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Ripple effects of house prices: considering spatial correlations in geography and demography

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Abstract:

Purpose

– Studies into ripple effects have previously focused on the interconnections between house price movements across cities over space and time. These interconnections were widely investigated in previous research using vector autoregression models. However, the effects generated from spatial information could not be captured by conventional vector autoregression models. This research aimed to incorporate spatial lags into a vector autoregression model to illustrate spatial-temporal interconnections between house price movements across the Australian capital cities.

Design/methodology/approach

– Geographic and demographic correlations were captured by assessing geographic distances and demographic structures between each pair of cities, respectively. Development scales of the housing market were also used to adjust spatial weights. Impulse response functions based on the estimated SpVAR model were further carried out to illustrate the ripple effects.

Findings

– The results confirmed spatial correlations exist in housing price dynamics in the Australian capital cities. The spatial correlations are dependent more on the geographic rather than the demographic information.

Originality/value

– This research investigated the spatial heterogeneity and autocorrelations of regional house prices within the context of demographic and geographic information. A spatial vector autoregression model was developed based on the demographic and geographic distance. The temporal and spatial effects on house prices in Australian capital cities were then depicted.
1 Introduction

Disparities and ripple effects are two of the most important issues raised in studies into regional house prices. The immobility of houses determines that they cannot be circulated over space like common goods; and thereby house prices in a specific region or city are affected by local economic factors, such as incomes, rents, interest rates, tax rates, and so on, which lead to disparity in house prices over space. Nevertheless, house prices in different cities do not appear absolutely divergent from each other. A shock of house prices in one specific city or region may spread out over other cities or regions with a temporal delay. This temporal and spatial spread of house price shock is recognised as a ripple effect. The theory of ripple effects was built on the consideration that the aggregated housing market should be made up of a series of interconnected regional and local markets (Meen, 1996).

Meen (1999) also proposed several factors that may explain ripple effects between house price movements, such as migrations, spatial arbitrage, equity transfers and spatial patterns.

A series of time-series econometric methods, like vector autoregression (VAR) models, were widely employed to investigate ripple effects between house price movements across regions. The house price ripple effect was raised in the early literature on the UK regional house prices. By using the Engle-Granger cointegration test and the vector autoregression Granger causality test, the relationships of regional housing markets were investigated in the South of England and in the North and Midlands of England (Alexander and Barrow, 1994). Pollakowski and Ray (1997) examined regional repeat sales house prices from 1975 to 1994 in the USA. Using the VAR model, they demonstrated that the market was inefficient and that contiguous regions release more influence than non-contiguous regions. Stevenson (2004) examined the causal relationships between Irish regional housing markets, supporting the argument that Dublin has a leading effect on other markets. Shi et al. (2009) investigated the ripple effects of house price movements in New Zealand. Granger causality test based on a vector error correction model was carried out, with results suggesting that ripple effects should be found within regions in New Zealand. They also mentioned that regional internal economy potentially played a more important role than migration and arbitrage in causing ripple effects.

Research on the issue of ripple effects in the Australian housing markets can also be found in previous literature. Maher (1994) estimated the distribution and dispersion in house prices in Australian major cities in the 1980s. The spatial variability at two levels including inter-metropolitan and intra-metropolitan was evidenced. Bourassa and Hendershott (1995) estimated real house prices separately for six cities in Australia to examine the divergence between them, pointing out that the main factors driving house prices should be income growth rates and migration. Tu (2000) found evidence for the interconnections between house prices at the national and sub-national levels in Australia. Using the Granger causality test, two diffusion paths, which formed a geographic diffusion pattern in the Australian housing market, were determined: starting from Brisbane via Sydney ending at Melbourne, and starting from Brisbane via a national path and ending at Melbourne. Liu et al. (2009) identified the interconnections among housing market dynamics of the Australian capital cities using variance decomposition.

Although previous research on ripple effects focused on exploring the correlations across space, the effects generated from the spatial information belonging to a specific city or region cannot really be taken into account due to the limitations of time-series regression methods. In this research, by incorporating the spatial econometric method into a panel regression model, both the temporal and
spatial effects of house price movements in the Australian capital cities can be captured. In addition, a demographic space is constructed, instead of geographic space. Ripple effects between house price movements in the Australian capital cities are subsequently investigated and simulated by the model and the impulse response functions, respectively. The rest of this paper is organised as follows. Section 2 presents the literature review on spatial econometric analysis in the real estate study area. Section 3 outlines the development and calculation of the spatial vector autoregression (SpVAR) model. Section 4 presents the estimates of the SpVAR model based on geographic distances and the model based on demographic distances for the ripple effects regarding information on Australia. Section 5 illustrates a further simulation of ripple effects of house prices in the Australian capital cities. The final section concludes.

