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Convergence and Spillover of House Prices in Chinese Cities

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Abstract

The issue of house price convergence in 34 Chinese cities is investigated. We augmented the convergence model with contemporaneous spatial dependence in house prices and found that price convergence and positive spatial spillover are both present. We explicitly addressed the endogeneity problem by introducing a Bayesian instrumental variable setup, which was estimated with particle filtering techniques. From a growth poles perspective, the empirical evidence indicates that the spread effect in regional house prices outweighs the backwash effect. The identified positive spatial spillover has two effects on the growth of house prices in Chinese cities. First, the spillover elevates the trajectories of the steady-state growth paths of house prices. Second, the spillover narrows the gaps between the growth paths of house prices in neighboring cities. Shocks to the socioeconomic variables of a city generate their own effects on domestic house prices that dominate the effects arising from cross-city price feedbacks, thus mitigating the prospect of level convergence. Our findings also suggest a collaborating role between time and spatial dependence parameters. The identification of inter-city spillover, which is a conditioning factor for regional house price convergence, offers implications to policies that are most likely to be effective in reducing regional disparity.

Keywords: China house prices; Spatial dynamic panel model; Convergence; Spillover.
JEL Classifications: R12; R21; C5.

1. Introduction

Are house prices in less developed cities catching up with those in more developed ones, and if so, at what pace and by what means? House price convergence at the city level has long been a topic of profound interest in the economics and urban planning literature. The relevance of this convergence stems from the possible revelation of the linkage between changes in relative house prices and those in economic activities. On the one hand, relative house prices can influence labor mobility through housing affordability and relocation costs. On the other hand, these prices largely reflect cities' relative wealth levels because houses are usually the most important asset in homeowners' portfolios. Economists and policy makers alike cannot afford to overlook these subjects.

The life-cycle theory of consumption suggests that consumers' expenditure depends on human capital, viz, the present value of expected incomes from the supply of labor and the value of tangible and financial assets (Deaton, 1992). If such is the case, a stagnant housing market can lead to stagnant consumption and consequently a contraction in a city's economy. As a consumption good, housing has a strong non-traded component (i.e., land and labor) and a small traded component (e.g., construction materials) (Hiebert and Roma, 2010). The non-traded component can limit the prospect of house price convergence across geographic regions. Therefore, house prices at the city level are expected to mainly reflect local factors such as regional per capita income and population. House prices may converge if housing demand fundamentals (e.g., per capita income or productivity) converge among cities (e.g., Rebelo, 1991; Leung, 2001, 2003; Cheng *et al.*, 2010). Specifically, economic theory suggests that less developed cities will grow faster over time as investments move to these underdeveloped markets because entrepreneurs value inexpensive production factors. This theory has been extensively tested in the contexts of national economies (Barro, 1991) and metropolitan areas (Drennan et al., 1996; Pack, 2002). If convergence across cities actually exists, house prices of less prosperous cities are expected to appreciate faster than those of more prosperous ones.

However, past empirical evidence on house price convergence was mixed. Several studies used cointegration models to demonstrate a long-run equilibrium in the ratio of regional house prices, although the house prices of the concerned regions may diverge in the short run (MacDonald and Taylor, 1993; Alexander and Barrow, 1994; Petersen et al., 2002; Holly et al., 2010). However, other studies presented no supporting evidence for house price convergence. For instance, Drake (1995), Ashworth and Parker (1997), Meen (1999), Petersen et al. (2002), and Holmes and Grimes (2008) reported either no or very weak evidence for stationarity in the ratio of regional house prices to the aggregate house prices in the United Kingdom. Similarly, Gallet (2004) and Clark and Coggin (2009) found only mixed evidence for regional house price convergence among cities in the United States.

This study focuses on the possible house price convergence among Chinese cities. China's housing reform has been gradually implemented in the last two decades through market mechanisms. The year 1999 marked a turning point for China's housing-distribution system when the provision of all welfare housing through municipal and work-unit distribution was ended. Nevertheless, regional disparity of housing development remains a major challenge to the housing reform (e.g., Song and Chen, 2004). Utilizing the concept of absolute and conditional convergence, this study investigates whether the growth rates of house prices converge among major cities in China. Absolute convergence refers to the case in which the convergence dynamics is governed entirely by the initial distribution of house prices. The converging activities that flow through over time ensure that all cities can have the same steady-state house price[1]. In a way, the growth paths of house prices in cities converge. However, if the major determinants of house prices are idiosyncratic, the prices converge to parallel growth paths and the gaps between these trajectories are decided by city-specific socioeconomic variables (i.e., conditioning factors). In this latter case of conditional convergence, initial differences in house price determinants across cities can create permanent differences in price levels.

Past studies on house price convergence typically assumed cross-sectional independence. However, spatial correlation of house prices among adjacent regions is a common phenomenon. Statistics from the current study actually demonstrates significant and increasing spatial correlation among house prices in Chinese cities. Ignoring this spatial correlation may lead to biased and inconsistent estimates in convergence analysis (Anselin, 1988; Lesage and Pace, 2009). Our study contributes to the literature by considering not only regional-specific socioeconomic variables but also spatial correlation (i.e., spatial spillover) of house prices as factors of conditional convergence. Under such an empirical setting, conditional convergence and spatial spillover jointly govern the growth of regional house prices through distinct but interactive channels. First, conditional convergence implies that regional house prices converge to parallel growth paths in the steady state. Second, positive (negative) spatial spillover increases (decreases) the trajectories of steady-state growth paths of house prices. Third, positive (negative) spatial spillover narrows (widens) regional disparity in house price growth caused by regional differences in socioeconomic factors. This interplay of convergence and

[1] Following past studies (e.g., Abraham and Hendershott, 1994; Capozza *et al.*, 2002; Rodda and Goodman, 2005), steady-state house price is defined as the fundamental value for housing determined by economic conditions.

spatial spillover in the housing market can potentially yield policy implications for reducing regional disparity in China.

The spatial interaction of regional house prices is attributed to the well-known “ripple effect” hypothesis, which postulates that shocks to regional house prices tend to “ripple out” across the economy (e.g., Drake, 1995; Ashworth and Parker, 1997; Meen, 1999). According to Meen (1999), the extent of the ripple effect hinges on factors such as spatial patterns of house price determinants, migration, equity transfer, and spatial arbitrage. The spatial spillover effect complements the ripple effect and provides an analysis with a spatial perspective that conventional convergence studies ignore. Myrdal (1957) dichotomized regional growth dynamics into “spread” and “backwash” effects. The spread effect is the positive influence of growth in the core regions on the peripheral regions[2]. This effect can stem from backward linkages between the core and the periphery in which the latter functions as suppliers of inputs to the former. The spread effect can also be caused by diffusion of investment and innovation from the core to the periphery. By contrast, the backwash effect is the negative influence of the core’s growth on the periphery, and it results in, for instance, depopulation and capital shortages in the periphery caused by the migration of production factors from the periphery to the core. The backwash effect can also be attributed to the displacement of certain sectors in the periphery by their counterparts in the core.

Regional house prices are a manifestation of the regions’ economic strengths; therefore, the spread and backwash effects respectively create positive and negative linkages between house

[2] Core regions are places where favorable conditions for expanding employment opportunity and other economic activities exist. These conditions include a developed public infrastructure and current external economies.

prices of the core and the periphery. Richardson (1976) indicated that the spread and backwash effects usually occur simultaneously. For example, the migration of skilled and professional workers from the periphery to the core is a backwash effect, whereas decisions to decentralize by middle-class residences in the core represent a spread effect. Gaile's (1980) review of 21 studies up to the 1980s concluded that the spread effect is generally smaller than the backwash effect, and inter-regional interaction is limited to very short distances. In China, residents in a city without a local *hukou* (i.e., household registration) are not entitled to the same social benefits, such as the state-sponsored Urban Affordable Housing, as their local counterparts. This *hukou* system may reduce the backwash effect by restraining labor migration from the periphery to the core.[3]

With these building blocks, we specify a reduced-form spatial dynamic panel model (Kukenova and Monteiro, 2008; Parent and LeSage, 2010; Debarsy et al., 2011) that we estimate using Bayesian methodology. The rest of this article is organized as follows. Section 2 describes an endogenous growth model characterizing the steady-state growth paths of house price and real gross domestic product (GDP). Section 3 outlines the structure of an empirical model that considers both convergence and spatial spillover. Section 4 discusses the data and various estimation issues. Section 5 reviews the estimation results and their policy implications. Section 6 concludes.

[3] Different from previous studies (e.g., Henry and Barkley, 1997) that investigated the urban–rural development linkages, the current study examines the spread and backwash effects across a system of cities and their immediate surrounding area.

