Received: 2 July 2021 | Revised: 21 November 2021 | Accepted: 7 December 2021

DOI: 10.1111/manc.12397

ORIGINAL ARTICLE

The Manchester School WILEY

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

Chunping Liu[1] | **Zhirong Ou**[2]

[1]Department of Economics, Nottingham Trent University, Nottingham, UK

[2]Economics section, Cardiff University, Cardiff, UK

Correspondence
Zhirong Ou, Cardiff University, B14, Aberconway building, Colum Drive, CF10 3EU, Cardiff, UK.
Email: ouz@cardiff.ac.uk

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 may be partly related to the demand side before 2010, but seems more related to supply factors thereafter, due to the imposition of 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

Chinese megacities, cross-sectional heterogeneity and interdependencies, house price, PVAR

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 & 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. For some basic facts, in this period the real house prices in major Chinese cities were growing by 15%–20% per annum (Chen & Wen, 2017; Liu & Ou, 2021); annual real estate investment was about 20% of the stock of fixed assets and 10% of the GDP (Li & Malpezzi, 2015); urban residential floor space has grown to over $30\,\mathrm{m}^2$ per capita by the late 2000s compared the long-term pre-reform level of about $15\,\mathrm{m}^2$ (Chow & Niu, 2015). As pointed out by Sun (2020), the reform, which was a transition from welfare housing to private housing in the very period of rapid urban expansion, has brought about a series of social and political issues including a substantial decline in housing affordability.

The Chinese housing market is fairly unique compared to that in the main developed economies such as the United States and the United Kingdom. From the perspective of the demand side, houses, unlike other goods, are the most important asset of typical Chinese households which, in the Chinese culture, is a key measure of economic success and social status, and is therefore not just indispensable, but often 'the more the better'. According to Clark et al. (2021), the house ownership rate in China has exceeded 80%—compared to just over 60% in major 'ownership countries', and more than 20% of urban households own multiple homes—compared to 13% in the United States and some 10% in the United Kingdom. The under-development of financial markets and capital controls, which limit the choice of household investment, also make residential properties—weighing more than 60% of household assets, compared to about 30% in the United States (Huang et al., 2020)—more like a financial product than a pure home for living.

On the supply side, land supply—which is less manipulated in developed economies—is substantially affected by performance of the macroeconomy, and targets and financial health of the fiscal authority. The phenomenon is known as 'land financing', which refers to that local governments (which are monopoly supplier of lands) manipulate land sales to meet their financial needs. Many attribute the sustained house price boom to this behaviour, believing that the soared prices reflect a pass-on of high land costs manipulated by local governments which maximise land sale proceeds as they try to fulfil social and economic goals (e.g. urbanisation, poverty reduction and macro stability).[1] Hence, besides home developers, the supply side of China's housing market is also meddled by the public sector who is both a regulator and a stake holder.

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

[1]However, Liu and Ou (2019) point out that it is the soared house prices that lead to the soar of land costs, as developers compete to hoard lands. They argue that the fiscal authority (fiscal expansion) indeed plays a key role in inflating China's house prices; but this is because fiscal expansion brings a strong wealth effect that boosts the demand for houses; nevertheless, it would not matter whether such expansion is financed by land sale proceeds as long as the financing approach (such as taxing) does not imply a change in the *relative* price of houses.

of freedom, especially when time series information is lacking which is often the case with the 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 house price shock which is mostly explained by transient population and land prices. 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 may be partly related to the demand side before 2010, but seems more related to supply factors thereafter, due to the imposition of 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 (2021) 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 that the mechanism is at work, with house prices destabilised by generally deepened, prolonged responses to demand shocks, 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 prices), 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 & Goodman, 2013 vs. Chow & Niu, 2015, Liang & Cao, 2007 vs. Zhang, Hua, & Zhao, 2012). Nevertheless, most also agree that monetary expansion is one important cause (e.g. Guo & Huang, 2010 point to the inflow of 'hot money'; Zhang, An, & 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.[2] 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. Gong et al. (2016), however, find no evidence of price convergence among ten Pan-Pearl River Delta cities; but they echo the others on price diffusions from Guangzhou and Shenzhen. Zhang and Morley (2014), who study a panel of 35 capital cities

[2]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, 2005b), Tsai (2014) and Cook and Watson (2016) are among the most cited examples.

and municipalities, find similar results; there, they find Beijing and Shanghai are also sources of the diffusions. Zhang et al. (2017) study the whole country divided up to North, Northeast, East, South, Middle and West. They find that—compared to the national average—North and East (which are also more developed) are always deviating, while the other regions are catching up. They also verify the existence of 'spatial lags' in the spirit of Meen (1999), where they find North and 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) show this tend to follow the overheating (the 'exuberance') of local prices. Gong et al. (2020) in more recent work find city network externality (productivity and amenity gains from the prosperity of neighbouring cities) matters. The theoretical literature has pointed to migration (Alexander & Barrow, 1994; Giussani & Hadjimatheou, 1991), equity transfer (Muellbauer & Murphy, 1994) and spatial arbitrage (Pollakowski & 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 what follows.

