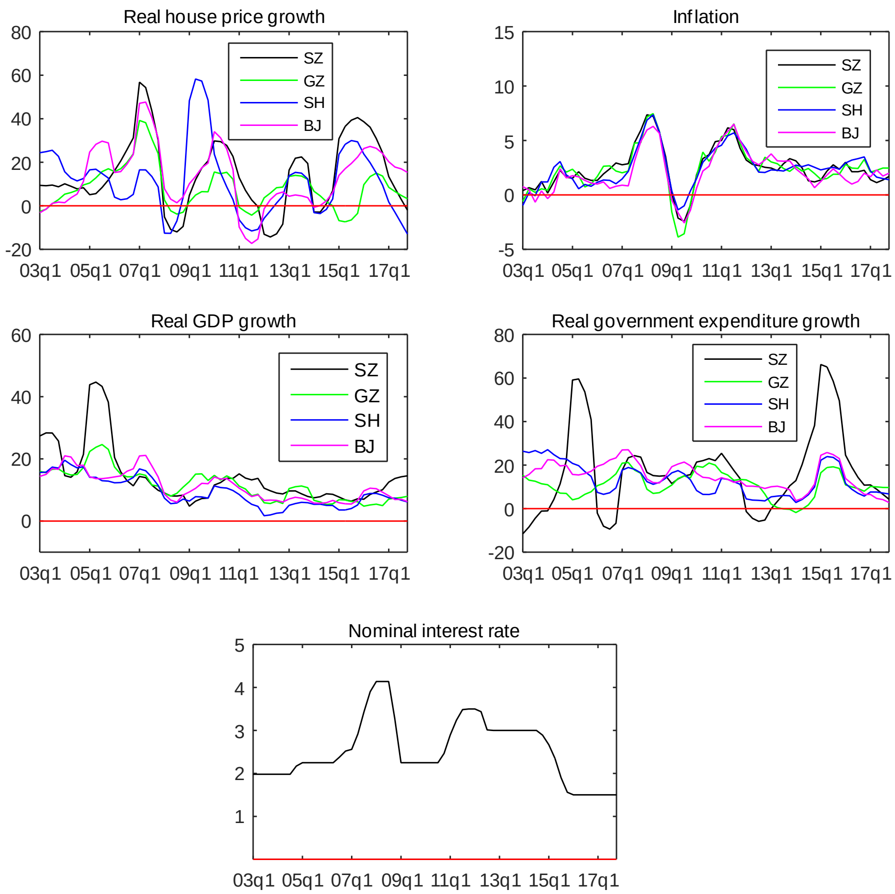
[4]For technical details, see Dieppe, et al. (2016).

We perform a total of 101,000 draws. Of these, the first 1,000 draws are dropped as the burn-in sample. We then keep from the post-burn sample 1 of every 50 draws until a subsample of 2,000 draws is collected. The posterior distributions of θ, σ and $\tilde{\Sigma}_{uu}$ are inferred from this retention[5].

3.2 Data

The data are collected from the National Bureau of Statistics of China and are available from 2003Q1 to 2017Q4. Housing price is measured by the average sales price of private houses. Inflation is measured by the year-on-year growth of CPI. GDP is measured by the gross metropolitan product. Government expenditure is measured by the general budgetary public expenditure. Nominal interest rate is measured by the PBoC 1-year benchmark deposit rate. Both housing price, GDP and government expenditure are deflated by CPI and enter the model as growth rates. The data are plotted in Figure 1. When they are used for estimating (5), they are demeaned and standardised.

Figure 1: Sample data (unit: %)



[5]We have checked the trace plots for each parameter to ensure convergence is obtained (Plots available on request). The program we used is the BEAR Toolbox 4.2 developed by Dieppe, et al. (2016) (https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html).

4 Findings

4.1 Identification of shocks

We first identify the 'structural' shocks from the reduced-form model by the Cholesky decomposition, with ordering of both the endogenous variables and the cross-sectional units carefully chosen as established in the literature. In particular, we follow Blanchard and Perotti (2002) to assume that implementation of fiscal policy is subject to a decision lag, such that shocks to GDP, inflation and house prices do not affect government expenditure contemporaneously. A shock to GDP has a contemporaneous impact on inflation and house prices due to the wealth effect. A shock to inflation only affects house prices contemporaneously as relative prices vary, but not GDP in the same period as it takes time for producers to adjust the input factors. A shock to house prices does not have a contemporaneous impact on all the other variables as the size of the housing market, compared to the whole macro-economy, is rather small[6]. These assumptions suggest an ordering of the endogenous variables within each cross-sectional unit as $(\dot{g}, \dot{y}, \pi, \dot{q}_h)\prime$, as presented in (5). The choice is broadly echoed by many others, including Fatás and Mihov (2001), Giordano et al. (2007) and Caldara and Kamps (2008).