2. Endogenous Growth Model with the Housing Sector

This section presents an endogenous growth model based on those proposed by Rebelo (1991), Leung (2001, 2003), and Cheng *et al*. (2010), in which the growth rates of the real GDP and house price are endogenously determined. This model provides theoretical underpinning for house price convergence. Consider a region where population is normalized to unity and land supply is fixed. Each individual derives utility from a utility function, $u(c_t, h_t) = \ln(c_t) + wln(h_t)$, where c_t is the consumption of non-housing goods, h_t is the stock of houses, and w is a preference parameter. Moreover, each individual owns a firm that produces non-housing goods and a firm that constructs houses. House construction requires both capital goods and land (represented by l_t). Following the assumptions of Leung (2003), each individual chooses c_t, k_{t+1}, k_{t+1}^h, h_{t+1}, h_t^m, and l_{t+1} to maximize the lifetime utility, $U = \sum_{t=0}^{\infty} \gamma^t u(c_{t,} h_t)$, subject to:

$$c_t + k_{t+1} + k_{t+1}^h + p_{l,t}(l_{t+1} - l_t) + p_t h_t^m = Ak_t; \tag{1}$$

$$h_{t+1} - h_t = h_t^m + \left(k_t^h\right)^\alpha (l_t)^{1-\alpha}, \tag{2}$$

where Ak_t and $\left(k_t^h\right)^\alpha (l_t)^{1-\alpha}$ are respectively the production functions of non-housing goods and houses, and A is a technology parameter. Equation (1) assumes that the unconsumed output of non-housing goods in each period is channeled into four types of other activities: (i) capital investment for the next-period non-housing goods production (k_{t+1}), (ii) capital investment for the next-period house construction (k_{t+1}^h), (iii) purchase of land ($l_{t+1} - l_t$) at a unit price $p_{l,t}$, and (iv) purchase of houses (h_t^m) at a unit price p_t. Equation (2) signifies that the increase in the stock of houses owned by an individual comprises the amount of self-production $\left(k_t^h\right)^{\alpha}(l_t)^{1-\alpha}$ and the amount purchased from the market h_t^m.

In accordance with typical growth models (e.g., Barro and Sala-I-Martin, 1990), the diminishing return to capital ensures that the growth rates of poor and prosperous regions converge because the former tends to have higher growth rates than the latter. Leung (2003) demonstrated that, in the steady state, the growth rate of the output of non-housing goods (g), the growth rate of the stock of houses (x), and the growth rate of house price (y) have the following relationships:

$$x \cong \alpha g, \tag{3}$$

$$y \cong (1-\alpha)g. \tag{4}$$

Equation (3) implies that the stock of houses cannot grow faster than the output of non-housing goods because of the fixed supply of land. Consequently, in Equation (4), the growth rate of house price increases with the proportion of land (1 – α) in house construction.

This model also clarifies the relationship between house price and the overall price index. Normalizing the unit price for non-housing goods to unity and assuming that $l_{t+1} - l_t = h_t^m$ = 0, the value of non-housing goods produced in year t is $Ak_t = c_t + k_{t+1} + k_{t+1}^h$ and that of new houses constructed is $p_t h_t x$. The overall price index defined as the value-weighted average price of non-housing goods and houses is

$$CPI = (1-\nu_t) \times 1 + \nu_t p_t, \tag{5}$$

where $v_t = p_t h_t x/(Ak_t + p_t h_t x)$ is the value of houses constructed as a share of the real GDP. From Equation (5), $\frac{\partial CPI}{\partial p_t} = (p_t - 1)\frac{\partial v_t}{\partial p_t} + v_t$. Since both v_t and $\frac{\partial v_t}{\partial p_t}$ are positive, $\frac{\partial CPI}{\partial p_t}$ is positive if p_t is larger than unity (i.e., the unit price for non-housing goods).

3. Empirical Model

The endogenous growth model presented in the previous section implies that, if a region's house price grows at a constant rate in the steady-state equilibrium, regions with initially different house prices eventually converge to parallel growth paths with the height of each path depending on region-specific conditioning factors (e.g., socioeconomic factors). Although typical convergence studies assume cross-sectional independence, Anselin (1988) and Lesage and Pace (2009) indicated that ignoring spatial correlation could lead to biased and inconsistent estimates. As Section 5 will demonstrate, a significant and increasing spatial correlation (in terms of Moran's I index) exists among house prices in Chinese cities. Therefore, the empirical model of this study considers not only socioeconomic factors but also spatial correlation (i.e., spatial spillover) as conditioning factors for house price convergence.

This study's empirical model is classified either as a dynamic spatial autoregressive panel model (Debarsy et al., 2011) or as a time-space simultaneous model (Anselin, 2001). Specifically,

$$y_t = \beta y_{t-1} + \rho W y_t + Z_t \phi + \mu + \varepsilon_t, \qquad (6)$$

where y_t is a $N \times 1$ vector of the rates of change in house prices of N cities under study over a period of $s + 1$ years, that is, $y_t = \ln(p_t/p_{t-s})$. $Z_t = \ln(X_t/X_{t-s})$ is the $N \times k$ matrix of growth rates in k socioeconomic variables. The term $\rho W y_t$ captures the spatial spillover, where W is the row-normalized spatial weight matrix. We use the inverse of geographical distances (d) among cities to characterize W, so the ij-th entry of the weight matrix before normalization is equal to $1/d_{ij}$. ϕ is a $k \times 1$ vector of coefficients and μ is a vector of individual fixed effects. β and ρ are the time dependence and the space dependence parameters, respectively. Similar to past convergence studies, Equation (6) examines if the regions converge to parallel growth paths in the variable of interest (i.e., house price).

Equation (6) is not a complete structural demand–supply model for the housing market *per se* but is a reduced form of the model suggestive of counterparts commonly found in the time series literature. Similar to the many variants of vector autoregression models, a key analytical aspect of the spatial model is to study the system's response to shocks or impulses over the time dimension. The notable difference here is the extra spatial perspective that enriches (and complicates) the response structure.

With Z_t and Wy_t as possible conditioning factors, Equation (6) allows for the validation of both absolute and conditional convergence in house prices. Imposing the restrictions $\rho = \phi = 0$ and μ having identical elements, the conventional test for absolute convergence estimates the regression $y_t = \beta_0 ln(p_0) + \mu + \varepsilon_t$ and verifies $\beta_0 < 0$. Convergence is ensured as long as $\beta < 1$ in Equation (6) because a simple derivation can show that $\beta = 1 + \beta_0$. Whether the convergence is absolute or conditional depend on the significance of the parameters ρ, ϕ, and μ. ρ signifies the degree of contemporaneous spillover in house prices. The sign of ρ is positive (negative) if the spread effect is larger (smaller) than the backwash effect. $\rho = 0$ if the spread effect is in exact balance with the backwash effect.

We can look at the interplay between convergence and spillover by manipulating the algebra in the model. First, if $\beta = 0$ and $\rho \neq 0$, Equation (6) can be rewritten as follows:

$$y_t = (I - \rho W)^{-1} Z_t \phi + (I - \rho W)^{-1} (\mu + \varepsilon_t) \tag{7}$$
$$= Z_t \phi + \rho W Z_t \phi + \rho^2 W^2 Z_t \phi + \rho^3 W^3 Z_t \phi + \cdots + (\mu + \varepsilon_t)$$
$$+ \rho W (\mu + \varepsilon_t) + \rho^2 W^2 (\mu + \varepsilon_t) + \cdots;$$

therefore, the growth rate of house prices in city *i* at time *t* is subject to the multiple-order effect of contemporary changes in socioeconomic variables and exogenous shocks in own and *neighboring* cities. Note that Equation (7) has spatial lag effects but no time lag effects. If $\beta \neq 0$ and $\rho = 0$, the model can be restated by repeated substitution as follows:

$$y_t = Z_t \phi + \beta Z_{t-1} \phi + \beta^2 Z_{t-2} \phi + \cdots + (\mu + \varepsilon_t) + \beta(\mu + \varepsilon_{t-1}) + \tag{8}$$
$$\beta^2 (\mu + \varepsilon_{t-2}) + \cdots;$$

therefore, the growth rate of city *i* is subject to multiple rounds of the lagged effect of its own shocks and changes in the socioeconomic variables in its own region. Spatial spillover is non-existent. If both β and ρ are nonzero, the model becomes

$$y_t = \sum_{j=0}^{\infty} (I - \rho W)^{-(1+j)} \beta^j \left[Z_{t-j} \phi + \mu + \varepsilon_{t-j} \right], \tag{9}$$

where there is interacting spatial and temporal dependence across all cities. The derivation of Equation (9) is presented in Appendix 1.

A non-technical view of the spillover–convergence account can be illustrated by the following. Suppose we have two groups of cities, *E* and *C*, with the former having higher house prices initially than the latter. Convergence (i.e., $\beta < 1$) implies a slowdown in the growth rates of *E* and faster growth rates in *C*. However, the convergence concept is independent of distance or the geographic distribution of *E* and *C* in China. A special feature of Equation (9) is that it also captures the spatial spillover effect (ρ) that is tied to geographical distance. For instance, if the backwash effect is concurrently larger (smaller) than the spread effect, that is, $\rho < 0$ (> 0), the members of C farther away from E (e.g., C_1) have higher (lower) catch-up growth. Those nearer to E (e.g., C_2) have lower (higher) growth than C_1, but it is still possible for C_2 to have growth rates that exceed those of E by virtue of convergence.

We can also contemplate the issue from the perspective of clustering. If the price distribution is initially such that a few high-priced cities are clustered along the coastal areas, with lower-priced cities more sparsely distributed toward the inner part and the fringe areas of the country, then cities that are farther away from the coast have above par growth rates in house prices than those near the coast by virtue of convergence. At the same time, backwash (spread) implies that (i) the original clusters along the coast can (cannot) gain further dominance, and (ii) there will be less (more) newly developed clusters as the effect of convergence is diluted (enhanced) by a negative (positive) spillover.