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 the 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)[3]:

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

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 $p = 1, \ldots, P$, and $B_{i,q}$ is a $G \times K$ matrix for each lag $q = 0, 1, \ldots, Q-1$.[4] We consider, for each

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

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

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 macroeconomy (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 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 macroeconomies, 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 $Z_t = I_{NG} \otimes W_t'$, $W_t' = (Y_{t-1}', Y_{t-2}', \ldots, Y_{t-P}', X_t', X_{t-1}', \ldots, X_{t-Q+1}')$, $\gamma = vec(\Gamma)$, $\Gamma = (A_{1,t-1}', \ldots, A_{1,t-P}', B_{1,t}', \ldots, B_{1,t-Q+1}', \ldots, A_{N,t-1}', \ldots, A_{N,t-P}', B_{N,t}', \ldots, B_{N,t-Q+1}')'$, and $U_t = (u_{1,t}', \ldots u_{N,t}')'$. 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 $\theta_{k, k=1,\ldots,4}$ are vectors containing loadings of the 'common components', 'unit-specific components', 'variable-specific components' and exogenous variables, respectively, for each cross-sectional units; $\Xi_{k, k=1,\ldots,4}$ 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:

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

$$
+
\underset{(=Z_t\Xi_3)}{\begin{bmatrix} F_{3,1,t} & 0 & 0 & 0 \\ 0 & F_{3,2,t} & 0 & 0 \\ 0 & 0 & F_{3,3,t} & 0 \\ 0 & 0 & 0 & F_{3,4,t} \\ F_{3,1,t} & 0 & 0 & 0 \\ 0 & F_{3,2,t} & 0 & 0 \\ 0 & 0 & F_{3,3,t} & 0 \\ 0 & 0 & 0 & F_{3,4,t} \\ F_{3,1,t} & 0 & 0 & 0 \\ 0 & F_{3,2,t} & 0 & 0 \\ 0 & 0 & F_{3,3,t} & 0 \\ 0 & 0 & 0 & F_{3,4,t} \\ F_{3,1,t} & 0 & 0 & 0 \\ 0 & F_{3,2,t} & 0 & 0 \\ 0 & 0 & F_{3,3,t} & 0 \\ 0 & 0 & 0 & F_{3,4,t} \end{bmatrix}}
\overbrace{\begin{bmatrix} \theta_{3,1} \\ \theta_{3,2} \\ \theta_{3,3} \\ \theta_{3,4} \end{bmatrix}}^{\theta_3}
+
\underset{(=Z_t\Xi_4)}{\begin{bmatrix} F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \\ F_{4,1,t} \end{bmatrix}}
\underbrace{\theta_4}_{1\times 1}
+
\underset{(=U_t)}{\begin{bmatrix} u_{1,t}^{SZ} \\ u_{2,t}^{SZ} \\ u_{3,t}^{SZ} \\ u_{4,t}^{SZ} \\ u_{1,t}^{GZ} \\ u_{2,t}^{GZ} \\ u_{3,t}^{GZ} \\ u_{4,t}^{GZ} \\ u_{1,t}^{SH} \\ u_{2,t}^{SH} \\ u_{3,t}^{SH} \\ u_{4,t}^{SH} \\ u_{1,t}^{BJ} \\ u_{2,t}^{BJ} \\ u_{3,t}^{BJ} \\ u_{4,t}^{BJ} \end{bmatrix}}
\tag{5}
$$

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.[5] 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 $\theta = \{\theta_1, \theta_2, \theta_3, \theta_4\}$, $U_t \sim N\left(0, \sigma \tilde{\Sigma}_{uu}\right)$, 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 $Y = \{Y_1, \ldots, Y_T\}$ 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 $\tilde{\Sigma}_{\epsilon\epsilon}$ 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:

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

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

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

[5]An alternative approach to reducing the model's dimension would be to use principal component analysis (PCA), by which the measured variables of the model are combined into a small number of 'components' best preserve the data's information. Nevertheless, we choose the factor approach here, as with it the measured variables are combined into interpretable, latent 'factors', which generally bear economic meanings and hence, are more intuitive. By contrast, the components constructed with PCA are hard to interpret as they are purely numerical.

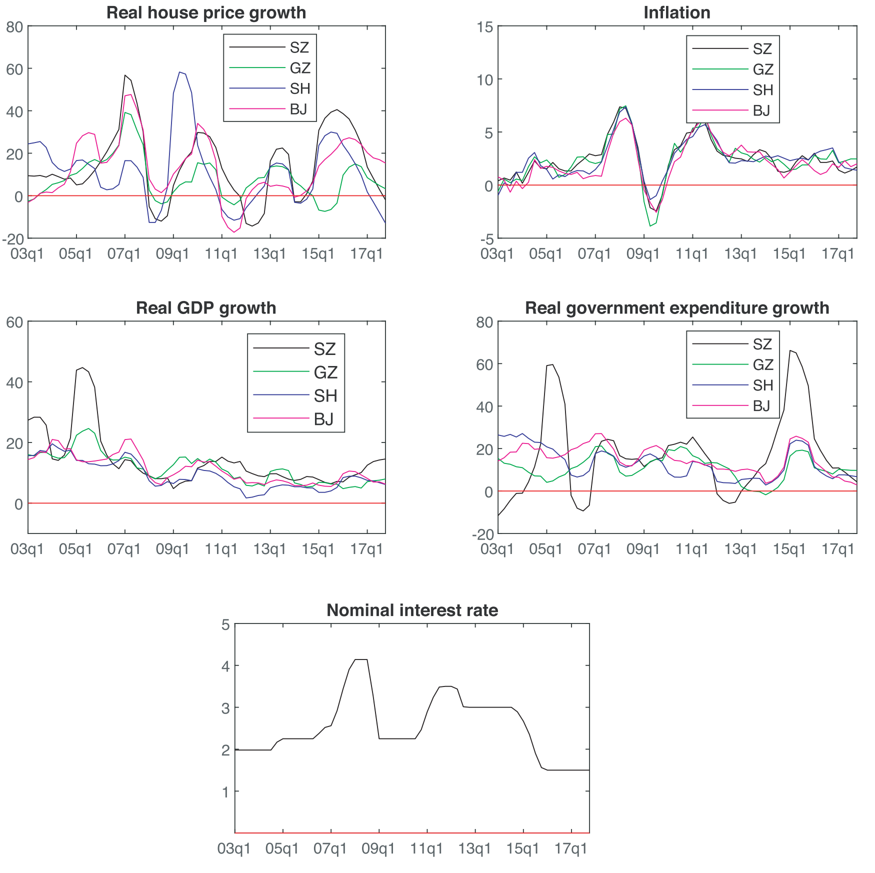

FIGURE 1 Sample data (unit: %)