Unfortunately, economic theories do not usually provide similar lead-lag relationships to inform Cholesky ordering between the cross-sectional units. In this case the data information is used. Since the focal point of this paper is house prices in the four cities, we refer to the empirical literature on house price spillovers between these cities (Zhang and Liu, 2009; Huang, Li and Li, 2010; Huang, Zhou and Li, 2010; Chiang, 2014; Zhang et al., 2017). It has been generally agreed that Shenzhen is always leading in the short run. What is less agreed is the relationships between the other three cities, but here we combine the existing evidence to assume Guangzhou leads Shanghai, which leads Beijing, contemporaneously. Our ordering of the cities is therefore (SZ, GZ, SH, BJ). Our robustness check confirms the ordering of the last three cities affects little[7].

We identify four structural shocks, which are the housing price shock, inflation shock, GDP shock and government expenditure shock. Since our model also includes the nominal interest rate as an exogenous variable, it can be viewed as the fifth 'shock' to the endogenous variables.

4.2 What determines house prices in the megacities?

We now proceed to investigate the determinants of house prices in the megacities. We start with the region as a whole. We then consider the individual cities, focusing on their heterogeneity and interdependencies. All exercises in the following are calculated at the posterior medians of the PVAR parameters.

4.2.1 The whole region

Figure 2 plots the average impulse responses of housing price to a one-standard-error realisation of the structural shocks including the nominal interest rate. A housing price shock raises house prices significantly with an impact lasting for more than five years. Evidence from structural models (e.g., Ng, 2015; Wen and He, 2015; Liu and Ou, 2020) suggests this could have reflected a rise in housing demand due to pure speculation, expanded population and, for China, also gender imbalance. An inflation shock reduces house prices, as the income effect dominates the substitution effect. In this case, house prices respond to a similar

[6] For example, the long run residential investment-GDP ratio in China is just under 3%.

[7] The alternative orderings we attempted are (SZ, GZ, BJ, SH), (SZ, SH, BJ, GZ), (SZ, BJ, SH, GZ), (SZ, SH, GZ, BJ) and (SZ, BJ, GZ, SH). The results are available on request.

extent, but the effect dies out much more quickly. Shocks to GDP, government expenditure and the nominal interest rate are found to affect little.

Figure 2: Impulse responses of regional housing price

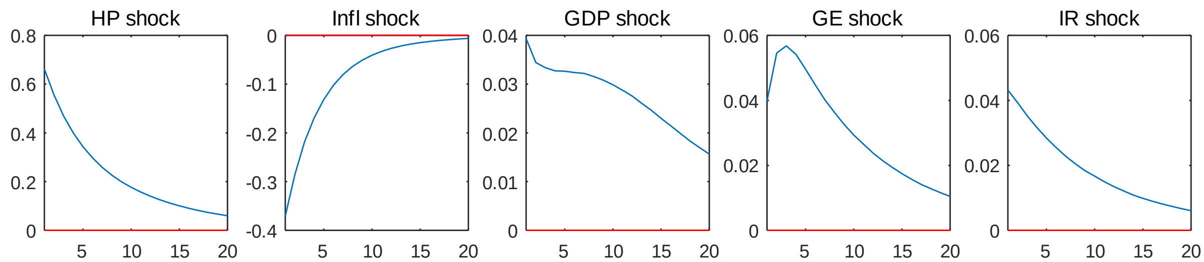
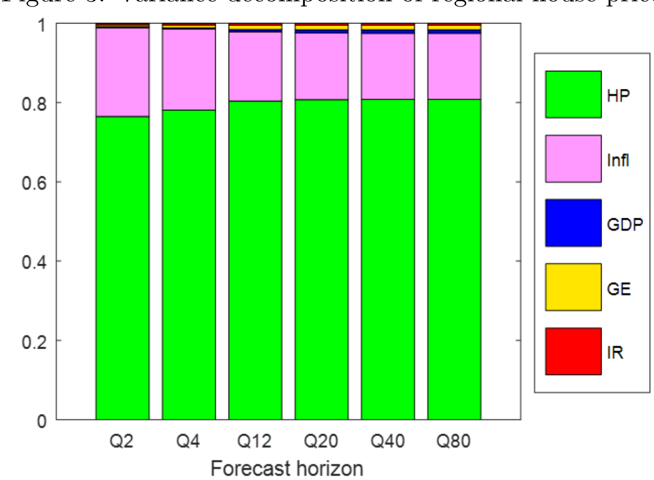


Figure 3 decomposes the forecast error variance of house prices into these shocks over a selection of time horizons. It shows the turbulence of house prices is literally a result of housing market disturbances, deepened by the inflation shock. The former accounts for more than 75% of the house price variations in the short run, and more overwhelmingly, for over 80% in the long run. The rest is dominated by the inflation shock. Since house prices respond little to GDP and the two policy shocks, there is no evidence that house prices of the region are materially affected by these factors.

Figure 3: Variance decomposition of regional house prices



4.2.2 Individual cities

A key feature of our panel data model is that it allows for cross-sectional heterogeneity in the determination of house prices. We now turn to the individual cities to investigate how they differ in this aspect. Since the model also allows for cross-sectional interdependencies, it is expected that house prices in one city may be determined not only by its own shocks, but also by shocks from the other cities via the interdependent model structure.