2 Literature review

The heterogeneity and spatial effects on movements of house prices and real estate markets have drawn attention from many researchers. Gelfand et al. (2004) raised the effects of dynamic locations on house prices. In order to capture the spatial correlation between house prices in different locations, they proposed a panel regressions model allowing cross-correlation in the error process. The importance of spatial effects on house prices was demonstrated by Sirmans et al. (2005). They reviewed a great huge number of prior studies on house price estimates with the hedonic model, and integrated the house attributes that were most frequently implemented in the previous studies. It was also claimed that most of the effects of these attributes on house prices would vary across regions. House characteristics contributed differently to house prices between regions, mainly due to the immobility of houses. Another study investigates spatial effects on Spain's regional house price series, indices and growth rates (Montero and Larraz, 2010). By taking into account the spatial correlations of house prices, the authors identify the importance of space when establishing a regional house price. Conway et al. (2010) investigated the spatial effects of greenspace on residential property values by implementing spatial lags into a hedonic model. They compared the results from non-spatial and spatial models and concluded that the greenspace effects significantly influenced the property values.

The advantages of spatial econometric analysis were argued by Anselin and Lozano-Gracia (2008). It was suggested that the conventional hedonic models can be improved in estimating house price movements by implementing spatial dependence and heteroskedasticity in the model to express the impact of air quality. Their findings also outline that the bias from ignoring the endogeneity in interpolated values might be substantial. The predictive power of spatial correlation modelling in house prices was also demonstrated in previous literature (Zhu et al., 2011). They proposed an approach to modelling anisotropic autocorrelation in house prices. By comparing the predictive accuracies generated from three different methods, they suggested that taking account for spatial autocorrelation should reduce forecast errors.

Spatial econometric techniques were also used to illustrate the correlations between regional house price movements across a country (Beenstock and Felsenstein, 2007). Their findings support the concept that the spatial VAR model can perform better in estimating the interconnections between house price movements. Another study established a spatial and temporal vector error correction model to investigate the house price diffusion in the UK (Holly et al., 2011). In their article London was selected as the dominant housing market of the regional housing markets of the UK. The geographic distances between London and the other regions were used to constructed spatial weights. The spatial characteristics of a city or region were assumed temporally invariable by previous studies. Leishman (2009) used a multi-level model to identify the housing sub-market. Meanwhile, it also
found evidence of spatial change over time. The findings indicated that spatial dynamics existed in the urban housing system. Analysis using a fixed spatial sub-market system might lead to aggregation error. Moreover, other spatial information beyond the context of geographic space may also influence house prices, which are ignored.

3 Spatial and temporal analysis of ripple effects

The importance of spatial dependence, especially spatial autocorrelation in econometric analysis, was highlighted by Anselin (1988). It is a notion of relative space or relative location determined spatial dependence, emphasising the effect of distance. In recent years, spatial techniques have been widely incorporated with conventional time-series methods to analyse the spatial and temporal econometric relationships. This developed approach can capture both spatial and temporal effects on house price movements. This section introduces the development of a SpVAR model used to investigate the ripple effects between house price movements across cities. Proximity of distance is constructed by demographic structures. The spatial weights are further adjusted by the market developing scales of cities. Moreover, Granger causality test and impulse response functions based on the SpVAR model are introduced.

3.1 Spatial vector autoregression model for ripple effect analysis

VAR models are widely used to investigate ripple effects which can be expressed as follows:

\[
\Delta p_{it} = \alpha_i + \beta_i \Delta p_{it-1} + \gamma_i \Delta p_{jt-1} + \delta_{it} \tag{1}
\]

Equation 1 Symbol $\Delta p_{it}$ denotes a logarithm value house price movement in region $i$ at time $t$, symbols $\Delta p_{it-1}$ and $\Delta p_{jt-1}$ denote a previous house price movement in region $i$ and a neighbouring region $j$, respectively, and symbol $\delta_{it}$ is an error term. Estimate $\alpha_i$ is a constant, indicating the regional specific effect of region $i$ on the house price movements, estimate $\beta_i$ suggests a degree of the impact from the previous movements, and estimates $\gamma_i$ show how much the previous movements from neighbouring regions influence the house price behaviour in region $i$. One drawback of the VAR models is that they ignore the potential existence of spatial autocorrelations between house price movements. Elhorst (2003) mentioned that an observation associated with a specific location to be dependent on observations at other regions is mainly because that distance affects economic behaviour. However, in equation (1) house price movements from the local city and the neighbouring cities are weighted equally. SpVAR can better reflect the spatial effects of the movements of house prices.