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.[6]

We perform a total of 101,000 draws. Of these, the first 1000 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 2000 draws is collected. The posterior distributions of θ, σ and $\tilde{\Sigma}_{uu}$ are inferred from this retention.[7]

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

[7]Some authors, such as Geyer (2011), suggest that burning in the Markov chain is not necessary as long as the chain is sufficiently long, such that it does not underrepresent the equilibrium distribution of the chain. This would be true (in theory) if the starting value picked by the random sampler is indeed from the targeted distribution. However, in practice this condition is not guaranteed. As van Ravenzwaaij et al. (2018) have pointed, burn-in is 'safe' (even it may not be necessary), as the post-burn sample is always more likely to be from the targeted ('true') distribution. Thus, in order that our Markov chain is least affected by the (potentially 'bad') starting value (which could imply a 'false' distribution), we follow the general practice of disregarding a burn-in sample—that is, a small fraction of the initial draws. 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.

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 People's Bank of China's 1-year benchmark deposit rate. Both housing price, GDP and government expenditure are deflated by CPI and enter the model as growth rates. All the data, except that for the nominal interest rate which is a national rate identical across all cities, are collected at the city level. The data are plotted in Figure 1. When they are used for estimating (5), they are demeaned and standardised; and we show in the appendix that the processed data, according to standard unit root tests (Table A1), are all stationary.

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 macroeconomy, is rather small.[8] 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 among 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 (Chiang, 2014; Huang, Li, & Li, 2010a; Huang, Zhou, & Li, 2010b; Zhang & Liu, 2009; 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 among 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.[9]

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

[9]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.

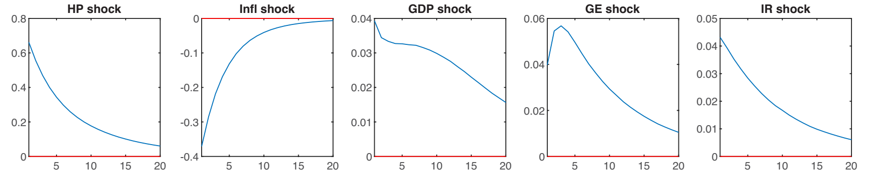

FIGURE 2 Impulse responses of regional housing price

We identify four structural shocks, which are the house 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 house price shock raises house prices significantly with an impact lasting for more than five years. As we show in Section 4.4.1 below, this shock is mainly explained by migration and land prices (For a comparison, structural (DSGE) analyses typically attribute this shock purely to the demand side; the existing evidence (e.g. Ng, 2015; Wen & He, 2015; Liu & Ou, 2021) usually points to pure speculation, 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 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 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 variation 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.

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

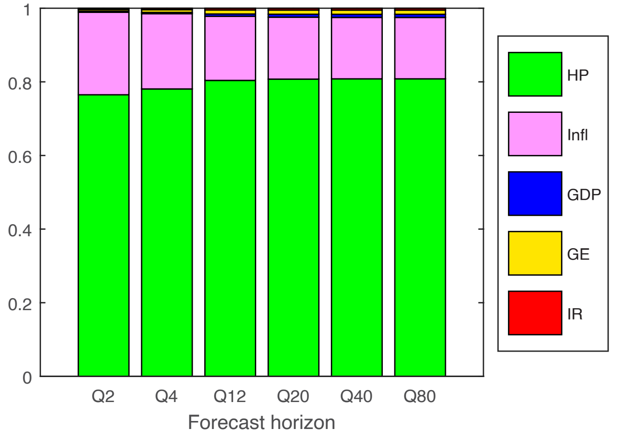

FIGURE 3 Variance decomposition of regional house prices

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 house 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 house price shock from Shenzhen to the other three cities, the house 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 5 shows the variance decomposition of the city house prices. The house price shock remains the most important determinant for each individual city, explaining 40%–80% of the house price variation, 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.

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. These 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. That house prices in Shenzhen are affected little by shocks from