As a caveat, our study does not consider Wy_{t-1} (i.e., a "second-order" spatial lag) in Equation (6) because our model blends together a dynamic spatial model with a Bayesian instrumental variable setup to handle endogeneity and feedback. Parent and LeSage (2012) pointed out that without such restriction it is impossible to separate the space and time dimensions in evaluating the impact of changes on variables.[4] In fact, excluding Wy_{t-1} does not totally rule out the possibility of intertemporal correlation among the sample cities' house prices because our

[4] This technical constraint is not unique to our study. Including only the first-order spatial lag in the model is a rather common practice in past related studies. For instance, in a brief survey conducted by Kukenova and Monteiro (2008), none of the reviewed models simultaneously contained both first- and second-order spatial lags, and majority of them did not have a second-order lag.

empirical framework allows the house price growth of city *i* to correlate with that of city *j* in period *t* (i.e., the space dimension), which in turn correlates with city *j*'s own house price growth in *t*+1 (i.e., the time dimension). Moreover, our findings are unlikely to be sensitive to the exclusion of Wy_{t-1} because the sample's cross-correlation between the current-period growth of city *j*'s house price against the lagged growth of city *i*'s house price is insignificant (the mean correlation coefficient is –0.0646).

4. Data and Estimation

4.1. Data

We compile a balanced panel of $N = 34$ Chinese cities from 2000 to 2008 based on data obtained from China Data Online.[5] The growth rate of house price (y_t) in Equation (6) is measured by the growth rate of the sale price index of houses rescaled to a base of 100 in 2000.[6] Distances among cities are obtained from the China Distance Calculator.[7] X_t includes the following k = 8 variables:

(i) GDP: Equation (4) of the endogenous growth model implies that house price growth is a fraction of the GDP growth in the long-run equilibrium when the two variables grow

[5] China Data Online is compiled by the China Data Center, University of Michigan, using data from China Statistical Yearbook. The city-level sale price index of houses is available until 2009. We compiled the sample until 2008 to avoid the possible effect of the global financial crisis on the real estate market. The sample cities are Beijing, Changchun, Changsha, Chengdu, Chongqing, Dailan, Fuzhou, Guangzhou, Guiyang, Haikou, Hangzhou, Harbin, Hefei, Hohhot, Jinan, Kunming, Lanzhou, Nanjing, Nanning, Ningbo, Qingdao, Shanghai, Shenyang, Shenzhen, Shijiazhuang, Taiyuan, Tianjin, Urumqi, Wuhan, Xiamen, Xi'an, Xining, Yinchuan, and Zhengzhou.

[6] To show that y_t in Equation (6) is equal to the growth rate of the house price index, let $h_t = p_t/p_0$ be the price index, where p_t is the actual house price in *t* (*t*=0 is the base year). The growth rate of $h_t = \ln(h_t/h_{t-1}) = \ln(h_t)–\ln(h_{t-1}) = \ln(p_t)–\ln(p_{t-1}) = \ln(p_t/p_{t-1}) = y_t$.

[7] http://www.distancecalculator.globefeed.com/China Distance Calculator.asp.

at constant rates. Since the growth rates of house price and GDP are endogenously determined in the theoretical model, our estimation approach controls for this potential endogeneity.

(ii) Consumer price index (CPI): Previous studies such as Ozanne and Thibodeau (1983) found house price to be positively associated with inflation. According to Campbell and Cocco (2015), rising inflation lowers real interest rates by increasing expected inflation, which decreases the user cost of housing and real mortgage payments.[8] Similar to the GDP, CPI is potentially endogenous because house price is included in the construction of CPI. Equation (5) suggests that the degree of such endogeneity increases with the price gap between houses and non-housing goods. Again, our estimation approach controls for this potential endogeneity.

(iii) Population: This study employs an endogenous growth model that assumes constant household population and land supply. Cheng *et al.* (2010) relaxed this assumption and found that the steady-state growth rate of house price increases with the excess of population growth over land supply growth. Assuming that land supply is fixed (or population grows considerably faster than land supply), house price growth is expected to increase with population growth.

(iv) Total wages: The expected relationship between the growth rates of house price and wages is uncertain. While a city's wage growth increases the city's demand for residential housing (e.g., Manning, 1989), wage growth across the entire country (e.g.,

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[8] Alternatively, the high expected inflation and nominal interest rates signify that nominal house prices tend to increase.

economic boom) is usually accompanied by high interest rates as a part of the contractionary monetary policy (Campbell and Cocco, 2015).

(v) Employment: The expected relationship between the growth rates of house price and employment is uncertain. While a city's employment level indicates the level of economic activity that is positively associated with the city's house price (e.g., Bourassa *et al*., 1999), nationwide employment growth is usually accompanied by high interest rates.

(vi) Outstanding amount of savings deposit: Engelhardt (1996) argued that the amount of savings deposit indicates homebuyers' financial ability to overcome liquidity constraints. Similarly, Campbell and Cocco (2015) showed that households with tight liquidity constraints have a high rate of mortgage default.

(vii) Number of regular secondary schools: Haurin and Brasington (1996) reported that education quality and house price are positively associated.

(viii) Total passenger traffic: This variable proxies the development of transportation infrastructure, such as roads and public transit, and it is expected to be positively associated with house price (e.g., Haider and Miller, 2007).

4.2. Estimation Approach

We feed the data into Equation (6) using $s = 2$ and divided the sample into $T = 3$ intervals of equal length (i.e., 2000–2002, 2003–2005, and 2006–2008). Each observation t represents a three-year interval, and the numerical value is the growth rate of the variable over a three-year period. Therefore, the period t and t – 1 variables in Equation (6) have an underlying coverage of six years, and they tend to span beyond a complete growth cycle of many economic time series (Harding and Pagan, 2002).[9] This strategy allows an optimal use of the limited data we have and prevents high-frequency variations of house prices to weigh on our analysis at the same time.

As previously mentioned, GDP and CPI are potentially endogenous in Equation (6). However, none of the existing approaches for estimating spatial dynamic panel data models, including generalized method of moments (GMM) (Kukenova and Monteiro, 2008) and Markov Chain Monte Carlo (MCMC) estimation (Parent and LeSage, 2010; Debarsy et al., 2011), offer an integrated solution to address endogeneity and potential time-varying parameters. To accommodate these possibilities, we place Equation (6) in a state-space setting and solve the model using Sequential Monte Carlo (SMC) methods (e.g., Doucet and Johansen, 2011). First, we decompose the socioeconomic variable Z_t into subsets of $\tilde{k}$ endogenous variables $\tilde{Z}_t$ (which includes the growth rates of GDP and CPI in our exercise) and $k-\tilde{k}=k^*$ exogenous counterpart Z_t^*. A first-order autoregressive structure is introduced to each variable in the former group[10] and a time-varying structure is specified for the coefficient vector ϕ. Thus, the model is augmented as follows:

$$\begin{bmatrix} I_N-\rho W & 0 \cdots & 0 \\ 0 & 1 & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 1 \end{bmatrix} \begin{bmatrix} y_t \\ \tilde{Z}_{1t} \\ \vdots \\ \tilde{Z}_{\tilde{k}t} \end{bmatrix} = \begin{bmatrix} y_{t-1} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \beta + \begin{bmatrix} \tilde{Z}_t & Z_t^* \\ 0 & 0 \\ \vdots & \vdots \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \tilde{\phi}_t \\ \phi_t^* \end{bmatrix} +$$

[9] We have experimented with the inclusion of *t*-2 endogenous variables as instruments in equation (5), and found counter-intuitive patterns in the direct-indirect effects and signs of coefficients. A possible reason is that the second-order lags of the instruments are weakly related to the endogenous variables given the large time gap separating them. We have also tried an alternative specification of setting the endogenous variables not as contemporaneous factors but as first lag inputs while retaining the first order autoregressive transitional dynamics. The results largely resemble those of the chosen model reported in this paper.

[10] The lagged terms of the endogenous variables can be replaced with instruments if they are readily available.

$$\begin{bmatrix} 0 & \cdots & 0 \\ \tilde{Z}_{1t-1} & 0 & \cdots \\ 0 & \ddots & \vdots \\ \vdots & 0 & \tilde{Z}_{\tilde{k}t-1} \end{bmatrix} \begin{bmatrix} a_1 \\ \vdots \\ a_{\tilde{k}} \end{bmatrix} + \begin{bmatrix} I_N \\ 0 \\ \vdots \\ 0 \end{bmatrix} \mu + \begin{bmatrix} \varepsilon_t \\ v_{1t} \\ \vdots \\ v_{\tilde{k}t} \end{bmatrix} \quad (10)$$

$$\begin{bmatrix} \tilde{\phi}_t \\ \phi_t^* \end{bmatrix} = \begin{bmatrix} B_{\tilde{k}} & 0 \\ 0 & C_{k^*} \end{bmatrix} \begin{bmatrix} \tilde{\phi}_{t-1} \\ \phi_{t-1}^* \end{bmatrix} + \xi_t. \quad (11)$$

$$\begin{bmatrix} \varepsilon_t \\ v_{1t} \\ \vdots \\ v_{\tilde{k}t} \end{bmatrix} \equiv \eta_t \sim N(0, \Omega), \quad \xi_t \sim N(0, \Psi), \quad (12)$$

where η_t and ξ_t are uncorrelated. The stacking of the variables in (10) resembles the standard Bayesian treatment of simultaneous equation problems except that the instruments are replaced by the lags of the endogenous variables.