SpVAR models with spatial dependence are classified into two types. One is the model incorporating a spatial autoregressive process in the error term, while the other model contains a spatially autoregressive dependent variable. A SpVAR model, which is estimated with spatial lags as well as temporal lags, can better reflect real economic performances. The application of spatial dependence allows the model to incorporate spatial and temporal dynamics. The model can be expressed as following:

\[
\Delta p_{it} = \beta_i \Delta p_{it-1} + \gamma_i \Delta p_{jt-1} + \delta_{it} \tag{2}
\]

Equation 2Equation 3 In equation (2), the estimates $\beta_i$ and $\gamma_i$ indicate the coefficients of the temporal and spatial lags, respectively. $W_{ij}$ is the element of the $i$th row and $j$th column of the spatial weight matrix $W_{ij}$, which is constructed by the distance between the cities. The term
\[ \sum_{j \neq i} W_{ij} \rho_{j,i-1} P_{j,t-1} \] is the spatial lag, standing for the impacts from the neighbouring housing markets of the city \( i \). Therefore, the spatial effects on house prices will be carried by the spatial weight. The symbol \( \epsilon_{it} \) is the error term of equation (2), which is estimated by equation (3). The error term of equation (3), \( \delta_{it} \), is assumed to be the independent and identically distributed.

This research assumes that spatial autocorrelations are carried by the spatial lags. Therefore, and \( \delta_{it} \) is the independent and identically distribution. Writing equation (2) in matrix form gives: Equation 4 The terms \( P_t \) and \( P_{t-1} \) are \( N \times 1 \) vectors, where \( N \) is the number of cities. The weight matrix \( W \) is an \( N \times N \) matrix with the diagonal elements being 0. Vector \( A \) is an \( N \times 1 \) estimated vector denoting the regional specific effects from cities, matrix \( B \) is an \( N \times N \) estimated diagonal matrix with the parameters in the diagonal, matrix \( C \) is an \( N \times N \) estimated diagonal matrix and \( D \) is the error term. Since the ordinary least square (OLS) method can no longer obtain the continuous unbiased estimates, seemingly unrelated regression (SUR) method (Hsiao, 2007) is employed in this study to estimate the model.

3.2 Construction of demographic distances

Although spatial econometric analysis can perform better than pure time-series analysis, one controversial issue raised in the area is the proximity of distances, which is a general measure of the potential interaction between two spatial units. The original suggestion is to use a combination of distance measures and the relative length of the common border between two spatial units, as mentioned in above literature. However, this method tends to be less meaningful since the notions of boundary length and area are largely artificial or the spatial interaction phenomenon is determined by factors having little to do with the spatial configuration of boundaries on a physical map (Anselin, 1988). Krugman (2011) suggests that the spatial models, which focus more on the tangible causes of spatial interconnections of economic activities than on intangible information spillovers, are less relevant in describing economies. Therefore, this research builds a spatial space with demographic information, which is also close to house price movements.

Demographic structures can represent the economic structures of regions, which deeply influence the regional housing markets. The regional housing demand and supply markets are not influenced by the proportion of children significantly in population, although the future demand market may be affected by the proportion of future generation. On the other hand, people of working age contribute to the regional housing markets dramatically. This group of people always have relatively stronger interest and capacity to purchase, sell and invest in regional housing markets. The population the working age people are important to the regional housing markets. Older people potentially have less interest than working age people in purchasing houses. However, older people represent a proportion of the population into a higher probability of selling houses in the region, which can affect the regional demand housing market. Azomahou et al. (2009) first studied the spatial persistence of demographic shocks and economic growth. Their research constructed demographic distance in two ways: one was based on the population proportion, while the other was based on the long-memory population. It is suggested that per capita income growth could be significantly affected by the variation in demographic distance. Since the demographic structures are closely linked to the regional economy and housing markets, this research is to construct a demographic space and to investigate the regional
house price convergence within the constructed space. In a demographic space, house prices can be recognised as spatial autocorrelation if a common shock in house price can create similar effects in regions with a short demographic distance but distinct effects in regions which are demographically far from each other.