Figure 4 plots the city-level impulse responses of housing price to the structural shocks making a distinction of the shocks' origins. It turns out that house prices in the four cities respond so differently, even to their respective local shocks: the housing price shock is found to have a strong and lasting impact in Shenzhen and Guangzhou, while its impacts in Shanghai and Beijing are modest and short-lived; the inflation shock hardly matters in Shenzhen, though it affects negatively in the other cities for about two quarters; the GDP shock reduces house prices in Shenzhen, Shanghai and Beijing on impact, but affects little in Guangzhou;

the government expenditure shock affects positively in Shenzhen but negatively in Guangzhou, while its impacts in Shanghai and Beijing are trivial. The cross-sectional interdependencies also bring on rich shock spillovers from one city to another, of which the most substantial ones include the housing price shock from Shenzhen to the other three cities, the housing price shock from Guangzhou to Beijing, the inflation shock from Shenzhen to Shanghai, the GDP shock from Guangzhou to Shanghai, and the government expenditure shock from Shenzhen to Beijing.

Figure 4: Impulse responses of city house prices

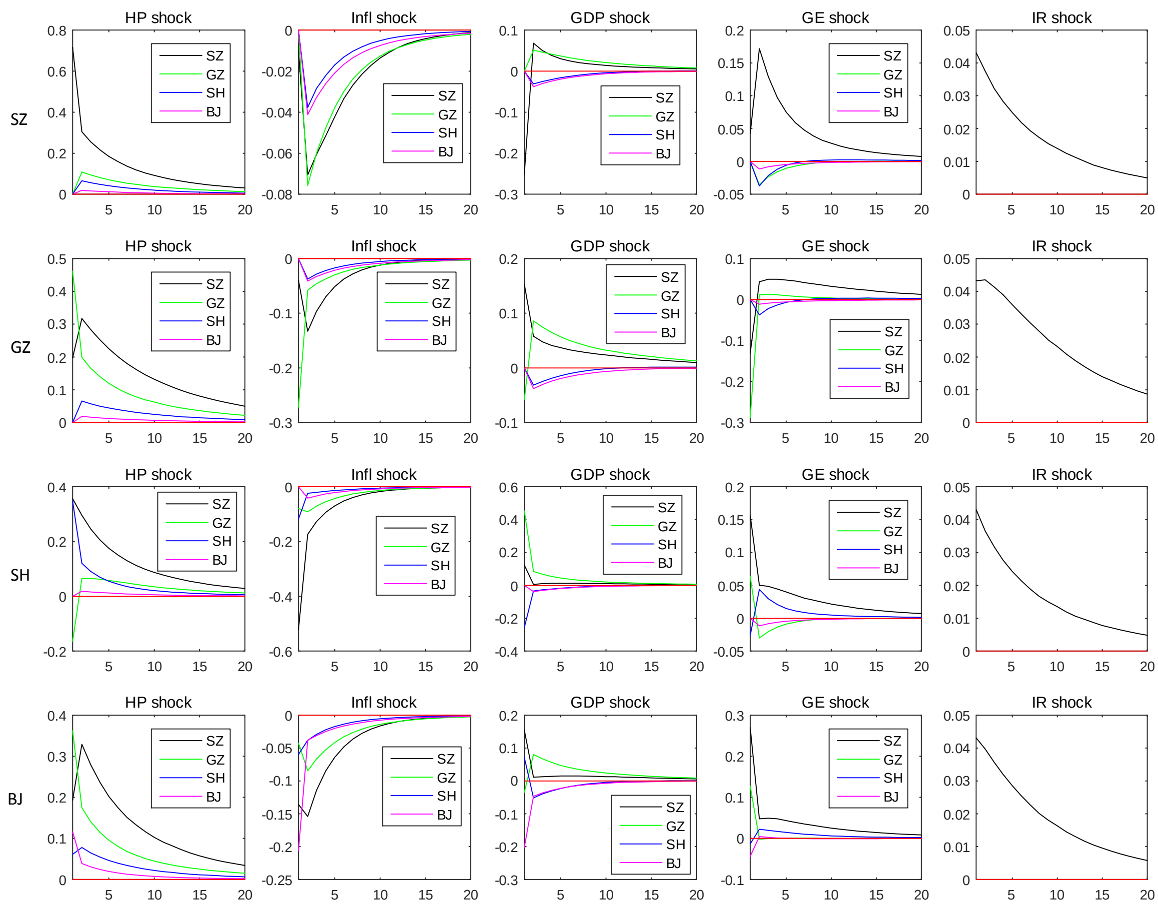
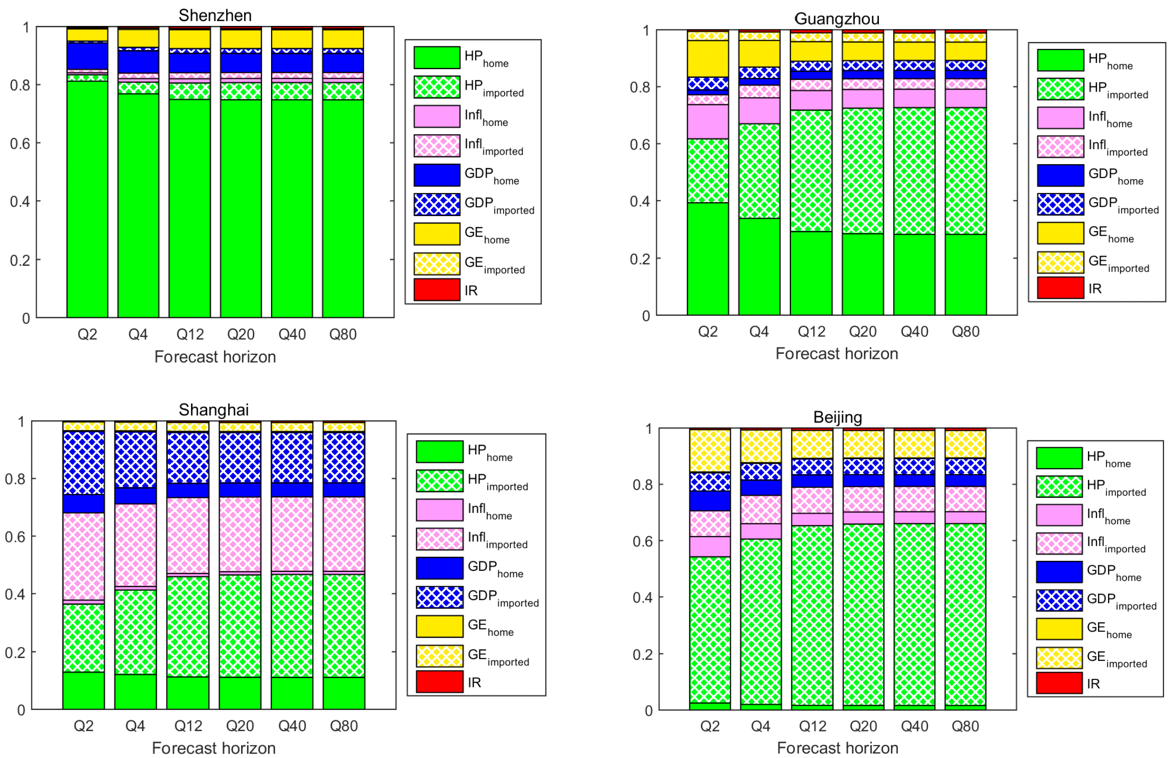