The covariance matrix Ω has non-zero off-diagonal elements indicating the correlation between ε_t and v_t. The dimension of the parameters can be significantly reduced[11] if we restrict Ω to

$$\Omega = \begin{bmatrix} \Omega_\varepsilon & \Omega_{v1,\varepsilon}{}' & \Omega_{v2,\varepsilon}{}' \\ \Omega_{v1,\varepsilon} & \Omega_{v1} & \Omega_{v2,v1}{}' \\ \Omega_{v2,\varepsilon} & \Omega_{v2,v1} & \Omega_{v2} \end{bmatrix}, \ \Omega_{i,j} = \Omega_i^{1/2\prime} c_{i,j} \Omega_j^{1/2} \quad , (13)$$

where v_1 and v_2 are the error terms of the first-order autoregression of the two endogenous variables, namely, GDP growth and inflation, and the subscripts v_1, v_2, and ε to Ω represent the parameter pairs that the correlation term defines. The correlation matrices $c_{i,j}$ and Ω_i are diagonal, thus implying that endogeneity only exists among variables within the same city.

[11] The order of reduction is from $[(\tilde{k}+1)N][(\tilde{k}+1)N+1]/2$ to $\left[\binom{\tilde{k}+1}{2} + \tilde{k} + 1\right] N$. Reducing the dimension can make the numerical computation of likelihoods easier.

Stationarity of the system requires $|(I_N \beta)(I_N - \rho W)^{-1}| < 1$ (Parent and LeSage, 2010). In previous studies, imposing the constraints $|\beta| < 1$ and $1/\omega_{min} < \rho < 1/\omega_{max}$ is common, where ω_{max} and ω_{min} are the largest and smallest eigenvalues of the weight matrix, respectively. As the posterior of β and ρ can be non-regular or multi-modal, we relax the conventional practice of constraining β between [–1, 1] to exclude this case of non-convergence in our context. The eventual prior we use for β has a wider support than that typically adopted.

The state space Equations (10)–(12) can be estimated through various means. The sheer dimension of the model has prompted us to choose a method that is numerically easy to implement. The Liu–West (Liu and West, 2001) particle-filtering algorithm we adopted uses discrete approximation to obtain draws (i.e., "particles") of the state vectors from the joint posterior distribution and to make inference. The parameters are sampled using kernel smoothing techniques through the mixtures of normals. Although not particularly relevant in our case, particle filtering is congenial to the online learning of complex nonlinear state space models. Steps applied to implement the Liu–West algorithm are provided in Appendix 2. A full coverage of the Sequential Monte Carlo method is beyond the scope of this paper as the articulated descriptions are already presented in Lopes and Tsay (2011) and Liu and West (2001). We would, however, outline the prior distributions and major iteration steps.

A simple fixed effects panel data model is run to provide a perspective of reasonable ranges of parameter values that can appropriately define the prior distributions. In particular, the prior means and variances of the state vector ϕ in Equation (11), the individual effects μ in Equation (10), and Ω_ε in Equation (12) equal the estimates of the fixed effect model whenever applicable. The initial observations y_0 and Z_0 are unobservable, and they have to be sampled to initialize the algorithm. These values are generated from normal distributions with prior means that equal the first available observations y_1 and Z_1.[12] The time and space dependence parameters are distributed as $\beta \sim U(-2, 2)$ and $\rho \sim U(-1, 1)$ respectively. The endogenous vector $\tilde{Z}_t$ in Equation (10) and the state vector in Equation (11) are assumed to follow random walks *a priori*, and they define the probabilistic structure of parameters $a_{\tilde{k}}$, $B_{\tilde{k}}$, and C_{k^*}. Finally, the correlation coefficients in $c_{i,j}$ are uniform, and they have the usual bounds of –1 and 1. Ψ is assumed to have an inverted Wishart prior with a hyperparameter of a tightened identity matrix.

The number of particles is first selected ($M = 10{,}000$ in our exercise). For each particle, the parameters and an initial state vector are drawn from their corresponding priors. The particle weights are then evaluated on the basis of the likelihood function[13]. With the inflow of new information/data through the measurement equation, resampling from the existing particles is completed with the state vector propagated and the parameters updated. A re-weighting based on likelihood ratios is performed to prepare for the resampling in the next filtering time step. The weighted averages (or weighted medians in case of bi-modal posteriors) of the particle values are eventually obtained as the model estimates.

5. Estimation Results

5.1. Convergence and Spillover Parameters

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[12] In a Bayesian analysis, the importance of the prior distribution diminishes as the sample size grows. In the context of particle filtering applied in this study, the filter becomes asymptotically optimal as the number of particles increases (i.e., partition of the state space becomes increasingly fine) (e.g., Crisan and Miguez, 2013).

[13] Typically, log-likelihoods are highly feasible computationally in high-dimensional problems.

The estimation results are reported in Tables 1 and 2. Table 1 reports the posterior means and medians of the major parameters and their standard errors estimated from our spatial dynamic panel model. For comparison, Table 2 reports estimates from four auxiliary panel data models, namely, standard fixed effects model (FE), random effects model (RE), simple spatial autoregressive lag model (SAR), and spatial error correlation model (SEM).

[Insert Tables 1 and 2 here]

Regarding the state vector, the signs of the coefficients on the socioeconomic variables presented in Table 1 match those from the reference models in Table 2. The Hausman test statistics reported in Table 2 rejects the null hypothesis that the RE is more efficient and favors the FE instead. Table 2 also reports the Moran's I index over the three model periods; this index is positive in each case and displays an increasing pattern from the first period (0.521) to the third period (0.885).[14] This finding indicates the increased spatial correlation in the growth rates of house prices and thus justifies the inclusion of spatial spillover in our empirical model.

In Table 1, we find evidence supporting the convergence hypothesis and the positive spatial spillover in house prices, which is robust in the variations in prior parameters we explored. The weighted mean of $\beta = -0.159$ in our model, and the conventional convergence parameter $\beta_0 = -1.15$ because $\beta = 1 + \beta_0$.[15] The positive spatial dependence parameter ($\rho = 0.2615$)

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[14] Moran's I index ranges between –1 and +1. A positive (negative) value indicates a positive (negative) spatial correlation (e.g., Li *et al*., 2007).

[15] The estimation is under the assumption that the convergence parameter is time invariant. To explore the possibility of a time-varying convergence parameter, we re-estimated the model using observations $t = \{1, 2\}$ and $t = \{2, 3\}$ separately and determined that the values of β from the two subsamples are –0.0143 and –0.0246, respectively. Considering that the actual convergence parameter is $\beta_0 = \beta - 1$, the speed of convergence is indeed stable over the sample period.

suggests that the spread effect outweighs the backwash effect, which offers a magnifying factor (together with the distance matrix) for multiple rounds of instantaneous cross-city price feedback. In each round, a $\Delta\%$ change in the house price of a neighboring city causes a *at most* $0.2615\Delta\%$ change in the house price in the subject city in the same direction because the distance matrix has been normalized. The magnitudes of subsequent rounds continue to decline.[16] The pure spatial lag model results in a large estimate for the spatial dependence parameter ($\rho = 0.3190$) by excluding the time dependence parameter.

[Insert Figure 1 here]

From the upper panel of Figure 1, ρ is clearly bi-modal.[17] Although we have relaxed the tight support of [–1, 1] for β, the parameter values in excess of the range on either side do not appear to be admissible when the stationarity rule is applied. To deliver a desired estimate for ρ, the weighted median rather than the weighted mean of ρ is presented in Table 1.

To further assess the adequacy of the spatial dynamic panel model, we compute the Bayes Factor (BF) against alternative specifications. Two competing scenarios are evaluated, one is a case of divergence (no convergence), that is, $\beta > 1$, and the other is a case in which the space dependence is negative, that is, $\rho < 0$. In the SMC literature, the principal tool for hypothesis testing is the BF, which is essentially a likelihood ratio. The particle filter we used

[16] Here is a possible misnomer as all rounds are supposed to take effect instantaneously.

[17] The raw values presented in Figure 1 are unweighted. Different from the MCMC estimates that give equal weights to all sampled points, the particle-filtering algorithm employed in our study attaches small weights to pairs of β and ρ (i.e., particles) that violate the stationarity condition, in which the weights are functions of the likelihoods. The pairs of β and ρ that violate the stationarity condition have a slight effect on the posterior estimates because they receive small weights and the chance of their values being drawn in the re-sampling step of the algorithm is small.

enables the sequential update of the BF using the Monte Carlo approximation of marginal likelihoods. Specifically, the sequential BF is computed as follows:

$$\mathcal{BF}_{12,t} = \frac{\prod_{\tau=1}^{t} p(Y_\tau | Y_{0:\tau-1}, \mathcal{M}_1)}{\prod_{\tau=1}^{t} p(Y_\tau | Y_{0:\tau-1}, \mathcal{M}_2)}, \quad t = 1, \cdots, T, \tag{14}$$

$$p(Y_\tau | Y_{0:\tau-1}, \mathcal{M}) \approx \frac{1}{M} \sum_{i=1}^{M} p\left(Y_\tau | \{x_{\tau-1}, \theta\}^{(i)}\right), \tag{15}$$

where $x_{\tau-1}$ is the state vector at time $\tau - 1$, θ is the set of constant parameters, and $\mathcal{M}$ is the model under the hypothesis. The logarithmic-transformed sequential BFs are reported in Table 1. The evidence indicates a general preference for the basic unrestricted model over the non-convergence and negative spatial spillover alternatives.

5.2. Effect of Socioeconomic Variables

As expected, Table 1 suggests that GDP growth, inflation (i.e., CPI growth), population growth, savings deposit growth, and traffic growth all contribute positively to the steady-state growth rates of house prices. In particular, the house price growth rate is a fraction of the GDP growth rate (i.e., $1-\alpha < 1$) as predicted by Equation (4). However, employment growth and wage growth tend to have the opposite effect. As previously mentioned, the expected relationship between house price and wages is ambiguous because a city's wage growth increases the city's housing demand, whereas nationwide wage growth is usually accompanied by high interest rates. The dominating negative effect is due to the large degree of co-movement in wage growth among Chinese cities (the mean cross-sectional correlation coefficient of wage growth is 0.5143). A similar explanation is applicable to the negative effect of employment growth on house price growth.