Demographic distance, as utilised in this study, is constructed by logarithm values of the estimated population of children, working age people and older people in each Australian region. The Australian Bureau of Statistics classifies children, working age people and older people from 0 to 14, 15 to 64, and 65 and older, respectively. The logarithm values of the population aged 0-14, 15-64 and 65+, in a region i at period t is denoted as demo_{i,14}, demo_{i,15-64} and demo_{i,65}, respectively. The demographic distance between regions i and j (dij,tdemo) is constructed by the Euclidean distance with three artificial location spots. The calculation of the demographic distance is expressed as follows: Equation 5

3.3 Spatial weights based on geographic and demographic distances

As well as the distance between geographic locations or demographic structures, the developing sizes of housing markets should also be taken account for spatial effects. In this research, market scales are perceived as an important indicator representing spatial information of regional markets. It is expected that neighbouring markets, with relatively large-scales, should result in more significant spatial effects on the local housing market than those with smaller scales. Bearing this in mind, this research uses numbers of new dwelling units (nod) across the cities to stand for the housing market developing scales. Moreover, both the geographic and demographic distances are combined with the market scales to propose spatial weights. The geographic weight (G-weight) is expressed as follows: Equation 6dij denotes the distance between city i and city j, and nod_{it} stands for the number of new dwelling unit in city i at time t. The spatial weights are larger for closer or neighbouring markets with bigger numbers of new dwelling units, but smaller for further markets or neighbouring markets with smaller number of dwelling units.

Another consideration in the concept of spatial dependence is the demographic distance relative to regional house prices. Demography and market development of regions also accounts for house price movements. In order to capture demographic and market effects, the demographic spatial weight (D-weight) is constructed by replacing the geographic distance in equation (6) with the demographic distance. The calculation of the D-weights is expressed as follows: Equation 7

3.4 Grange causality and impulse response functions

Granger causality in conventional econometrics is used to describe the extent to which the current value of a specific series can be explained by its past values, and adding the lagged value of an extra series can improve the explanation (Granger, 1969). Once the explanation is proved to be improved, the series is said to be Granger caused by the extra series. Since increasing attention is paid to the panel data analysis in recent studies, the Granger causality tests are also applied to panel data models. In the work of Lu et al. (2006) the Granger causality tests for panel data models are used to investigate the spatial spillovers of R&D to productivity growth. In this research, the method of Granger causality tests for panel regression models is adapted. It is used to find out whether spatial effects of neighbouring cities are helpful to explain house price dynamics in a specific city, in the demographic space. Based on the regression expressed as equation (3), the null hypothesis of the
Granger causality tests is that the correlation coefficients of the spatial lags are 0, while the alternative hypothesis is that those coefficients are significantly different from 0. The test statistic is calculated as following: Equation 8 where $\text{RSS}_1$ and $\text{RSS}_2$ imply the residual sums of squares of equation (4) and the model under the null hypothesis, respectively. $N$ denotes the number of cities, $p$ stands for the temporal lags, and $T$ indicates the time periods.

Impulse response function is another widely used measure to simulate ripple effects. Impulse response was historically built on a VAR model, indicating the dynamic effects on each variable when a shock is injected into the system, which is the so-called innovation. In this way the system can be characterized by plotting the impulse response functions (Greene, 2002). The impulse response based on a SpVAR model may be used to simulate the spatial-temporal dynamic effects of innovations on variables. However, it is more complex than in VAR because shocks propagate across cities as well as over time (Beenstock and Felsenstein, 2007). Denote $I$ is an $8\times8$ unit matrix, $\Gamma=B+CW$ and $L$ is the lagged operator. equation (4) can be rewritten by: Equation 9Equation 10 Since $\Gamma$ is depended on $W$, the response of the SpVAR under an innovation in $D$ will depend upon the spatial lag coefficient, $C$. Therefore, in the SpVAR construct, a given shock affects the house price in the same region directly, while influencing the house prices in other cities through the spatial lag terms. The shock of the house price in one city is transmitted to the neighbouring housing markets in the following period, weighted by $W$.

4 Modelling ripple effects of house prices in Australian capital cities

4.1 General descriptions of correlated information in Australian capital cities

Australian property markets play an important role in Australian economy development. It has been argued that the Australian property sector showed a median economic push to the national economy, and the residential property sector played a more important role than the commercial sector in the economy (Song and Liu, 2005). In this research, the house price indexes (HPI) for residential property in Australian capital cities were used as the indicator of housing markets (ABS, 2011c). The Australian Bureau of Statistics (ABS) used the stratification approach, which stratified the medium prices of groups of houses to minimize the physical heterogeneity of houses, and weight the groups of prices to construct the HPI of the entire stock of residential dwellings. The HPI reference was based on 1989-1990=100, although the ABS had changed the reference base since 2005 (ABS, 2005). To maintain constancy, all the data used in this research has been converted to values which take 1989-1990 as a reference base. The observation period was from the March quarter 1993 to the December quarter 2010. The descriptive statistics of the HPI are shown in Figure 1.