Figure 5 shows the variance decomposition of the city house prices. The housing price shock remains the most important determinant for each individual city, explaining 40-80% of the house price variations, but a substantial proportion of those in Guangzhou and Shanghai and almost all of that in Beijing are due to imported shocks. The inflation shock and the GDP shock mainly affect Shanghai, each accounting for about 30%, mostly due to imported shocks. The government expenditure shock mainly affects Guangzhou and Beijing in the short run, accounting for 15-20%, but shocks in the former are mostly home shocks, whereas those in the latter are imported. The nominal interest rate is found to be irrelevant in any city.

Figure 5: Variance decomposition of city house prices



To sum up, we find that house prices in Shenzhen are driven mainly by local factors, dominated by housing market disturbances. Such disturbances also dominate in Guangzhou and Beijing, but those in the former are a balanced mix of home and imported factors, whereas those in the latter are literally imported. Such disturbances also lead (but do not dominate) the others in Shanghai, where inflation and growth both play a significant role; in this case, we find over two thirds of the housing market disturbances are imported.

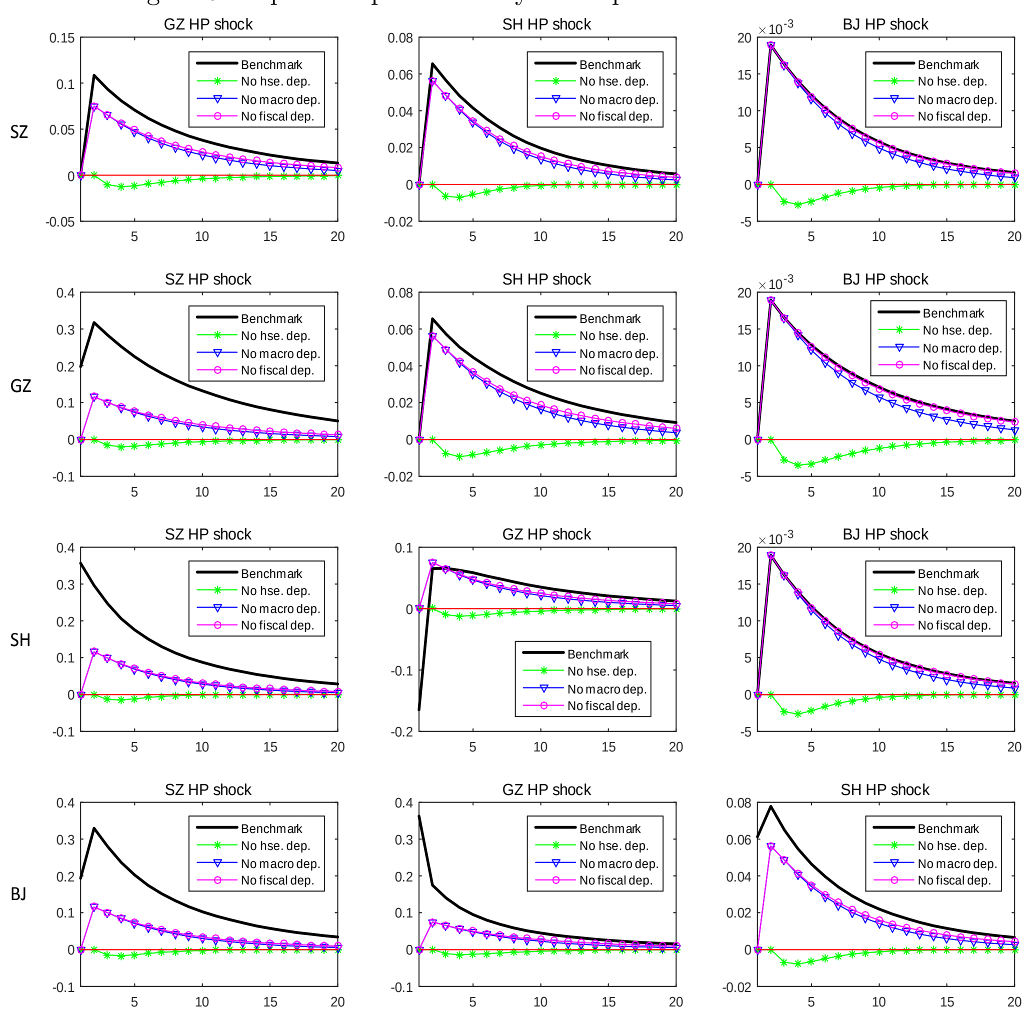
4.3 On the cross-border house price diffusion: what makes it happen?

Our study on the individual cities finds that all the megacities except for Shenzhen are heavily affected by the housing price shock from the other cities. Such price diffusion, known as house price spillovers, is widely documented in the literature, though little has been established *as evidence* of what could have made it happen. The lack of evidence is partly because the existing studies, focusing on testing as a pure statistical matter whether the phenomenon is present, generally fail to account for cross-sectional interdependencies which are at the heart of the spillovers. Such interdependencies are a reflection of the complex structural linkages between the local economies. Depending on the model specification, these can be categorised into different types where in our model we have allowed for interdependencies in the housing market, the macro-economy, fiscal policy, and those between different sectors across the megacities.