Switches in signs of the estimated coefficients are infrequent among the socioeconomic variables, but their values can slightly vary periodically. Most of the growth elasticities are smaller than 1 in absolute value, and this value partly explains why we observe very small indirect effects, which we will discuss below. One obvious exception is the elasticity to CPI growth (≈ 0.5), which demonstrates a reasonable level given that houses are important fixed assets and their returns may track inflation to a certain extent.

Using these model estimates, we can predict house prices and observe how they compare with the actual levels. Figure 2 gives the predicted average growth in house prices for all the cities between 2000 and 2008 along with the actual growth rates. Despite the hundreds of parameters incorporated in our model and the inherent heterogeneity in the data, we observe a rather good fit of the actual data.

[Insert Figure 2 here]

As our specification considers the issue of endogeneity, we can also assess the pervasiveness of the problem in our sample. The vector $diag(c_{i,\varepsilon})$ captures the degree of endogeneity between the *i*-th endogenous variable and house price. A positive element in this vector implies that the error in the house price equation is positively related to that in the endogenous variable equation [i.e., Equation (10)] for the corresponding city. The numbers vary from city to city. The average error correlation between inflation and house price in the 34 cities is –0.16 and that between GDP growth and house price is 0.07. These results indicate a weak endogeneity between house price and the two explanatory variables.

The last issue concerning the socioeconomic variables is the decomposition of their effect into direct and indirect ones. The terminology may be vague as diffusions into one's own house price and into those of others are evident. Direct effect refers to the own (instantaneous, spatial spillover and time diffusion, all inclusive) effect of a change in the *r*-th factor in city *i* on the growth in house price in the same city. Indirect effect is the response of *j*'s house price to a shock originating from city *i* through spatial and temporal spillover. Debarsy et al. (2011) demonstrated how these effects could be evaluated when the coefficients are time invariant. Essentially, these effects are functions of ρ and β as implied by Equation (9). In our case, ϕ is not constant, and the direct and indirect effects depend on the time of impact.

Manipulating Equation (9) results in the $\partial Y_{it}/\partial Z_{jt-h}$ we need. Here, h is the time lag between current time *t* and the time of impact, $i = j,\ h = 0,1,\cdots$ gives the direct effect, and $i \neq j,\ h = 0,1,\cdots$ yields the indirect effect. To save space, we report only the average cumulative direct (i.e., averaged over all shock-originating cities *i*) and indirect effects of the socioeconomic variables (i.e., averaged over all non-shock-originating cities *j*) in Table 3. An element-by-element summation of the figures gives the average cumulative total effect of a change in the socioeconomic variable concerned.

As expected, the direct effect at the time of impact should be slightly larger than the corresponding coefficient because of the presence of positive spillover. Stationarity of the system guarantees that the non-cumulative response will die down eventually, but the negative time dependence implies that the adjustment will not be monotonic. These facts are reflected in the cumulative figures in the table. The indirect effects are much smaller in magnitude but share the same signs as the direct effects because of the aforementioned spatial spillover. On average, population growth, inflation, and GDP growth are the most influential factors that propel house prices regardless of the city of shock origin.

[Insert Table 3 here]

As previously mentioned, house prices may converge if there is convergence in housing demand fundamentals, such as incomes. Therefore, the dynamic relationship between the growth rates of house prices and GDP deserves further investigation. First, as the degree of endogeneity between the two variables is weak, GDP growth tends to be a conditioning factor for house price convergence but not the opposite. To compare their convergence speeds, Figure 3 plots the house price and GDP growth rates for $t = \{1, 2\}$ and $t = \{2, 3\}$ in the form of a scatter diagram.

[Insert Figure 3 here]

A visual inspection of the figure reveals that the observations of the two variables are aligned in similar directions and patterns. Specifically, both variables flatten as time lapses, thus indicating that their convergence speeds do not differ exceedingly from each other.

Alternatively, the magnitude by which a vector variable changes between any two time instances can be measured by the angle of the two vectors evaluated at the two time points. The angle of the two vectors of any variable (*Y*) between *t* and *t*+*k* is defined as follows:

$$Angle \equiv \angle = arccos\left(\frac{\|Y_{t+k}\|^2 + \|Y_t\|^2 - \|D\|^2}{2\|Y_{t+k}\|\|Y_t\|}\right), \qquad (11)$$

$$Norm \equiv \|D\| = \left(\sum_{i=1}^{N} \left(y_{i,t+k} - y_{i,t}\right)^2\right)^{1/2}.$$

The change is small when the angle is close to zero. The angles of GDP between t = 1 to 2 and t = 2 to 3 are 0.3405 and 0.2980, and the corresponding figures for house price are 0.6861 and 0.6125, respectively. The growth rates of house price and GDP decline by similar percentages (approximately 12% and 11%, respectively) over the sample period, thus indicating that GDP and house price tend to have similar convergence speeds.

5.3. Interpretation

The results reported in this paper indicate a distinct possibility that house prices in Chinese cities conditionally converge to parallel growth paths in the steady state, and absolute convergence is unlikely. The positive spatial spillover governs the growth of the house prices in the cities in the following means. First, as a factor of conditional convergence, the positive spatial spillover elevates the trajectories of the steady-state (parallel) growth paths of house prices. Second, the positive spatial spillover implies that the house price growth of a city tends to spillover to nearby cities, and this spillover helps narrow the gap among the growth paths of house prices in neighboring cities.

As we have observed, the direct effect of a change in a socioeconomic variable is dominated by the non-diffusion inspired own effect. While the spatial spillover allows other cities to share the impact and benefit from the spread effect, the relatively small space dependence parameter means that exogenous jumps in the house prices of certain cities can make catching up entirely or surpassing difficult for others.

Figure 4 illustrates the distribution of actual sale price of houses in Chinese cities in 2001[18]. The data are categorized in quintiles. The large and dark dots indicate the high house prices in the city concerned. In 2001, cities with house prices in the top 20th percentile were clustering

[18] No comparable data for 2000 are available. The data can be found in the official website of the National Bureau of Statistics of China http://www.stats.gov.cn/was40/gjtjj outline.jsp.

along the coastline of the country. If absolute convergence applies, long-term growth rates of the house prices in the cities are expected to accelerate as they expand from the coast. Figure 5 depicts the total growth in house prices from 2000 to 2008, which is again categorized in quintiles. In contrast to the prediction of absolute convergence, the highest growth rates remain clustered along or near the coast. However, an increase in the concentration of high growth cities is evident toward the inner parts of China (e.g., the provinces of Hebei, Henan, and Shangdong). This increase is consistent with the price convergence accompanied by spread effects, as discussed in section 1. In addition, far away regions, such as the Northeast and the Northwest, do not appear to have benefited from any spillover. This finding gives some credibility to our distance-weighted spillover structure.

To further differentiate the convergence experiences of Chinese cities, we apply our spatial model to two subsets of our sample, namely, East–West and North–South[19]. The procedures are the same as those specified in section 3. The nexuses include East, West, Central, and Northeast regions (25 cities) in the first batch and North, South, Central, and Northeast regions (16 cities) in the second. The segregation enables the exclusion of a different set of cities in each exercise to prevent identification and interpretation problems. The results suggest that convergence is present in both nexuses: $\beta = -0.9663$ and $\rho = 0.0581$ for the E–W nexus, and $\beta = 0.1813$ and $\rho = 0.1881$ for the N-S nexus. In summary, convergence is exceedingly slower in the N–S nexus than in the E–W one although the former is compensated by a slightly higher spread effect than the latter. A possible explanation of this phenomenon

[19] North: Beijing, Hohhot, Shijiazhuang, Taiyuan, and Tianjin. South: Guangzhou, Haikou, Nanning, and Shenzhen. East: Fuzhou, Hangzhou, Hefei, Jinan, Nanjing, Ningbo, Qingdao, Shanghai, and Xiamen. West: Chengdu, Chongqing, Guiyang, Kunming, Lanzhou, Urumqi, Xi'an, Xining, and Yinchuan. Central: Changsha, Wuhan, and Zhengzhou. Northeast: Changchun, Dailan, Harbin, and Shenyang.

can be the exclusion of the clusters of high growth coastal cities in the N–S nexus, thus leaving only a few low growth cities in the Central to bridge the N–S corridor (Figure 5). In the E–W batch, we have a large network of high-growth cities in the East and Northeast that helps establish the convergence relationship.

[Insert Figures 4 and 5 here.]

Provided that there exists regional house price interactions in the data which cannot be fully explained by idiosyncratic factors, observable or not, the burden will be borne by either the space dependence parameter or the time dependence parameter or both. If convergence is in place but is statistically underestimated, the discrepancy will be usurped by an overestimated positive spatial spillover effect. Conversely, an overestimated convergence phenomenon will have to be balanced by a smaller-than-actual spatial spillover effect to match the data pattern. In essence, the closing of gaps in house prices is a statistical phenomenon of growth appropriation.

5.4. Policy Implications

China's housing reform that began in 1978 is part of the overall economic reform. Under the housing reform, the Chinese government introduced market elements to urban housing by commercializing and decentralizing housing investment (Wang and Murie, 1996). The government also considered housing conditions as a major indicator of living standards and assigned urban housing investment as a national priority. However, regional disparity of housing development remains a major challenge (e.g., Song and Chen, 2004). Findings from this study suggest that regional house price convergence is conditional on region-specific factors and that regional disparity in housing development can be a permanent phenomenon.