From 1993 to 2010, the biggest change in house prices was in Darwin with an increase of 350.3 per cent, followed by Brisbane (318.7 per cent) and Adelaide (286.9 per cent). The Darwin housing market showed a very different pattern, while the other seven displayed a slow increase trend at first which was followed by a sharp increase. Melbourne's boom started in the December quarter 1996 while the booms in Adelaide, Perth and Sydney started in the March quarter 1997, followed by Canberra and Hobart at June quarter 2000, and Brisbane at June quarter 2002. Darwin started its first sharp increase from the beginning of the observation period until the June quarter 1997, with an average change rate of 3.62 per cent per quarter followed by a steady increase until the September quarter 2000. The latest sharp increase in Darwin started from the December quarter 2001. Nevertheless, the HPI of Sydney has shown a decline since 2004, while the house prices in other cities
continued increasing until 2008, except Darwin, the HPI of which increased in 2008 with a drop in the March quarter. The HPI in Australian capital cities increased with some fluctuations after 2008.

Furthermore, the regional demographic structures were used to construct the demography-distance. The Australian Demographic Statistics has been published quarterly by the Australian Bureau of Statistics (ABS, 2011a). For each state and territory, over half of the population is resident in the capital cities. In this research, the population was divided into three groups, namely age 0-14, age 15-64 and age over 65. Table I reported the average population in each state and territory from 1993 to 2010.

The Australian state population is distributed asymmetrically. Over 70 per cent of the population are located in the eastern states of Australia, which include New South Wales, Victoria and Queensland. The population of the Northern Territory and Tasmania count for less than 5 per cent. While there are significant differences in regional population size, demographic data on regional age ranges is comparable. Northern Territory had the highest proportion of young people of 25.5 per cent, while South Australia had the lowest proportion at 19.2 per cent. The proportion of working people ranged from 65.5 per cent in Tasmania to 71.3 per cent in Australia Capital Territory. The highest record of retired people was located in South Australia. Northern Territory had the lowest proportion of population aged over 65.

Moreover, the approved numbers of new houses in the Australian capital cities were used to adjust the spatial weight matrix. The approved numbers of new houses were published by the ABS, which presents monthly details of approved building work and focuses on the scales of each capital city's real estate changes, selected to adjust the spatial effects of dynamics of each residential property market (ABS, 2011b). The original monthly data were converted into quarterly data by collating the numbers per three months, in order to match the frequency of HPI. Table II shows the basic statistics for the number of dwelling units during the observation period.

The quarterly average approved numbers of new houses in Darwin, Hobart and Canberra were smallest, at 122.76, 222.36 and 351.42, respectively. The remaining statistical values for the above cities were lowest, indicating the smallest residential market scale in Darwin, Hobart and Canberra. Melbourne, however, had the largest number of dwelling units. The average number of new dwellings was about 5,129.24 from 1993 to 2010, followed by Perth at 3,057.04, Sydney at 2,741.47 and Brisbane at 2,713.32. Melbourne also had the highest maximum, minimum and standard deviation, suggesting fast and fluctuating development in the Melbourne housing market scale. The housing market scales of Brisbane and Perth also increased rapidly but were smoother when compared to Melbourne and Sydney.

4.2 Estimates of the model for the ripple effects in the Australian capital cities

The SpVAR shown in equation (4) consists of eight equations, each with a constant term, a temporal lag and a spatial lag for the house prices of each Australian capital city. The first panel of Table III reported the estimated results of the geographic distance based model. All the regional effects were positive except Canberra, indicating that the increasing house price speeds should accelerate from quarter to quarter. In other words, local regional effects should keep pushing growth rates of house
prices higher in the Australian capital cities. The highest regional effect was observed in Melbourne, followed by Darwin, Perth and Sydney, while the smallest regional effect was found in Canberra.

The parameter $\beta_i$ denotes the elasticity of the effects generated from temporal lags of the local house price movements. The results confirm that the elasticity of the effects from own market is significant in Brisbane, Darwin, Perth and Sydney, at a 5 per cent confidence level. This suggests that house price movements in these cities are influenced by their previous movements. The elasticity of house prices in Adelaide, Canberra, Hobart and Melbourne are not significant even at a 10 per cent confidence level, suggesting that the residential house price dynamics are difficult to be influenced by the historical movements of their local markets. The elasticity of the spatial lags is significant and positive in most of the capital cities, except in Darwin and Perth. The significant relationships between dependent variables and the geographic-spatial lags suggest that the residential property markets are influenced by their neighbouring markets.