In this section, we probe deeper into the problem by asking which of these interdependencies are key to the spillovers, which has never been studied before. We focus on the impact of the housing price shock. The purpose is to establish, for each city, empirical evidence of what causes the spillovers, based on a model actually allowing them to happen. We do so by first calculating the impulse responses of home house prices to all imported house price shocks. We then repeat the experiment, nevertheless, shutting down in turn the different channels of cross-sectional interdependence, and compare the changes to the benchmark impulse responses[8]. These changes show the impact of the shut-down channel on transporting the housing price shock from the other cities to the home city.

We consider the three homogeneous interdependencies – thus in the housing market, the macro-economy and fiscal policy, respectively – allowed by the model, without discriminating cross-*sectoral* interdependency for the last is hard to interpret and insignificant. The impulse responses are compared in Figure 6. It turns out that housing market interdependence is the primary source of house price spillovers, as when this channel is shut down (green) local house prices can hardly be disturbed by house price shocks from the other cities. The other two channels – macroeconomic and fiscal policy interdependencies – have literally the same effect (blue and purple); they hardly matter in most cases, but are more influential in several, namely, the spillover from Shenzhen to the other cities, and that from Guangzhou to Beijing. The whole exercise suggests that the pervasive spillovers therefore are a combined outcome of strong housing market interdependence across the entire region, aided by modest macroeconomic and fiscal policy interdependencies in part of the region.

Figure 6: Impulse responses of city house prices with omitted channels



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[8]Thus, by shutting down each channel, we impose $\frac{\partial y_{i,t}(n)}{\partial y_{j,t-1}(n)} = 0$ and $\frac{\partial y_{i,t}(n)}{\partial \varepsilon_{j,t}(n)} = 0$, where $i \neq j$, $y_{i,t}(n)$ is the n^{th} element in $y_{i,t}$, $\varepsilon_{j,t}(n)$ is the n^{th} element in $\varepsilon_{j,t}$, $\varepsilon_t = (\varepsilon'_{1,t}, ...\varepsilon'_{N,t})' = L^{-1}U_t$, and L is the lower triangular of the Cholesky decomposition of $\sigma\tilde{\Sigma}_{uu}$.

4.4 Policy implications

What do the above findings tell us about house price stabilisation in the megacities? In this section we briefly comment on what was found above, linking together other evidence established in the literature.