Thus, identifying the conditioning factors for regional house price convergence and targeting the interventions and public resources toward the regions that need them the most are the key to reducing regional disparity.

The findings reveal that house price convergence among major Chinese cities is partly conditional on the spatial dependence of house prices. Increases in steady-state house prices tend to spillover from the more developed cities to their less developed counterparts, and this spillover helps reduce regional disparity. According to growth pole theory, the two opposing forces governing the sign and the magnitude of such spillover are the spread and backwash effects. This study establishes that the spread effect outweighs the backwash effect, and this result is favorable to narrowing the gaps between Chinese cities' house prices. This finding may be partly attributable to China's *hukou* (i.e., household registration) system that restrains inter-regional labor migration[20]. Chen *et al*. (2011) argued that migrants without a *hukou* in coastal provinces usually find entering the housing markets there unaffordable.

In general, policy makers should recognize the coexistence of the two opposing forces when crafting regional development strategy. If the government prefers to enhance the existing economic center, for instance, a highly significant spread–backwash pattern can be expected between the center and the less developed regions. Government policies aiming to reduce regional disparity can be highly effective if the policies are both conducive to the spread effect and obstructive to the backwash effect.

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[20] To curb the increasing house prices in major cities, for instance, non-local-registered families that have not paid local social security or income taxes for several years are banned from buying local properties in major cities. Whalley and Zhang's (2004) simulation suggests that abolishing the *hukou* system can enhance rural-urban labor migration and thus positively affect urban house prices.

One possible approach is to foster specialization and collaboration among the more developed cities and their less developed counterparts through economic restructuring. An example is the "Rise of Central China Plan" announced by the Chinese government in 2004 in an attempt to close the widening gap between the central and the eastern regions[21]. Under the plan, the central region will be a connecting link between eastern and western developments because the central region has advantages in certain industrial sectors and it is situated between the booming eastern region and the relatively backward but resource-rich western region (Xinhua News Agency, February 17, 2006). The plan has become part of the country's overall strategy to promote a coordinated development of different regions that emphasize the formation of a new development pattern in which the eastern, central, and western parts of the country can interact, complement each other, and contribute to each other's development.

6. Conclusion

We investigated the house price dynamics of 34 Chinese cities between 2000 and 2008. Strong evidence favors conditional convergence and contemporary spatial dependence of house prices in different cities at the same time. Nevertheless, the estimated effect of spatial spillover is small. A shock to a socioeconomic variable exerts a strong direct effect on domestic house price and induces a relatively meager indirect effect that originates from cross-city house price and intertemporal feedback. This phenomenon creates an environment that favors convergence in growth paths of house prices rather than in levels. From a social science perspective, the

[21] The Plan was a strategic decision made by the Chinese government following its earlier decision to prioritize the development of the eastern region, develop the central region through urbanization, and rejuvenate the old industrial bases.

empirical findings support the fact that the spread effect dominates the backwash effect. Finally, we found that spatial spillover and convergence are inter-related numerically and intuitively, so excluding the convergence factor in our model could result in a biased estimate of spatial interaction. A limitation of this study is that the spread and backwash effects that constitute positive spatial spillover are not separately identifiable in the existing data set. Incorporating the determinants of spread and backwash effects such as inter-city factor flows into the empirical model is a possible extension of this study.

Appendix 1: Derivation of Equation (4)

Equation (9) can be obtained by repeated substitution with the main Equation (6). First,

$$y_t = \beta y_{t-1} + \rho W y_t + Z_t \phi + \mu + \varepsilon_t. \tag{I}$$

$$\Rightarrow (I - \rho W) y_t = \beta y_{t-1} + Z_t \phi + \mu + \varepsilon_t. \tag{II}$$

$$\Rightarrow y_t = (I - \rho W)^{-1} [\beta y_{t-1} + Z_t \phi + \mu + \varepsilon_t].$$

Lagging the above equation for one period gives the following:

$$y_{t-1} = (I - \rho W)^{-1} [\beta y_{t-2} + Z_{t-1} \phi + \mu + \varepsilon_{t-1}]. \tag{III}$$

Substituting (III) into (II),

$$(I - \rho W) y_t = \beta \{(I - \rho W)^{-1} [\beta y_{t-2} + Z_{t-1} \phi + \mu + \varepsilon_{t-1}]\} + Z_t \phi + \mu + \varepsilon_t.$$

Applying (III) to y_{t-2},

$$(I - \rho W) y_t = \beta \{(I - \rho W)^{-1} [\beta [(I - \rho W)^{-1} \{\beta y_{t-3} + Z_{t-2} \phi + \mu + \varepsilon_{t-2}\}] +$$

$$Z_{t-1} \phi + \mu + \varepsilon_{t-1}]\} + Z_t \phi + \mu + \varepsilon_t.$$

Expanding and collecting terms gives the following:

$$\begin{aligned}(I - \rho W) y_t &= (Z_t \phi + \mu + \varepsilon_t) + \\ &\beta (I - \rho W)^{-1} (Z_{t-1} \phi + \mu + \varepsilon_{t-1}) + \\ &\beta^2 (I - \rho W)^{-2} (Z_{t-2} \phi + \mu + \varepsilon_{t-2}) + \\ &\beta^2 (I - \rho W)^{-2} (\beta y_{t-3}) \ \ldots\end{aligned} \tag{IV}$$

Continually expanding the last term of (IV) gives Equation (9).

Appendix 2: Steps applied to implement the Liu–West Algorithm

- Let x_t denote the time-varying coefficients and θ_t the set of all other unknown parameters. A particle set of size *M* is represented by $\{(x_t, \theta_t)^{(i)}\}_{i=1}^{M}$.
- Let $\bar{\theta}_t$ and V_t be the Monte Carlo posterior mean and variance of θ_t. Define $m\left(\theta_t^{(i)}\right) = a\theta_t^{(i)} + (1-a)\bar{\theta}_t$ and $g\left(x_t^{(i)}\right) = E\left(x_{t+1}|x_t^{(i)}, m\left(\theta_t^{(i)}\right)\right)$ with a and h as the pre-defined parameters.
- Resample $\left\{\left(\tilde{x}_t, \tilde{\theta}_t\right)^{(i)}\right\}_{i=1}^{M}$ from the current particle set with the following weights: $\varphi_{t+1}^{(i)} \propto p\left(y_{t+1}|g\left(x_t^{(i)}\right), m\left(\theta_t^{(i)}\right)\right)$.
- For each particle, sample $\tilde{\theta}_{t+1}^{(i)}$ from $N\left(m\left(\tilde{\theta}_t^{(i)}\right), h^2 V_t\right)$.
- Sample $\tilde{x}_{t+1}^{(i)}$ from $p\left(x_{t+1}|\tilde{x}_t^{(i)}, \tilde{\theta}_{t+1}^{(i)}\right)$.
- Compute weights $w_{t+1}^{(i)} \propto p\left(y_{t+1}|\tilde{x}_{t+1}^{(i)}, \tilde{\theta}_{t+1}^{(i)}\right) / p\left(y_{t+1}|g\left(\tilde{x}_t^{(i)}\right), m\left(\tilde{\theta}_t^{(i)}\right)\right)$.
- Sample $\{(x_{t+1}, \theta_{t+1})^{(i)}\}_{i=1}^{M}$ from the updated particle set with weights $\left\{w_{t+1}^{(i)}\right\}_{i=1}^{M}$.

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Figure 1. Posterior Distributions of ρ and β.

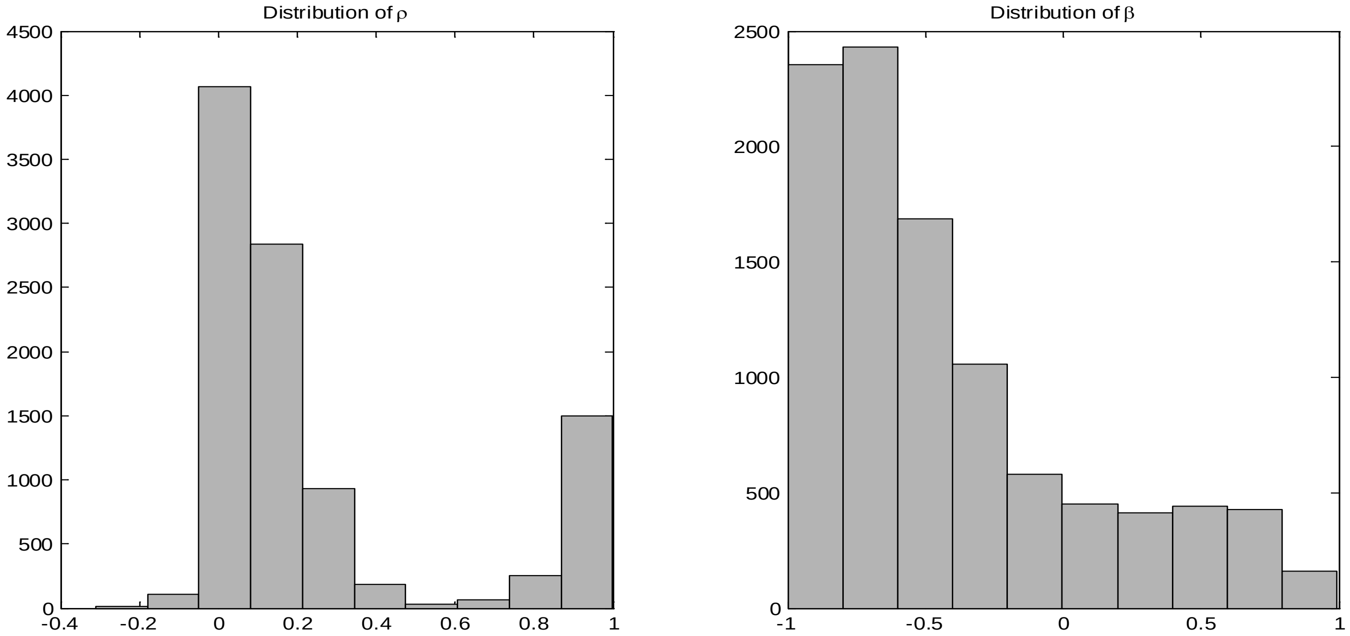


Figure 2. Average Growth in House Prices in 34 Cities, 2000-2008.