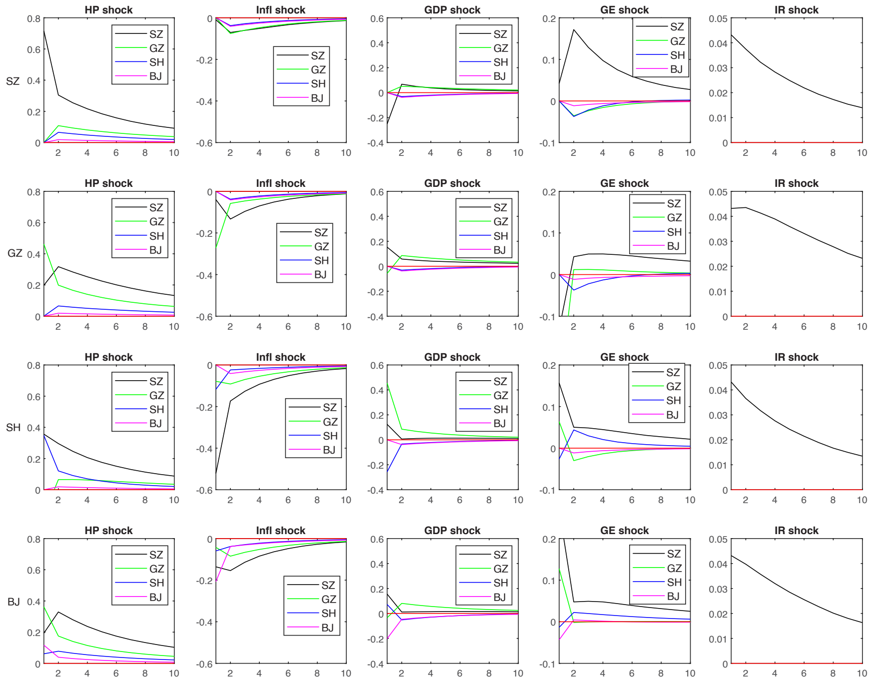

FIGURE 4 Impulse responses of city house prices

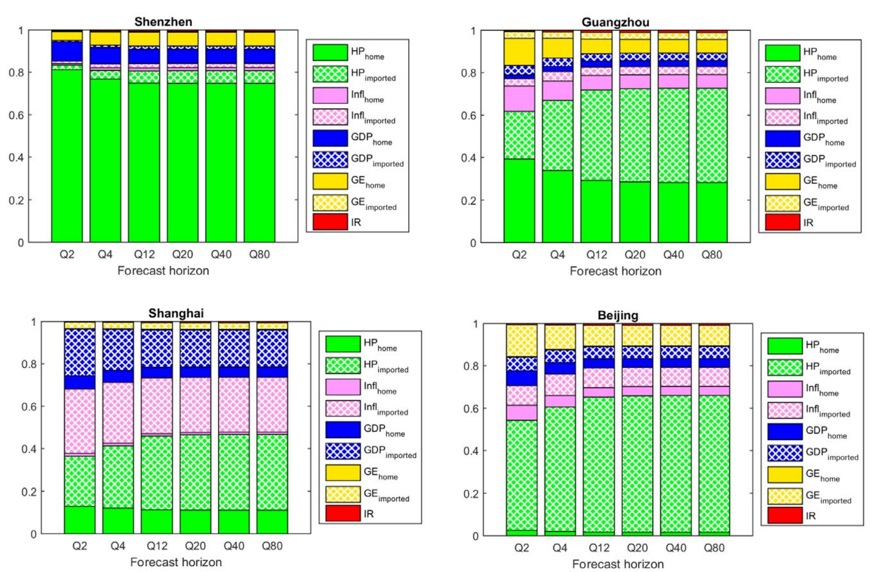

FIGURE 5 Variance decomposition of city house prices

the other cities does not, however, mean that Shenzhen is an isolated market or that there is an asymmetry in cross-city market interdependence. As we show in the following (Figure 6), housing market interdependence (governed by $\theta_{3,4}$ in (5)) does allow house prices in Shenzhen to partly depend on those in the other cities, and by assumption such cross-city interdependence is symmetric

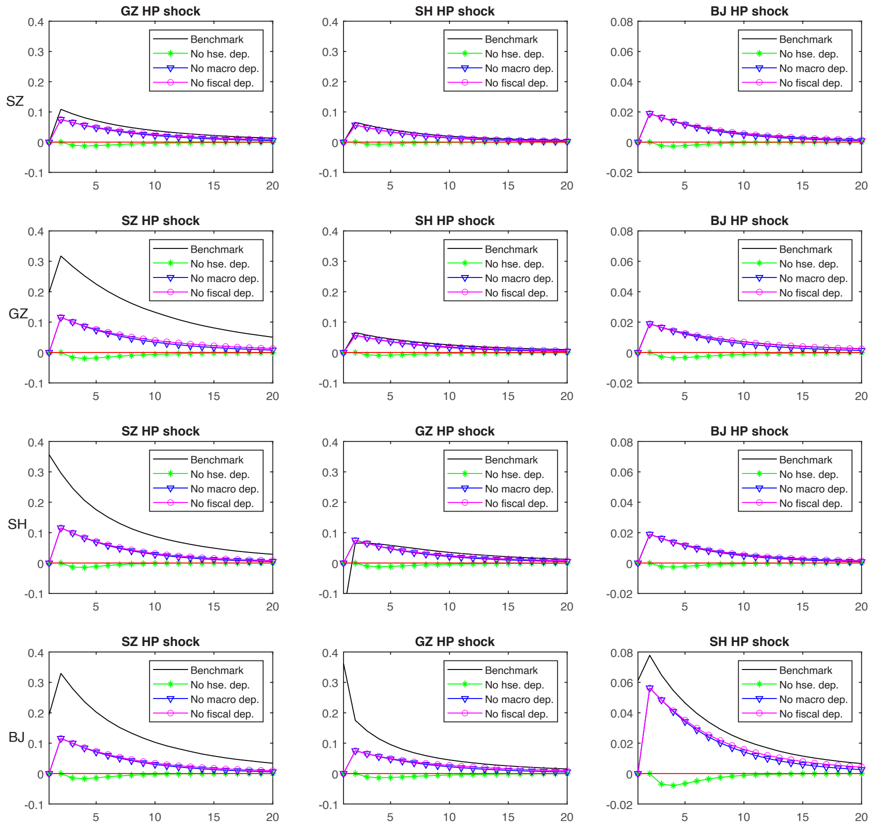

FIGURE 6 Impulse responses of city house prices with omitted channels

TABLE 1 Standard error of the house price shock

Shenzhen	Guangzhou	Shanghai	Beijing
0.7455	0.4549	0.3900	0.1126

(just like 'openness' in open economy models). Thus, the *empirical* unimportance of external shocks to Shenzhen is essentially a result of dominance of local shocks in size—that is, although shocks from the other cities do flow into Shenzhen, they are too small (compared to the local shocks) to reveal an impact. When we calculate the standard error of the house price shock of each city (Table 1), we find shocks from Shenzhen are clearly more sizable; for example, they are more than double the size of an average shock from the other three cities, and compared to shocks from Beijing they are larger by over six times. Thus, we see that cross-city heterogeneity of the housing market is also reflected by the different scales of local market risk.

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 house price shock from the other cities. Such price diffusion, known as house price

TABLE 2 What explains the house price shock?