Our regional investigation finds that the housing price shock dominates the determinants of house prices in the megacities. The finding is echoed by many others who study the country as a whole using either a panel model or a single country model. The structural (DSGE) model evidence of Ng (2015) and Liu and Ou (2020) suggests that this shock is mainly from the demand side. Ng finds this could be gender imbalance, stock market performance, the number of potential buyers and urban unemployment; Liu and Ou show this shock is essential for a house price boom/'bubble'. Thus, they are also factors worth carefully monitoring for the megacities[9].

Nevertheless each megacity reveals their uniqueness, as the city-specific analyses showed. This is an important new finding which suggests existing work categorising these cities into the same type – mostly simply because they are all economically and politically important, 'first-tier' cities – may be misleading. The fact that we find house prices in these cities are governed by quite different mixes of factors suggests local stabilisation policies should fully respect such heterogeneity.

In addition, interdependencies among these cities lead to pervasive spillovers, including direct house price spillovers which have been widely reported in empirical work. We find – for the first time, using our semi-structural model here – that such direct house price spillovers are mostly due to housing market interdependence among these cites. According to the theoretical literature this could be equity transfer (Muellbauer and Murphy, 1994) or spatial arbitrage (Pollakowski and Ray, 1997), where demand for houses flows from one city to another. Nevertheless, at least from 2010 onwards (which counts for half of the data sample) these are not likely, as property purchase restrictions are imposed in all these cities preventing households from buying houses in cities where they do not reside. Such 'interdependence' in this episode is therefore more likely to be a reduced-form representation of spatial patterns of the determinants of house prices (Holmans, 1990, 1995) not explicitly accounted by our model. Since property purchase restrictions would have segregated the demand sides, these tend to be factors – such as land price and construction costs (Wang and Zhang, 2014) – from the supply side, where both equity transfer and spatial arbitrage could occur. They can also be similar housing market policies operating in all these cities, where property purchase restrictions are themselves a perfect example. Such spillovers cannot be caused by migration (Giussani and Hadjimatheou, 1991; Alexander and Barrow, 1994), as the latter does not generally happen between the megacities[10]. Nor can they be just statistical artefacts due to spatial patterns of the structural parameters (Meen, 1999; Zhang et al., 2017), as cross-sectional heterogeneity has been well accounted for by our model.

Finally, we also identify strong cross-*sectoral* spillovers from the macro-economy to the housing market in Shanghai, and similar but milder spillovers echoed by fiscal spillovers in Beijing. Such spillovers come from the dependencies of local macro-economy and fiscal policy of these cities on those of the others, which have never been identified in the literature. What we find here suggests that policy-makers in these cities should also monitor how macro and fiscal shocks develop in the other cities, as these may, too, destabilise home house prices substantially.

[9] Another potential factor could be urban population (e.g., Wang and Zhang, 2014); however we are unable to verify it in our model directly as different scales of measurement are adopted by these cities.

[10] In China, this normally happens between regions with a clear difference in economic development, as labour in less developed regions (where there are excess supplies) moves to more developed regions (where there are excess demands). The flow is normally from the 'third-tier' cities to the 'second-' or first-tier cities, or from the second-tier cities to the first-tier cities, but not between cities within the same tier.

5 Conclusion

What determines house prices in Chinese cities? While tremendous efforts have been made, most in the literature have adopted a model that fails to account for either cross-sectional heterogeneity or interdependencies, or both, among a set of chosen cities – most likely because of the empirical difficulty of parameter dimensionality – despite their realism. In this paper we revisited this problem taking such realism into account. We did so by estimating a panel vector autoregressive model converted to a structural factor model in the spirit of Canova and Ciccarelli (2009, 2013), on data of China's megacities, viz., Beijing, Shanghai, Guangzhou and Shenzhen. The model was estimated using the Bayesian method, and identified by the Cholesky decomposition with a robust ordering. We found that house prices in these cities, considered as a region, are dominated by housing market disturbances – presumably due to demand factors, which is echoed by the structural model literature. However, each city has its uniqueness besides simple fixed effects when they are evaluated alone; and there are rich inter-city spillovers, mostly caused by direct housing market interdependence.

Our finding suggests that city-level stabilisation of house prices should fully respect local features, including how local markets respond to shocks from outside the city border. Previous regional studies on the same topic, where cities are typically categorised into different subgroups based on their economic and political importance, may have overstated the role of such factors; and we confirmed that, at the regional level, neither GDP nor fiscal policy matters. Indeed, by ignoring cross-sectional heterogeneity and interdependencies which are proven so important here, such work seems biased and is worth revisiting. Unfortunately, due to limited time series information compared to what would be needed for a sufficient degrees of freedom, we were unable to expand our city listing substantially for a more comprehensive revisit. This would be an interesting extension for future research. Nevertheless, we believe what we have established with the megacities delivers the clear message that, both cross-sectional heterogeneity and interdependencies are important model properties which deserve more attention in regional house price studies, as well as other similar topics in regional economics.

References

[1] Alexander, C. & Barrow, M. (1994), 'Seasonality and Cointegration of Regional House Prices in the UK', *Urban Studies*, Vol. 31(10), pp. 1667-1689.