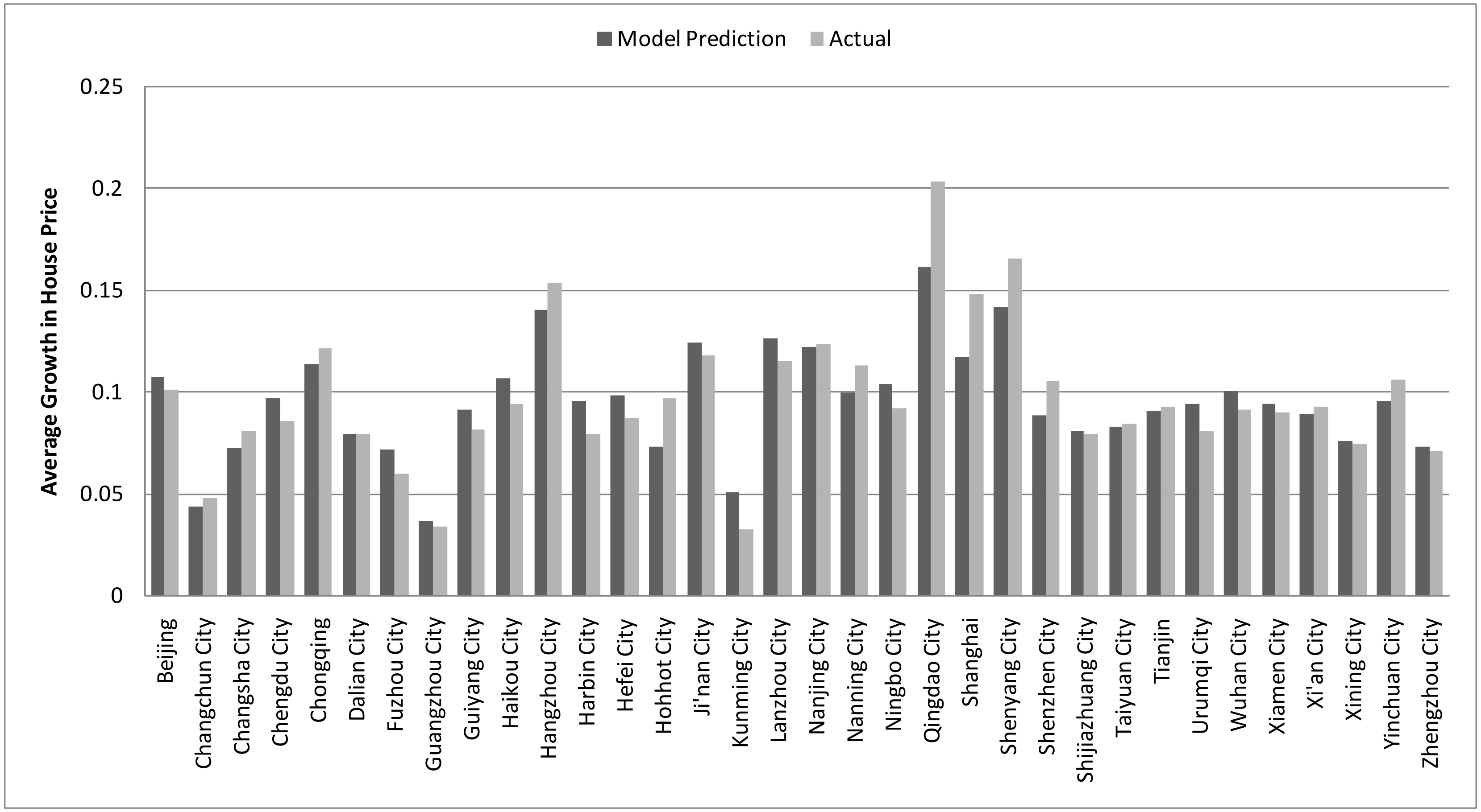


Figure 3. Scatter Diagram of GDP Growth and House Price Growth across Time

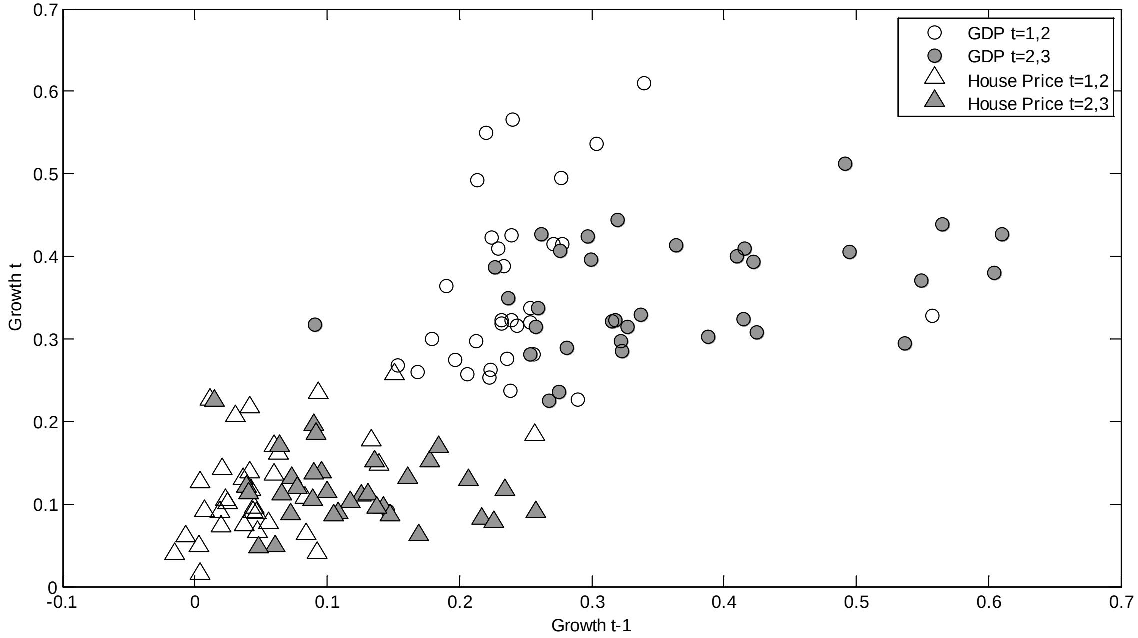
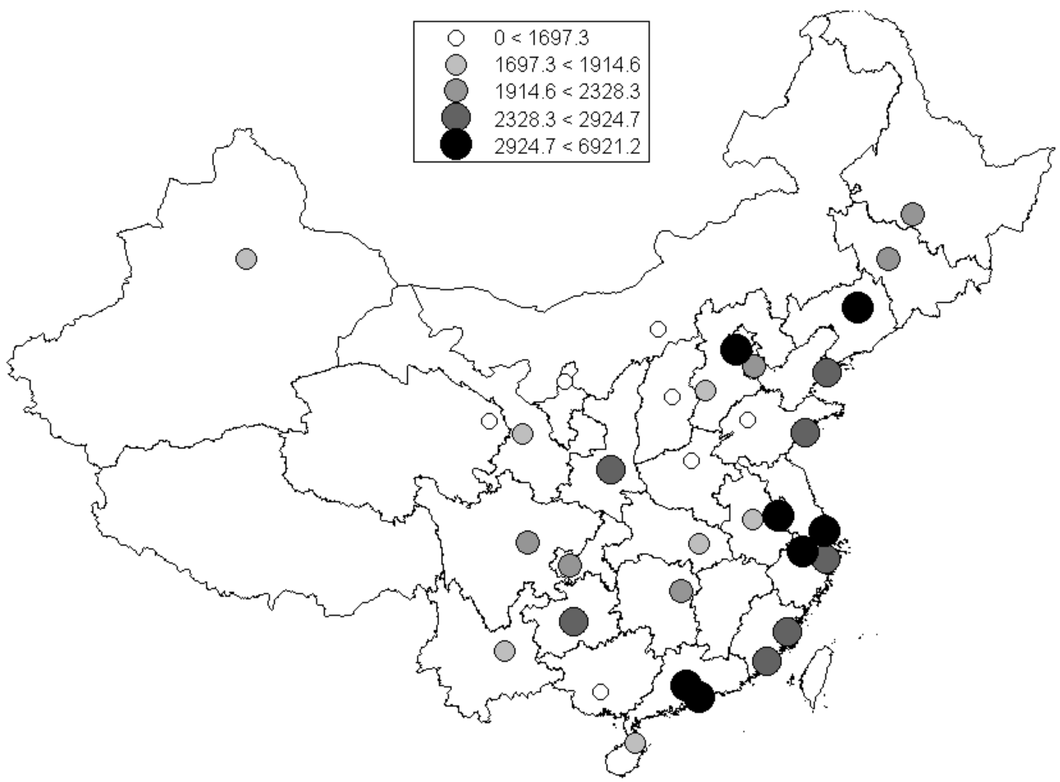
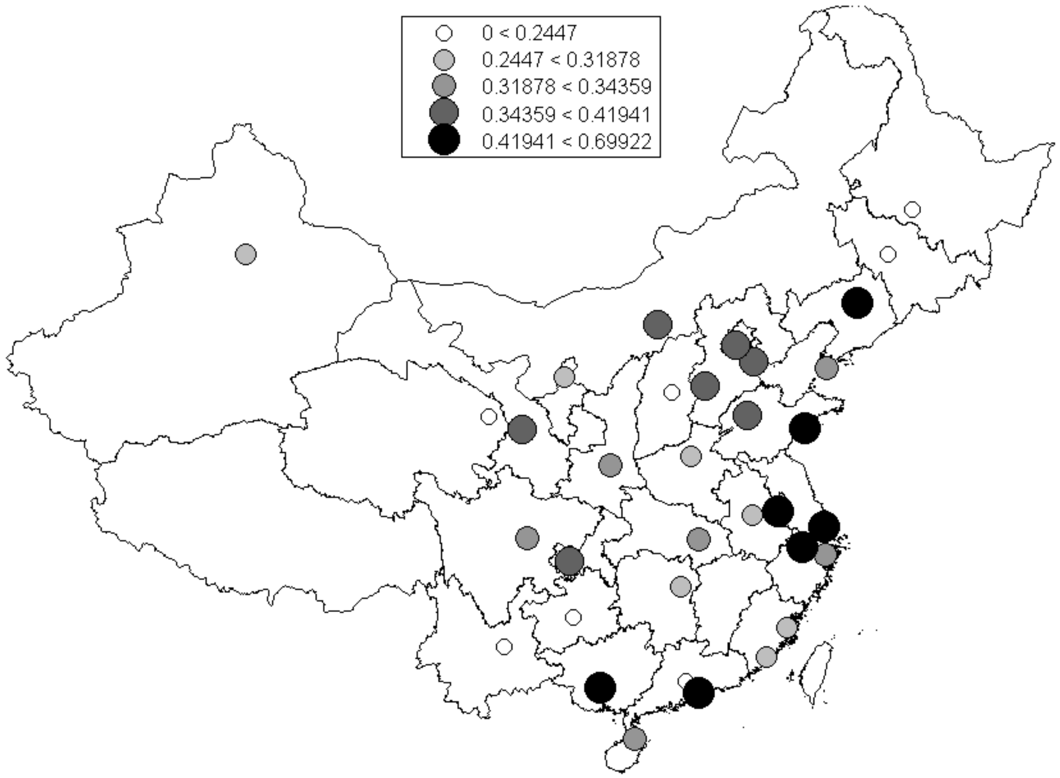