The results of the Granger causality test indicate Australian housing markets are Granger caused by their neighbouring markets significantly. This once again supports the existence of spatial autocorrelations between the housing prices of Australian capital cities. However, when considering the markets separately, Granger causality cannot be proved in every individual city. The movements of housing prices in Adelaide, Hobart and Sydney were Granger caused by their relevant neighbouring markets, demonstrating the housing markets of those cities are correlated tightly with their neighbouring housing markets. However, the causalities in Canberra, Darwin, Melbourne and Perth were not significant at the 5 per cent critical level.

The second panel presents the results of the model based on the demographic distances. Positive regional effects are observed in every capital city. The highest regional effect was observed in Melbourne, followed by the one in Darwin, Sydney and Perth, while the smallest regional effect was found in Hobart. The temporal elasticity is significant in Adelaide, Brisbane, Canberra, Darwin and Perth, at a 5 per cent confidence level, while the elasticity of house prices in Melbourne, Hobart and Sydney were not significant even at a 10 per cent confidence level. This suggests that the house price movements in Adelaide, Brisbane, Hobart and Sydney are influenced by their previous movements. In contrast, housing markets in Melbourne, Hobart and Sydney are not affected by the historical movements of their local markets. The spatial lags are significant and positive in Adelaide and Hobart. The significant relationships between dependent variables and the demographic-spatial lags suggest that the residential property markets in Adelaide and Hobart were influenced by their neighbouring markets. Meanwhile, the estimated coefficients of spatial lags in Adelaide and Hobart were larger than those in other capital cities. In addition, positive and less significant elasticity is found in Canberra. The spatial effects on these two abated with longer demographic distances. The markets in Brisbane, Melbourne, Perth and Darwin were not influenced by their corresponding neighbours. The neighbouring market effects on Perth and Darwin were $-0.1215$ and $0.0055$, respectively, which were the two lowest. Moreover, the Australian housing markets are Granger caused by their neighbouring markets significantly. The movements of housing prices in Adelaide, Hobart and Sydney are Granger caused by the relevant neighbouring markets, while the causalities in Brisbane, Canberra, Darwin, Melbourne and Perth were not significant at the 5 per cent critical level, indicating that these four markets were conservative.
The significances of the estimated spatial correlation coefficients of the geographic and demographic models are summarised and reported in Table IV.

Six spatial correlations of housing price dynamics are observed significant at a critical level of 5 per cent by applying the SpVAR model based on geographic distance. When the SpVAR model based on demographic distance was applied, only three spatial correlations were found significant at a critical level of 5 per cent, with one significant spatial correlation at a critical level of 10 per cent. The findings imply that the spatial correlations of housing price dynamics in the Australian capital cities should rely more on the combination of geographic locations and the local housing market scales, rather than urban demographic differences. Therefore, the subsequent section of this paper implements an impulse response function into the estimated SpVAR model based on geographic distance to depict the spread of housing dynamic in a specific city across space and time.

5 Simulating ripple effects of house prices in Australian capital cities

The impulse response function of the estimated SpVAR model was employed to simulate the house price dynamics of Australian capital cities. The dynamic effects of shocks that occurred in one city upon the house prices in the same city, as well as the other cities, were described by plotting the impulse responses at each time point. In this study, the forecasting period was composed of 20 quarters. In order to investigate how a housing price shock in a specific city spreads over time and space, impulse response functions were carried out based on the estimated time-varied spatial model. A one-unit positive shock was assumed to occur in an individual capital city. The results of the responses to the initial shock were plotted across the cities at different predicting periods, namely period 1, 2, 3, 4, 5, 10, 15, and 20 in Figure 2. Each chart of Figure 2 shows the spatial and temporal spreading process of an initial housing price shock in the corresponding capital city. The cities indicated by the abscissa axis were ordered by the distances to the city where the initial shock occurred. The temporal decay of the responses to a unit shock on housing price movements was obvious. No matter where an initial shock occurred, the effects on the housing price movements in a capital city were increasing weaker as time went by. It was indicated that a housing price shock became stabilised in less than ten quarters. The initial housing price shock in Melbourne caused a decrease in Melbourne housing price in the first quarter, considering the negative temporal effects in Melbourne housing price movements. Driven by both the temporal and spatial effects, the housing price in Melbourne increased with reduced speeds in the following quarters. When an initial shock appeared in other capital cities, the responses of housing prices in Perth and Darwin were slight, increasing by less than 0.02 over the 20 quarters.