[2] Ashworth, J. & Parker, S. (1997), 'Modelling Regional House Prices in the UK', *Scottish Journal of Political Economy*, Vol. 44(3), pp. 225-46.

[3] Blanchard, O. & Perotti, R. (2002), 'An Empirical Characterization of the Dynamic Effects of Changes in Government Spending and Taxes on Output', *The Quarterly Journal of Economics*, Vol. 117(4), pp. 1329-1368.

[4] Caldara, D. & Kamps, C. (2008), 'What are the effects of fiscal policy shocks? A VAR-based comparative analysis', Working Paper, European Central Bank, Available at: https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp877.pdf

[5] Canova, F. & Ciccarelli, M. (2009), 'Estimating multicountry VAR models', *International Economic Review*, 50, Vol. 3, pp. 929-959.

[6] Canova, F. & Ciccarelli, M. (2013), 'Panel vector autoregressive models: a survey', Working Paper, European Central Bank. Available at: https://EconPapers.repec.org/RePEc:ecb:ecbwps:20131507.

[7] Canova, F., Ciccarelli, M. & Ortega, E., (2012), 'Do institutional changes affect business cycles?', *Journal of Economic Dynamics and Control*, Vol. 36, pp. 1520-1533.

[8] Canova, F. & Pappa, E. (2007), 'Price Differentials in Monetary Unions: The Role of Fiscal Shocks', *The Economic Journal*, Vol. 117, pp. 713-737.

[9] Chen, K. & Wen, Y. (2017), 'The Great Housing Boom of China', *American Economic Journal: Macroeconomics*, Vol. 9(2), pp. 73-114.

[10] Chiang, S. (2014), 'Housing Markets in China and Policy Implications: Comovement or Ripple Effect', *China & World Economy*, Vol. 22(6), pp. 103-120.

[11] Chow, G.C. & Niu, L. (2015), 'Housing Prices in Urban China as Determined by Demand and Supply', *Pacific Economic Review*, Vol. 20(1), pp. 1-16.

[12] Cook, S. (2003), 'The Convergence of Regional House Prices in the UK', *Urban Studies*, Vol. 40(11), pp. 2285–2294.

[13] Cook, S. (2005a), 'Regional house price behaviour in the UK: application of a joint testing procedure', *Physica A: Statistical Mechanics and its Applications*, Vol. 345(3), pp. 611-621.

[14] Cook, S. (2005b), 'Detecting long-run relationships in regional house prices in the UK', *International Review of Applied Economics*, Vol. 19(1), pp. 107-118.

[15] Cook, S. & Watson, D. (2016). 'A new perspective on the ripple effect in the UK housing market: Comovement, cyclical subsamples and alternative indices', *Urban Studies*, Vol. 53(14), pp. 3048–3062.

[16] Deng, C., Ma, Y., & Chiang, Y. (2009), 'The Dynamic Behavior of Chinese Housing Prices', *International Real Estate Review*, Vol. 12(2), pp. 121-134.

[17] Dieppe, A., van Roye, B. & Legrand, R. (2016), 'The BEAR toolbox', Working Paper, European Central Bank, Available at: https://www.ecb.europa.eu/pub/research/working-papers/html/bear-toolbox.en.html

[18] Drake, L. (1995), 'Testing for Convergence between UK Regional House Prices', *Regional Studies*, Vol. 29(4), pp. 357-366.

[19] Fatás, A. & Mihov, I. (2001), 'The Effects of Fiscal Policy on Consumption and Employment: Theory and Evidence', Discussion Paper, CEPR, Available at: https://faculty.insead.edu/fatas/fiscal.pdf

[20] Giordano, R., Momigliano, S., Neri, S. & Perotti, R. (2007), 'The Effects of Fiscal Policy in Italy: Evidence from a VAR Model', *European Journal of Political Economy*, Vol. 23, pp.707-733.

[21] Giussani, B. & Hadjimatheou, G. (1991), 'Modeling Regional House Prices In The United Kingdom', *Papers in Regional Science*, Vol. 70(2), pp. 201-219.

[22] Guo, F. & Huang, Y.S. (2010), 'Does "hot money" drive China's real estate and stock markets?', *International Review of Economics & Finance,* Vol. 19(3), pp. 452-466.

[23] Holmans, A. (1990), 'House prices: changes through time at national and sub-national level', Government Economic Service Working Paper No. 110.

[24] Holmans, A. (1995), 'What has happened to the north-south divide in house prices and the housing market?', in: S. Wilcox (Ed.) *Housing Finance Review 1995/96* (York, Joseph Rowntree Foundation).

[25] Huang, F., Li, C. & Li, Y. (2010), 'Ripple Effect of Housing Prices among Chinese Deputy Provincial Cities Based on an Alternative Approach', *International Journal of Business Administration*, Vol. 1.

[26] Huang, F., Zhou, Y. & Li, C. (2010), 'Ripple Effect of Housing Prices Fluctuations among Nine Cities of China', *Management Science and Engineering*, Vol. 4(3), pp. 41-54.