Expl var	Coefficient	t-statistic	Remarks
const (ave)	−0.0194	−0.1915	Dep var: house price shock
Income	0.0197	0.3160	Years: 2003Q3–2017Q4
Reg pop	−0.0022	−0.0308	Cross-sections: SZ,GZ,SH,BJ
Trans pop	0.1843**	2.0686	Obs: 232
Unemp	−0.0700	−0.6246	Fixed-effect dummy: yes
Stock index	0.0627	1.1111	Est method: panel OLS
Floor space	−0.0165	−0.2590	
Land price	0.2300***	3.8800	Adj R^2: 0.2908
$AR(1)$	0.4915***	8.3941	

Notes: * and *** represent significance at the 10% and 1% levels respectively. All variables, except unemployment, are measured as the growth rate. All time series are standardised.

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 macroeconomy, 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 house 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.[10] These changes show the impact of the shut-down channel on transporting the house price shock from the other cities to the home city.

We consider the three homogeneous interdependencies—thus in the housing market, the macroeconomy and fiscal policy, respectively—allowed by the model, without discriminating cross-*sectoral* interdependency for that this last type is both insignificant and hard to interpret. 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

[10]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 $\varepsilon_{j,t}$, $\varepsilon_t = (\varepsilon'_{1,t}, \ldots \varepsilon'_{N,t})' = L^{-1}U_t$, and L is the lower triangular of the Cholesky decomposition of $\sigma\tilde{\Sigma}_{uu}$.

housing market interdependence across the entire region, aided by modest macroeconomic and fiscal policy interdependencies in part of the region.

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.

4.4.1 | What are included in the house price shock?

Our regional investigation finds that the house 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 (2021) 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'.

But what constitutes this shock in the megacities? Plainly, it may embrace anything from either the demand side or the supply side, or both, which is not explicitly modelled by (5). In order to understand the nature of this shock, we estimate it on a set of typical demand and supply factors in a panel regression.[11] The demand factors we consider are disposable income per capita, population (divided into census registered population and transient population), unemployment and stock market index; the supply factors considered are new floor space constructed and land prices.[12] The regression is shown by Equation (10). In Table 2 we report the OLS estimates.

$$
\begin{aligned}
Shock_{i,t}^{HP} \quad = \quad & \alpha_{i.t} + \beta_1 Income_{i,t} + \beta_2 RegPop_{i,t} + \beta_3 TransPop_{i,t} + \beta_4 Unemp_{i,t} \\
& + \beta_5 Stock_t + \beta_6 Floor_{i,t} + \beta_7 LP_{i,t} + \varepsilon_{i,t} \qquad \varepsilon_{i,t} \tilde{} AR(1)
\end{aligned} \tag{10}
$$

What we see from this exercise is that, among these potential factors, only transient population and land prices are significant in explaining the house price shock. Both the variables have a positive coefficient, as expected, suggesting that there are both 'demand-pull' and 'supply-push' elements in these shocks to house prices. In particular, such demand-push element due to population is only relevant to transient population, but irrelevant to census registered population; thus, the force comes from new migrants who have moved to these cities but have yet to become a 'permanent resident'. On the other hand, the variation of land prices, which is more a matter of shortfall in residential lands in megacities, is translated to that of house prices; this is in line with

[11] Had we not needed to allow for cross-sectional heterogeneity and interdependencies (in which case dimensionality would much less likely to be a concern), it is possible to simply include all these factors in the PVAR.

[12] Another popular supply factor considered in the literature would be construction costs. However, time series of this variable are unavailable for the megacities due to missing data.

the fact that local governments of these cities generally have a healthy budget and are therefore, less tempted to sell lands for revenue. The other factors, including the performance of the stock market, are proven not relevant, though by and large they have the expected sign of coefficient. Interestingly, we find the regression error is autocorrelated in order one. While this can simply be that the error is persistent, it can also be that there are omitted variables which we are unable to include in the regression due to the lack of data (e.g. construction costs, as we explained in Footnote 12, could be one of them).

What this exercise suggests, therefore, is that controlling inward migration and supply of residential lands remain the key for stabilising house prices in megacities. At present, both Guangzhou, Shanghai and Beijing have set rather tough migration criteria via the 'Hukou' system (the household registration system for permanent residency in China), with Shenzhen being relatively more open. But as we have just seen, the pressure of population does not come from permanent residents, the census registered population; rather, it is from the inflow in general whether or not some of them may in the end become permanent residents. Thus, although maintaining tough migration criteria may help reduce the desire of moving to megacities, even if just temporarily, a more realistic, long-run remedy would be for these cities to take on less burden of leading development and growth—thus, from the whole country's perspective, to mitigate regional imbalance in key aspects, such as employment, income distribution, infrastructure development, education, health care and social welfare, which would reduce the now tremendous gap between ordinary cities and megacities. On the supply of lands, it requests local governments of megacities to establish a stable supply pattern, even if they do not rely on 'land financing'; and they should encourage and promote more effective use of lands, such as, within an acceptable range, increasing the floor area ratio and building-to-land ratio.

4.4.2 | Cross-city heterogeneity and interdependencies

Our city-specific analyses confirms that each of the megacities bears their own characteristics. This is an important new finding which suggests that the common practice of grouping these cities into the same bloc—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 that local stabilisation policies should fully respect such heterogeneity. Gong et al. (2016), who find no market (price) convergence among the Pan-Pearl River Delta cities, share a similar view.

In addition, interdependencies among these cities lead to pervasive spillovers, including direct house price spillovers which have been widely reported in the empirical literature. Our counterfactual experiments in Section 4.3 find the latter are mostly due to interdependency among local housing markets, while that among local macroeconomies and fiscal policies is not much related. While diving deeper into what such 'housing market interdependency' may be would require a multi-region structural model, which is beyond the scope of this paper, the representative work we cited in the literature review section is worth reflecting; the five popular explanations are 'migration', 'equity transfer', 'spatial arbitrage', 'spatial pattern of determinants', and 'spatial pattern of economic structure'. The intuition of each of these explanations is as the following:

- Migration (Alexander & Barrow, 1994; Giussani & Hadjimatheou, 1991): households migrate from one market to another.