The spatial decay of the responses to a unit shock on housing price movement was clearly observed when an initial shock occurred in Brisbane or Sydney. When a housing price shock occurred in Darwin or Perth, the responses were weaker as they affected the first two nearest cities; and became stronger as the effects spread further. This posits that the housing price movements in Darwin and Perth cannot spread to the cities being located further from them. In other words, housing market in Perth pushed up the Australian housing price level mainly by increasing the price levels in the same city continuously, while Brisbane and Sydney spread their influences over time and cities. The initial housing price shock spread in a more complicated manner, when occurring in Adelaide, Canberra, Hobart, and Melbourne. The effects of the initial shock on the housing price movements in Darwin and Perth were slight, while the effects on other cities were fluctuant. For example, a one-unit housing price increase in Melbourne, indicated by Figure 2(f), led to −0.0029 change in the Melbourne housing market and 0.1175, 0.1045, 0.1269 increases in Canberra, Hobart and Adelaide, respectively.
The same shock influenced the housing price movements in Perth and Darwin by only 0.0006 and 0.0201.

In order to integrate the responses of housing price movements to an initial shock at an aggregate perspective, this research summed the responses over the 20 periods for each capital city. It was confirmed that an increase in the housing prices in Perth, Brisbane and Sydney drove up the housing price level of Australia the most, although the depths of the effects of Brisbane and Sydney on the Australian housing price movements were much lower than the effects of Perth. The summed impulse responses show that the largest effect on housing price movements is generated by the unit shock that occurred in Perth, at 8.4009. The effects, caused by the shocks in Brisbane and Sydney, are ranked as the second and third, at 5.0075 and 4.3924, respectively. When shocks started in Darwin, Canberra, Melbourne, Adelaide and Hobart, a similar level of effect on the housing price movements in the Australian capital cities appeared over the 20 quarters. The summed responses range from 3.9074 in Darwin to 3.6041 in Adelaide.

6 Conclusions

This study analysed the interconnections between the quarterly house prices of the Australian capital cities from the March quarter 1993 to the December quarter 2010. Unlike prior studies ignoring the impacts of spatial dependences, this study combined the VAR model with spatial lags to capture both the temporal and the spatial impacts on house price movements. A geographic and a demographic distance between each pair of cities, combined with the approved numbers of new houses in the capital cities, implemented into the SpVAR model. The following conclusions were generated.

First of all, a SpVAR model was estimated to illustrate the spatial and temporal interconnections between house prices of the Australian capital cities. The results of Granger causality tests confirmed that the performances of the whole housing market of Australia could be explained by the neighbouring market movements. However, the causality could not be found in the respective individual markets.

In addition, the spatial correlations were observed by both models based on geographic and demographic distances. However, the spatial correlations generated from the model based on geographic distance appear much more significant than the correlations from the model based on demographic distance. This indicates that geographic information influences the urban housing dynamics more than the demographic information.

Finally, the response of the Australian housing price movement to a shock in the markets sensitive to spatial-temporal factors declined significantly over time period; the shock effects of a market sensitive to temporal factors appeared to increase on the closer neighbourhood markets but decrease as the distance increased; the spreading processes were fluctuant over the space when a shock occurred in a spatial factor sensitive market. Significant temporal decay of a shock effect is observed in the majority of the Australian capital cities’ housing price movements, with the exception of Perth and Darwin.
\[ \Delta p_i = \alpha_i + \beta_i \Delta p_{i,t-1} + \sum_{j \neq i}^{N} \gamma_{ij} \Delta p_{j,t-1} + \delta_{it} \]  

(1)

\[ p_{it} = \mu_i + \beta_p p_{i,t-1} + \chi_{i} \sum_{j} w_{ij,t-1} p_{j,t-1} + \delta_{it} \]  

(2)

\[ \delta_{it} = \rho \delta_{i,t-1} + \varphi \sum_{j} w_{ij,t-1} \delta_{j,t-1} + \epsilon_{it} \]  

(3)

\[ P_t = A + BP_{t-1} + CWP_{t-1} + D_t \]  

(4)

\[ d_{i,t}^{\text{demo}} = \left[ \left( demo_{ij}^{14} - demo_{ij}^{14} \right)^2 + \left( demo_{ij}^{15-64} - demo_{ij}^{15-64} \right)^2 \right]^{1/2} \]  

(5)

\[ w_{ij,t}^{G} = d_{ij}^{-1} \times \frac{n_jt}{\text{nod}_{it} + \text{nod}_{jt}} \]  

(6)

\[ w_{ij,t}^{H} = \frac{1}{d_{ij}^{\text{demo}}} \times \frac{n_jt}{\text{nod}_{it} + \text{nod}_{jt}} \]  

(7)

\[ F = \frac{RSS_2 - RSS_1}{RSS_1/\left[ NT - N(1+p) - p \right]} \]  

(8)

\[ (I - \Gamma L)P_t = D_t \]  

(9a)

\[ P_t = (I - \Gamma L)^{-1} D_t \]  