[27] Iacoviello, M. & Neri, S. (2010), 'Housing Market Spillovers: Evidence from an Estimated DSGE Model', *American Economic Journal*: *Macroeconomics*, Vol. 2, pp. 125-164, American Economic Association.

[28] Li, Q. & Chand, S. (2013), 'House prices and market fundamentals in urban China', *Habitat International*, Vol. 40, pp. 148-153.

[29] Liang, Q. & Cao, H. (2007), 'Property prices and bank lending in China', *Journal of Asian Economics,* Vol. 18(1), pp. 63-75.

[30] Liu, C. & Ou, Z. (2019), 'Has fiscal expansion inflated house prices in China? Evidence from an estimated DSGE model', Working Paper, Cardiff University, Available at: http://carbsecon.com/wp/index_abstracts.html

[31] Liu, C. & Ou, Z. (2020), 'What determines China's housing price dynamics? New evidence from a DSGE-VAR', *International Journal of Finance and Economics*, forthcoming.

[32] MacDonald, R. & Taylor, M. (1993), 'The Monetary Approach to the Exchange Rate: Rational Expectations, Long-Run Equilibrium, and Forecasting', *IMF Staff Papers*, Vol. 40(1), pp. 89-107.

[33] Meen, G. P. (1996), 'Spatial aggregation, spatial dependence and predictability in the UK housing market', *Housing Studies*, Vol. 11(3), pp. 345-372.

[34] Meen, G. P. (1999), 'Regional House Prices and the Ripple Effect: A New Interpretation', *Housing Studies*, Vol. 14(6), pp.733-753.

[35] Minetti, R., Peng, T. & Jiang, T. (2019), 'Keeping up with the Zhangs and house price dynamics in China', *Journal of Economic Dynamics and Control*, Vol. 109(December), Available at: https://doi.org/10.1016/j.jedc.2019.103778.

[36] Muellbauer, J. & Murphy, A. (1994), 'Explaining regional house prices in the UK', Working Papers, University College Dublin. Available at: https://EconPapers.repec.org/RePEc:ucn:wpaper:199421

[37] Ng, E.C.Y. (2015), 'Housing market dynamics in China: Findings from an estimated DSGE model', *Journal of Housing Economics*, Vol. 29, pp. 26-40.

[38] Pollakowski, H. & Ray, T. (1997), 'Housing Price Diffusion Patterns at Different Aggregation Levels: An Examination of Housing Market Efficiency', *Journal of Housing Research*, Vol. 8(1), pp. 107-124.

[39] Toda, H. Y. & Yamamoto, T. (1995), 'Statistical inference in vector autoregressions with possibly integrated processes', *Journal of Econometrics*, Vol. 66 (1-2), pp. 225-250.

[40] Tsai, I. C. (2014), 'Ripple effect in house prices and trading volume in the UK housing market: New viewpoint and evidence', *Economic Modelling*, Vol. 40(C), pp. 68-75.

[41] Tsai, I. C. & Chiang, S.H. (2019), 'Exuberance and spillovers in housing markets: Evidence from first- and second-tier cities in China', *Regional Science and Urban Economics*, Vol. 77(C), pp. 75-86.

[42] Wang, S., Yang, Z. & Liu, H. (2011), 'Impact of urban economic openness on real estate prices: Evidence from thirty-five cities in China', *China Economic Review*, Vol. 22, pp. 42–54.

[43] Wang, Z. & Zhang, Q. (2014), 'Fundamental factors in the housing markets of China', *Journal of Housing Economics*, Vol. 25, pp. 53-61.

[44] Wen, H. & Goodman, A.C. (2013), 'Relationship between urban land price and housing price: Evidence from 21 provincial capitals in China', *Habitat International*, Vol. 40, pp. 9-17.

[45] Wen, X.W. & He, L. (2015), 'Housing demand or money supply? A new Keynesian dynamic stochastic general equilibrium model on China's housing market fluctuations', *Physica A: Statistical Mechanics and its Applications*, Vol. 432, pp. 257-268.

[46] Xu, X.E. & Chen, T. (2012), 'The effect of monetary policy on real estate price growth in China', *Pacific-Basin Finance Journal*, Vol. 20(1), pp. 62-77.

[47] Zhang, C., An, G. & Yu, X. (2012), 'What Drives China's House Prices: Marriage or Money?', *China &World Economy*, Vol. 20(4), pp. 19-36.

[48] Zhang, F. & Morley, B. (2014), 'The convergence of regional house prices in China', *Applied Economics Letters*, Vol. 21(3), pp. 205-208.

[49] Zhang, H. & Liu, L. (2009), 'Empirical Research on Housing Price Ripple Effect between China's Cities', *2009 IITA International Conference on Services Science*, pp. 43-46.

[50] Zhang, L., Hui, E. & Wen, H. (2017), 'The regional house prices in China: Ripple effect or differentiation', *Habitat International*. Vol. 67, pp. 118-128.

[51] Zhang, Y., Hua, X. & Zhao, L. (2012), 'Exploring determinants of housing prices: A case study of Chinese experience in 1999–2010', *Economic Modelling*, Vol. 29, pp. 2349–2361.