- Equity transfer (Muellbauer & Murphy, 1994): house owners from a more expensive market move up the housing ladder by reinvesting in a cheaper market, exploiting the markets' price differential.
- Spatial arbitrage (Pollakowski & Ray, 1997): buyers exploit the inefficiency (such as information inefficiency) of the market by investing in a sub-market where prices have yet to fully reflect the market fundamentals.
- Spatial pattern in the determinants of house prices (Holmans, 1990, 1995): housing market interdependency is a statistical artefact, reflecting interdependencies among the same determinants of house prices in different markets.
- Spatial pattern of economic structure (Meen, 1999): housing market interdependency is a statistical artefact, reflecting spatial patterns of the structural parameters in different markets due to associated, but variable, responses of house prices to their determinants, or unique market environments (market heterogeneity), or both.

The first three explanations all involve flows of housing demand from one city to another; the rest two deny any functional interdependency in the housing market, but attribute the seeming market 'association' to pure statistical relationships. We argue that, as far as the four megacities are considered, such 'interdependence', if any, is in the main less likely a result of cross-city demand movements. It cannot be caused by migration, as in China this normally happens between regions with a clear difference in economic development, as labour in less developed regions moves to more developed regions; 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. It could be partly caused by equity transfer and spatial arbitrage; but at least from 2010 onwards (which weighs half of our data sample) these activities could hardly happen due to the imposition of property purchase restrictions which prevents households from buying houses in cities where they are not permanent residents. Plainly it cannot be spatial patterns in the structural parameters, either, since cross-city heterogeneity has been well accounted for by our model.

What is most likely, by contrast, is that there are spatial patterns in the determinants of house prices not explicitly accounted by our PVAR. Given that property purchase restrictions have been in place, such factors tend to be from the supply side; for example, they can be land prices and construction costs, since both equity transfer and spatial arbitrage on lands and construction materials are still possible under property purchase restrictions. They can also be patterns in city-level housing market policies which are similar in form, but different in detail, where property purchase restrictions are themselves a perfect example.

Finally, we also identify strong cross-*sectoral* spillovers from the macroeconomy 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 macroeconomy 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.

4.4.3 | The role of monetary and fiscal policies

Both monetary and fiscal policies are, at the regional level, not drivers of house prices; but at the city level, government expenditure plays a modest role in Guangzhou and Beijing, especially in the short run. The impulse responses in Figure 4 find that a rise in local government expenditure lowers the prices in Guangzhou. This finding is consistent with Liu and Ou (2019) who, based on their estimated structural model allowing for non-separability between housing demand and government expenditure, interpret this as a crowding out effect of the latter on the former caused by households' trading (sacrifice) of living space with living quality (such as amenities and services) enhanced by the fiscal authority—intuitively, better living quality may be itself utility-enhancing and therefore, a substitute for living space (housing demand). In the case of Beijing (where only imported shocks matter), government expenditure inflates house prices. This case is in line with Tiebout (1956) who suggests government expenditure may well, on the other hand, be 'capitalised' into house prices if households see public amenities and services complementary to housing. Thus, we find government expenditure has quite varied implications for house prices at the city level, which may reflect a cultural difference in households' preference in housing, which deserves notice by policy-makers.[13]

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 core 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 due to transient population and land prices. 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 external shocks. Previous regional studies on the same topic, where cities were typically grouped into different blocs based on their economic and political importance, might have overstated the role of such factors; and we confirmed that, at the regional level, neither GDP nor fiscal policy mattered. 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 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

[13]It is worth pointing, however, that such 'expenditure', as measured by the time series published by the National Bureau of Statistics of China (NBSC) and used by this paper, is confined to genuine, 'non-investment' expenses of the public sector; it does not include 'government investment' which is embraced by the time series of 'Gross Capital Formation' (which makes no discrimination between public and private investments), as reported by the NBSC. As reviewed at the beginning of the paper, Liu and Ou (2019) find government investment—by generating a wealth effect—has a positive impact on housing demand and hence, also house prices.

and interdependencies are important model properties which deserve more attention in regional house price studies, as well as other studies in regional economics where spillovers are a non-trivial matter.

ACKNOWLEDGEMENTS

We are grateful to the managing editor (Akos Valentinyi), the editor (Walter Beckert), four anonymous referees, and David Meenagh for helpful comments. Any remaining errors will be ours.

REFERENCES

Andrews, D. W. K. (1991). Heteroskedasticity and autocorrelation consistent covariance matrix estimation. *Econometrica*, *59*, 817–858.

Alexander, C., & Barrow, M. (1994). Seasonality and cointegration of regional house prices in the UK. *Urban Studies*, *31*(10), 1667–1689.

Ashworth, J., & Parker, S. (1997). Modelling regional house prices in the UK. *Scottish Journal of Political Economy*, *44*(3), 225–46.

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*, *117*(4), 1329–1368.

Caldara, D., & Kamps, C. (2008). *What are the effects of fiscal policy shocks? A VAR-based comparative analysis* (Working Paper 877). European Central Bank, Retrieved from https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp877.pdf

Canova, F., & Ciccarelli, M. (2009). Estimating multicountry VAR models. *International Economic Review*, *50*(3), 929–959.

Canova, F., & Ciccarelli, M. (2013). *Panel vector autoregressive models: A survey* (Working Paper 1507). European Central Bank. Retrieved from https://EconPapers.repec.org/RePEc:ecb:ecbwps:20131507

Canova, F., Ciccarelli, M., & Ortega, E. (2012). Do institutional changes affect business cycles? *Journal of Economic Dynamics and Control*, *36*, 1520–1533.

Canova, F., & Pappa, E. (2007). Price differentials in monetary unions: The role of fiscal shocks. *The Economic Journal*, *117*, 713–737.