(9b)
Figure 13

<table>
<thead>
<tr>
<th></th>
<th>NSW</th>
<th>Vic</th>
<th>Qld</th>
<th>SA</th>
<th>WA</th>
<th>Tas</th>
<th>NT</th>
<th>ACT</th>
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<tbody>
<tr>
<td>Annual average</td>
<td>0.14</td>
<td>132.206</td>
<td>933.377</td>
<td>784.814</td>
<td>292.752</td>
<td>403.686</td>
<td>190.293</td>
<td>50.491</td>
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<tr>
<td>Demographic structures</td>
<td>15.64</td>
<td>4,386.700</td>
<td>3,389.574</td>
<td>2,525.699</td>
<td>1,911.389</td>
<td>1,318.731</td>
<td>51.159</td>
<td>139.364</td>
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<tr>
<td>in Australia regions</td>
<td>Over 64</td>
<td>847.951</td>
<td>627.845</td>
<td>631.022</td>
<td>217.392</td>
<td>211.965</td>
<td>65.343</td>
<td>7.906</td>
</tr>
</tbody>
</table>

Figure 14

<table>
<thead>
<tr>
<th></th>
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<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
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</thead>
<tbody>
<tr>
<td>Minimum</td>
<td>698</td>
<td>1.646</td>
<td>179</td>
<td>46</td>
<td>87</td>
<td>2.256</td>
<td>1.266</td>
<td>1.322</td>
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<tr>
<td>Maximum</td>
<td>2,037</td>
<td>4,924</td>
<td>627</td>
<td>289</td>
<td>365</td>
<td>7,465</td>
<td>4,127</td>
<td>4,650</td>
</tr>
<tr>
<td>Mean</td>
<td>1,387.75</td>
<td>2,713.32</td>
<td>351.42</td>
<td>122.76</td>
<td>222.36</td>
<td>5,128.24</td>
<td>2,741.47</td>
<td></td>
</tr>
</tbody>
</table>

Figure 15

**SpVAR model based on geographic distance**

<table>
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<tr>
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<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.003</td>
<td>0.009</td>
<td>-0.010</td>
<td>0.015</td>
<td>0.000</td>
<td>0.015</td>
<td>0.005</td>
<td>0.002</td>
</tr>
<tr>
<td>p-value</td>
<td>0.3443</td>
<td>0.0000</td>
<td>0.1107</td>
<td>0.0159</td>
<td>0.0241</td>
<td>0.8744</td>
<td>0.0000</td>
<td>0.0055</td>
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</tbody>
</table>

**Granger Causality of the geographic-spatial effects**

<table>
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<tr>
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<th>CAN</th>
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<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistics</td>
<td>21.759</td>
<td>6.008</td>
<td>1.565</td>
<td>0.005</td>
<td>13.516</td>
<td>1.813</td>
<td>0.158</td>
<td>57.965</td>
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</tbody>
</table>

**SpVAR model based on demographic distance**

<table>
<thead>
<tr>
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<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimates</td>
<td>0.0020</td>
<td>0.0062</td>
<td>0.0062</td>
<td>0.0147</td>
<td>0.0050</td>
<td>0.0191</td>
<td>0.0072</td>
<td>0.0072</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

**Granger Causality of the demographic-spatial effects**

<table>
<thead>
<tr>
<th></th>
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<th>CAN</th>
<th>DAR</th>
<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-statistics</td>
<td>3.493</td>
<td>1.93</td>
<td>0.85</td>
<td>0.01</td>
<td>3.90</td>
<td>1.08</td>
<td>0.57</td>
<td>3.46</td>
</tr>
</tbody>
</table>

Table III: Estimates of the SpVAR model and Granger Causality

Notes: Rejecting the null hypothesis at the critical level of 5% per cent; the numbers in the brackets indicate the p-values of the t-statistics.

Figure 16

**Comparison of the significance of spatial lags**

<table>
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<tr>
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<th>HOB</th>
<th>MEL</th>
<th>PER</th>
<th>SYD</th>
</tr>
</thead>
<tbody>
<tr>
<td>GSyVAR</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
<td>**</td>
</tr>
<tr>
<td>DSPyVAR</td>
<td>**</td>
<td>Nil</td>
<td>*</td>
<td>**</td>
<td>**</td>
<td>Nil</td>
<td>**</td>
<td>**</td>
</tr>
</tbody>
</table>

Notes: The estimated elasticity of the spatial lag is significantly different from 0 at *10 and **5 per cent, respectively; while Nil indicates that the elasticity is insignificant.
References

1. ABS (2005), Renovating the Established House Price Index, Cat no. 6417.0, Australian Bureau of Statistics, Canberra.


**Corresponding author**

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