Figure 4. Actual Sale Prices of Houses in Chinese Cities as of 2001



Notes: Sale prices categorized into 20 percentiles. The top 20 percentile has the biggest and darkest dots and the lowest 20 percentile the smallest and the lightest.

Figure 5. Actual Growth in House Prices in Chinese Cities between 2000 and 2008



Notes: Total growth in house prices between 2000 and 2008 categorized into 20 percentiles. The top 20 percentile has the biggest and darkest dots and the lowest 20 percentile the smallest and the lightest.

Table 1. Estimates of the Spatial Dynamic Panel Model

		Spatial Dynamic Panel Model					
		t = 1		t = 2		t = 3	
Coefficient of:		Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
(i)	GDP growth	0.1059	(0.0061)	0.0905	(0.0471)	0.1239	(0.0471)
(ii)	CPI growth	0.4862	(0.0314)	0.4938	(0.0316)	0.4849	(0.0316)
(iii)	Population Growth	0.2461	(0.0473)	0.2139	(0.0471)	0.2332	(0.0471)
(iv)	Wage growth	–0.0733	(0.0111)	–0.0593	(0.0112)	–0.1172	(0.0112)
(v)	Employment growth	–0.0014	(0.0013)	–0.0515	(0.0013)	–0.0068	(0.0013)
(vi)	Saving growth	0.0353	(0.0006)	0.0389	(0.0006)	0.0405	(0.0006)
(vii)	Secondary School growth	–0.1020	(0.0081)	–0.0588	(0.0081)	–0.0933	(0.0081)
(viii)	Traffic growth	0.0086	(0.0002)	0.0095	(0.0002)	0.0150	(0.0002)
	ρ spatial dependence	0.2615	(0.0016)				
	β time dependence	–0.1590	(0.0020)				
Model Adequacy:							
Sequential (log) Bayes Factor							
Estimated Model against the alternative of β divergence (>1)		1.1046e+14		1.2799e+24		1.2798e+24	
Estimated Model against the alternative of $\rho < 0$		–4.6937e+13		7.4613e+24		7.4613e+24	

Table 2. Estimates of Standard Panel Data and Spatial Panel Data Models

		Ordinary Panel Data				Spatial Panel Data			
		Fixed Effects (FE)		Random Effects (RE)		Spatial Autoregressive Lag		Spatial Error Model	
Coefficient of:		Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
(i)	GDP growth	0.1198	(0.0622)	0.0690	(0.0635)	0.0842	(0.0727)	0.0693	(0.0751)
(ii)	CPI growth	0.4890	(0.1421)	0.3386	(0.1437)	0.3792	(0.1962)	0.5686	(0.1931)
(iii)	Population Growth	0.2420	(0.1735)	0.0792	(0.1654)	0.2104	(0.2010)	0.2000	(0.1980)
(iv)	Wage growth	–0.0763	(0.0848)	0.0652	(0.0780)	–0.0654	(0.0981)	–0.0565	(0.0961)
(v)	Employment growth	–0.0001	(0.0284)	–0.0114	(0.0285)	–0.0124	(0.0330)	–0.0156	(0.0333)
(vi)	Saving growth	0.0403	(0.0189)	0.0290	(0.0205)	0.0350	(0.0218)	0.0331	(0.0220)
(vii)	Secondary School growth	–0.0924	(0.0716)	–0.0786	(0.0716)	–0.0709	(0.0834)	–0.0706	(0.0826)
(viii)	Traffic growth	0.0097	(0.0124)	0.0056	(0.0146)	0.0099	(0.0143)	0.0129	(0.0144)
	ρ spatial dependence	n.a.		n.a.		0.3190	(0.2147)	n.a.	
	β time dependence	n.a.		n.a.		n.a.		n.a.	
	spatial error autocorrelation	n.a.		n.a.		n.a.		0.4020	(0.2158)
Model Adequacy:									
	R^2	0.3785		0.0160		0.3816		0.3665	
Specific Tests									
(i)	Hausman Test for FE/RE	Chi-squared statistics $=$ 28.5019		p value $=$ 0.0004					
(ii)	Moran's I Index for Spatial Correlation	$I_{t=1} =$ 0.5207		$I_{t=2} =$ 0.8123		$I_{t=3} =$ 0.8850			

Remarks: The R^2 reported are the overall R^2.

Table 3. Direct and Indirect Effects of Shocks to Socioeconomic Variables over Five Three-year Intervals

	Socioeconomic Variables	t = 1 Impact Time	t = 2	t = 3	t = 4	t = 5
	Shock in:	Direct Effect (cumulative) averaged over all shock originating cities				
(i)	GDP growth	0.1063	0.0893	0.0920	0.0916	0.0917
(ii)	CPI growth	0.4882	0.4099	0.4225	0.4205	0.4208
(iii)	Pop. growth	0.2471	0.2075	0.2139	0.2128	0.2130
(iv)	Wage growth	–0.0736	–0.0618	–0.0637	–0.0634	–0.0634
(v)	Employ growth	–0.0014	–0.0012	–0.0012	–0.0012	–0.0012
(vi)	Saving growth	0.0354	0.0298	0.0307	0.0305	0.0305
(vii)	Sec School growth	–0.1024	–0.0860	–0.0886	–0.0882	–0.0883
(viii)	Traffic growth	0.0086	0.0073	0.0075	0.0074	0.0075
	Shock in:	Indirect Effect (cumulative) averaged over all neighboring cities				
(i)	GDP growth	0.0011	0.0007	0.0008	0.0008	0.0008
(ii)	CPI growth	0.0052	0.0032	0.0038	0.0036	0.0037
(iii)	Pop. growth	0.0026	0.0016	0.0019	0.0018	0.0019
(iv)	Wage growth	–0.78 e –3	–0.49 e –3	–0.57 e –3	–0.55 e –3	–0.55 e –3
(v)	Employ growth	–0.15 e –4	–0.09 e –4	–0.11 e –4	–0.10 e –4	–0.11 e –4
(vi)	Saving growth	0.37 e –3	0.23 e –3	0.27 e –3	0.26 e –3	0.27 e -3
(vii)	Sec School growth	–0.0011	–0.0007	–0.0008	–0.0008	–0.0008
(viii)	Traffic growth	0.91 e –4	0.57 e –4	0.67 e –4	0.64 e –4	0.65 e –4

Remarks: Each observation t represents a three-year interval. The direct effect is the own effect of a change in the r-th explanatory variable in city $i$on the growth in house price in city i. The indirect effect captures the effect of the same shock originated in city i on j’s house price growth via the spillover from city i. Shock is assumed to originate at calendar time t =1 of the data sample.