Chen, K., & Wen, Y. (2017). The great housing boom of China. *American Economic Journal: Macroeconomics*, *9*(2), 73–114.

Chiang, S. (2014). Housing markets in China and policy implications: Comovement or ripple effect. *China & World Economy*, *22*(6), 103–120.

Chow, G. C., & Niu, L. (2015). Housing prices in urban China as determined by demand and supply. *Pacific Economic Review*, *20*(1), 1–16.

Clark, W. A. V., Huang, Y., & Yi, D. (2021). Can millennials access homeownership in urban China? *Journal of Housing and the Built Environment*, *36*, 69–87.

Cook, S. (2003). The convergence of regional house prices in the UK. *Urban Studies*, *40*(11), 2285–2294.

Cook, S. (2005a). Regional house price behaviour in the UK: Application of a joint testing procedure. *Physica A: Statistical Mechanics and its Applications*, *345*(3), 611–621.

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

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*, *53*(14), 3048–3062.

Deng, C., Ma, Y., & Chiang, Y. (2009). The dynamic behavior of Chinese housing prices. *International Real Estate Review*, *12*(2), 121–134.

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

Drake, L. (1995). Testing for convergence between UK regional house prices. *Regional Studies*, *29*(4), 357–366.

Fatás, A., & Mihov, I. (2001). *The effects of fiscal policy on consumption and employment: Theory and evidence* (Discussion Paper 2760). CEPR, Retrieved from https://faculty.insead.edu/fatas/fiscal.pdf

Geyer, C. (2011). Introduction to MCMC. In S. Brooks, A. Gelman, G. L. Jones, & X. Meng (Eds.), *Handbook of Markov Chain Monte Carlo*.

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*, *23*, 707–733.

Giussani, B., & Hadjimatheou, G. (1991). Modeling regional house prices in the United Kingdom. *Papers in Regional Science*, *70*(2), 201–219.

Gong, Y., de Haan, J., & Boelhouwer, P. (2020). Cross-city spillovers in Chinese housing markets: From a city network perspective. *Papers in Regional Science*, *99*, 1065–1085.

Gong, Y., Hu, J., & Boelhouwer, P. (2016). Spatial interrelationships of Chinese housing markets: Spatial causality, convergence and diffusion. *Regional Science and Urban Economics*, *59*, 103–117.

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

Holmans, A. (1990). *House prices: Changes through time at national and sub-national level* (Government Economic Service Working Paper 110). Department of the Environment of the Great Britain.

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 1995/1996*. York.

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*, *1*.

Huang, F., Zhou, Y., & Li, C. (2010). Ripple effect of housing prices fluctuations among nine cities of China. *Management Science and Engineering*, *4*(3), 41–54.

Huang, Y., Yi, D., & Clark, W. A. V. (2020). Multiple home ownership in Chinese cities: An institutional and cultural perspective. *Cities*, *97*, 102518.

Iacoviello, M., & Neri, S. (2010). Housing market spillovers: Evidence from an estimated DSGE model. *American Economic Journal: Macroeconomics*, *2*, 125–164. American Economic Association.

Li, L., & Malpezzi, S. (2015). *Housing supply and regulation in 35 Chinese cities* (Working Paper 15LL1). Lincoln Institute of Land Policy.

Li, Q., & Chand, S. (2013). House prices and market fundamentals in urban China. *Habitat International*, *40*, 148–153.

Liang, Q., & Cao, H. (2007). Property prices and bank lending in China. *Journal of Asian Economics*, *18*(1), 63–75.

Liu, C., & Ou, Z. (2019). *Has fiscal expansion inflated house prices in China? Evidence from an estimated DSGE model* (Working Paper E2019/18). Cardiff University, Retrieved from http://carbsecon.com/wp/index_abstracts.html

Liu, C., & Ou, Z. (2021). What determines China's housing price dynamics? *New evidence from a DSGE-VAR', International Journal of Finance and Economics*, *26*, 3269–3305.

MacDonald, R., & Taylor, M. (1993). The monetary approach to the exchange rate: Rational expectations, long-run equilibrium, and forecasting. *IMF Staff Papers*, *40*(1), 89–107.

Meen, G. P. (1996). Spatial aggregation, spatial dependence and predictability in the UK housing market. *Housing Studies*, *11*(3), 345–372.

Meen, G. P. (1999). Regional house prices and the ripple effect: A new interpretation. *Housing Studies*, *14*(6), 733–753.

Minetti, R., Peng, T., & Jiang, T. (2019). Keeping up with the Zhangs and house price dynamics in China. *Journal of Economic Dynamics and Control*, *109*, https://doi.org/10.1016/j.jedc.2019.103778

Muellbauer, J., & Murphy, A. (1994). *Explaining regional house prices in the UK* (Working Paper WP94/21). University College Dublin, Retrieved from https://EconPapers.repec.org/RePEc:ucn:wpaper:199421

Ng, E. C. Y. (2015). Housing market dynamics in China: Findings from an estimated DSGE model. *Journal of Housing Economics*, *29*, 26–40.

Pollakowski, H., & Ray, T. (1997). Housing price diffusion patterns at different aggregation levels: An examination of housing market efficiency. *Journal of Housing Research*, *8*(1), 107–124.

Sun, L. (2020). *Housing affordability in Chinese cities* (Working Paper 20LS1). Lincoln Institute of Land Policy.

Tiebout, C. (1956). A pure theory of local expenditures. *Journal of Political Economy*, *64*(5), 416–424.

Toda, H. Y., & Yamamoto, T. (1995). Statistical inference in vector autoregressions with possibly integrated processes. *Journal of Econometrics*, *66*(1–2), 225–250.

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

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*, *77*(C), 75–86.

vanRavenzwaaij, D., Cassey, P., & Brown, S. D. (2018). A simple introduction to Markov Chain Monte-Carlo sampling. *Psychonomic Bulletin and Review*, *25*, 143–154.

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*, *22*, 42–54.

Wang, Z., & Zhang, Q. (2014). Fundamental factors in the housing markets of China. *Journal of Housing Economics*, *25*, 53–61.

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

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*, *432*, 257–268.

Xu, X. E., & Chen, T. (2012). The effect of monetary policy on real estate price growth in China. *Pacific-Basin Finance Journal*, *20*(1), 62–77.

Zhang, C., An, G., & Yu, X. (2012). What drives China's house prices: marriage or money? *China & World Economy*, *20*(4), 19–36.

Zhang, F., & Morley, B. (2014). The convergence of regional house prices in China. *Applied Economics Letters*, *21*(3), 205–208.

Zhang, H., & Liu, L. (2009). Empirical research on housing price ripple effect between China's cities. In *2009 IITA International Conference on Services Science* (pp. 43–46).

Zhang, L., Hui, E., & Wen, H. (2017). The regional house prices in China: Ripple effect or differentiation. *Habitat International.*, *67*, 118–128.

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

How to cite this article: Liu, C., & Ou, Z. (2022). Revisiting the determinants of house prices in China's megacities: Cross-sectional heterogeneity, interdependencies and spillovers. *The Manchester School*, 00, 1–23. https://doi.org/10.1111/manc.12397

APPENDIX A

UNIT ROOT TESTS OF THE DATA

The original data are collected from the National Bureau of Statistics of China and are available from 2003Q1 to 2017Q4. Housing price (q_h) is measured by the average sales price of private houses. Inflation (π) is measured by the year-on-year growth of CPI. GDP (y) is measured by the gross metropolitan product. Government expenditure (g) is measured by the general budgetary public expenditure. Nominal interest rate (R) 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 (marked with a '·').

The processed data (which are used for estimating the model) are demeaned and standardised. Both the ADF test and the KPSS test are used for testing the stationarity of them. All the time series are stationary according to the KPSS test. The ADF test, which is less prone to reject unit root in general, also finds that about half of them are stationary.

TABLE A1 Unit root tests of the processed data

Variables	ADF test stat	Conclusion	KPSS test stat	Conclusion
$\dot{g}_t^{SZ}$	−1.2913	Non-stationary at the 10% level.	0.1848	Stationarity at the 10% level
$\dot{y}_t^{SZ}$	−2.3890**	Stationary at the 5% level	0.3494*	Stationarity at the 5% level
π_t^{SZ}	−2.3697**	Stationary at the 5% level	0.1649	Stationarity at the 10% level
$\dot{q}_{h,t}^{SZ}$	−0.9088	Non-stationary at the 10% level	0.0619	Stationarity at the 10% level
$\dot{g}_t^{GZ}$	−0.1467	Non-stationary at the 10% level	0.1560	Stationarity at the 10% level
$\dot{y}_t^{GZ}$	−1.1999	Non-stationary at the 10% level	0.3638*	Stationarity at the 5% level
π_t^{GZ}	−1.43983	Non-stationary at the 10% level	0.2097	Stationarity at the 10% level
$\dot{q}_{h,t}^{GZ}$	−1.08734	Non-stationary at the 10% level.	0.1872	Stationarity at the 10% level
$\dot{g}_t^{SH}$	−1.7064*	Stationary at the 10% level.	0.3922*	Stationarity at the 5% level
$\dot{y}_t^{SH}$	−2.2411**	Stationary at the 5% level.	0.3339	Stationarity at the 10% level
π_t^{SH}	−1.1865	Non-stationary at the 10% level	0.2767	Stationarity at the 10% level
$\dot{q}_{h,t}^{SH}$	−2.2853**	Stationary at the 5% level.	0.2189	Stationarity at the 10% level
$\dot{g}_t^{BJ}$	-1.2043	Non-stationary at the 10% level.	0.3630*	Stationarity at the 5% level
$\dot{y}_t^{BJ}$	−1.7641*	Stationary at the 10% level.	0.3482*	Stationarity at the 5% level
π_t^{BJ}	−2.3567**	Stationary at the 5% level.	0.2098	Stationarity at the 10% level
$\dot{q}_{h,t}^{BJ}$	−1.0437	Non-stationary at the 10% level.	0.0935	Stationarity at the 10% level
R_t	-0.8132	Non-stationary at the 10% level.	0.2018	Stationarity at the 10% level

Notes: *, **, *** indicate rejection of H_0 at the 10%, 5% and 1% levels respectively. H_0 of the ADF test: the time series has a unit root; H_0 of the KPSS test: the time series is stationary. Critical values of the ADF test: −2.6054 (1%), −1.9465 (5%), −1.6132 (10%); critical values of the KPSS test: 0.7390 (1%), 0.4630 (5%), 0.3470 (10%); Sample: 2003Q1—2017Q4; KPSS test bandwidth selection criteria: Andrews (1991).

APPENDIX B

PRIORS AND POSTERIORS OF THE VAR PARAMETERS

TABLE B1 Priors and posteriors of the VAR parameters

	Prior			Posterior	
Parameter	distr.	Mean	*SD*	Median	*SD*
θ_1	Normal	0	1000	-0.0348	0.0060
$\theta_{2,1}$	Normal	0	1000	0.1627	0.0145
$\theta_{2,2}$	Normal	0	1000	0.1952	0.0111
$\theta_{2,3}$	Normal	0	1000	0.1576	0.0157
$\theta_{2,4}$	Normal	0	1000	0.1750	0.0105
$\theta_{3,1}$	Normal	0	1000	0.1162	0.0161
$\theta_{3,2}$	Normal	0	1000	0.2013	0.0107
$\theta_{3,3}$	Normal	0	1000	0.1660	0.0174
$\theta_{3,4}$	Normal	0	1000	0.1973	0.0151
θ_4	Normal	0	1000	0.0433	0.0270